Estimating Poverty and Inequality in the Absence of Consumption Data: An Application to the Middle East and North Africa

By[1]
Caroline Krafft[2]

Ragui Assaad[3]

Hanan Nazier[4]

Racha Ramadan[5]

Atiyeh Vahidmanesh[6]

and
Sami Zouari[7]

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Abstract
Measures of consumption and poverty are critical metrics of the wellbeing of individuals, their households, communities, and countries. Collecting data on consumption and poverty is challenging and costly, and therefore these measures are only infrequently available in survey data. In this paper, we demonstrate how information commonly available in household surveys can be used to impute consumption, even recovering the original variance, which is crucial for assessments of poverty and inequality. Our application adds consumption estimates to the publicly available Labor Market Panel Surveys for Egypt, Jordan, and Tunisia, which can act as a valuable resource for researchers interested in the intersection of inequality, poverty, and a host of labor market behaviors in the Middle East and North Africa.

Keywords: Inequality; consumption; poverty; Labor Market Panel Surveys

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[2] Corresponding author. Assistant Professor of Economics, St. Catherine University. ORCID: 0000-0001-6906-9418. E-mail: cgkrafft@stkate.edu
[3] Professor, Humphrey School of Public Affairs, University of Minnesota. E-mail: assaad@umn.edu
[4] Assistant Professor, Faculty of Economics and Political Science, Cairo University. E-mail: hanan.nazier@feps.edu.eg
[5] Assistant Professor, Faculty of Economics and Political Science, Cairo University. E-mail: racha.ramadan@feps.edu.eg
[6] PhD Candidate of Economics, Virginia Tech, Email: atieh@vt.edu
[7] Instructor of Economics, Department of Economics, University of Sfax. E-mail: sami.zouari@isgis.rnu.tn

1 Introduction

How can policymakers and researchers quantify the wellbeing of individuals, households, communities, and countries? Two of the most common measures used in quantifying economic wellbeing are consumption levels, how much a household spends each year on goods and services, and poverty rates, the prevalence of acute shortfalls in consumption. In addition to concerns with average consumption and poverty rates, issues of inequality have been increasingly at the forefront of development, particularly in the Middle East and North Africa (MENA) region. Calls for greater social justice were an important part of the recent Arab Spring uprisings in the region, and reflected a strong sense of inequality (Diwan, 2013; Richards, Waterbury, Cammett, & Diwan, 2014; Verme, Milanovic, Al-Shawarby, et al., 2014). Improving average wellbeing, reducing poverty, and tackling inequality requires not only information on the distribution of consumption and poverty, but also information on how consumption, poverty, and inequality are related to a host of human and economic development phenomena.

In the developing world, Household Income, Expenditure, and Consumption Surveys (HIECSs) typically quantify the distribution of consumption and poverty at regular intervals. The goal of these surveys is to collect accurate and detailed consumption data, a challenging and expensive task. These surveys are not performed frequently. For instance, Tunisia fields its consumption survey every five years. The surveys are also limited in their geographic scope. While they can provide representative statistics on national and often regional income and poverty rates, only sampled areas have these estimates, precluding national efforts to provide localized targeting of services. Additionally, while HIECSs also collect supplemental data on individuals' and households' characteristics, such as individuals' education, their place of residence, and their labor market status, these supplemental data are limited. For instance, while inequality in consumption can be calculated with HIECSs, intergenerational transmission of poverty and inequality cannot typically be examined, because data are not collected on the characteristics of individuals' parents. Thus, while the HIECSs have information crucial to assessing wellbeing, poverty, and inequality, it is difficult to link these critical sources to issues of economic and human development.

Recent econometric advances make it possible to overcome the limitations of the HIECSs by modeling consumption in HIECSs and using such models to predict consumption, including recovering the original variance of consumption. Such innovations allow for mapping consumption from survey-to-census data to provide highly localized estimates of poverty, consumption, and inequality for entire nations (Elbers, Lanjouw, & Lanjouw, 2003; Hentschel, Lanjouw, Lanjouw, & Poggi, 2000). More frequent estimates can also be provided, for instance with quarterly labor force surveys (Dang, Lanjouw, & Serajuddin, 2014). Particularly important for understanding the nature of poverty and inequality, these techniques also allow mapping consumption data on to richer data sources capturing more detail on human development and labor market phenomena—but not detailed consumption data (Ferreira, Gignoux, & Aran, 2011).

This paper illustrates the recent econometric advances by predicting per capita consumption and thence poverty and inequality from HIECSs onto a series of labor market panel surveys (LMPSs) in the MENA region. The LMPSs have been vital resources for researchers investigating a host of human and economic development issues, and have been especially critical as the workhorse of labor market analyses in the region. This paper imputes estimates of consumption, poverty, and inequality in the LMPSs for Egypt (1998, 2006, and 2012), Jordan (2010) and Tunisia (2014) based on proximate rounds of HIECSs. The data are compared to the HIECS along a number of dimensions, as well as to other data sources, such as wages and assets, to demonstrate their consistency. The predicted consumption values are publicly available with the LMPSs for researchers to use in further investigations of consumption, inequality, poverty, human development, and economic development.

2 Methods and Applications for Imputing Consumption

2.1 Poverty Mapping: Origins and Applications

The methods for imputing consumption to generate poverty and inequality statistics were primarily pioneered by the World Bank with the goal of improving targeting of anti-poverty programs. While developing countries had sample-based surveys of consumption, expenditure, and income, such estimates were not collected by censuses. Thus, it was difficult to know where the poor lived, where poverty rates were high, and where to target anti-poverty programs and spending. Consumption imputation from surveys to censuses was thus a critical tool for identifying the poor and targeting high-poverty localities with interventions on a disaggregated level (Bedi, Coudouel, & Simler, 2007; Tarozzi & Deaton, 2009). These techniques yielded fine-grained "poverty maps" and hence the technique of imputing consumption to local levels was often referred to as poverty mapping. These techniques were implemented in Hentschel et al. (2000) and then the methodology further developed and detailed in Elbers, Lanjouw, and Lanjouw (2003).

The poverty map technique imputing income onto censuses has since been applied to a large number of developing countries in order to provide geographically disaggregated estimates of poverty and inequality (Alderman, Babita, Demombynes, Makhatha, & Özler, 2003; Bedi, Coudouel, & Simler, 2007; Demombynes, Elbers, Lanjouw, et al., 2002; Elbers, Fujii, Lanjouw, Özler, & Yip, 2007). Studies have then used local poverty and inequality information to investigate their links with issues ranging from the effect of inequality on malnutrition (Larrea & Kawachi, 2005) to crime (Demombynes & Ozler, 2005). Dimensions other than geography have been used for imputation, for instance to assess poverty and inequality among ethnic groups

(Agnosti, Brown, & Roman, 2010). As well as survey-to-census imputation, there has been a recent trend of survey-to-survey imputation, mapping from surveys with consumption data to those with other outcomes of interest, unavailable in consumption surveys (Dabalen, Graham, Himelein, & Mungai, 2014; Dang, Lanjouw, & Serajuddin, 2014; Elbers, Lanjouw, Lanjouw, & Leite, 2004; Ferreira, Gignoux, & Aran, 2011). This paper follows in the tradition of survey-to-survey imputation.

2.2 Methods

Our goal is to use data from a country's HIECS survey to predict consumption onto a contemporaneous LMPS, modeling and recovering the original variance in order to ensure representative poverty and inequality estimates. Specifically, we rely on the methods of Elbers, Lanjouw and Lanjouw (2003) to impute per capita expenditure as our measure of wellbeing and calculate inequality and poverty based on this expenditure. Here we describe their methods as they pertain to our case of HIECS to LMPS imputation. Denote per capita household expenditure in household *h* residing in cluster *c*, as measured in a HIECS, as y_{ch}. The first step of imputation is to estimate a model of expenditure in a HIECS sample based on covariates, X_{ch},[8] that are available in both the HIECS and corresponding LMPS:

$$\ln(y_{ch}) = \beta X_{ch} + u_{ch} \quad (1)$$

Where β are the *k* parameters to be estimated and u_{ch} is a vector of disturbances. Because localities (clusters) are likely to have correlated disturbances, the u_{ch} disturbances can be decomposed into a cluster effect, η_c, and an idiosyncratic error, ε_{ch}, as (Elbers, Lanjouw, & Lanjouw, 2003):

$$u_{ch} = \eta_c + \varepsilon_{ch} \quad (2)$$

[8] Since our goal is prediction, not interpreting coefficients, included X_{ch} variables may be endogenous without yielding estimation problems.

The two components of the error term, η_c and ε_{ch} are assumed to be, first, independent of each other, and second, uncorrelated with covariates X_{ch}.

After β is estimated from equation (1), the estimated residuals, $\hat{u}_{ch}$, can be generated. Since there are typically only a small number of clusters sampled within a survey, the variance of the cluster effect cannot be modeled with heteroscedasticity, but the idiosyncratic element can be allowed heteroscedasticity of the form $\sigma^2_{\varepsilon,ch}$ by decomposing the residuals as follows (Elbers, Lanjouw, & Lanjouw, 2003):

$$\hat{u}_{ch} = \hat{u}_{c.} + (\hat{u}_{ch} - \hat{u}_{c.}) = \hat{\eta}_c + e_{ch} \tag{3}$$

with $\hat{u}_{c.}$ denoting the average over cluster c. Here, the average values of $\hat{u}_{ch}$ residuals within a cluster generate the cluster fixed effect and the idiosyncratic error is then the remainder of the $\hat{u}_{ch}$ term.

This decomposition allows for a modeled estimate of the variance of ε_{ch} assuming a logistic functional form (Elbers, Lanjouw, & Lanjouw, 2003):

$$\sigma^2(z_{ch}, \alpha, A, B) = \left[\frac{Ae^{z_{ch}\alpha} + B}{1 + e^{z_{ch}\alpha}}\right] \tag{4}$$

with A and B acting as upper and lower bounds that can be estimated along with parameters α on z_{ch}, which are functions of the covariates X_{ch}.

Simulations are then required to generate the residuals η_c and ε_{ch}. Cluster residuals are the $\hat{\eta}_c$ from (3) and the standardized household residuals, e^*_{ch}, can be generated as (Elbers, Lanjouw, & Lanjouw, 2003):

$$e^*_{ch} = \frac{e_{ch}}{\hat{\sigma}_{\varepsilon,ch}} - \left[\frac{1}{H}\Sigma_{ch}\frac{e_{ch}}{\hat{\sigma}_{\varepsilon,ch}}\right] \tag{5}$$

Where H denotes the number of observations. These can be sampled from directly for simulations to avoid functional form assumptions or generated from an assumed parametric distribution (Tarozzi & Deaton, 2009).

With these elements, it is now possible to generate estimates of per capita expenditure for r simulations (Elbers, Lanjouw, & Lanjouw, 2003; Tarozzi & Deaton, 2009). Parameters, β, are estimated for the consumption model using the HIECS as are the required parameters in the variance of the heteroscedastic error model in (4). Clusters in the LMPSs are then assigned cluster errors based on draws from the observed distribution. Idiosyncratic errors then are generated in normalized terms from either the observed distribution or a parametric distribution. Heteroscedasticity is introduced into the errors using the model in (4). Lastly, simulated imputed values of $\ln(y_{ch}^{r})$ are generated for the LMPSs as (Tarozzi & Deaton, 2009):

$$\ln(y_{ch}^{r}) = \hat{\beta}^{r} X_{ch} + \hat{\eta}_{c}^{r} + e_{ch}^{r} \tag{6}$$

With the imputed values of consumption, it is possible to assess a variety of different poverty and inequality statistics, deriving the mean and standard error by bootstrapping the simulations.[9] We compare these statistics across the HIECS and the LMPSs.

Based on the poverty lines,[10] we calculate both the poverty rate (also called the headcount ratio, capturing the proportion below the poverty line), and the average poverty gap, that is the average distance between the poverty line and consumption for the poor. We also assess inequality in imputed consumption using seven different measures. The first two are percentile ratios, specifically the ratio of consumption at the 90th percentile to that of consumption at the 10th percentile (p90/p10) and the ratio of consumption at the 75th percentile to that of consumption in the 25th percentile (p75/p25). These estimates assess inequality at specific points in the distribution. Our remaining estimates calculate inequality over the entire distribution, the Gini coefficient and the four (-1, 0, 1, 2) general entropy measures.[11] All our estimates rely on

[9] Specifically, we bootstrap not only over 100 repetitions of the imputed consumption, but also we redraw the LMPS sample five times for each r (and different redraws as we move through the different imputed consumptions) in order to incorporate the variability from using a second survey rather than the census. This yields 500 repetitions of the bootstrap, which are redrawn accounting for the sampling structure (PSUs) of the various surveys.
[10] See Krafft et al. (2017) for data on the poverty lines.
[11] See Krafft et al. (2017) for the underlying equations for these inequality indices.

poverty mapping implemented in PovMap2, a World Bank software package, and calculations of inequality and poverty are further implemented using STATA. Additionally, all our 100 imputed values for each survey are publicly available through the Economic Research Forum (ERF)'s Open Access Microdata Initiative (OAMDI) as a supplement to the publicly available LMPSs, along with the poverty lines used in our estimates.

3 Data

Recall that we are implementing five different consumption imputations over pairs of relatively similar HIECS and LMPSs. Here we first describe the general features of the HIECS and the LMPSs, and then discuss specifically each pair of surveys used in imputation. All of the HIECS surveys collect detailed information on consumption and expenditure, allowing us to calculate our dependent variable for the imputations, annual expenditure per capita. Additionally, all have detailed demographic information on household members, their assets, and housing, which act as the key X variables for mapping across surveys. The LMPSs are designed, first and foremost, to capture much more detailed information on labor market statuses and histories than is typically available in countries' annual or quarterly labor force surveys. Additionally, they collect detailed information on a host of behaviors related to labor markets and human development, including housing, assets, parental background, education experiences and outcomes, mobility and migration, income and transfers, time use, marriage and fertility, women's empowerment, savings and borrowing, household enterprises, and agriculture.

Both sets of surveys include information on household size, the age, gender, education, and labor market status of household members, their place of residence (urban/rural, governorate), their housing conditions (sanitation, water), and their durable assets (for instance, owning a car or air conditioner). In order to create models with the greatest possible predictive power, although we necessarily limited our models to X variables available in two of a pair of surveys, we did not limit the set of variables to be identical across all five pairs of surveys. Particularly in regards to assets, the different surveys collected different information on ownership across countries and over time. Across the surveys, we identify as many characteristics as possible that can serve as predictors of consumption (*X* variables). Because the original data are sometimes collected with slightly different questions, definitions, and categories, some harmonization work was necessary.[12]

The HIECSs and LMPSs sample individuals and households in a similar fashion. Clusters (enumeration areas, or primary sampling units (PSUs)) are selected within each country (and often within strata, such as urban/rural or by governorate), and then a number of households selected within each cluster. All individuals within the selected households are then surveyed. Sample weights are used with the surveys to generate representative statistics.

We now describe each pair of surveys in turn. The earliest survey we have is from 1998 in Egypt, the Egypt Labor Market Survey (ELMS), the first (base) round of the ELMPS. It sampled 4,816 households and 23,997 individuals (Assaad & Barsoum, 2000; OAMDI, 2013a). The corresponding HIECS survey is from 1999/2000. The original survey covered approximately 48,000 households, and we use here the 50% sample made available publicly through ERF, covering 23,975 households and 113,267 individuals (OAMDI, 2014a).[13]

The second pair of surveys covering Egypt consists of the 2006 round of the ELMPS and the 2004/2005 HIECS. The 2006 ELMPS followed 1998 round households and split households, as well as adding a refresher sample, for a total of 8,351 households and 37,140 individuals (Assaad & Roushdy, 2009; Barsoum, 2009; OAMDI, 2013b). The 2004/2005 HIECS covered

[12] The degree to which the surveys find similar characteristics, given the harmonization, can be assessed with the summary tables in the supplemental Appendix. In general, the differences are small.
[13] In all of the analyses of Egypt, because the ELMPSs exclude the Frontier governorates, we likewise exclude these areas from the samples of the HIECS in implementing the poverty mapping.

approximately 48,000 households, and we use here the 50% sample made available publicly through ERF, covering 23,548 households and 103,609 individuals (OAMDI, 2014b).

The third pair of surveys for Egypt consists of the 2012 round of the ELMPS and the 2012/13 HIECS. The 2012 ELMPS followed previous round households, split households, and added a refresher sample for a total of 12,060 households and 49,186 individuals (Assaad & Krafft, 2013; OAMDI, 2013c). The HIECS 2012/13 publicly available sample from ERF covers 50% of the original survey data, specifically 7,528 households and 32,732 individuals (OAMDI, 2014c).

The two surveys for Jordan are the 2010 Jordan Labor Market Panel Survey (JLMPS) and the 2010 Household Expenditure and Income Survey (HEIS). The JLMPS 2010 survey is the base round of a panel survey of Jordan, which sampled 5,102 households and 25,969 individuals (Assaad, 2014; OAMDI, 2014d). The 2010 HEIS covered 2,845 households and 15,472 individuals (OAMDI, 2014e).

In Tunisia, the two surveys used are the 2014 Tunisian Labor Market Panel Survey (TLMPS) and the 2010 National Survey on Household Budget, Consumption, and Standard of Living (EBCNV). The 2014 TLMPS sampled 4,521 households and 16,430 individuals, but because of missing data problems we include only 2,525 households in our consumption mapping (Assaad, Ghazouani, Krafft, & Rolando, 2016; OAMDI, 2016). The 2010 EBCNV sampled 11,281 households and 50,371 individuals (OAMDI, 2014f).

4 Results

The results of the poverty mapping are first presented in terms of the models for predicting consumption, followed by comparisons of distributions of consumption, poverty rates and inequality across the different pairs of surveys.

4.1 Models of consumption

Recall that the first step of creating the consumption model is estimating the relationship between the covariates, *X*, and annual per capita consumption (ln *y*) as per equation (1) using the HIECS for each country. The models for all five of our HIECS surveys are presented in the supplemental Appendix. The most critical aspect of the models is how well they predict consumption, as that will determine how accurate the poverty predictions are for the LMPSs. The adjusted R-squared values for all the models of log consumption per capita are all quite good, between 65% to 70%. In Egypt for 1999 the adjusted R-squared is 69.6%, Egypt 2004/5 68.6%, Egypt 2012/13 65.3%, Jordan 66.2%, and Tunisia 67.8%. While the models can explain two-thirds of the variation in log consumption per capita, one-third is not explained and therefore the relationship between unobserved characteristics and per capita consumption in the LMPSs is not represented. The characteristics that predict per capita consumption vary across countries and rounds, but the patterns overall are quite consistent with expectations. The household effect models, attempting to model the variance, do not show clear or consistent patterns of predictors. They have low adjusted R-squareds, 3.8% in Egypt 1999, 3.6% in Egypt 2004/5, 2.7% in Egypt 2012/13, and 1.6% in Jordan and Tunisia.

4.2 Comparing distributions of consumption

The models of consumption generate fairly similar distributions of consumption across the paired surveys. The reproduction of a similar distribution, both overall and across common characteristics, is the purpose of using these specific prediction methods. Thus, similar results are expected, but important to verify. Figure 1 shows, for pairs of surveys, the observed distribution of annual per capita consumption (kernel densities) for individuals in each HIECS and the mapped distribution for the corresponding LMPS. In Egypt, the HIECS shows a more peaked distribution across surveys than the LMPS. This difference in distributions, as shown below, leads to some differences in poverty estimates and inequality. The Jordan observed values in the HIECS likewise show a more peaked observed value while the predictions are slightly more dispersed for the JLMPS. However, the distributions are very similar for low values of the consumption with the differences being largely in terms of the JLMPS having more individuals with higher consumption. The Tunisia distributions are very similar in shape, but the 2014 TLMPS predicted values appear essentially shifted to higher values than the observed 2010 values. Given that four years passed between the surveys, this shift likely represents real changes in consumption.

Table 1 (for Egypt), Table 2 (for Jordan), and Table 3 (for Tunisia) present mean annual expenditure per capita both overall and by characteristics across pairs of surveys. Although the overall distribution is a bit different in Egypt, as expected, mean values are similar for all three rounds. Total values are also close in Jordan and in both Egypt and Jordan the values for each survey fall within the other's 95% confidence interval. In Tunisia the mean is substantially higher (3838 international PPP dollars (I$)) in 2014 compared to 2010 (I$3581), as expected given the passage of time. We can only compare across characteristics common to both surveys, which are the same characteristics used in the predictions. Thus, we would expect, due to the predictive method, similar results by characteristics so long as characteristics themselves are similar across surveys. There are only modest differences by the sex of the household head, but more variation when looking at differences by region; some are predicted more accurately than others. The expected head education and consumption per capita gradient is apparent. Lower levels of education show more consistency than the (rarer and more elite) higher levels. Age groups show the expected gradient, with younger children living in household with less expenditure per capita. Predictions by age group are quite similar to observed values. Differences by employment status are generally small, although self-employment in Tunisia and Jordan is not well matched.

Although wages are only one source of income or funds for consumption, it is informative to examine the relationship between log annual wages and log annual expenditure per capita in Figure 2. As both variables are logs, the relationship presented is an elasticity. Note that these data are only for wage workers, a select share of individuals. The relationship between log wage work and log consumption appears strongest in 1998 for Egypt, a correlation of 0.323, which falls to 0.250 in 2006 and 0.186 in 2012. In Jordan the correlation is 0.208 and in Tunisia 0.291. These relationships are not so much reflective of the explanatory power of the models (although that does fall slightly in Egypt over time) as the share of wages in income and consumption.

Another measure that ought to be related to consumption is wealth; in the LMPSs there are wealth quintiles based on a factor analysis of assets. Many of these same assets are inputs in the consumption regression. The two distributions are clearly related, although unsurprisingly not identical, as shown in Figure 3. There is substantial overlap particularly at the bottom and top of the distribution; In Egypt in 1998 45% of those in the poorest wealth quintile are in the poorest consumption quintile. Likewise in Egypt in 2012, 48% of the richest wealth quintile is identified as in the richest consumption quintile. Very few of the richest, in terms of assets, are identified as poor in terms of consumption, and likewise very few of those poor in terms of assets are identified as having high consumption. Distinctions in the middle asset quintiles are less closely related; in Egypt in 1998, 24% of those in the middle wealth quintile are in the 2nd, 3rd, and 4th consumption quintiles each (72% in total), with 13% in the richest consumption quintile and 15% in the poorest. Overall, assets and consumption per capita are clearly related, albeit somewhat different measures of wellbeing.

4.3 Comparing Distributions of Inequality

One of the key uses of this new database is examining inequality and its relationship with other characteristics that are not typically captured in consumption surveys, such as parental background (Assaad, Krafft, Roemer, & Salehi-Isfahani, 2016, 2017). Table 4 shows key inequality measures (and poverty measures, which are discussed below) across the different surveys. For the general entropy measure, the GE(1) and GE(2) measures place increasing emphasis on inequality at the higher end of the distribution compared to GE(-1) and GE(0). Therefore comparing across these measures, and also the P90/P10 versus P75/P25 measures, suggests how similar the distributions are when emphasizing on different segments of the distribution. Given that the goal of the prediction method used was to replicate the original consumption distribution, we would also expect these inequality and poverty measures to be similar across the original and predicted measures. The GE(0) and GE(-1) measures do tend to be quite similar. The mapped statistics typically fall within the 95% confidence intervals of the observed statistics (and vice versa), indicating that observed differences are statistically insignificant and may simply be due to sampling variability across the different surveys.

The data in Egypt show a clear decline in inequality in 2012 compared to previous years, and lower inequality than in Jordan or Tunisia. The TLMPS GE(0) of 0.191 is lower than that of the EBCNV, 0.251, and falls outside the confidence interval, likely due to changes over the intervening four years. The GE(1) and GE(2) measures show higher inequality in the HIECS than LMPS in all three countries, although this gap diminishes over time in Egypt and usually statistics are within 95% confidence intervals. Higher GE(1) and GE(2) differences are likely driven by outliers at the very high end of the distribution, as the LMPS actually have slightly higher P90/P10 and P75/P25 ratios than the HIECS everywhere except Tunisia. These statistics are relatively close across surveys, for instance a P75/P25 ratio of 2.285 in Jordan 2010 with the

LMPS and 2.150 with the HIECS, and results are usually statistically indistinguishable. The Gini measures of inequality are akin to the GE(0) measures in being very similar (at most 0.012 apart and not significantly different) in all pairs except Tunisia, where the LMPS measures a Gini of 0.337 and the EBCNV 0.385. As with the GE(0) measures, using the Gini there is a clear decline in inequality in Egypt and lower inequality in 2012 than for Jordan in 2010 or Tunisia in 2014.

An important use of these data is analyses of disparities within and across groups. Appendix Tables A1 (for Egypt), A2 (for Jordan), and A3 (for Tunisia) show GE(0) measures by characteristics. These can be thought of as within-group inequality where the group has in common a particular characteristic. Since the household models are predicting on common characteristics, it is unsurprising to see comparable distributions within groups as we did across groups. After considering the small differences in the overall inequality, Egypt shows some differences in the overall inequality in each region when comparing survey pairs, although the relative ranking (for instance, rural areas being more homogeneous and urban heterogeneous) persists. Likewise the mapped consumption shows the same declining gradient in inequality within groups by education in both survey pairs. Inequality within different labor market segments is generally similar in Egypt and Tunisia, but less so in Jordan.

4.4 Comparing Distributions of Poverty

As well as examining inequality, the predicted consumption data can be used to study poverty. The poverty rates from the year of the HIECS are used for the LMPSs. The head count ratio, in Table 4, is the proportion of individuals who fall below the poverty line. The average poverty gap is the average normalized distance between the poverty line and consumption for the poor. In Egypt in 1998 the ELMPS estimated poverty rate is higher (24.1%) in 1998 than in the 1999 HIECS (18.2%). Likewise the 2006 ELMPS poverty rate of 22.9% is higher than the rate of 19.8% for the 2004/5 HIECS. The opposite case pertains in 2012, when the poverty rate from the

ELMPS of 26.8% is slightly lower than from the HIECS (28.2%). In Jordan, the poverty rates are identical for 2010, 15.0% from both sources. In Tunisia, the EBCNV poverty rate of 2010 was 14.2% and the ELMPS rate in 2014 was substantially lower, 7.6%, likely due (at least in part) to the passage of time. Aside from Egypt in 1998/1999 and Tunisia, the poverty rates fall within each others' 95% confidence intervals, as we would expect if successfully predicting distributions across the surveys.

Understanding how poverty relates to measures of human and economic development is a critical application for these data. Appendix Tables A4 (for Egypt), A5 (for Jordan) and A6 (for Tunisia) show how the poverty rate varies by characteristic. The overall rates are, of course, in line with Table 4 and thus much of the variation across survey pairs follows this as well. In terms of the poverty gap, the average normalized distance below the poverty line of the poor (Table 4), this measure is 0.059 in the ELMPS 1998 compared to 0.033 in the 1999 HIECS, following a similar pattern to the differences in poverty rates. Likewise the 2006 ELMPS has a poverty gap of 0.058, compared to 0.037 for the 2004/5 HIECS. The average poverty gap measure is much closer in 2012, 0.064 with the ELMPS and 0.058 with the HIECS. The gap is fairly close in Jordan as well, 0.036 with the JLMPS and 0.029 with the HIECS. As with the poverty rates and likely due to the gap of four years, Tunisia has a larger difference in the average poverty gap, 0.036 in 2010 with the EBCNV and 0.017 in 2014 with the TLMPS. The poverty gaps are significantly different in most cases, based on the 95% confidence intervals.

4.5 Application: Dynamics and Determinants of Poverty

There are myriad applications of the consumption and poverty measures. In this section we demonstrate two potential applications. First, exploiting the panel nature of the ELMPS data, we descriptively investigate poverty dynamics. Second, we model poverty determinants across countries and rounds, using variables uniquely available in the LMPSs on family background.

Figure 4 illustrates the dynamics of poverty over three periods: (1) from 1998 to 2006, (2) from 2006 to 2012, and (3) across 1998, 2006, and 2012. The graphs condition on poverty status in the base period of the pair or set. From 1998 to 2006, 14% of the non-poor became poor, while 55% of the poor exited poverty and became non-poor. From 2006 to 2012, 19% of the non-poor became poor, while half (50%) of the poor exited poverty and became non-poor. Both more individuals falling in to poverty and greater persistence in poverty for the poor occurred in the latter period. Some caution is required in that imputed consumption inherently has measurement error and thus dynamics are inherently over-estimated. The transitions out of poverty are more dynamic than estimates from a 1997-1999 panel (Haddad & Ahmed, 2003), but cover a longer period as well.

Examining the three-period dynamics, we can see patterns of chronic, transitory, and recurrent poverty as well as more persistent exit from poverty. While 33% of those who were poor in 1998 were non-poor in both subsequent periods, at the same time 25% were chronically poor (poor in both 2006 and 2012). Around a fifth (20%) of the poor in 1998 exited poverty in 2006 but fell back into poverty by 2012. Likewise, a fifth (22%) of those who were poor in 1998 persisted in poverty in 2006 but exited in 2012. Among those who were non-poor in 1998, 7% then fell into persistent poverty, 8% entered poverty in 2006 but exited again in 2012, 11% remained non-poor in 2006 but then fell into poverty in 2012, and the remaining three-quarters (75%) remained non-poor throughout the period. These dynamics suggest that while there is a substantial population that remains outside of poverty, a large share of Egyptians experience poverty over their life course.

Table 5 presents the determinants of poverty for individuals in the LMPS, in terms of logit model marginal effects. Determinants in the model include the individual's sex, region, education level, age group, labor market status, mother's education, father's education, father's employment status and occupation (when the individual was age 15), and whether their mother worked (also when the individual was age 15). Information on parental characteristics and thus socio-economic mobility is not available in the HIECS and is one of the unique features of the LMPSs. Across countries and rounds, there are not significant differences by sex in the probability of poverty (it must be kept in mind that underlying the poverty measures are household level estimates of per capita consumption). There are significant differences in the probability of poverty by own education; the gradient notably weakened for lower levels of education over time in Egypt, but a similar gap between illiterates and university graduates remained (around a 18.5 percentage point decrease in poverty for university graduates versus illiterates in Egypt in 2012). The education-poverty relationship was weaker in Tunisia, as were most relationships, suggesting poverty is a problem across backgrounds in Tunisia. Regional differences were substantial and significant in Tunisia, even more so in Egypt, but not significant in Jordan.

Compared to the reference of children 6-11, no country had significant differences for those 12-14, but significant differences occurred at older ages. Poverty decreased steadily with age up until at least 60-64, but in some cases was not quite as reduced for those 65 and older. Differences by labor market status were rare. In Egypt 2012 and Jordan 2010, those who were wage workers in private agriculture were significantly more likely to be poor. Employers outside of agriculture were less likely to be poor across countries, significantly so, with the exception of Tunisia 2014.

Having a mother who could read and write did not significantly reduce poverty, but there were significant effects of basic in Egypt in 1998, which dissipated subsequently, and for secondary and higher education across Egypt and Jordan. Marginal effects were similar in magnitude to own education in Egypt (17.6 percentage points to 14.2 percentage points over time in Egypt) but smaller in Jordan; since own education and mother's education are linked these effects will compound each other. Father's education also had significant effects, albeit generally smaller in magnitude, potentially because male education expanded earlier, mother's education is a better marker of class, or mother's education matters (causally) more for child outcomes. There were few significant differences by father's employment status and occupation. Although not all dimensions of parental background were significant, socio-economic background and especially parental education played an important role in the chances of being impoverished, and such data are only available in the LMPSs. Examining the role of parental background in poverty is just one example of potential applications of the data.

5 Discussion and Conclusions

Consumption levels, poverty, and inequality are central measures of economic development. These outcomes are also critically related to opportunities for human development and individuals' wellbeing and happiness. Although important, these outcomes are also quite difficult to measure, and in MENA, as in most developing countries, surveys with detailed information on consumption are not fielded regularly. Those surveys that are fielded also focus primarily on consumption, limiting the ability of researchers to study the links between consumption and other issues such as intergenerational inequality or the relationship between poverty and fertility. Advances in econometrics, specifically in predicting consumption and recovering its original variance by mapping from survey-to-census or survey-to-survey, now allow researchers to overcome these data challenges.

This paper has presented the methods, data, and validation of consumption and poverty mapping from five MENA HIECS onto contemporaneous LMPSs. The results are promising; as well as high explanatory power in the consumption models (in the 65%-70% range), resulting measures of consumption, poverty, and inequality are similar across survey pairs, as expected from the prediction method. Particularly for the data in Jordan and Egypt, and especially the more recent data for Egypt, key measures are only insignificantly different, with the small differences observed likely due to sampling variability across the surveys.

A few limitations must be kept in mind for applications. Although it is promising that the original consumption data align with the predicted consumption estimates in the LMPSs, including across the comparable characteristics, this result is unsurprising and inherent to predicting so long as observed characteristics are comparable. Depending on how much observable characteristics are related to unobservables, measurement of inequality along other dimensions will vary from its true value. For instance, the HIECS lack migration histories, and thus the quality of any analyses relating poverty to migration histories using the LMPS depends on the relationship between the predictors of consumption and migration. Additionally, the data are based on household consumption; thus, intra-household disparities (for instance, between men and women or youth and adults) are assuredly under-estimated.

Since both the HIECS and LMPSs are samples, and consumption values in the LMPS are predicted, care must be taken in generating standard errors. We bootstrap over the 100 estimates of imputed consumption and vary our redraw of the LMPS sample five times for each consumption estimate. We recommend other users do likewise and have made our STATA .do files available online[14] to facilitate implementation. Although some caution is required in using the data, empirical applications to poverty dynamics and poverty determinants in this paper demonstrate its potential. Key disparities on both socio-economic and demographic lines are visible in the data, including high rates of child poverty in the region as well as specific

[14] Replication files available at https://sites.google.com/site/carolinekrafft/publications

disparities within countries, such as the role of parents' education in the probability of being impoverished.

These results are just scratching the surface of what can be done with these data. Such information is a public good, and therefore the consumption estimates have been publicly released by ERF through OAMDI to facilitate further research on these issues. Already the data have been used to examine the evolution of inequality of opportunity over time in Egypt (Assaad, Krafft, Roemer, & Salehi-Isfahani, 2017) and in comparative work (Assaad, Krafft, Roemer, & Salehi-Isfahani, 2016). We hope to see future work utilizing the LMPSs and predicted consumption data that takes advantage of the rich information in the surveys. The panel nature of the Egypt data in particular can allow for examinations of the relationship between different human development and labor market dynamics and patterns of consumption, inequality and poverty. Topics such as health, education, job characteristics, marriage, fertility, women's status, and savings and borrowing can be linked to consumption, poverty, and inequality using this data and the LMPSs. Just as the creation and application of poverty mapping allowed for localized targeting of poverty programs, the rich data of the LMPSs combined with the predicted consumption data can allow for a more detailed understanding of critical human and economic development challenges.

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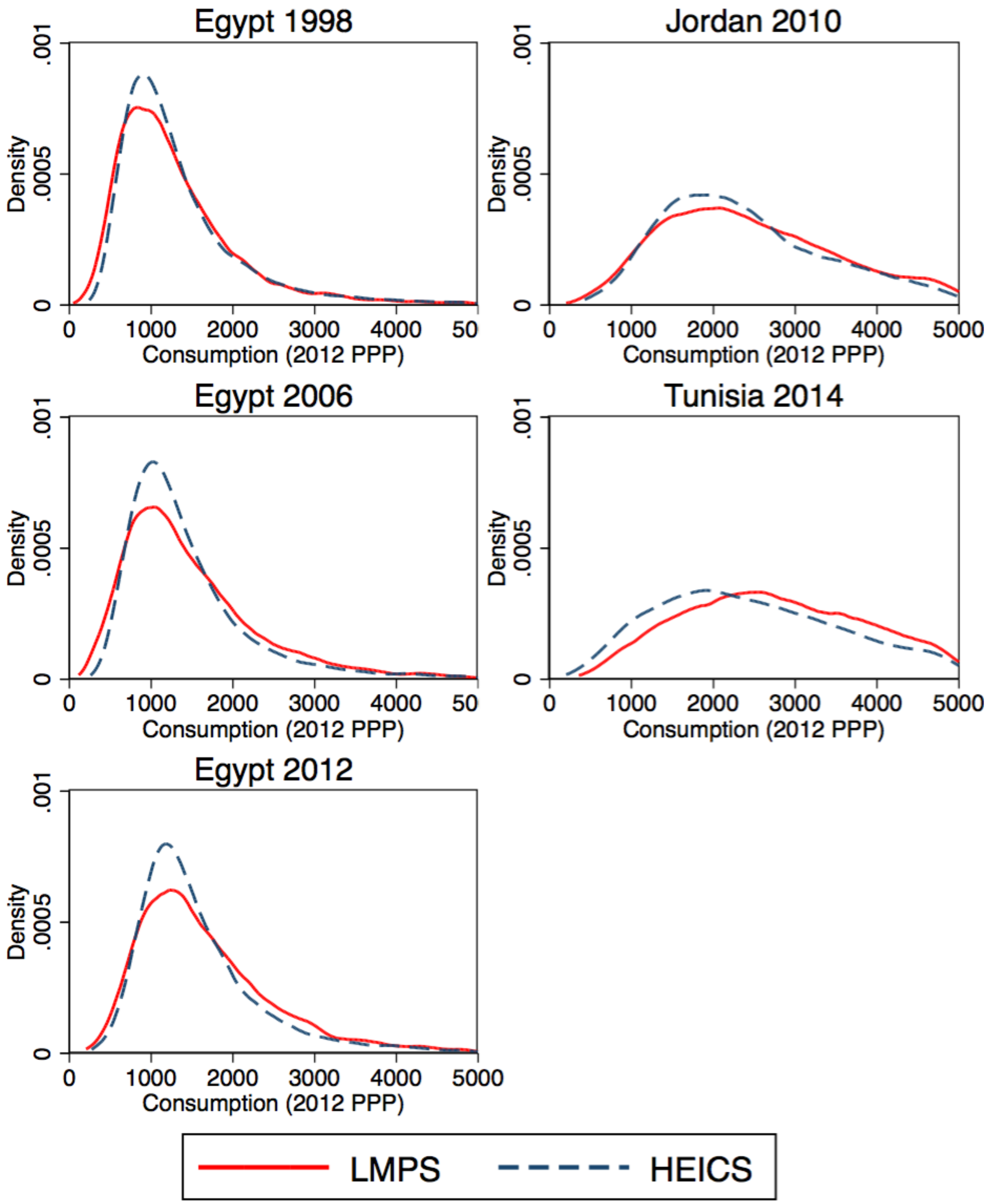
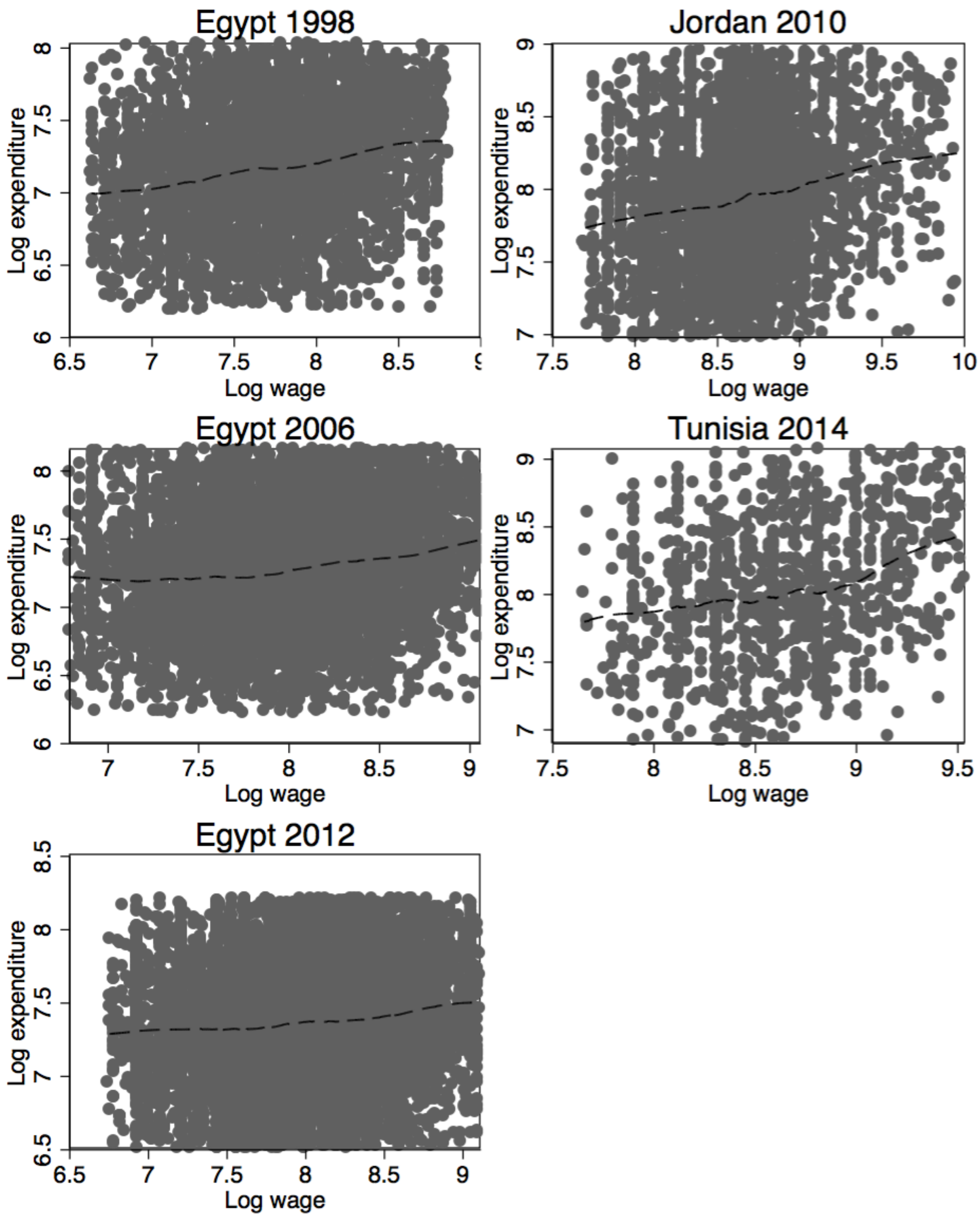
Figures

Figure 1. Observed and Mapped Distributions of Annual per Capita Consumption over Survey Pairs



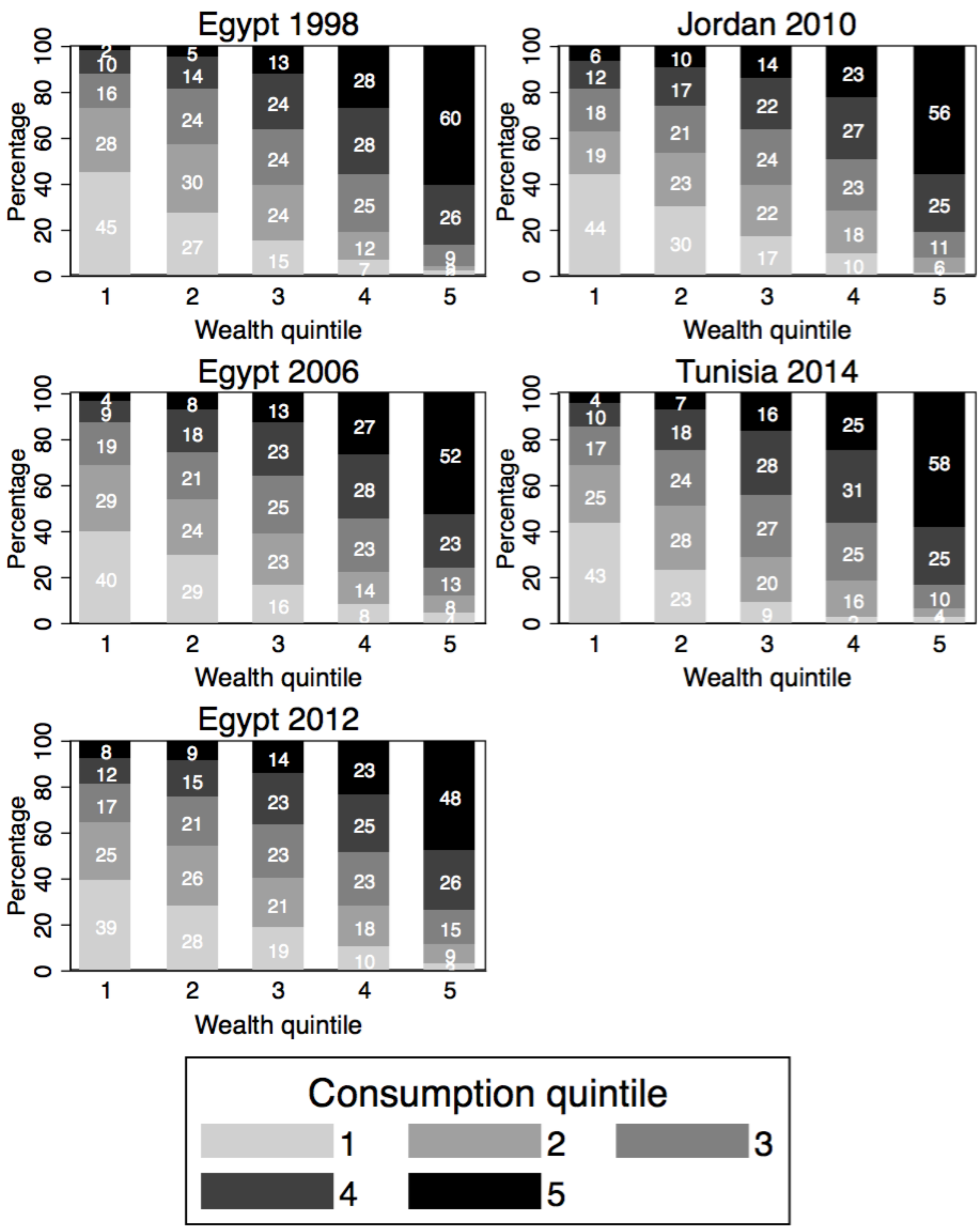
Source: Authors' calculations based on HIECS (observed) and LMPS (mapped)
Note: Bandwidth 100 for Egypt, 200 for Jordan and Tunisia. One iteration of consumption is shown, selected by a random number generator.

Figure 2. Mapped Distributions of Log Annual per Capita Consumption versus Log Annual Wages, LMPSs



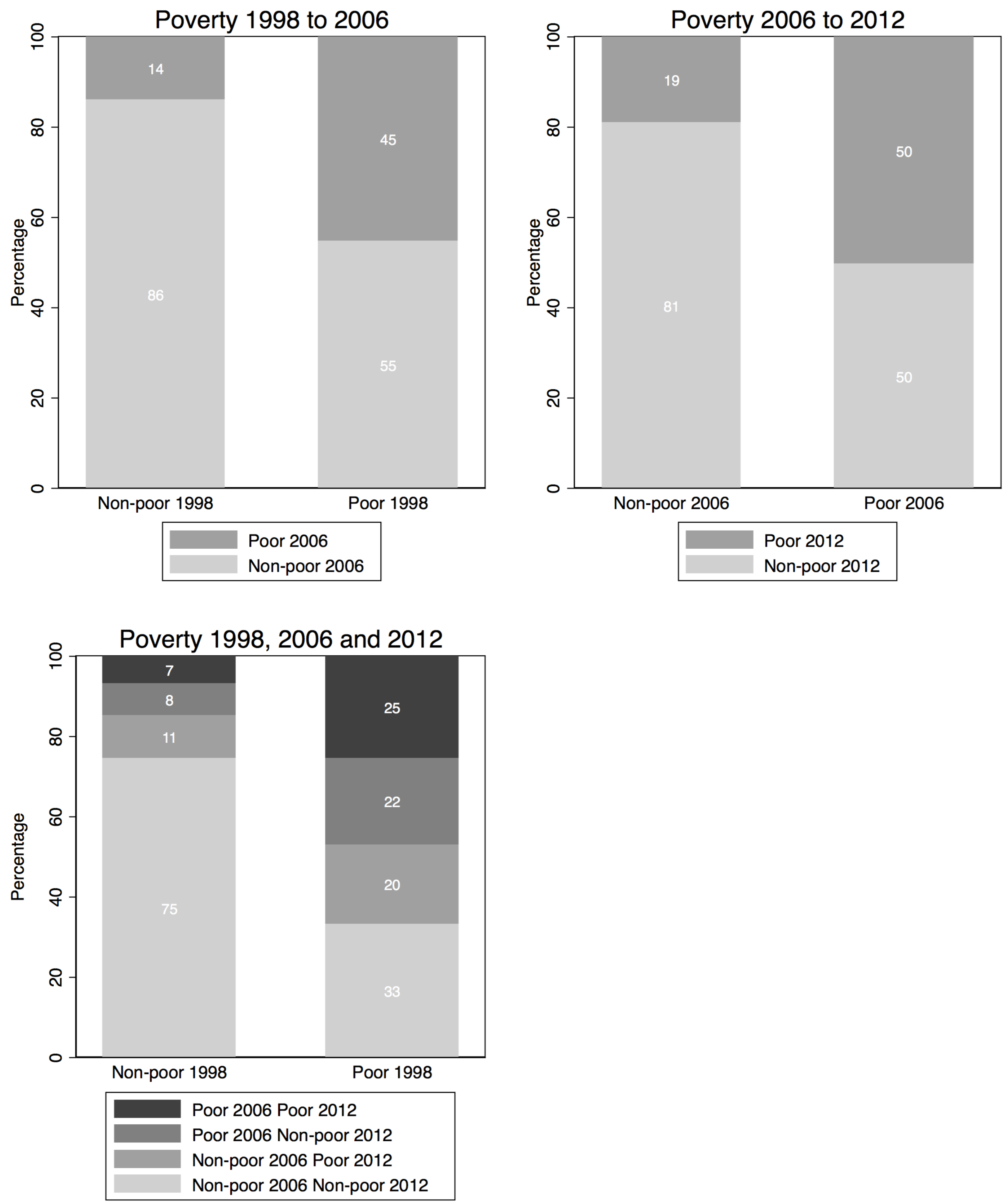
Source: Authors' calculations based on LMPS (mapped)
Notes: restricted to 5th-95th percentiles of the distribution for visibility. Lowess with bandwidth of 0.3. One iteration of consumption is shown, selected by a random number generator.

Figure 3. Mapped Distributions of Annual per Capita Consumption Quintile versus Wealth Quintile, LMPSs



Source: Authors' calculations based on LMPS (mapped).
Notes: One iteration of consumption is shown, selected by a random number generator.

Figure 4. Poverty Dynamics, Percentage of Base Round Poor in Subsequent Round, by Base Round Poverty, 1998-2006, 2006-2012, and 1998-2006-2012, LMPSs



Source: Authors' calculations based on LMPS (mapped).
Notes: One iteration of consumption is shown, selected by a random number generator.

Tables

Table 1. Observed and Mapped Mean Annual per Capita Consumption (in 2012 International PPP Dollars) by Characteristics over Survey Pairs, Egypt

	Egypt					
	1998		2006		2012	
	LMPS	**HIECS**	**LMPS**	**HIECS**	**LMPS**	**HIECS**
Total	1381	1473	1564	1567	1749	1720
	(53)	(154)	(44)	(144)	(37)	(105)
Sex						
Male	1382	1474	1561	1565	1734	1714
	(53)	(153)	(44)	(144)	(37)	(101)
Female	1381	1473	1567	1570	1763	1727
	(54)	(155)	(44)	(143)	(39)	(108)
Region						
Gr. Cairo	2133	2589	2493	2466	2358	2504
	(124)	(259)	(133)	(160)	(135)	(93)
Alex. & Suez	2203	1582	2217	1749	2471	1708
	(132)	(203)	(124)	(260)	(127)	(200)
Urban-Lower	1534	1563	1747	1701	2017	2035
	(58)	(77)	(60)	(131)	(61)	(95)
Urban-Upper	1259	1245	1534	1304	1587	1540
	(84)	(93)	(96)	(54)	(65)	(58)
Rural-Lower	1148	1170	1287	1310	1670	1651
	(52)	(42)	(36)	(74)	(35)	(49)
Rural-Upper	889	918	1032	1034	1155	1174
	(45)	(43)	(38)	(55)	(28)	(58)
Education Level						
None	1166	1221	1326	1349	1528	1535
	(39)	(68)	(34)	(76)	(28)	(66)
Primary	1431	1462	1515	1518	1680	1653
	(51)	(135)	(42)	(125)	(34)	(85)
Secondary	1639	1729	1701	1735	1881	1894
	(64)	(170)	(43)	(139)	(40)	(109)
Post-Secondary	1887	1880	2087	2017	2224	2135
	(96)	(153)	(80)	(165)	(104)	(125)
University	2615	3129	2807	3072	2794	2895
	(138)	(475)	(135)	(421)	(127)	(282)
Age Group						
0-5	1135	1218	1300	1300	1482	1395
	(41)	(95)	(36)	(92)	(31)	(55)
6-11	1194	1248	1290	1327	1453	1463
	(48)	(110)	(38)	(110)	(34)	(79)
12-14	1246	1306	1373	1380	1497	1553
	(52)	(119)	(48)	(128)	(41)	(101)

	Egypt					
	1998		2006		2012	
	LMPS	HIECS	LMPS	HIECS	LMPS	HIECS
15-19	1329	1426	1472	1484	1713	1658
	(55)	(142)	(42)	(129)	(43)	(101)
20-29	1442	1526	1642	1639	1845	1791
	(55)	(141)	(48)	(135)	(43)	(97)
30-39	1412	1511	1557	1556	1722	1617
	(55)	(151)	(45)	(138)	(44)	(93)
40-49	1515	1675	1670	1688	1787	1804
	(62)	(211)	(52)	(174)	(44)	(112)
50-59	1728	1836	1901	1971	2196	2123
	(91)	(224)	(67)	(213)	(71)	(120)
60-64	1767	1948	2050	2042	2352	2319
	(98)	(268)	(95)	(197)	(110)	(182)
Over 65	1624	1763	2008	2090	2269	2391
	(100)	(206)	(105)	(210)	(72)	(221)
Labor Market Status						
Wage worker gov.	1737	1818	1984	1957	2211	2182
	(72)	(192)	(70)	(209)	(61)	(133)
Wage worker pub.	1896	1977	2183	2124	2497	2330
	(117)	(196)	(105)	(224)	(169)	(170)
Wage worker priv. non-ag.	1455	1622	1677	1727	1834	1755
	(62)	(182)	(59)	(171)	(53)	(115)
Wage worker priv. ag.	911	915	1054	1031	1267	1245
	(46)	(35)	(42)	(45)	(46)	(59)
Employer ag.	1087	1146	1256	1325	1564	1548
	(62)	(33)	(40)	(38)	(52)	(59)
Employer non-ag.	2069	2671	2144	2323	2352	2368
	(128)	(486)	(101)	(279)	(117)	(238)
Self-emp. Ag.	1052	1096	1165	1235	1366	1434
	(73)	(38)	(57)	(40)	(62)	(55)
Self-emp. Non-ag.	1510	1478	1638	1592	1807	1769
	(103)	(106)	(64)	(127)	(64)	(93)
OLF, Unemp.	1368	1444	1550	1538	1742	1674
	(53)	(150)	(44)	(142)	(38)	(106)
N	23849	111176	37131	102146	49167	32131

Source: Authors' calculations based on HIECS (observed) and LMPS (mapped)
Notes: Bootstrapped standard errors (500 iterations for HIECS; 5 iterations each of 100 consumption distributions) in parentheses.

Table 2. Observed and Mapped Mean Annual per Capita Consumption (in 2012 International PPP Dollars) by Characteristics over Survey Pairs, Jordan

	Jordan 2010	
	LMPS	**HIECS**
Total	3341	3236
	(134)	(375)
Sex		
Male	3321	3163
	(133)	(330)
Female	3362	3307
	(138)	(419)
Region		
Middle	3676	3619
	(183)	(484)
North	2823	2623
	(123)	(108)
South	2731	2484
	(140)	(186)
Education Level		
None	2785	2851
	(115)	(293)
Primary	3080	2882
	(101)	(233)
Secondary	4040	4072
	(180)	(522)
Post-Secondary	4146	3975
	(182)	(381)
University	5771	5458
	(380)	(961)
Age Group		
0-5	2827	2626
	(122)	(200)
6-11	2538	2499
	(106)	(204)
12-14	2585	2443
	(114)	(238)
15-19	3081	2925
	(126)	(287)
20-29	3920	3597
	(166)	(350)
30-39	3277	3314
	(141)	(408)
40-49	3334	3128
	(151)	(366)

	Jordan 2010	
	LMPS	HIECS
50-59	4645	4516
	(258)	(685)
60-64	5520	4958
	(404)	(735)
Over 65	5144	5128
	(399)	(897)
Labor Market Status		
Wage worker gov.	3470	3033
	(161)	(161)
Wage worker priv. non-ag.	3483	3925
	(371)	(569)
Wage worker priv. ag.	3980	2547
	(193)	(373)
Employer ag.	2282	2682
	(266)	(621)
Employer non-ag.	3339	6545
	(676)	(1464)
Self-emp. Ag.	5505	3973
	(479)	(703)
Self-emp. Non-ag.	2751	3125
	(469)	(263)
OLF, Unemp.	3601	3101
	(188)	(339)
N	25967	15472

Source: Authors' calculations based on HIECS (observed) and LMPS (mapped)
Notes: Bootstrapped standard errors (500 iterations for HIECS; 5 iterations each of 100 consumption distributions) in parentheses.

Table 3. Observed and Mapped Mean Annual per Capita Consumption (in 2012 International PPP Dollars) by Characteristics over Survey Pairs, Tunisia

	Tunisia 2014	
	LMPS	**EBCNV**
Total	3958	3581
	(132)	(404)
Sex		
Male	3986	3596
	(140)	(401)
Female	3932	3566
	(135)	(408)
Region		
North	4573	4167
	(223)	(739)
Northwest	2769	2414
	(208)	(445)
Center East	4526	4241
	(294)	(861)
Center West	2808	2234
	(264)	(375)
South East	3823	3392
	(261)	(646)
South West	3438	2842
	(296)	(400)
Education Level		
None	3444	2776
	(116)	(264)
Primary	3810	3227
	(131)	(314)
Secondary	4852	4434
	(239)	(432)
Post-Secondary	5805	5746
	(463)	(624)
University	6245	7146
	(446)	(986)
Age Group		
0-5	3479	3120
	(178)	(353)
6-11	3195	2948
	(155)	(349)
12-14	3277	2984
	(177)	(330)
15-19	3772	3209
	(203)	(334)

	Tunisia 2014	
	LMPS	EBCNV
20-29	4293	3700
	(177)	(383)
30-39	4212	3606
	(178)	(382)
40-49	3866	3559
	(158)	(377)
50-59	4517	4212
	(214)	(489)
60-64	4962	4620
	(307)	(608)
Over 65	3863	4001
	(322)	(547)
Labor Market Status		
Wage worker gov.	5127	5308
	(332)	(507)
Wage worker pub.	4450	5786
	(420)	(648)
Wage worker priv. non-ag.	4163	3486
	(175)	(311)
Wage worker priv. ag.	2875	2040
	(228)	(111)
Employer ag.	3603	3518
	(503)	(264)
Employer non-ag.	6248	6082
	(580)	(766)
Self-emp. Ag.	2959	2418
	(182)	(183)
Self-emp. Non-ag.	4147	3780
	(261)	(276)
OLF, Unemp.	3885	3475
	(133)	(403)
N	10157	50371

Source: Authors' calculations based on HIECS (observed) and LMPS (mapped)
Notes: Bootstrapped standard errors (100 iterations (for the mapped values 500 iterations for HIECS; 5 iterations each of 100 consumption distributions) in parentheses

Table 4. Observed and Mapped Distributions of Inequality and Poverty over Survey Pairs

	Egypt						Jordan		Tunisia	
	1998		2006		2012		2010		2014	
	LMPS	**HIECS**	**LMPS**	**HIECS**	**LMPS**	**HIECS**	**LMPS**	**HIECS**	**LMPS**	**EBCNV**
GE(-1)	0.209	0.188	0.210	0.169	0.161	0.147	0.245	0.231	0.237	0.315
	(0.024)	(0.037)	(0.021)	(0.029)	(0.009)	(0.020)	(0.020)	(0.041)	(0.018)	(0.034)
GE(0)	0.178	0.189	0.180	0.169	0.144	0.146	0.206	0.216	0.191	0.251
	(0.011)	(0.034)	(0.010)	(0.028)	(0.009)	(0.019)	(0.014)	(0.038)	(0.013)	(0.022)
GE(1)	0.194	0.237	0.195	0.205	0.156	0.174	0.216	0.273	0.189	0.263
	(0.016)	(0.045)	(0.014)	(0.034)	(0.013)	(0.024)	(0.016)	(0.063)	(0.014)	(0.024)
GE(2)	0.297	0.438	0.281	0.339	0.217	0.267	0.284	0.886	0.227	0.384
	(0.197)	(0.096)	(0.040)	(0.060)	(0.051)	(0.045)	(0.029)	(0.371)	(0.022)	(0.044)
P90/P10	4.168	3.738	4.160	3.537	3.619	3.208	4.934	4.518	4.905	5.903
	(0.194)	(0.437)	(0.171)	(0.369)	(0.112)	(0.230)	(0.269)	(0.514)	(0.310)	(0.509)
P75/P25	2.092	1.933	2.074	1.862	1.925	1.763	2.285	2.150	2.290	2.440
	(0.065)	(0.121)	(0.050)	(0.091)	(0.034)	(0.061)	(0.070)	(0.156)	(0.090)	(0.103)
Gini	0.327	0.339	0.328	0.320	0.295	0.297	0.353	0.362	0.337	0.385
	(0.010)	(0.033)	(0.009)	(0.028)	(0.008)	(0.020)	(0.012)	(0.034)	(0.011)	(0.017)
Head count ratio	0.241	0.182	0.229	0.198	0.268	0.282	0.150	0.150	0.076	0.142
	(0.023)	(0.028)	(0.017)	(0.034)	(0.014)	(0.034)	(0.014)	(0.027)	(0.013)	(0.029)
Average Poverty Gap	0.059	0.033	0.058	0.037	0.064	0.058	0.036	0.029	0.017	0.036
	(0.007)	(0.006)	(0.006)	(0.008)	(0.005)	(0.010)	(0.004)	(0.006)	(0.003)	(0.009)
N (Observations)	23849	111176	37131	102146	49167	32131	25967	15472	10157	50371

Source: Authors' calculations based on HIECS (observed) and LMPS (mapped)
Notes: Bootstrapped standard errors (500 iterations for HIECS; 5 iterations each of 100 consumption distributions) in parentheses

Table 5. Determinants of Poverty (Logit Model Marginal Effects)

	Egypt 1998	Egypt 2006	Egypt 2012	Jordan 2010	Tunisia 2014
Sex (male omit.)					
Female	-0.013	-0.011	-0.012	-0.001	0.005
	(0.010)	(0.007)	(0.007)	(0.007)	(0.011)
Education (illit. omit.)					
Read & write	-0.049**	-0.029	-0.034*	-0.047*	-0.013
	(0.016)	(0.016)	(0.016)	(0.021)	(0.017)
Basic	-0.077***	-0.054***	-0.045***	-0.095***	-0.024
	(0.018)	(0.015)	(0.013)	(0.023)	(0.017)
Secondary	-0.120***	-0.099***	-0.097***	-0.141***	-0.049*
	(0.022)	(0.016)	(0.014)	(0.024)	(0.022)
Post-secondary	-0.165***	-0.152***	-0.137***	-0.154***	-0.055
	(0.035)	(0.021)	(0.025)	(0.025)	(0.032)
University+	-0.197***	-0.171***	-0.185***	-0.193***	-0.067**
	(0.027)	(0.019)	(0.017)	(0.026)	(0.023)
Age group (6-11 omit.)					
12-14	-0.012	-0.015	-0.032	-0.001	0.013
	(0.019)	(0.018)	(0.019)	(0.013)	(0.036)
15-19	-0.058*	-0.049*	-0.116***	-0.015	-0.038
	(0.023)	(0.019)	(0.021)	(0.019)	(0.031)
20-29	-0.095***	-0.069***	-0.136***	-0.113***	-0.076*
	(0.023)	(0.020)	(0.021)	(0.022)	(0.034)
30-39	-0.108***	-0.076***	-0.090***	-0.108***	-0.079*
	(0.021)	(0.020)	(0.021)	(0.021)	(0.036)
40-49	-0.139***	-0.118***	-0.156***	-0.118***	-0.079*
	(0.021)	(0.020)	(0.023)	(0.022)	(0.034)
50-59	-0.182***	-0.154***	-0.238***	-0.190***	-0.102**
	(0.024)	(0.022)	(0.024)	(0.023)	(0.034)
60-64	-0.211***	-0.177***	-0.254***	-0.211***	-0.122**
	(0.030)	(0.024)	(0.026)	(0.023)	(0.038)
Over 65	-0.204***	-0.181***	-0.263***	-0.215***	-0.102*
	(0.025)	(0.022)	(0.024)	(0.023)	(0.046)
Labor Market Status (Wage worker gov. omit.)					

	Egypt 1998	Egypt 2006	Egypt 2012	Jordan 2010	Tunisia 2014
Wage worker pub.	-0.048	-0.069	-0.036	0.000	-0.015
	(0.041)	(0.037)	(0.040)	(0.055)	(0.045)
Wage worker priv. non-ag.	0.001	-0.001	0.015	-0.005	0.004
	(0.028)	(0.018)	(0.017)	(0.016)	(0.033)
Wage worker priv. ag.	0.070	0.038	0.059*	0.107*	0.026
	(0.039)	(0.029)	(0.027)	(0.054)	(0.042)
Employer ag.	0.021	0.004	0.012	0.069	0.002
	(0.033)	(0.020)	(0.022)	(0.099)	(0.061)
Employer non-ag.	-0.089*	-0.061*	-0.078**	-0.068**	-0.039
	(0.038)	(0.025)	(0.026)	(0.024)	(0.041)
Self-emp. ag.	-0.016	0.005	0.063	0.106	0.005
	(0.058)	(0.032)	(0.036)	(0.073)	(0.034)
Self-emp. non-ag.	-0.017	-0.017	0.016	0.009	-0.004
	(0.034)	(0.022)	(0.024)	(0.025)	(0.041)
OLF, unemp.	-0.007	0.003	0.023	0.020	-0.006
	(0.023)	(0.016)	(0.015)	(0.013)	(0.035)
Mother's education (illit. omit)					
Read & write	-0.049	-0.038	-0.021	-0.030	-0.015
	(0.034)	(0.023)	(0.023)	(0.020)	(0.031)
Basic	-0.083*	-0.038	-0.011	-0.053	-0.031
	(0.035)	(0.023)	(0.023)	(0.027)	(0.020)
Secondary	-0.130***	-0.086**	-0.078***	-0.096***	
	(0.037)	(0.028)	(0.020)	(0.027)	
Higher ed.	-0.176***	-0.156***	-0.142***	-0.098**	
	(0.050)	(0.037)	(0.028)	(0.030)	
Secondary or higher (Tunisia only)					-0.052
					(0.028)
Father's education (illit. omit)					
Read & write	-0.053*	-0.026	-0.037*	-0.029	-0.012
	(0.021)	(0.017)	(0.015)	(0.018)	(0.030)
Basic	-0.054	-0.040	-0.044*	-0.059*	-0.009
	(0.032)	(0.021)	(0.017)	(0.028)	(0.018)
Secondary	-0.092*	-0.076***	-0.041	-0.100***	

	Egypt 1998	Egypt 2006	Egypt 2012	Jordan 2010	Tunisia 2014
	(0.040)	(0.023)	(0.021)	(0.026)	
Higher ed.	-0.151***	-0.121***	-0.119***	-0.136***	
	(0.043)	(0.030)	(0.027)	(0.026)	
Secondary or higher (Tunisia only)					-0.053
					(0.032)
Father's employment status (public wage omit.)					
Private wage	-0.006	0.028	0.028*	-0.028	-0.002
	(0.027)	(0.018)	(0.014)	(0.018)	(0.023)
Non-wage	-0.022	-0.005	-0.010	-0.052**	-0.013
	(0.024)	(0.017)	(0.015)	(0.018)	(0.031)
No job or don't know	0.002	0.051	0.031	-0.058	-0.004
	(0.050)	(0.032)	(0.027)	(0.031)	(0.036)
Father's occup. (white collar omit.)					
Blue collar	0.003	-0.013	0.023	0.027	0.008
	(0.022)	(0.016)	(0.014)	(0.014)	(0.025)
Ag. and other	0.029	0.005	0.029	0.063**	0.008
	(0.027)	(0.018)	(0.015)	(0.024)	(0.021)
Mother work (no work omit.)					
Work	-0.035	0.017	-0.030*	0.001	0.005
	(0.034)	(0.017)	(0.014)	(0.024)	(0.019)
Region: Egypt (Gr. Cairo omit.)					
Alex. & Suez	-0.039	0.011	-0.073		
	(0.033)	(0.025)	(0.040)		
Urban-Lower	0.017	0.053*	-0.073*		
	(0.031)	(0.025)	(0.033)		
Urban-Upper	0.204***	0.204***	0.165***		
	(0.038)	(0.033)	(0.039)		
Rural-Lower	0.088*	0.156***	-0.010		
	(0.035)	(0.029)	(0.032)		
Rural-Upper	0.287***	0.286***	0.231***		
	(0.042)	(0.034)	(0.039)		
Region: Jordan (Middle omit.)					
North				0.048	
				(0.027)	

	Egypt 1998	Egypt 2006	Egypt 2012	Jordan 2010	Tunisia 2014
South				0.036	
				(0.028)	
Region (North omit.)					
Northwest					0.100**
					(0.031)
Center East					0.004
					(0.031)
Center West					0.090**
					(0.033)
South East					0.031
					(0.031)
South West					0.042
					(0.041)
N	20700	30903	40542	21789	7427

Source: Authors' calculations based on LMPS (mapped)
Notes: *p<0.05; **p<0.01; ***p<0.001
Bootstrapped standard errors (5 iterations each of 100 consumption distributions) in parentheses