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

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Paper prepared for the IARIW-CAPMAS Special Conference "Experiences and Challenges in Measuring Income, Wealth, Poverty and Inequality in the Middle East and North Africa"

Cairo, Egypt
November 23-25, 2015

Session 3: Poverty II
Monday, November 23, 2015
14:00-16:00

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Preliminary DRAFT – not to be cited

Abstract: 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 imputations (using household budgetary and labor force surveys), poverty projections (based on sector GDP, unemployment and inflation) and alternative consumption (full and comparable) models. Results are robust and conclusive: 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. Results also confirm emerging biases: imputations tend to overestimate the observed poverty incidence, while projections tend to underestimate it. These are all important results for Tunisia, the MENA region (with serious deficiencies in frequent, updated and accessible poverty statistics) and all post revolution contexts.

Key words: Poverty**, c**ross-survey imputation, projections, Tunisia, residuals-based imputation

JEL classification: 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.

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1. 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. 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. 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. 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 (World Bank 2012). 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 catch-22 situation 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 provides 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*, in French) 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 macro indicators such as growth and employment into the microdata (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 different imputation techniques, several projection scenarios and full and 'comparable' consumption model all in the same exercise, for the same country. Secondly, findings from this exercise help inform feasible approaches to project poverty in other countries in the Maghreb and Middle East regions where data frequency and access are typically seriously limited.

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 methods and data applied in this study. Section 3 describes data sources used while Section 4 presents and discusses the results obtained. Section 5 concludes.

2. Survey-to-survey Imputation Methodologies

2.1. 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).[1] 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

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

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 (for example, in the case of Tunisia, the definition of urban areas) 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 was then used to estimate an ordinary least square (OLS) household consumption model. In particular, the variables used as regressors in the model are the following:

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

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:

- **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;
- **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[2] 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). Household consumption was divided by the number of

[2] This final list is the result of an iterative process where additional variables (for example, referring to durable ownership and access to basic services) and alternative specifications of the variables (for example, regarding different groupings of educational attainment) were tried in search of a robust model maximizing statistical performance (that is, statistical representativeness of variables and explanatory power).

household members to obtain a per capita measure without accounting for any age or gender based scaling.[3]

Before applying the cross-survey imputation, it was confirmed that the common variables in both the ENBCV and ENPE (*Enquete Nationale sur la Population and l'Emploi,* in French) surveys were consistent in terms of their definitions. Sample design was also comparable, both consistent with the 2004 census. 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 noncommunal areas). Surveys used 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 can be then 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 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[4] 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.[5] 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

[3] 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.

[4] 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.

[5] 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.

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 an alternative to decile-based residual imputation. Their approach estimates a clustered random effects 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.[6] 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.

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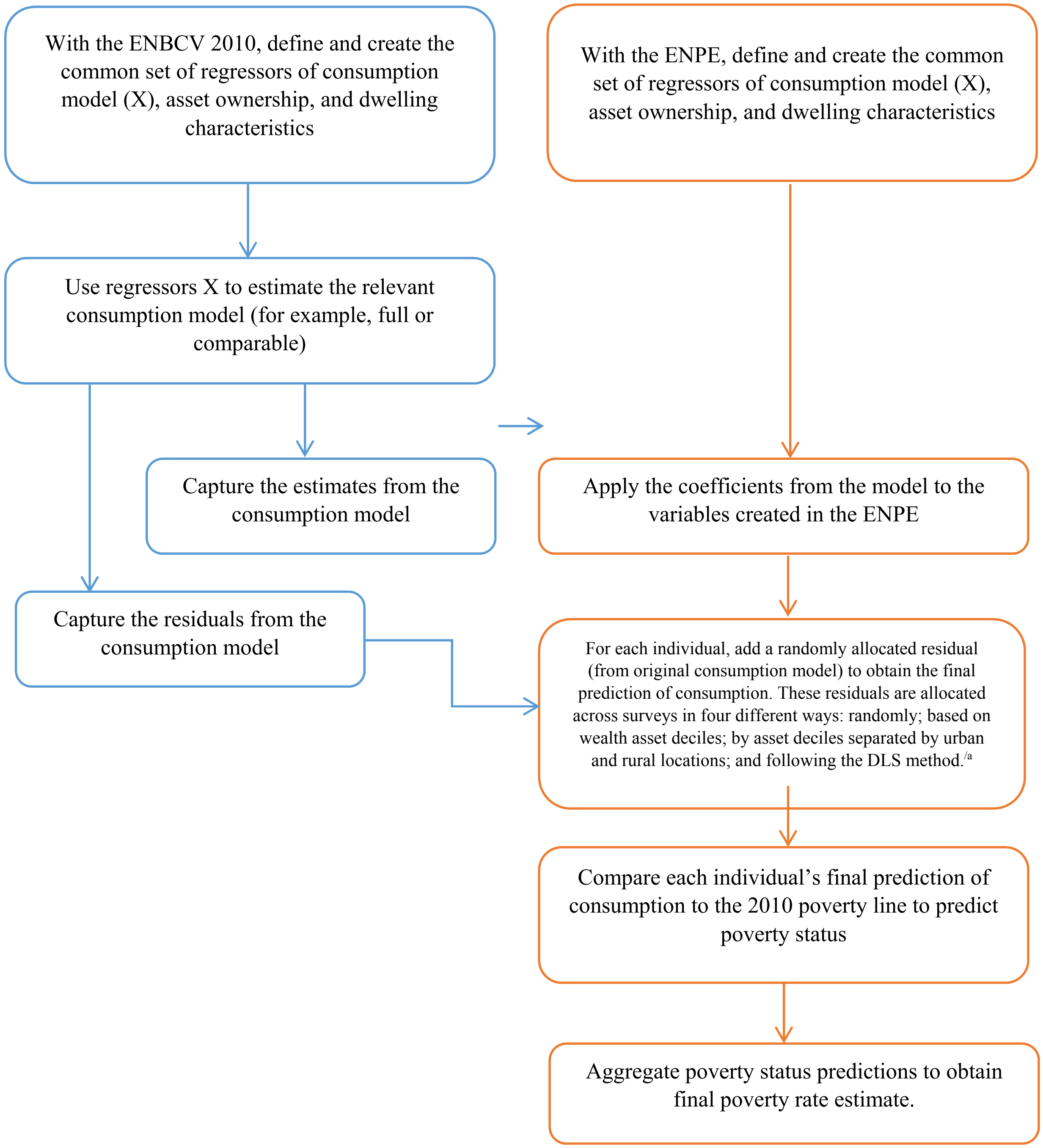
[6] Thus, from a set of commonly available assets in survey A and B, an index is calculated from factor decomposition analysis. From the resulting index, asset-based deciles are estimated. The distribution of residuals specific to each decile from survey A are then imputed into survey B according to constructed deciles based on the same asset-based index.

Figure 1. Major Phases of Survey-to-Survey Imputation



Source: Authors.

a. This step (along with subsequent steps) is typically boostrapped. DLS model refers to the Dang, Lanjouw, and Serajuddin (2014) cluster random effects model that includes asset ownership and dwelling characteristics.

2.2. Macro-based projections

Complementary to the analysis above, this technique includes developments relative to GDP growth, sector composition, unemployment, and CPI as inputs within a partial equilibrium model. Other determinants should be expected to affect poverty, however, but 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, for which skill changes are not 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.

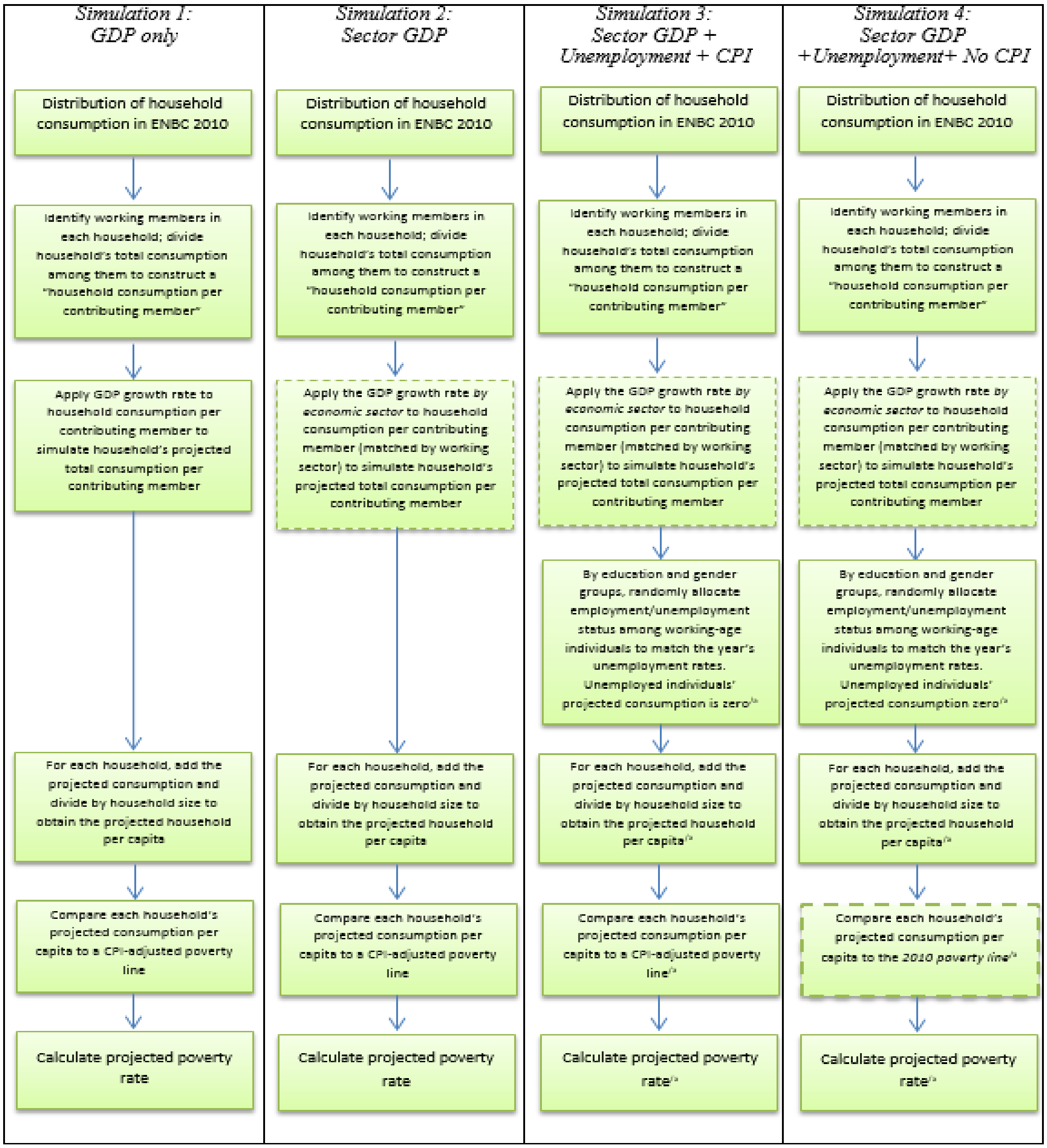
For those changes considered in the exercise—GDP, unemployment, and CPI—the proposed analysis imputes the observed changes in those variables in 2011 and 2012 back into the original distribution of households' consumption obtained from ENCBV 2010. So the distributions of consumption for 2011 and 2012 result from "shocking" the observed consumption distribution in 2010 with the changes in GDP, unemployment, and CPI 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.

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. Figure 2 presents the steps to construct this simulation scenario. 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 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, thus averaging out any heterogeneity that takes place across activities within each sector.

A third and more sophisticated projection, **simulation 3 (sector GDP, unemployment, and CPI)** explicitly includes the observed unemployment rates in 2011 and 2012. In Tunisia, official data on unemployment rates is disaggregated by educational level (that is, unable to read, individuals with primary education, secondary education, and tertiary education). Unfortunately, INS reports disaggregate unemployment rates for 2011 and 2012, but not for 2013 or 2014, for which projections in this scenario (and the rest for comparability) are limited to 2011 and 2012. Also, unemployment rates by education level could not be further disaggregated by age and gender, 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. Individuals who are assigned unemployment status in the simulation are imputed no consumption per capita from labor. Finally, annual poverty lines are adjusted for inflation using the national CPI to reflect the increasing cost of living. This simulation procedure is replicated 100 times and a projected poverty rate is obtained from the average poverty rate of all replications.

Figure 2. Diagrammatic Representation of Poverty Simulations



Source: Authors
a. These steps are bootstrapped 100 times account for the random allocation process of employment status.

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.

3. 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 2015 ENBCV is expected to be completely collected at the end of 2015, with results not released until mid-2016. 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.[7] 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,[8] 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 "survey A," that 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 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 preferred model for 2010, the "**full model**," and apply it only to ENPE 2012. A second option is to find a model that is truly comparable for all years, which implies simplifying the full model by not including number of children in the household and household head and

[7] 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).
[8] 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.

members' labor occupation. This model, "**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.

4. Results

4.1. Survey-to-survey-imputation projections in Tunisia

Table 1 presents the results of the consumption prediction model using data from ENBCV 2010 and OLS regression. Table 2 shows that the estimated consumption model provides a reasonable approximation to the observed poverty rates in 2010, something that is corroborated in Appendix 1 when comparing observed and predicted consumption distributions). Looking at the first column in Table 2, "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 17.6 percent when urban and rural populations are separated. Using models that are comparable for all years confirms the results obtained from the full model. Estimates under the comparable model suggest that the Dang, Lanjouw, and Serajuddin (2014) method of imputation, with a predicted rate of 16.1 percent, provides a closer estimate of poverty to the official rate in 2010.

Table 1. Consumption Model Used for Prediction

Dependent variable: Log(annual consumption per capita, *millimes*)	
Controls	
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)
Number of household members who are unemployed^{+}	-0.079***
	(0.008)
Number of household members who attended *primary*$^{+}$	0.061***
	(0.006)
Number of household members who attended *secondary*$^{+}$	0.125***
	(0.007)
Number 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

Source: Authors' calculations using the ENBCV 2010.
Notes: 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.

When consumption models from the ENBCV 2010 are imputed into the 2010 ENPE (Table 2, column “ENPE 2010 predicted”), results from the different methods all show lower poverty rates than the officially report. 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 2, 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 2. Survey-to-Survey Imputation of Consumption-Based Poverty in Tunisia

Consumption model	Survey-to-survey method	ENBCV 2010 (predicted)	ENPE 2009 (predicted)			ENPE 2010 (predicted)			ENPE 2012 (predicted)		
		National	National	Urban	Rural	National	Urban	Rural	National	Urban	Rural
Full model: Comparable to ENPE 2010, 2012	Random residuals	16.8 (0.34)				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	17.8 (0.34)				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	17.6 (0.33)				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	16.8 (0.34)	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	17.7 (0.36)	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	16.1 (0.41)	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)

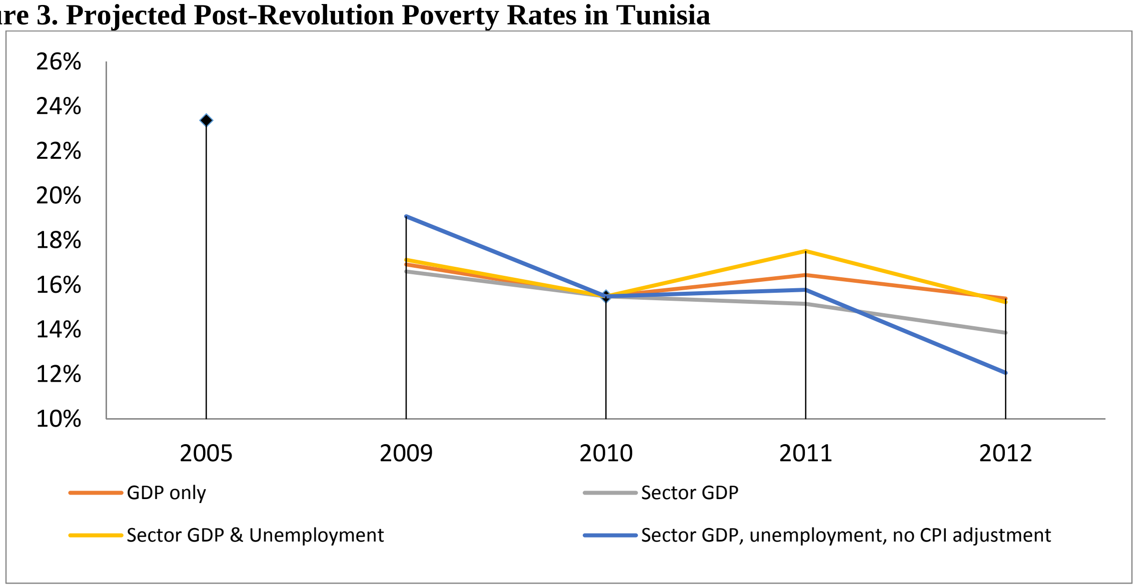
Source: Authors’ calculations using ENBCV and ENPE data.
Notes: Official poverty rate for 2010 was 15.5. The point estimates are obtained from the average estimates from 100 bootstrap simulations. The corresponding standard deviations are shown in parenthesis.

4.2. GDP-based projections

Table 3 and Figure 3 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.

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 3. 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.

Table 3. Projected Poverty Rates, 2011–12

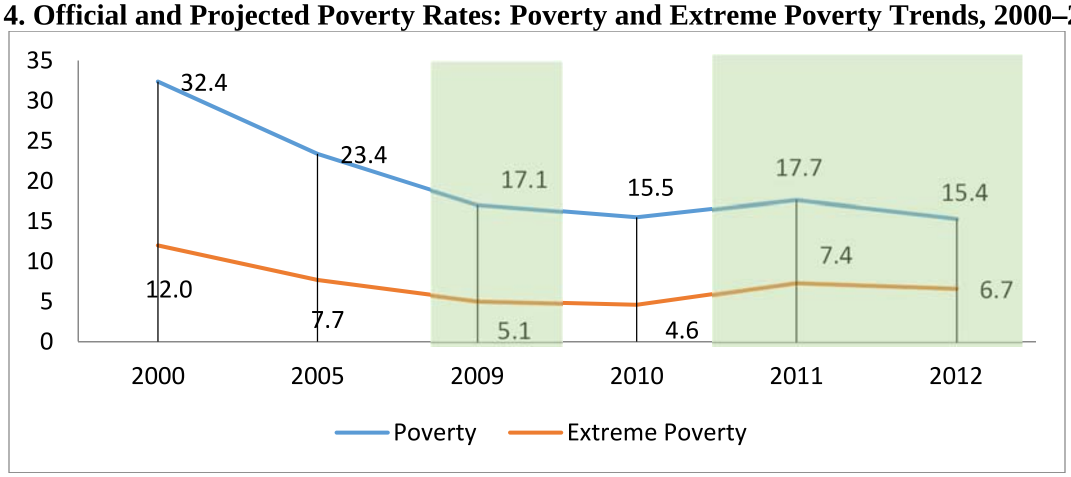
	Official (baseline, %)	Simulation 1: GDP only (%)	Simulation 2: Sector GDP (%)	Simulation 3: Sector GDP and unemployment (%)	Simulation 4: Sector GDP, unemployment, and no adjustment for CPI (%)
2005	23.4				
2009		16.9	16.6	17.1 (0.16)	19.1 (0.16)
2010	15.5	15.5	15.5	15.5	15.5
2011		16.4	15.2	17.5 (0.37)	15.8 (0.37)
2012		15.4	13.9	15.2 (0.26)	12.1 (0.25)

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

Figure 4 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, 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.

Figure 4. 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. Nonshadowed rates are official estimates.

5. 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. Thus, to explore how poverty 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.

Did poverty increase after the revolution? Estimates suggest that poverty rates increased in 2011 immediately after the revolution and decreased in 2012. The poverty impact of the revolution in 2011 oscillates between 0.9 and 2.2 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: 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 above the levels estimated in 2010, depending on the assumptions made to impute consumption across surveys.

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. 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 that are customized to the specific circumstances of Tunisia render robust results. 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 (see appendix 1). 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.

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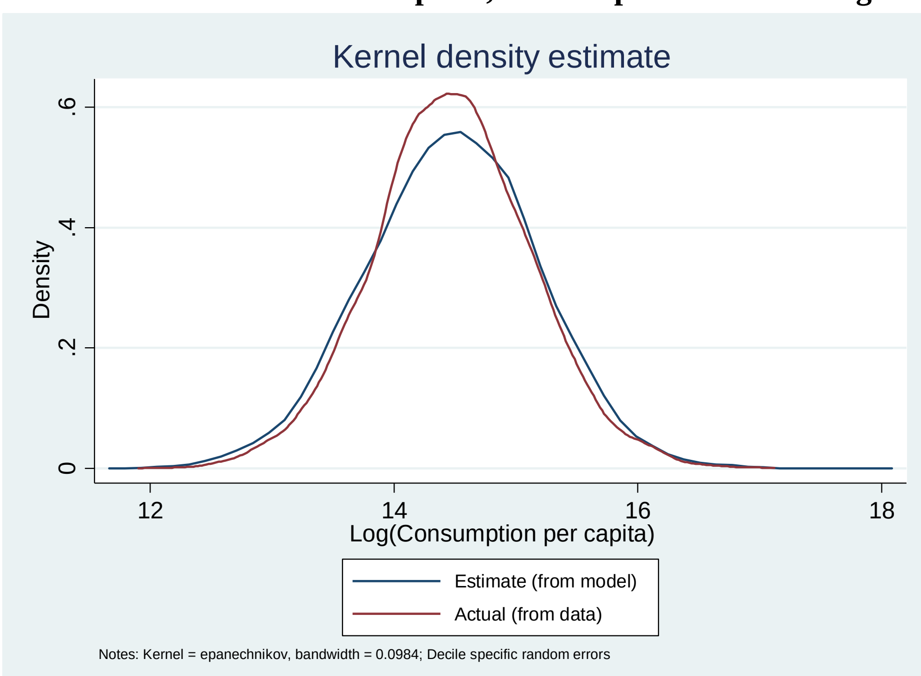
Appendix: Modeling Consumption in Tunisia

The projections that use survey-to-survey imputation methods relied on the definition and estimation of a prediction model for household consumption. Using data from the ENBCV 2010, an ordinary least squares (OLS) regression was estimated that used the logarithm of annual consumption per capita (in millimes) as the dependent variable. The regressors included a series of demographic, location, labor, access to services, and asset ownership variables that could be found consistently across the "source" survey (that is, ENBCV 2010), survey A, and the "destination" surveys, survey B (that is, 2009 and 2012 ENPEs).

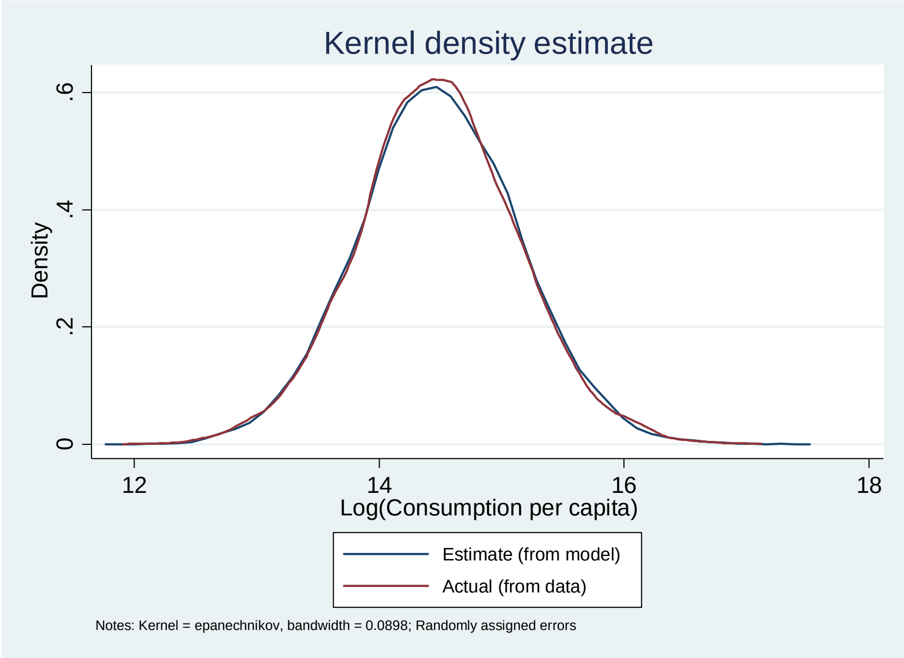
The results from the consumption model provide a good fit and reliable predictions of household consumption when paired with a process that would randomly assign an error term to the prediction of household consumption. Figures A.1 and A.2 show the superposition of the actual household consumption found in the ENBCV 2010 and the predictions based on the consumption model and two methods to randomly assigned error terms to complement the prediction: a decile-specific random assignment and a fully random assignment. The first process assigns an error term to the household consumption prediction that is randomly obtained from the same wealth decile to which the household belongs. Wealth deciles are based on an asset-based index obtained from a principal component analysis.

Figure A1. Actual and Estimated Consumption, Decile-Specific Error Assignment



Source: Authors' calculations using the ENBCV 2010.

Figure A2. Actual and Estimated Consumption, Random Error Assignment



Source: Authors' calculations using the ENBCV 2010.