Representativeness of Top Expenditures in Arab Region Household Surveys

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Abstract

This study investigates evidence of measurement errors among households with the highest expenditures in eleven harmonized expenditure surveys from five Arab countries. Distribution of expenditures and the corresponding Gini index are corrected by replacing top expenditures with values predicted under smooth parametric distributions. Pareto distribution among expenditures classified as top expenditures, and generalized beta distribution of type II on the entire national distribution of household expenditures are fitted and used as alternative specifications for replacing top expenditures. Across the eleven surveys, inequality of expenditures is found to be modest, and neither parametric correction performed debunks this conclusion. Gini is consistently between 29 and 31 in Egyptian surveys, and between 36 and 41 in the rest of surveys. Jordanian and Palestinian 2010 data are found to include clear outliers that influence inequality estimates upward. Other surveys exhibit better representativeness for the expected distribution of expenditures that may be approximated by parametric distributions. Pareto law holds well among top expenditures in Egypt and Palestine, justifying Pareto specification. In Jordan, Sudan and Tunisia, however, a four-parameter generalized beta distribution appears more appropriate. Ginis estimated under generalized beta distribution are somewhat higher than nonparametric or Pareto-distribution Ginis in Jordan and Palestine, similar in Egypt, and lower in Sudan and Tunisia. These patterns are consistent across alternative sample delineations and across survey waves. Nevertheless, the alternative estimates of Ginis are within one another's confidence intervals, implying that neither set of estimates is clearly preferred. Whether nonparametric, or Pareto or generalized-beta parametric Ginis are closest to true statistics remains a question for future research.

JEL: D31, D63, N35.

Keywords: Top expenditures, inequality, Pareto law, generalized beta distribution, Arab region,

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1. Introduction

It has been well documented that values in the uppermost tail of income or expenditure distributions can significantly influence estimates of inequality (Cowell and Victoria-Feser, 1996a; Cowell and Flachaire, 2007). The fact that the density of top incomes and expenditures has been rising and the fact that they are difficult to capture precisely in household surveys can lead to great sampling uncertainty and even inconsistency of inequality estimates even in large micro datasets. Richer households may under or over-report their expenditures, and in some national surveys data on the upper tail are censored on purpose in public dissemination files by statistical agencies. Some national statistical agencies winsorize (or top-code) or "rank-proximity swap" expenditure aggregates or individual expenditure components to comply with privacy norms (Burkhauser *et al.* 2009, 2010, 2011, 2012).

This study attempts to provide a perspective on biases introduced by such mismeasurement of top expenditure observations in the Arab region, where a long-standing debate exists regarding the true level and nature of inequality and its role in the stirring up of uprisings (e.g., Bibi and Nabli 2010; Ncube and Anyanwu 2012; Hlasny and Verme 2016; Alvaredo and Piketty 2014). The study deals with the suspected top expenditure issues by replacing actual top observations with values predicted under theoretical distributions. Two alternative distributions are considered in recognition of their use in existing literature as good approximations to true population distributions across countries and years. Predicted values from these distributions are not subject to measurement errors or data censoring. In particular, Pareto distribution of type I among expenditures classified as top expenditures, and generalized beta distribution of type II (GB2) on the entire national distribution of household expenditures are used as alternative models favored by two separate streams of literature. Cowell and Victoria-Feser (2007), Lakner and Milanovic (2013) are some studies relying on the good fit of the Pareto distribution to empirical distributions. Appropriate parametric distributions can be estimated robust to influential observations (Van Kerm 2007). Jenkins *et al.* (2011) advocate the use of a four-parameter GB2 distribution for its flexibility to idiosyncrasies in all parts of the income or expenditure distribution.

Empirical studies using these parametric distributions on Arab region data are presently very rare (Bibi and Nabli 2009). Hlasny and Verme (2016) found that replacing actual top incomes in the Egyptian Household Income, Expenditure and Consumption Survey (HIECS) sample with Pareto parametric estimates did not affect the computed Gini noticeably regardless of what other statistical issues were accounted for, on account of high quality of the data. Alvaredo and Piketty (2014) estimated inequality using a mix of Pareto distributions for top incomes and log-normal distributions for the rest of incomes. In Egypt as well as in the rest of the Arab region, this approach yielded higher estimates of inequality, suggesting systematic underreporting of top incomes. Assouad (2015), applying the same methodology used in Alvaredo and Piketty (2014) to the individual tax returns and national accounts data in Lebanon, finds one of the highest income concentrations among all the countries included in the World Top Income Database due to the disproportional effect of profits and rents in the top quantiles. Hlasny and Verme (2015) evaluated the dispersion of top incomes in the Egyptian HIECS as well as the US Current Population Survey (CPS) and the EU Surveys of Income and Living Conditions (SILC) by comparing the actual dispersion to that predicted under a Pareto or a GB2 distribution. They found that the use of Pareto distributions resulted in larger corrections as compared to the use of GB2 distributions but the differences were modest. In Egypt, the observed top 0.1% of incomes were found to be extreme or overstated (commanding a downward correction), accounting for an undue share of national income, while the following 1% of incomes followed typical distributions more closely.[1]

The contribution of this study is thus to add to the emerging literature on the precision of top observations in the distribution of household incomes and expenditures in the Arab region. By comparing the fit of the Pareto and the GB2 distributions, and evaluating the actual dispersion of top expenditures to predicted patterns, the study contributes to methodological literature with evidence on the appropriate modeling of top quantiles of welfare aggregates in developing and transition economies. Our method accounts for problems when some expenditures (or their components) are randomly under- or over-reported, or rank-proximity swapped, even though it cannot account for systematic underreporting or top-coding of expenditures.

Expenditure, rather than income, is evaluated here for a number of reasons. Firstly, expenditures are typically used instead of incomes in emerging economies. Our usage of expenditures facilitates comparison with other countries in the region as well as worldwide. Secondly, expenditure data may be more precise given that income tends to be underreported and given that expenditure is smoother than income, especially in developing and rural areas. Thirdly, expenditure data in the Arab region have been found to exhibit significantly lower inequality than incomes (Bibi and Nabli 2010; Belhaj Hassine 2011) which may be puzzling to observers of the economic and political developments in the region. This may also suggest that mismeasurement of top expenditures is more serious than that of top incomes, even if the rest of the expenditure distribution is reported carefully. Finally, one empirical reason for considering expenditures rather than incomes in this study is that Tunisian surveys do not report total or disposable income.

The paper is organized as follows. Section two briefly describes data under analysis. The following section outlines methods used in empirical analysis. Section four presents main results and section five discusses their implications for the general problem of evaluating economic inequality across Arab countries and over time.

[1] In the EU SILC, the results were analogous. In the US CPS, the correction was positive under a Pareto approximation. Income share of the super-rich 0.1% of households was estimated to be not as high as in other income distributions or under a smooth Pareto curve, but the income share of the next 1% of incomes was higher. That suggested that topmost incomes in the US CPS are top-coded, or that extreme observations appear among the top 1% of incomes rather than among the super-rich 0.1% (Hlasny and Verme 2015).

2. Data sources

This study utilizes household income and expenditure surveys (HHIES) harmonized and made available by Economic Research Forum (ERF).[2] Survey data are comparable across countries and across years, but individual households cannot be tracked over time. Pooled cross-sectional data analysis is thus possible, while longitudinal analysis is not.

Specific variables used in this study include total annual household expenditures per capita and cross-sectional household sampling weights. ERF adds up expenditure items according to the Classification of Individual Consumption According to Purpose rules. Expenditures cover food and beverages, alcoholic drinks and smokes, clothes, textiles and shoes, residence and its accessories, furniture, durables, health care and services, transportation, telecommunications, culture and entertainment, education, restaurants and hotels, various services and commodities. Expenditures are converted to international dollars, purchasing-power parity (UNSD 2015) and divided by the number of household members to obtain expenditures per capita.[3] Sampling weights allow inference from survey sample to the entire sampling universe. ERF sampling weights at the level of households are multiplied by household size to assign greater weights to households where more individuals benefit from particular levels of expenditure per capita.

[Table 1 to appear here]

3. Sources of measurement issues

Commonly used measures of inequality are sensitive to the inclusion and exact values of bottommost and uppermost observations. Some inequality measures such as the Theil index and other Generalized Entropy indices are known to be very sensitive, but even Gini coefficient is not robust to them (Cowell and Victoria-Feser 1996). To evaluate how inequality measurement is sensitive to extreme expenditure observations, without judgment on the authenticity of their values, we may try to identify outliers and estimate measures of inequality with and without them. Neri *et al.* (2009), for example, define outliers in the EU Surveys on Income and Living Conditions

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[2] ERF provides access to survey micro data to non-commercial researchers free of charge, upon registration intended to monitor access and ensure data confidentiality. Access is limited to five surveys during a six-month period. Original data sources are cited in the References section at the end of this study.

[3] Using of UNSD (2015) currency conversion factors or the quantitatively different World Bank (2015) estimates yields essentially the same results: nonparametric and Pareto parametric Gini coefficients are identical under both sets of conversion factors, while generalized-beta parametric Ginis differ trivially. Dividing by the number of household members is chosen in deference to previous literature in the aim to facilitate comparison of Gini coefficients across studies. An alternative approach is to use a modified OECD adult-equivalence scale whereas household size is computed as $[1 + 0.7\,(N_{adults}-1) + \alpha\,N_{children} + \alpha\,N_{elderly}]$ where α is taken to be 0.3 to account for a lesser role played by children under the age of 14 and the elderly aged 65+ years (Glewwe and Twum-Baah, 1991, as cited in Haughton and Khandker 2009:29). This alternative, evaluated for Jordan 2010, leads to a 2 percentage-point reduction in the estimated nonparametric as well as all quasi-parametric Ginis. All other qualitative results of this study are robust to this modification. Figure A1 in the appendix illustrates.

(SILC) as observations exceeding the median 4-5 times, and find that this comprises 0.1-0.2% of households.

On the one hand, extreme observations could reflect true values of expenditures in the population, and should in that case be included in measurement. On the other hand, extreme observations could arise from various errors and, if included, should be corrected for the identified errors. Measurement errors may arise for a number of reasons, including errors in recollection or data entry. Top expenditures may also be deliberately obscured by national statistical agencies to comply with privacy norms. Many agencies replace rare high values with the minimum or mean of the variable in a similar group of units.

Before any analysis with the available sample, it is worth checking whether extreme observations are simply errors such as data-entry errors or they are true values incidentally very distant from the central moments of the distribution. Table 2 lists the top twenty per-capita expenditure observations in each survey, representing 0.18–0.31 percent of all individuals (household observations adjusted by sampling weights and household size).

Table 2 shows that the eleven surveys differ significantly in the level and the dispersion of highest expenditures. Egyptian data exhibit modest dispersion among the highest twenty expenditures. Jordanian data show substantial dispersion, and include an influential observation in the 2010 wave. In the 2006 wave, the highest observed expenditure per capita exceeds the second highest one by 64 percent, and the twentieth highest one by 354 percent. In the 2010 wave, the highest expenditure per capita is more than seven times as high as the one in the second place, and more than twelve times as high as the one ranked twentieth. This observation is for a three-member household, so the conversion to per-capita terms does not explain the unusual value. Rather, the household includes two earners, one of a very high age.[4] Evaluation of individual expenditure components does not reveal the existence of any data-entry errors. The household's possession of various household durables confirms the household's level of wealth. Correspondingly, expenditure on furniture, housing equipment, appliances, transportation vehicles, culture and recreation, energy, miscellaneous goods and various fees are very high. Expenditures on health and medical treatment abroad are also high. Finally worth noting, because of its rarity, this household has an above-average sampling weight, implying that it is quite influential in any estimation of population statistics.

In the three Palestinian surveys, similarly, the highest one or two expenditures appear extreme. In the 2007 and 2011 waves, the single highest expenditure is 29–43 percent higher than the second highest expenditure, and 188–261 percent higher than the one ranked twentieth. In the 2010 wave, the top expenditure is 133 percent higher than the next one, and more than seven times as high as the twentieth one.

[4] Using an alternative adult-equivalence scale giving lesser weight to the elderly further increase the expenditure per capita of this household to $324,719. Yet, under this alternative scale, Jordan's Gini falls by 2 percentage points.

In Sudan, the highest observed expenditure per capita exceeds the second highest one by 29 percent, and the twentieth highest one by 288 percent. In both waves of the Tunisian survey, the household with the highest expenditure per capita exceeds the expenditure of the second highest household by mere 17–23 percent. It exceeds the expenditure of the twentieth household only twofold, by 211–213 percent.

These patterns may represent the underlying national populations accurately or may arise from measurement errors. Jordanian and Palestinian data may suffer from bad quality or misreporting, making the dispersion appear greater than it is. Alternatively, Tunisian data may suffer from underreporting or top-coding of the highest expenditures, making them appear concentrated within a narrower range than in reality. Finally, the last row in table 2 reports the share that the richest twenty households in terms of expenditures per capita command of aggregate expenditures. Expenditure share of the richest households is a common measure of economic inequality. In agreement with our finding regarding the dispersion of top expenditures, these expenditures shares are higher in Jordan, Palestine and Sudan and lower in Egypt and Tunisia, even accounting for the different shares that the twenty observations represent in the national survey samples (refer to the second to last row in table 2).

[Table 2 to appear here]

Table 3 provides additional information on the actual distribution of top expenditures: the share of aggregate expenditures accounted for by the top 0.1 percent of observations (or 7–11 households across surveys) to as many as 20 percent of observations (or 780–2,662 households). These results confirm a disproportionate concentration of wealth among the super-wealthy 0.2 percent of households (19–21 units) in Jordan ‘10 and in Sudan, where they command over 2.9–3.0 percent of aggregate expenditures. Tunisia ‘05 is also nearly at that level of concentration among the uppermost expenditure households. Regarding expenditure shares among the following 20 percent of households, Sudan and Tunisia ‘05 exhibit disproportionate concentrations. The richest 1 (10, or 20) percent of households control 7.6–7.8 (30.8–32.4 or 46.3–48.0, respectively) percent of aggregate expenditures there.

Replacement using values from a Pareto distribution

To evaluate the distribution of top expenditures and study the presence of extreme values in our data, we follow an approach pioneered by Pareto (1896) and recently applied by Atkinson, Cowell, Jenkins, Piketty and others to summarize the dispersion of economic outcomes by a parametric distribution, report properties of the estimated distribution, and use the estimates to correct top incomes for statistical problems (Atkinson *et al.* 2011). The approach is motivated by an empirical regularity that top observations across countries and years follow a particular pattern represented well by the Pareto distribution. The Pareto distribution is one of the distributions suggested by the Cowell *et al.* literature for evaluating potentially imprecise top incomes vis-à-vis expected values.

Inequality estimates imputed from a parametric distribution function can be less sensitive to extreme observations than non-parametric observations from actual survey data. Parametric estimates for the top of the distribution could be combined with non-parametric statistics for the rest of the distribution to obtain more robust estimates (Cowell and Victoria-Feser 1996; Cowell and Victoria-Feser 2007). Burkhauser *et al.* (2010) compared four methods for dealing with top-coding in the survey data – essentially replacing top-coded values using four alternative parametric estimators and combining the estimates with non-topcoded observations. They found that most parametric methods underestimate the variance of true incomes with the exception of the Stoppa distribution, which uses the true mean and variance of latent values to replace top-coded observations and manages to offset nearly all of the underestimation in a top-coded distribution.

Pareto distribution is a particular type of distribution which is skewed and heavy-tailed. It has been used to model various types of phenomena and it is thought to be suitable to model upper incomes and expenditures. As expenditures grow larger, the number of observations declines following a law dictated by a constant parameter. The Pareto distribution can be described by its probability density function as follows:

$$f(x) = \frac{\theta}{x^{\theta+1}}\ , 1 \leq x \leq \infty\,. \qquad (1)$$

Here θ is a fixed Pareto coefficient and *x* is the variable of interest, which in our case will be expenditure per capita in international dollars, purchasing-power parity (UNSD 2015). This distribution function is one alternative to modeling the right hand tail of a general expenditure distribution.

Coefficient θ can be estimated by maximum likelihood methods. Gini coefficient under the estimated Pareto distribution for the *k* top-expenditure households, in the sample of size *n*, can be derived as $1\,/(2\theta - 1)$ (Cowell 2011). Gini coefficient is used in this study for its property as less sensitive to extreme observations than other commonly used indices such as the Theil index and other Generalized Entropy indices. The results of inequality corrections in this study can thus be viewed as conservative estimates for the true effects of extreme observations on inequality measurement in general, under the baseline hypothesis that top-income measurement issues do not affect inequality measurement in the Arab region. To the extent that the estimated Gini is affected by measurement issues, we may safely conclude that the consequences for other measures would be as large or larger.

Standard error of the Gini is a function of sampling error under the Pareto distribution, $4\theta(\theta - 1)/[n(\theta - 2)(2\theta - 1)^2(3\theta - 2)]$ (Modarres and Gastwirth 2006), and estimation error due to imprecision in the estimation of θ, $\eta/(2\theta^2 - 2\theta - 2\theta\eta + \eta + 0.5)$, where η is the standard error of the estimate $\hat{\theta}$.

Finally, parametric Gini coefficient from the Pareto distribution can be combined with a non-parametric Gini coefficient for the *n-k* lower-expenditure observations using simple geometric properties of the Lorenz curves as

$$Gini_{semi} = (1 + Gini_k)\frac{k}{n}s_k - (1 - Gini_{n-k})\left(1 - \frac{k}{n}\right)(1 - s_k) + \left(1 - \frac{2k}{n}\right). \quad (2)$$

Its variance is $\left[\varepsilon_k \frac{k}{n} s_k\right]^2 + \left[\varepsilon_{n-k}\left(1 - \frac{k}{n}\right)(1 - s_k)\right]^2$, where ε_k and ε_{n-k} are the standard errors of the two respective Gini indexes. Here s_k refers to the share of aggregate expenditure held by the richest k households. This variance does not account for correlation between ε_k and ε_{n-k} or for uncertainty about s_k, which are issues of lower significance and greater complexity of resolving (Hlasny and Verme 2016).

As long as it was correct to assume that top expenditures in the population are distributed as Pareto, this semi-parametric Gini coefficient can be compared to an uncorrected non-parametric estimate for the observed expenditure distribution. A difference between the semi-parametric and non-parametric estimates would indicate that some observed high expenditures may have been generated by a statistical process other than Pareto, and that our inequality measure is sensitive to this. Semi-parametric Gini that is lower than a non-parametric Gini can be interpreted as evidence that some top expenditures in the sample are extreme compared to those predicted under the Pareto distribution. A higher semi-parametric Gini would indicate that the observed top expenditures are lower than what the Pareto distribution would predict, potentially implying under-representation of rich units or underreporting of top expenditures in the sample.

Replacement using values from a generalized beta type II distribution

While Pareto distribution approximates well the dispersal of top expenditures, it is not representative of expenditures in the middle or bottom of the expenditure distribution. Generalized beta distribution of the second kind (GB2), also known as the Feller-Pareto distribution, has been proposed as a suitable functional form representing well the entire expenditure distributions (McDonald, 1984). The upper tail of the distribution is heavy and decays like a power function. Four estimable parameters give the distribution flexibility to fit various empirical expenditure distributions. Cumulative distribution function of the GB2 distribution is

$$F(x) = I\left(p, q, \frac{(x/b)^a}{1 + (x/b)^a}\right) \quad (3)$$

where *I(p,q,y)* is the regularized incomplete beta function, and *y* is the per-capita expenditure normalized to be in the unit interval. Parameters *a*, *p*, and *q* are distributional shape parameters and b a scale parameter. These parameters can be estimated by pseudo maximum likelihood. Other suitable candidates for a distribution function, the Singh-Maddala (1976) and the Dagum (1980) distributions, are limiting cases of the GB2 distribution with parameter p (q, respectively) restricted to one (McDonald, 1984).

Gini index of expenditure inequality under the GB2 distribution can be computed by evaluating the generalized hypergeometric function ${}_3F_2$ with the estimated parameters as arguments, and its standard error can be computed using the delta method (McDonald, 1984; Jenkins, 2009).

Replacement using randomly drawn rather than predicted values

One issue with replacing of potentially imprecise top expenditure observations with fitted values from the Pareto or generalized beta distribution is that the resulting measures of expenditure distribution and inequality do not account for parameter-estimation error and sampling error in the available dataset. This problem is on top of the issue of combining standard errors of the parametric Gini among top incomes and nonparametric Gini among lower incomes (refer to equation 2 and the following discussion). An and Little (2007), and Jenkins *et al.* (2011) account for sampling error by drawing random values from the estimated distribution for all potentially imprecise top observations, combining them with actual lower-level values, and calculating a quasi-nonparametric inequality measure with its bootstrap standard error. Repeating the exercise multiple times, we can note variability in the obtained inequality measure.[5] Following Reiter (2003), as used by An and Little (2007) and Jenkins *et al.* (2011), the expected measure of inequality in such partially synthetic data can be computed as a simple mean of inequality measures from individual random draws, $Gini_{quasi}$:

$$\widehat{Gini_{quasi}} = \sum_{i=1}^{m} Gini_{quasi\ i} \Big/ m \qquad (4)$$

Its sampling variance can be computed as:

$$\widehat{var} = \frac{\sum_{i=1}^{m} \left(Gini_{quasi\ i} - \widehat{Gini_{quasi}}\right)^2 \Big/ (m-1)}{m} + \sum_{i=1}^{m} var_{quasi\ i} \Big/ m. \qquad (5)$$

The first term is the sampling variance across different draws from the Pareto distribution, and the second term is the mean sampling variance within an individual draw. m refers to the number of repetitions and $var_{quasi\ i}$ is the variance of the quasi-nonparametric Gini coefficient from an individual draw i. This methodology still ignores standard error from the estimation of parameters

[5] Since top incomes in the U.S. CPS do not appear to follow Pareto distribution exactly, Jenkins *et al.* (2011) fit the GB2 distribution instead. Since top-coding occurs at the level of individual components of income, this estimation is done at the level of income components, and the randomly drawn values for top coded components are added to actual values for non-top coded components.

in the Pareto or GB2 distribution. However, this standard error is expected to be quite small compared to the sampling error, and can be ignored in large datasets where parameters have been estimated precisely (Jenkins *et al*. 2011).

4. Results

Table 3 presents quasi-nonparametric estimates of Gini coefficients, obtained by replacing the highest top 0.1–20.0 percent of expenditure observations with random values drawn from smooth Pareto distributions estimated among these top observations. The first row shows the benchmark nonparametric estimates of the Gini for each survey. The following rows present the quasi-nonparametric estimates from the distributions of household expenditures per capita where the top 0.1–20.0 percent of values are replaced by numbers drawn randomly from Pareto distributions corresponding to the top observations.

Table 3 shows that the correction for non-representative distribution of top expenditures varies across the eleven surveys. In the three Egyptian surveys, replacement of top 0.1–5 percent of expenditure observations leads to a small but systematic increase in the Gini from 31.3 to 31.7 in 2008; from 31.4 to 31.7 in 2010; and from 29.6 to 30.0 in 2012. This suggests that reported values are distributed slightly more narrowly compared to what one would expect under the Pareto law. In Jordan '06 and in all waves of the Palestinian and Tunisian data, the estimated quasi-nonparametric Ginis are nearly identical to the nonparametric statistics, particularly when 5 percent or fewer observations are replaced. In Jordan '10, replacement of top expenditures leads to a large drop in the Gini, presumably on account of the single outlying expenditure observation. Replacement of this outlier and of the following 34–88 expenditures (0.5–2% of the overall sample) decreases the estimated Gini from 36.2 to 35.4. In the Sudanese sample, replacement of top 0.2–5.0% of actual expenditures with Pareto draws leads to a small but systematic fall in the Gini from 39.9 to 39.7–39.8.

Across all eleven surveys, when 10–20% of observations are replaced with Pareto random draws, the estimated quasi-nonparametric Ginis consistently exceed the nonparametric values, suggesting that in that range, actual expenditures per capita are dispersed more narrowly than would be predicted under smooth Pareto distributions (relative to the dispersion of the topmost 0.1–5% of expenditures). This is most significant in Jordan '06 and in all waves of Palestinian and Tunisian surveys. Because this replacement of 10–20% of observations with randomly drawn values involves a large number of observations, this finding cannot be due to a few unlucky draws but reflects a systematic departure of the observed distributions to the theoretically expected ones. Figure 1 (left panels) illustrates these trends.

Another measure of dispersion among top-expenditure observations and a measure of the share of aggregate expenditures accounted for by them is provided by the inverted Pareto-Lorenz coefficient, computed as $\beta = \theta/(\theta - 1)$ (Atkinson *et al*. 2011). This coefficient reflects a property of the Pareto law that the ratio of mean expenditure above a threshold for the delineation of top expenditures ($\bar{x}$) to that threshold is constant. Expressed as $\beta = E(x|x \geq \bar{x})/\bar{x}$, the coefficient measures the thickness of the upper tail of an income distribution. This coefficient can vary over time and variation in it can be explained by economic and demographic factors. Estimation in table 3 yields inverted Pareto-Lorenz coefficients of 1.30–1.71 in Egypt, 1.31–1.92 in Palestine, 1.58–2.15 in Sudan, and 1.33–1.92 in Tunisia. In Jordan the inverted Pareto-Lorenz coefficients are 1.24–1.77 in the 2006 wave and 1.25–3.49 in 2010. These results support our previous finding that the dispersion of top expenditures is most serious in Jordan '10 and in Sudan, and least serious in Egypt and in Tunisia.

In all surveys except for Jordan '10, the inverted Pareto-Lorenz coefficient increases nearly monotonically as a greater percentage of top observations are evaluated (refer to figure 2). This suggests that as more of narrowly-distributed lower expenditures are added to the analysis, the degree of dispersion at the top increases as does the expenditure share of topmost (0.1–5%) observations. In Egypt and Tunisia, the increase in the inverted Pareto-Lorenz coefficient is timid as 1–20 percent of top expenditures are evaluated (the coefficient stagnates at 1.6–1.7 in Egypt '08 and '10), suggesting that a Pareto distribution with a single parameter may describe that entire range of expenditures rather well. On the other hand, in Jordan '10, the inverted Pareto-Lorenz coefficient falls drastically from 3.49 when only the top 0.5% of observations are evaluated to 1.25 when top 1% are evaluated. This is clearly due to the single highest influential observation.

These values are in the lower part of the range put forward by Atkinson *et al.* (2011) for income distributions in various countries, confirming that top-expenditure inequality in our sample of surveys is modest, corroborating the finding by Belhaj Hassine (2011) that overall inequality in the Arab region is moderate.[6] The trends identified in Egypt agree with the results by Hlasny and Verme (2015, 2016) that inequality there is low and that top observations are distributed rather smoothly and can well be approximated as Pareto. Our findings for Jordan '10 and for Sudan corroborate an observation by Alvaredo and Piketty (2014) that the inverted Pareto-Lorenz coefficient often falls as more of top observations are evaluated, suggesting that extreme observations in the uppermost part of the distribution are problematic in some countries.

These findings suggest that the exact cutoff for expenditures under analysis affects the estimated shape of the top expenditure distribution. Different surveys display different sensitivity to the choice. The estimated Pareto coefficient varies by less than 0.4 in Egypt '08 and '10 and in Sudan; by 0.7–0.9 in Egypt '12, in Jordan '06 and in Tunisia; by 0.8–1.2 in Palestine; and by as much as

[6] That expenditures and consumption are distributed more equally than incomes has been observed around the world, due to households' incentives for misreporting each variable, and households' propensity to save (Heathcote *et al.* 2010; Fisher *et al.* 2014). We thank Jeff Larrimore for raising this point. The finding that topmost expenditures in the Arab region are distributed more narrowly than topmost incomes worldwide is only partially attributable to these tendencies.

2.7 ($\theta \in [2.27,4.94]$) in Jordan '10 depending whether only the topmost 1% of households or fewer, or as many as top 20% are evaluated.

Consequently, the estimated Gini coefficients are also affected by the method of modeling of top expenditures.[7] The correction for potentially imprecise top expenditures varies from -0.01 to 0.43 percentage points of the Gini in Egypt; -0.81 to +1.23 percentage points in Jordan; -0.08 to 1.95 percentage points in Palestine; -0.19 to +0.65 percentage points in Sudan; -0.05 to +1.56 percentage points in Tunisia.[8] While not trivial, these differences in corrections are modest in size, particularly in view of the size of standard errors on all the Ginis (0.28–2.00). Consequently, individual specifications of the top income distribution (nonparametric, Pareto or generalized beta) cannot be clearly rejected in favor of other specifications. Moreover, confidence intervals around the various Pareto estimates and the nonparametric estimates of the Ginis have a substantial overlap, implying that neither set of estimates can be clearly rejected regardless whether Pareto or nonparametric estimation (or neither) was appropriate. Figure 1 illustrates.

[Table 3 to appear here]

An alternative parametric specification of the top of the expenditure distribution

One potential criticism of the above approach is that it relied on the fit of observed top expenditures to the Pareto distribution. While Pareto distribution has been accepted as providing a good fit for many national income and expenditure distributions around the world, its fit to incomes in the US CPS, for instance, has been questioned (Jenkins *et al.* 2011). Several studies have suggested other, more flexible statistical distributions as providing a better fit, such as the three-parameter Singh-Maddala and Dagum distributions. These are limit cases of a four-parameter GB2 distribution.

One method to evaluate whether it was appropriate to model the distributions of top expenditures in the eleven survey samples as Pareto type I is to draw the Hill plots of these distributions (Drees, de Haan and Resnick 2000). These plots show how the estimated Pareto parameter changes as one

[7] An alternative method to compute quasi-nonparametric Ginis could involve computing the inverted Pareto-Lorenz coefficient using the cutoff value for top expenditures and mean value among the top expenditures, $\beta = E(x|x \geq \bar{x})/\bar{x}$, then computing the parametric Pareto coefficient from this as $\theta = \beta/(\beta - 1)$, and finally deriving the Gini coefficient among top expenditures – under the assumed Pareto curve – as $Gini = 1/(2\theta - 1)$. This method may be more robust to the actual dispersion and individual measurement errors among top expenditures, but it is very sensitive to the estimated mean among top expenditures. In view of this, we have opted for the first method. Both methods are sensitive to the validity of the Pareto-distribution assumption, and neither method is robust to systematical underreporting of top expenditures. The degree of sensitivity depends on the form of misreporting, and cannot be easily ranked between the two methods.

[8] These corrections are the differences between quasi-nonparametric and nonparametric Ginis. Quasi-nonparametric Ginis were estimated by replacing top incomes with randomly drawn numbers from the corresponding Pareto distributions, then iterating the exercise 100 times and taking an average of the 100 obtained Ginis. These Ginis from random draws differ by up to 0.89 percentage points in absolute value from non-randomized smooth-distribution Ginis from equation 2 in Jordanian surveys, by up to 0.45 percentage points in Sudan, and by up to 1.08 percentage points in Tunisian surveys (mean difference in absolute value across these eleven surveys is 0.27 percentage points).

changes the delimitation of top incomes. If the plots are flat lines, a stable Pareto distribution with a single parameter can characterize the entire top end of the income distribution, while if the plot is non-stationary, different parametric distributions (Pareto or not) would characterize different subgroups of top incomes. Figure 3 shows that the Hill plots for the Egyptian and Palestinian surveys (top row) are stationary at a single parameter value across the top 0.5–20 percent of expenditure observations. Hill plots for the Jordanian, Sudanese and Tunisian surveys (bottom row), on the other hand, slope downward throughout most the range of top expenditures. These Hill plots jointly indicate that a one-parameter Pareto distribution appears adequate at approximating the entire actual top-expenditure distributions in Egypt and Palestine, but not in the other three countries, particularly past 5 percent of the topmost expenditures. Only in Sudan '09 and Tunisia '05 the plots are relatively stable and hump-shaped (rather than falling monotonically) until top 5 percent of the respective samples, suggesting that even in these surveys Pareto approximation may be possible for the topmost 5 percent of the expenditure distributions.

Another method to evaluate Pareto is to estimate another distribution, and compare measures of fit between them as well as in relation to the nonparametric distribution. In this section we re-estimate the quasi-nonparametric Gini coefficients assuming household expenditures per capita to be distributed as GB2 and replacing top observations with fitted values or values drawn randomly from the estimated distributions. Table 4 reports the results.

[Table 4 to appear here]

Most coefficient estimates in table 4, particularly for Egypt, Sudan and Tunisia, carry small standard errors suggesting good quality of fit of the GB2 distribution. Coefficient estimates imply that the GB2 distribution cannot be easily approximated by the more parsimonious Singh-Maddala or Dagum distributions because *E(p)* and *E(q)*, respectively, exceed unity across all surveys. In Egypt '12 a case could be made for the Singh-Maddala distribution, because unity is contained in the narrow 95% confidence interval around *E(p)*. In Jordanian and Palestinian surveys, neither Singh-Maddala nor Dagum distribution can be rejected due to the width of confidence intervals around *E(p)* and *E(q)*, a likely consequence of influential extreme observations. Even for these surveys, GB2 distribution is retained as the robust, albeit potentially inefficient, specification.

Comparing Ginis estimated under the GB2 distribution to nonparametric estimates, we find that the parametric and quasi-nonparametric Ginis under the assumed GB2 distribution tend to be lower in the 2008 and 2010 waves of Egyptian surveys, but higher in the 2012 wave, implying that actual expenditures were distributed more widely in the former two waves (and more narrowly in 2012) than expenditures predicted under the respective GB2 distributions. In Jordanian and Palestinian samples, the estimates were also higher by 0.1–0.9 percentage points– with the notable exception of the topmost 0.1% in Jordan '10, again suggesting underdispersion in actual data. In Sudan, GB2 estimates of the Ginis fall short of the nonparametric statistic by 0.2–0.4 percentage points, implying modest overdispersion in the actual data. In Tunisian samples, GB2 estimates appear on par with nonparametric values across all delineations of potentially-imprecise top expenditures. Finally, comparing quasi-nonparametric Ginis to GB2 parametric estimates (middle row in table 4), we confirm that using random expenditure draws produces a nearly identical correction of the Gini as numerical inference of the Gini under a smooth distribution – with all quasi-nonparametric estimates within one standard deviation of the parametric one – vouching for accuracy of the procedure.

Corrections under the GB2 distribution differ systematically from those under the Pareto distribution. In Jordanian and Palestinian samples, GB2 estimates consistently exceed Pareto estimates by 0.02–1.52 percentage points (except when k≥10%). In Sudanese and Tunisian samples, on the other hand, GB2 estimates are nearly universally lower by up to 1.7 percentage points. In Egypt, GB2 estimates tend to be lower in the 2008 and 2010 waves (up to 0.8 pc.pt. in magnitude), and higher in the 2012 wave (up to 0.6 pc.pt.). Hence, the estimated GB2 distributions predict wider dispersion of expenditures than the corresponding Pareto distributions in Egypt '12, Jordan and Palestine, but narrower dispersion in Egypt '08–'10, Sudan and Tunisia.

In Egypt '12, Jordan '06 and Palestine, the small upward correction to the Gini derived under Pareto is now estimated to be larger, while in Sudan, the small downward correction is now also estimated to be larger in absolute value. In Egypt '08–'10 and in Tunisia, the small downward correction is now estimated weaker in magnitude. Finally, in Jordan '10, the small downward correction under Pareto now becomes a small upward correction. These results suggest that our assumption about the distribution of true expenditures affects our correction for extreme observations. In absolute terms, however, the differences are modest, ranging from -1.7 to 1.5 percentage points across all surveys and top-expenditure delineations (mean -0.03 pc.pt.; 0.39 pc.pt. in absolute value). This may be viewed as confirming plausible distribution or acceptable quality of top expenditure observations in the eleven surveys.

Figure 1 shows the estimated corrections to the Gini coefficients across the eleven surveys and the two parametric specifications for the distribution of top expenditures. The results clearly differ across the five countries, while they are similar across different waves of Egyptian, Jordanian, Palestinian and Tunisian surveys, confirming that the distribution of household expenditures is relatively stable within countries. The results differ to some degree between the Pareto and the GB2 specifications, suggesting that the parametric assumption affects our conclusion regarding the representativeness of the observed top expenditures. However, because of the width of confidence intervals around the nonparametric and quasi-nonparametric estimates, there are few instances where either quasi-nonparametric estimate differs statistically significantly from its other quasi-nonparametric or nonparametric alternatives.[9] In Tunisia '05

[9] In all surveys with the exception of Jordan '10, bootstrap estimates of standard errors of nonparametric Ginis are greater – and thus the confidence intervals around nonparametric Ginis are also wider – than those of quasi-nonparametric Ginis. This reflects large sampling errors in the observed data. In Jordan and in Palestine '07, small sample sizes give rise to large standard errors of quasi-nonparametric Ginis using individual random draws and to

and ‘10, only when top 20 percent of expenditure observations are replaced by Pareto randomly drawn values, the resulting quasi-nonparametric Gini is outside of a confidence interval for a nonparametric Gini (and vice versa, nonparametric Gini is on the edge of a quasi-nonparametric confidence interval). Similarly, in Jordan ‘06, only upon replacement of top 20 percent of expenditures, the quasi-nonparametric Gini rises to near the upper bound of the nonparametric estimate confidence interval. All GB2 estimates are within the confidence intervals of nonparametric Ginis.

substantial variability in these Ginis across random draws. In Jordan ‘10 and Palestine ‘10–‘11, outlying observations introduce sampling uncertainty which raises standard errors on all Gini estimates for these surveys.

5. Discussion

This study has attempted to evaluate and correct for non-representative distributions of top expenditure observations in eleven surveys from five Arab region countries. Inspection of the eleven surveys indicates that the uppermost expenditures exhibit different dispersion patterns across surveys. The twenty topmost expenditures in Egyptian, Sudanese and Tunisian surveys are distributed relatively narrowly, while in Jordanian and Palestinian surveys they are quite dispersed. The 2010 waves of Jordanian and Palestinian surveys contain outliers that affect measurement of inequality seriously. We thus attempted to correct for such non-representative values, allowing parametric distributions to guide our correction. The method used was to replace potentially mismeasured expenditures with values predicted or randomly drawn from two alternative smooth parametric distributions – the Pareto type I or the generalized beta type II distributions.

This method could account for problems when some expenditures (or their components) are randomly under- or over-reported, or rank-proximity swapped, even if it could not account for systematic underreporting or top-coding of expenditures. To the extent that there is limited evidence in academic literature regarding systematic underreporting of incomes or expenditures in the Arab region, and the statistical agencies do not practice top-coding, this method appears relevant and appropriate.[10]

Across the eleven surveys, inequality of expenditures is found to be modest, and none of the various corrections performed debunk this conclusion. This is in contrast to the findings by Alvaredo and Piketty (2014) and Assouad (2015) who, using external data for the tops of income distributions, derived greater corrections and higher estimates of the Gini coefficient. In the Arab region, however, external data such as national accounts and tax record data are not well compatible with survey data on household expenditures, due to issues such as the presence of the oil sector, remittances from abroad, neighborhood and family transfers across households, and tax avoidance. In our study using only survey data, Gini coefficient is consistently between 29 and 31 in Egyptian surveys, and between 36 and 41 in the rest of surveys. Replacing observed top expenditures with fitted or random values from parametric distributions helps to refine the estimated Gini index of inequality systematically but modestly. Using Pareto-distribution approximation, the method left Gini estimates nearly unchanged in all surveys with the exception of Jordan ‘10, or unless we replaced as many as 20 percent of top observations. In Jordan ‘10, replacement of top expenditures led to a sizable drop in the Gini of 0.8 percentage points, on account of a single influential expenditure observation. Across all surveys, replacing of top 20% of expenditures with Pareto values yielded higher Gini estimates suggesting that, in that range of expenditures, actual values are dispersed more narrowly than would be predicted under smooth Pareto distributions (relative to the dispersion of the topmost 0.1–10% of expenditures). This is

[10] In the presence of these additional problems with topmost observations, the method would likely underestimate the dispersion of true expenditures. Whether the estimated Gini would be nearer to the true statistic than the uncorrected Gini would depend on the exact form of underreporting and top-coding.

corroborated by the estimated inverted Pareto-Lorenz coefficients. In all surveys except for Jordan '10, these coefficients increased as a greater percentage of top observations were evaluated – nearly monotonically after the topmost 0.5% and further observations were replaced by more representative values – implying that as more of narrowly-dispersed lower expenditures are added to the analysis, the aggregate expenditure share of the topmost 0.1–5% observations rises. However, different countries exhibit different sensitivity to the correction of top expenditures. In Egypt and Tunisia, the increase in the inverted Pareto-Lorenz coefficient is timid, suggesting that a Pareto distribution with a single parameter may describe that entire range of top expenditures rather well. In Palestine the coefficient rises sharply, and in Jordan and Sudan it fluctuates, suggesting that Pareto distribution does not track the upper tail of these expenditure distributions too closely.

Outliers in Jordanian '10 and Palestinian '10 data are found to significantly affect estimates of inequality relative to statistics expected under the Pareto distribution. Whether the observed or the Pareto-predicted values are closer to the true degree of inequality is unclear and depends on the cause of the outlying observation. Other surveys exhibit better representativeness for the expected distribution of expenditures that may be approximated by parametric distributions. Pareto law appears to hold well among top expenditures in Egypt and Palestine – single parameter explains well dispersion among actual top 1–20 percent of expenditures. This finding justifies Pareto parametric specification in those countries. On the other hand, in Jordan, Sudan and Tunisia, the Pareto law does not hold.[11] Concurring with Jenkins *et al.*'s (2011) resolutions regarding incomes in the US, modeling of top expenditures in these countries may require a four-parameter generalized beta distribution.

The assumption regarding the true distribution of top incomes had some effect on the correction. Ginis estimated under the assumed GB2 distribution tended to be somewhat higher than nonparametric Ginis in Jordan and Palestine, similar in Egypt, and lower in Sudan and Tunisia. This suggests that actual expenditures in Jordan and Palestine (Sudan and Tunisia) are dispersed slightly more narrowly (widely, respectively) than expenditures predicted under the respective GB2 distributions. Comparing the Pareto and the GB2 estimates of the Ginis, results also differed systematically across the eleven surveys. In Egypt 2008 and 2010, in Jordan and in Palestine, GB2 estimates consistently exceeded Pareto estimates by up to 1.5 percentage points, while in Egypt 2012, in Sudan and in Tunisia, GB2 estimates were nearly universally lower than Pareto-distribution estimates by up to 1.7 percentage points.

These Gini coefficient estimates and differences in them across the Pareto versus the GB2 specifications appear meaningful, as they are consistent across small changes in model specifications. They evolve nearly monotonically as more of top expenditures are analyzed. Across

[11] These conclusions are based on the assumption that the observed expenditures on which parametric distributions were estimated are not systematically underreported or top-coded. With these additional problems, the parametric approximations would likely be different and would depend on the exact form of underreporting and top-coding.

the multiple waves of Egyptian, Jordanian, Palestinian and Tunisian surveys, the Gini estimates also exhibit analogous patterns, suggesting that in expenditure distributions sharing similar properties, the methods evaluated in this study yield similar corrections.

Nevertheless, differences across the various sets of estimates are modest in view of the absolute levels of the Ginis and their differences across countries. Even the statistically insignificant 1.7 percentage point difference between the Pareto versus the GB2 Ginis represents a moderate change in the measure of inequality given that nonparametric Ginis vary by as much as 11.8 percentage points across the five countries (29.6 in Egypt '12 to 41.4 in Tunisia '05). Moreover, the width of confidence intervals around all estimates – shown in Figure 1 – implies that neither set of estimates can be clearly favored over others.

We may take this claim further and surmise as follows: under the assumption that nonparametric estimates are consistent for latent true Ginis but potentially inefficient due to measurement errors, and that parametric and quasi-nonparametric estimates may be more efficient but potentially inconsistent due to misspecification, similarity of the two sets of estimates suggests that neither measurement errors nor specification errors are sufficiently grave to let us clearly reject either set of the Ginis. Whether the nonparametric or GB2 parametric (or even Pareto parametric) Gini coefficients are closest to the latent true Ginis remains a question for future research. For the time being, we should take caution relying on single – typically nonparametric – estimates, instead considering alternative estimates when we construct intervals of plausible values of the countries' true degrees of economic inequality. Finally, if we are interested in measures of inequality other than the Gini coefficient, we should remember that the modest correction of the Gini for top-income measurement issues can be viewed as a lower bound, but the corrections under alternative inequality measures are likely to be greater.

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Data sources

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Table 1. Data sources and summary statistics

Country, year	Survey	Households	Mean expenditures per capita (st.dev.)[a]	Median expend. per capita
Egypt 2008	HEICS 2008/09 (OAMDI 2014a)[bc]	23,428	1,425.38 (1,221.58)	1,151.06
Egypt 2010	HEICS 2010/11 (OAMDI 2014b)	7,719	1,603.37 (1352.69)	1,287.40
Egypt 2012	HEICS 2012/13 (OAMDI 2014c)	7,525	1,719.77 (1251.38)	1,414.53
Jordan, 2006	HEIS 2006 (OAMDI 2014d)	2,897	2,500.05 (2,274.26)	1,927.28
Jordan, 2010	HEIS 2010/11 (ERF & DOS, 2013)	2,845	3,108.79 (4,139.79)	2,348.79
Palestine 2007	PECS 2007 (OAMDI 2014e)	1,231	3,759.11 (3756.81)	2,759.62
Palestine 2010	PECS 2010 (OAMDI 2014f)	3,537	5,138.56 (5012.92)	3,771.70
Palestine 2011	PECS 2011 (OAMDI 2014g)	4,317	5,280.86 (4878.28)	3,964.53
Sudan, 2009	NBHS 2009 (OAMDI 2014h)	7,913	1,164.74 (1,260.34)	881.01
Tunisia, 2005	EBCNV 2005 (OAMDI 2014i)	12,318	2,600.67 (2,818.96)	1,894.29
Tunisia, 2010	EBCNV 2010 (OAMDI 2014j)	11,281	3,332.21 (2,930.51)	2,542.90

[a] Converted using purchasing power parity exchange rate to international dollars (UNSD 2015). For lack of availability of newest data, year-2007 conversion rate is used for all Palestinian surveys. Summary statistics account for household sampling weights and household size.

[b] HEICS = Household Expenditure, Income and Consumption Survey; HEIS = Household Expenditure and Income Survey; PECS = Palestinian Expenditure and Consumption Survey; NBHS = National Baseline Household Survey; EBCNV = National Survey on Household Budget, Consumption and Standard of Living.

[c] ERF data are 30-50% random extractions from original HEICS surveys administered by Egyptian Central Agency for Public Mobilization and Statistics, which include 48,658 (HEICS 2008/2009), 26,500 (HEICS 2010/2011) and 24,863 households (HEICS 2012/2013).

Table 2. Top twenty household expenditures per capita across national surveys

Rank in survey sample	Egypt '08	Egypt '10	Egypt '12	Jordan '06	Jordan '10	Palestine '07	Palestine '10	Palestine '11	Sudan '09	Tunisia '05	Tunisia '10
1	53,157.94	42,165.61	26,548.15	67,948.41	216,479.50	71,114.78	306,455.70	114,961.80	38,637.37	77,738.57	75,322.65
2	44,649.02	36,707.64	23,906.70	41,531.91	30,406.46	49,659.20	131,242.00	89,052.73	30,016.97	63,151.43	64,153.63
3	37,195.29	29,176.12	19,151.00	34,790.27	25,944.99	41,153.54	83,083.49	80,502.95	27,198.69	61,852.86	61,214.38
4	31,339.21	24,892.83	18,037.32	30,315.73	24,987.13	40,396.23	74,492.45	62,696.21	26,639.26	42,332.86	59,424.60
5	29,683.66	24,584.93	17,949.00	27,772.65	24,722.63	31,365.09	69,019.34	59,075.16	17,399.68	37,254.29	39,110.84
6	24,938.04	23,122.48	17,488.60	27,096.44	23,521.76	28,966.98	64,400.47	52,244.81	16,767.88	35,855.71	37,755.88
7	23,993.49	21,897.13	16,970.23	25,220.63	21,287.35	28,400.31	63,939.15	50,660.85	16,333.86	35,164.29	35,766.84
8	23,803.92	21,571.85	15,871.91	25,209.04	20,734.76	27,966.27	62,664.05	49,759.43	15,887.18	34,821.43	33,053.86
9	23,713.33	21,086.50	15,857.55	24,663.42	20,729.18	27,066.04	56,308.49	47,628.30	14,061.45	34,288.57	32,970.16
10	22,857.74	18,763.06	15,849.71	23,070.90	20,655.43	25,179.25	53,856.13	46,460.38	13,922.42	32,840.00	32,900.38
11	22,779.96	17,616.72	14,090.66	22,990.89	19,819.79	24,259.98	50,690.57	45,744.34	13,389.21	32,461.43	31,102.15
12	20,508.14	17,207.32	13,862.28	20,151.54	19,717.65	24,145.60	50,257.55	44,476.18	13,069.70	32,328.57	30,695.40
13	19,615.29	15,696.35	13,514.34	18,677.11	19,578.73	23,711.70	47,319.02	43,918.68	11,743.76	30,968.57	29,853.84
14	19,205.29	15,393.18	13,085.75	18,194.18	18,964.25	23,429.40	46,802.83	43,336.55	10,912.73	30,781.43	29,025.58
15	19,139.61	14,819.35	12,920.23	17,871.50	18,652.47	23,016.04	45,682.55	43,075.33	10,897.39	30,364.29	28,193.53
16	18,973.53	14,123.82	12,865.81	16,430.74	18,596.38	22,867.45	45,245.55	41,923.94	10,581.21	29,428.57	27,007.41
17	18,690.49	14,096.90	12,856.13	16,030.26	18,284.49	22,126.96	43,557.55	41,459.91	10,541.21	28,564.29	26,968.23
18	18,687.45	13,750.32	12,582.74	15,926.60	18,181.84	21,434.36	42,660.38	41,120.05	10,307.45	28,395.71	25,278.99
19	18,405.49	13,746.32	12,376.07	15,828.49	18,097.23	21,112.26	42,614.62	40,604.36	10,045.86	25,781.43	24,300.24
20	18,277.65	13,527.39	12,139.60	14,973.79	17,902.55	19,666.04	41,933.96	39,848.02	9,960.00	24,864.29	24,199.95
Cumul. density	0.05%	0.15%	0.14%	0.31%[b]	0.20%	0.79%	0.19%	0.24%	0.18%	0.18%	0.18%
Expend. share	0.81%	1.89%	1.34%	3.18%[c]	2.95%	6.13%	2.17%	2.47%	2.97%	2.77%	1.86%

[a] International dollars, purchasing power parity (UNSD 2015).
[b] Portion of the density of the entire survey sample, accounting for household sampling weights and household size.
[c] Portion of the aggregate expenditure of the entire survey sample, accounting for household sampling weights.

Table 3. Quasi-nonparametric estimates of Gini coefficients: Pareto distribution

	Egypt '08			Egypt '10			Egypt '12			Jordan '06			Jordan '10		
Correction for extreme observations	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)
non-param.	0 out of		31.32	0 out of		31.42	0 out of		29.60	0 out of		35.81	0 out of		36.21
estimation	23,428		(0.28)	7,719		(0.49)	7,528		(0.42)	2,897		(0.74)	2,845		(1.31)
quasi-nonparametr. Gini, top k% replaced															
k=0.1% × n	43	3.258	31.31	12	3.377	31.45	12	3.964	29.62	8	3.429	35.78	8	1.402	35.84
	[1.42%]	(0.637)	(0.28)	[1.42%]	(0.644)	(0.52)	[0.92%]	(0.867)	(0.43)	[1.44%]	(1.977)	(0.74)	[2.29%]	(1.009)	(1.03)
k=0.2% × n	82	3.071	31.34	27	2.749	31.47	27	4.290	29.62	9	5.258	35.76	19	2.188	35.63
	[2.28%]	(0.406)	(0.29)	[2.29%]	(0.503)	(0.54)	[1.70%]	(0.913)	(0.43)	[2.07%]	(3.616)	(0.76)	[2.88%]	(1.387)	(0.78)
k=0.5% × n	207	2.819	31.38	59	3.061	31.46	59	3.962	29.60	34	2.431	35.92	35	3.324	35.49
	[4.24%]	(0.221)	(0.30)	[4.24%]	(0.439)	(0.54)	[3.39%]	(0.552)	(0.43)	[4.23%]	(0.463)	(0.92)	[4.43%]	(1.451)	(0.76)
k=1% × n	393	2.701	31.41	123	2.531	31.51	116	3.312	29.69	67	2.981	35.73	44	4.940	35.43
	[6.68%]	(0.151)	(0.32)	[6.59%]	(0.248)	(0.56)	[5.72%]	(0.280)	(0.47)	[6.49%]	(0.531)	(0.70)	[6.47%]	(2.201)	(0.92)
k=2% × n	790	2.563	31.48	245	2.550	31.53	232	3.047	29.71	132	2.721	35.78	89	3.859	35.40
	[10.34%]	(0.103)	(0.34)	[10.24%]	(0.186)	(0.57)	[9.26%]	(0.205)	(0.49)	[10.22%]	(0.311)	(0.75)	[10.44%]	(0.619)	(0.80)
k=5% × n	1,966	2.402	31.68	605	2.428	31.71	591	2.539	30.02	285	2.706	35.97	216	2.801	35.88
	[18.02%]	(0.061)	(0.37)	[17.87%]	(0.115)	(0.64)	[16.80%]	(0.110)	(0.60)	[18.57%]	(0.193)	(0.87)	[19.18%]	(0.217)	(0.99)
k=10% × n	3,744	2.401	31.59	1,165	2.457	31.62	1,150	2.511	30.03	482	2.664	35.95	417	2.599	36.49
	[27.14%]	(1.714)	(0.39)	[27.12%]	(0.085)	(0.67)	[25.86%]	(0.084)	(0.56)	[28.54%]	(0.149)	(0.90)	[29.41%]	(0.179)	(1.48)
k=20% × n	6,778	2.456	31.39	2,173	2.472	31.53	2,082	2.551	29.90	848	2.307	37.04	780	2.269	37.05
	[40.94%]	(0.034)	(0.36)	[41.07%]	(0.061)	(0.63)	[39.66%]	(0.065)	(0.56)	[43.97%]	(0.084)	(1.37)	[44.58%]	(0.102)	(1.41)

Notes: For clarity, Ginis and their standard errors are multiplied by 100. Pareto coefficients are estimated among the top *k* expenditure observations using maximum likelihood methods. Quasi-nonparametric Gini coefficients are computed as in equation 4 using 100 random draws from the estimated respective Pareto distributions. Standard errors of the quasi-nonparametric Ginis are computed as in equation 5.
"--" indicates that estimates are unavailable due to small size of the sample of top *k* observations.

Table 3 (cont.). Quasi-nonparametric estimates of Gini coefficients: Pareto distribution

	Palestine '07			Palestine '10			Palestine '11			Sudan '09			Tunisia '05			Tunisia '10		
	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)	Observ. replaced [expend. share]	Pareto coef. θ (s.e.)	Gini (s.e.)
non-	0 out of		40.83	0 out of		39.18	0 out of		38.43	0 out of		39.88	0 out of		41.40	0 out of		38.49
par.	1,231		(1.00)	3,757		(0.57)	4,317		(0.68)	7,913		(0.74)	12,318		(0.55)	11,281		(0.42)
quasi-nonp. Gini, top % replaced																		
0.1	2	4.247	40.86	12	3.300	39.16	8	3.081	38.49	7	2.429	39.92	10	2.948	41.39	11	4.051	38.49
	[1.14%]	(2.924)	(1.02)	[1.20%]	(1.011)	(0.59)	[1.26%]	(1.296)	(0.77)	[2.08%]	(0.697)	(0.79)	[1.81%]	(1.160)	(0.55)	[1.18%]	(1.041)	(0.43)
0.2	6	2.534	40.99	20	4.093	39.12	17	3.363	38.44	21	1.866	39.99	21	2.458	41.49	22	2.928	38.51
	[2.35%]	(1.061)	(1.17)	[2.17%]	(1.012)	(0.59)	[2.00%]	(1.338)	(0.65)	[3.02%]	(0.482)	(0.81)	[2.84%]	(0.598)	(0.58)	[1.99%]	(0.571)	(0.43)
0.5	13	3.665	40.87	35	3.684	39.10	37	3.807	38.40	51	2.322	39.82	69	2.470	41.47	64	3.081	38.57
	[4.33%]	(1.413)	(1.04)	[4.12%]	(0.738)	(0.63)	[4.11%]	(1.087)	(0.65)	[5.15%]	(0.561)	(0.76)	[5.06%]	(0.428)	(0.56)	[3.72%]	(0.506)	(0.45)
1	24	3.217	40.85	65	3.330	39.14	79	3.006	38.51	109	2.523	39.75	144	2.760	41.35	128	3.335	38.48
	[7.14%]	(0.731)	(1.14)	[6.74%]	(0.373)	(0.64)	[6.72%]	(0.449)	(0.71)	[7.59%]	(0.429)	(0.70)	[7.80%]	(0.362)	(0.48)	[6.07%]	(0.439)	(0.40)
2	47	2.733	40.99	125	2.979	39.18	136	2.815	38.63	205	2.731	39.69	280	2.610	41.52	258	3.234	38.55
	[10.96%]	(0.378)	(1.13)	[10.64%]	(0.267)	(0.67)	[10.69%]	(0.306)	(0.84)	[11.46%]	(0.326)	(0.66)	[12.05%]	(0.216)	(0.57)	[9.92%]	(0.275)	(0.42)
5	102	2.884	40.96	261	2.802	39.33	333	2.667	38.71	505	2.643	39.78	674	2.578	41.51	613	2.906	38.71
	[20.81%]	(0.298)	(1.23)	[19.65%]	(0.173)	(0.78)	[19.52%]	(0.185)	(0.80)	[20.13%]	(0.179)	(0.66)	[21.14%]	(0.126)	(0.58)	[18.53%]	(0.142)	(0.47)
10	184	2.303	41.67	489	2.539	39.77	618	2.572	38.88	985	2.423	40.06	1,350	2.329	42.00	1,174	2.759	38.90
	[31.85%]	(0.159)	(1.77)	[30.89%]	(0.116)	(0.95)	[30.15%]	(0.129)	(0.86)	[30.76%]	(0.105)	(0.86)	[32.36%]	(0.072)	(0.66)	[29.36%]	(0.094)	(0.54)
20	340	2.082	42.37	969	2.129	41.13	1,141	2.210	39.95	1,901	2.306	40.53	2,662	2.088	42.96	2,348	2.376	39.76
	[47.55%]	(0.104)	(2.00)	[46.70%]	(0.067)	(1.27)	[45.81%]	(0.074)	(1.36)	[46.27%]	(0.07)	(0.85)	[48.00%]	(0.043)	(0.75)	[45.35%]	(0.052)	(0.61)

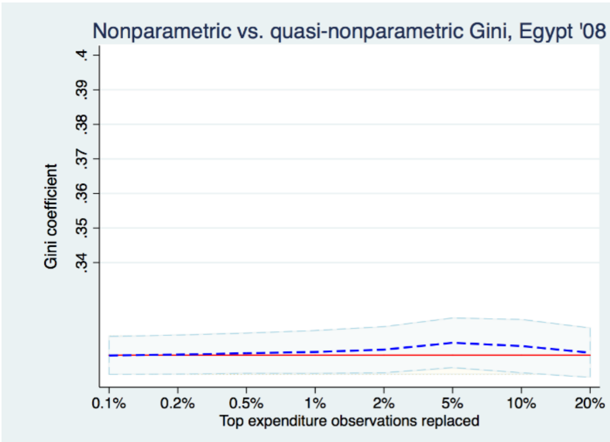
Notes: For clarity, Ginis and their standard errors are multiplied by 100. Pareto coefficients are estimated among the top *k* expenditure observations using maximum likelihood methods. Quasi-nonparametric Gini coefficients are computed as in equation 4 using 100 random draws from the estimated respective Pareto distributions. Standard errors of the quasi-nonparametric Ginis are computed as in equation 5.
"--" indicates that estimates are unavailable due to small size of the sample of top *k* observations.

Table 4. Parametric and quasi-nonparametric estimates of Ginis: Generalized beta distribution type II

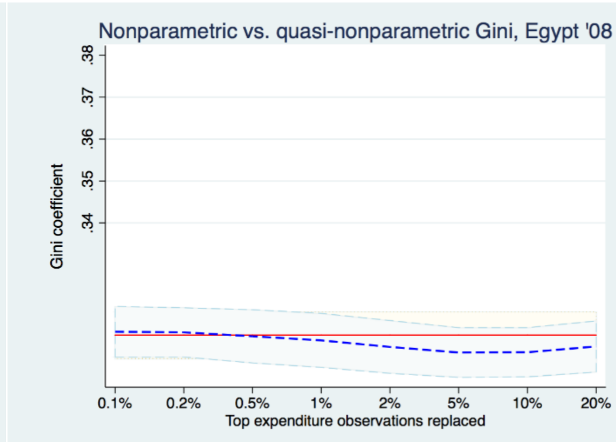
	Egypt '08	Egypt '10	Egypt '12	Jordan '06	Jordan '10	Palestine '07	Palestine '10	Palestine '11	Sudan '09	Tunisia '05	Tunisia '10
E(a)	4.008	3.527	5.162	2.218	2.045	1.657	1.167	1.353	1.858	1.231	1.113
	(0.203)	(0.319)	(0.450)	(0.410)	(0.507)	(0.422)	(0.243)	(0.328)	(0.193)	(0.147)	(0.172)
E(b)	884.212	914.705	1,154.312	1,353.274	1,295.177	2,013.049	1,053.091	1,810.728	850.215	1,102.625	1,867.039
	(17.325)	(43.916)	(25.519)	(159.250)	(308.692)	(337.498)	(609.263)	(743.082)	(41.658)	(137.030)	(202.647)
E(p)	1.346	1.805	0.965	2.252	3.528	2.374	9.741	5.471	1.594	4.236	4.588
	(0.120)	(0.326)	(0.130)	(0.794)	(1.949)	(1.104)	(6.520)	(3.518)	(0.267)	(1.057)	(1.373)
E(q)	0.648	0.739	0.504	1.178	1.242	1.537	2.430	2.102	1.511	2.340	3.327
	(0.040)	(0.083)	(0.053)	(0.297)	(0.422)	(0.569)	(0.725)	(0.728)	(0.249)	(0.438)	(0.873)
log(pseudo-lik.)	-858.52	-270.69	-260.26	-46,583	-53,155	-70.83	-210.06	-240.42	-229,743	-86,914	-94,502
sample size	23,428	7,719	7,528	2,897	2,845	1,231	3,757	4,317	7,913	12,317	11,281
nonparametric Gini	31.32	31.42	29.60	35.81	36.21	40.83	39.18	38.43	39.88	41.40	38.49
	(0.28)	(0.48)	(0.42)	(0.74)	(1.31)	(1.00)	(0.57)	(0.68)	(0.74)	(0.55)	(0.42)
parametric Gini	31.05	31.27	29.88	36.15	36.36	41.36	39.53	38.72	39.68	41.36	38.52
	(0.26)	(0.47)	(0.46)	(0.79)	(1.04)	(1.17)	(0.66)	(0.74)	(0.62)	(0.49)	(0.42)
quasi-nonparametric Gini, top k% replaced											
k=0.1% × n	31.40	31.47	29.88	35.97	35.86	40.94	39.33	38.65	39.55	41.34	38.50
	(0.31)	(0.55)	(0.49)	(0.81)	(0.85)	(1.09)	(0.61)	(0.75)	(0.63)	(0.54)	(0.45)
k=0.2% × n	31.39	31.45	30.00	35.95	36.11	41.26	39.51	38.67	39.51	41.30	38.49
	(0.30)	(0.57)	(0.51)	(0.92)	(0.85)	(1.19)	(0.70)	(0.72)	(0.60)	(0.51)	(0.42)
k=0.5% × n	31.29	31.42	30.15	36.21	36.50	41.41	39.68	38.79	39.52	41.37	38.56
	(0.32)	(0.57)	(0.55)	(1.07)	(0.99)	(1.19)	(0.83)	(0.77)	(0.64)	(0.50)	(0.42)
k=1% × n	31.19	31.33	29.98	36.20	36.58	41.71	39.74	38.70	39.63	41.37	38.59
	(0.33)	(0.55)	(0.55)	(0.82)	(1.56)	(1.82)	(0.76)	(0.71)	(0.67)	(0.48)	(0.41)
k=2% × n	31.04	31.26	29.89	36.27	36.92	41.43	39.78	38.72	39.66	41.41	38.60
	(0.32)	(0.56)	(0.55)	(0.82)	(2.89)	(1.32)	(0.80)	(0.74)	(0.67)	(0.49)	(0.40)
k=5% × n	30.91	31.15	29.85	36.39	36.60	41.31	39.76	38.82	39.70	41.30	38.60
	(0.30)	(0.63)	(0.58)	(0.94)	(1.18)	(1.31)	(0.88)	(0.79)	(0.68)	(0.48)	(0.41)
k=10% × n	30.91	31.17	29.85	36.16	36.57	41.47	39.55	38.81	39.65	41.30	38.55
	(0.30)	(0.54)	(0.57)	(0.89)	(1.22)	(1.52)	(0.83)	(0.88)	(0.65)	(0.49)	(0.42)
k=20% × n	31.05	31.16	30.05	36.14	36.51	41.18	39.54	38.68	39.65	41.27	38.42
	(0.31)	(0.53)	(0.63)	(1.17)	(1.79)	(1.50)	(0.95)	(0.84)	(0.65)	(0.47)	(0.40)

Notes: Income distributions converted to international dollars, purchasing power parity, are used (UNSD 2015). For clarity, Ginis and their standard errors are multiplied by 100. Standard errors are in parentheses. Parametric Ginis are calculated by numerical integration with 5,000 integration points. Quasi-nonparametric Ginis are computed as in equations 2 and 4. Standard errors of quasi-nonparametric Ginis are computed by bootstrapping and using 100 random draws from the estimated GB2 distribution as in equation 5.

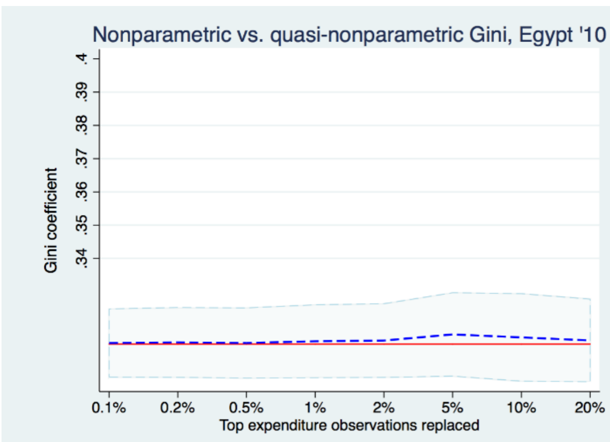
Figure 1. Gini uncorrected vs. corrected for non-representative distribution of highest expenditures



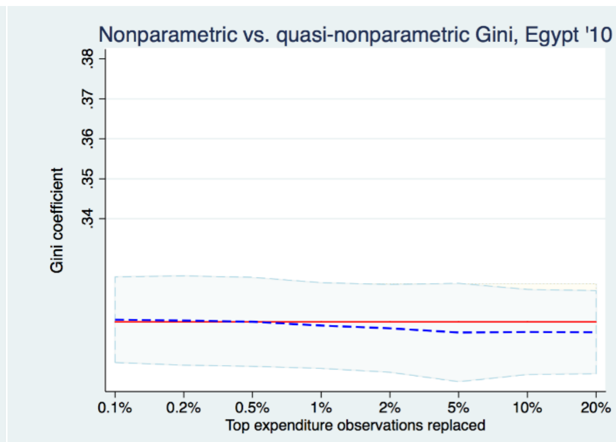
a. Pareto distribution correction, Egypt ’08



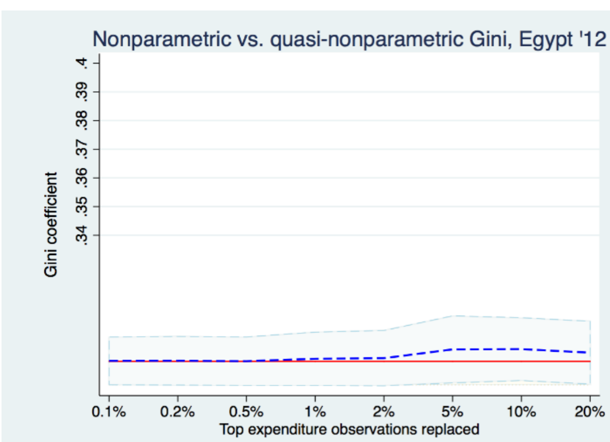
b. GB2 distribution correction, Egypt ‘08



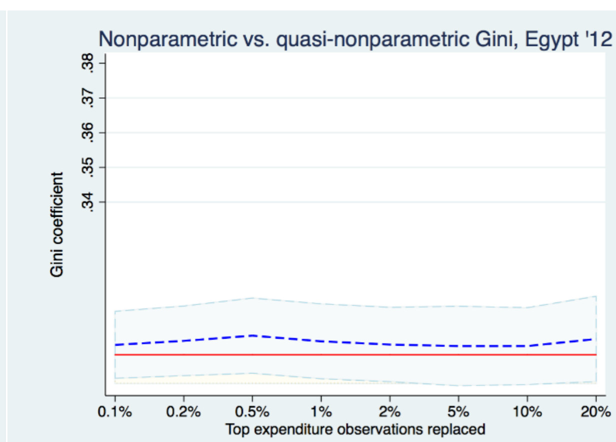
c. Pareto distribution correction, Egypt ‘10



d. GB2 distribution correction, Egypt ‘10



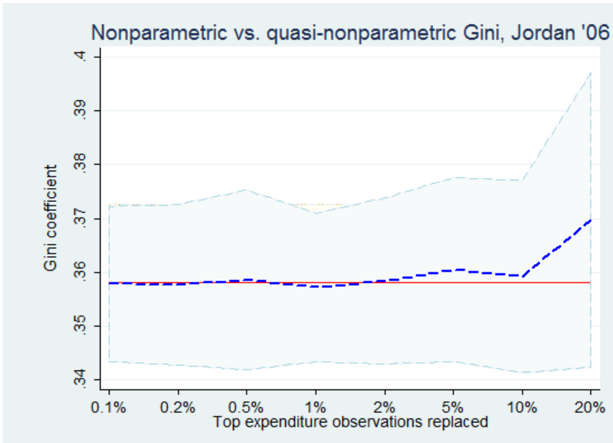
e. Pareto distribution correction, Egypt ‘12

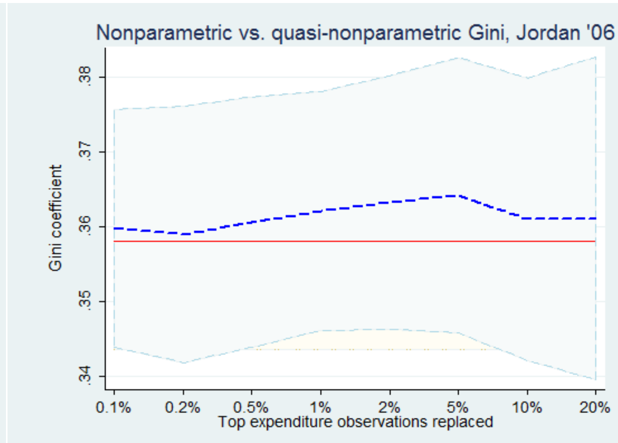


f. GB2 distribution correction, Egypt ‘12

Note: Scale in these figures may need to be adjusted at a later point when the authors receive access to data again.

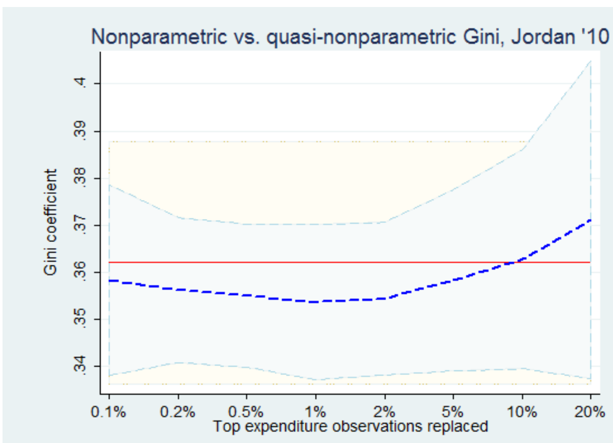
Figure 1 (cont.). Gini uncorrected vs. corrected for non-representative distribution of highest expenditures

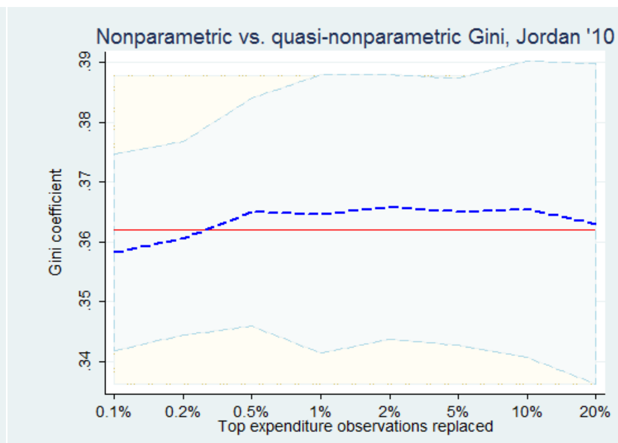




g. Pareto distribution correction, Jordan ’06

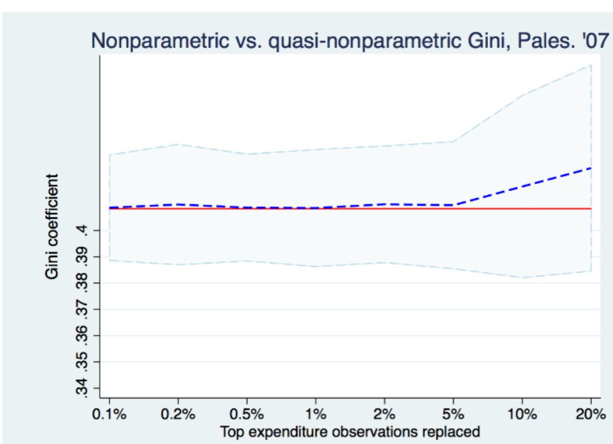
h. GB2 distribution correction, Jordan ‘06

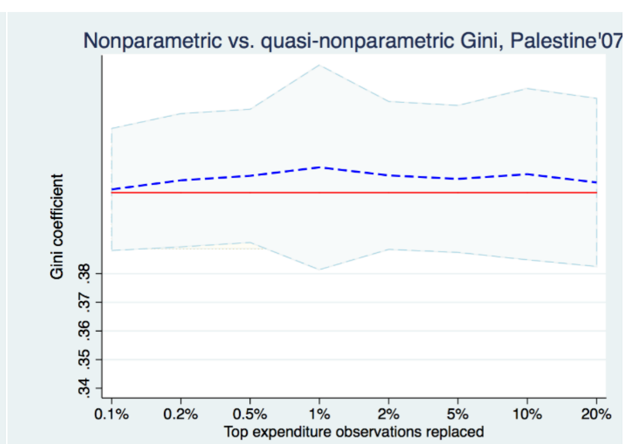




i. Pareto distribution correction, Jordan ‘10

j. GB2 distribution correction, Jordan ‘10



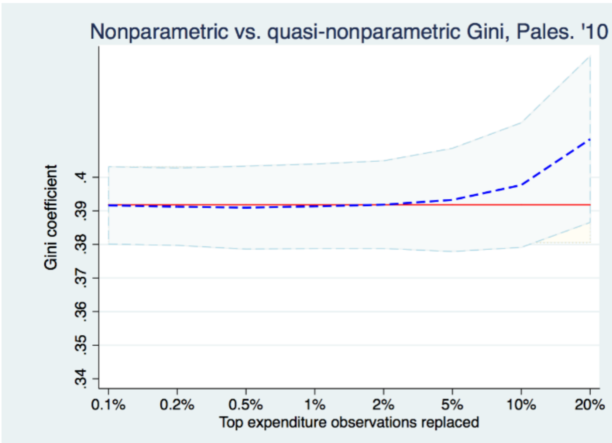


k. Pareto distribution correction, Palestine ‘07

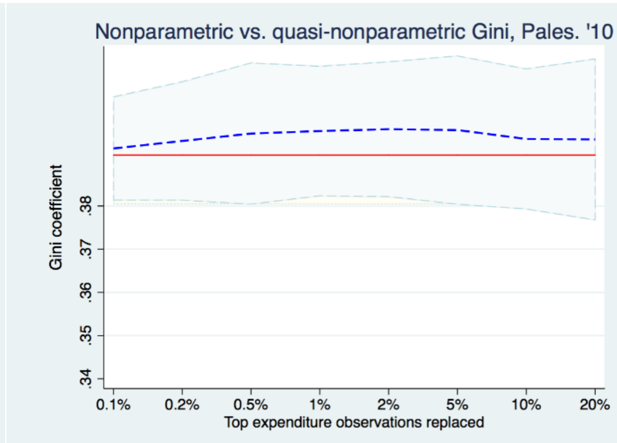
l. GB2 distribution correction, Palestine ‘07

Note: Scale in these figures may need to be adjusted at a later point when the authors receive access to data again.

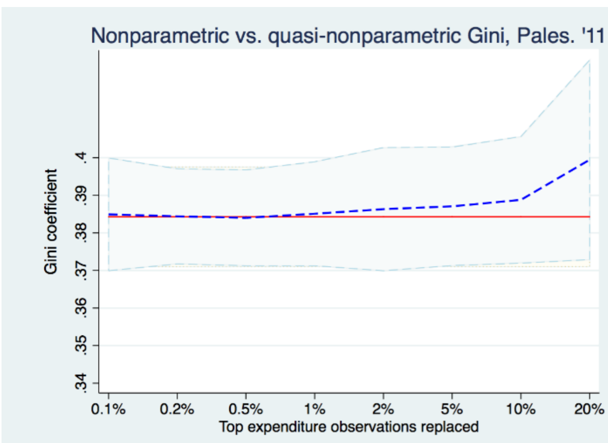
Figure 1 (cont.). Gini uncorrected vs. corrected for non-representative distribution of highest expenditures



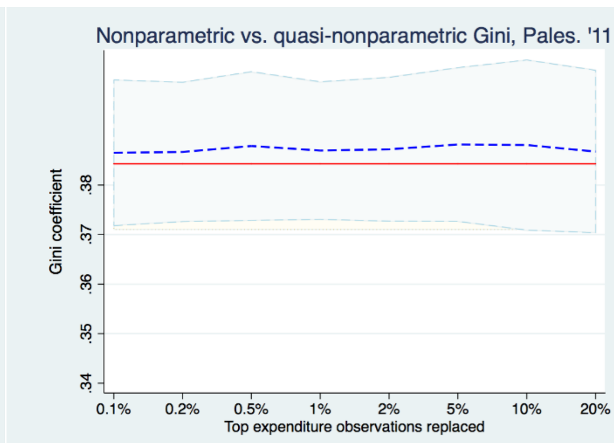
m. Pareto distribution correction, Palestine ‘10



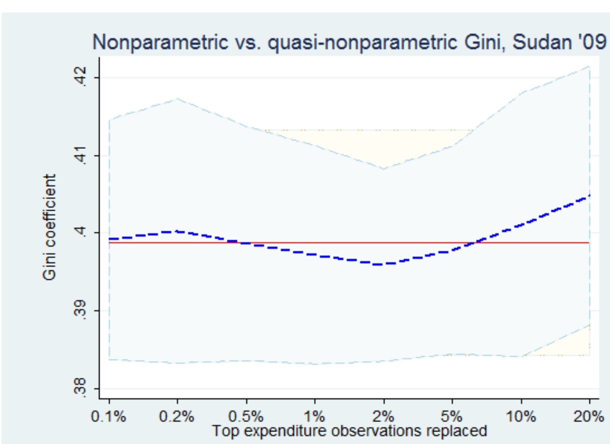
n. GB2 distribution correction, Palestine ‘10



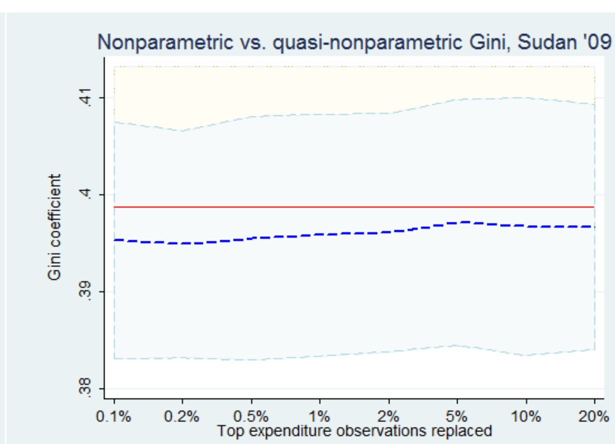
o. Pareto distribution correction, Palestine ‘11



p. GB2 distribution correction, Palestine ‘11



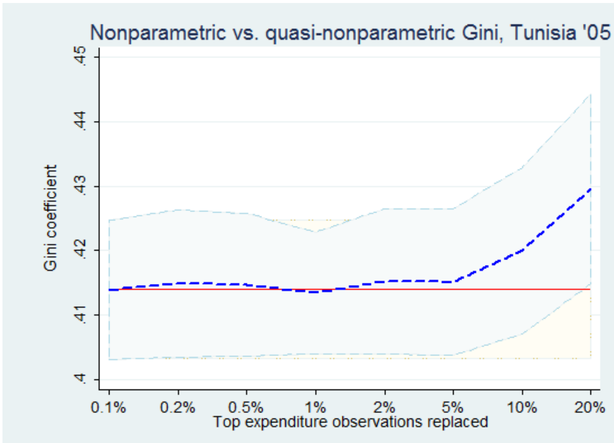
q. Pareto distribution correction, Sudan ’09



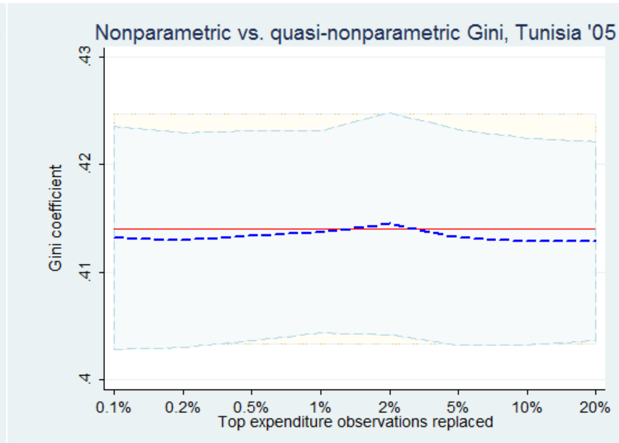
r. GB2 distribution correction, Sudan ‘09

Note: Scale in these figures may need to be adjusted at a later point when the authors receive access to data again.

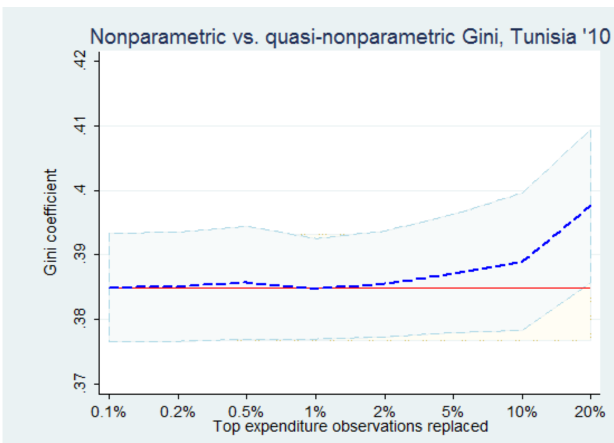
Figure 1 (cont.). Gini uncorrected vs. corrected for non-representative distribution of highest expenditures



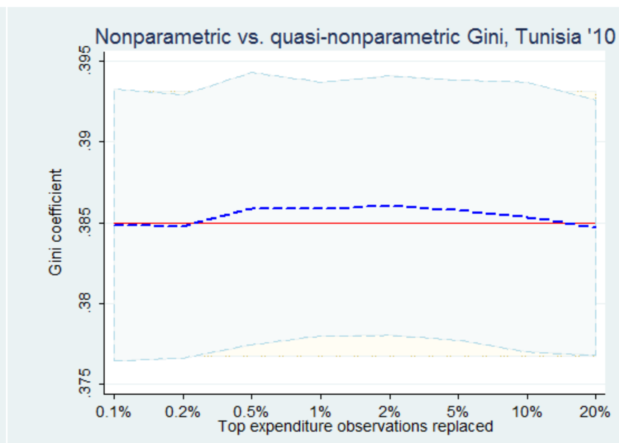
s. Pareto distribution correction, Tunisia '05



t. GB2 distribution correction, Tunisia '05



u. Pareto distribution correction, Tunisia '10



v. GB2 distribution correction, Tunisia '10

Notes: Blue dashed lines show the estimated quasi-nonparametric Ginis and 95% confidence intervals using bootstrap standard errors aggregated across 100 random draws as in equation 5, for alternative delineations of top *k* expenditures. Red solid lines show non-parametric Ginis with their 95% confidence intervals using bootstrap standard errors.

Figure 2. Inverted Pareto-Lorenz coefficient of top expenditure distribution

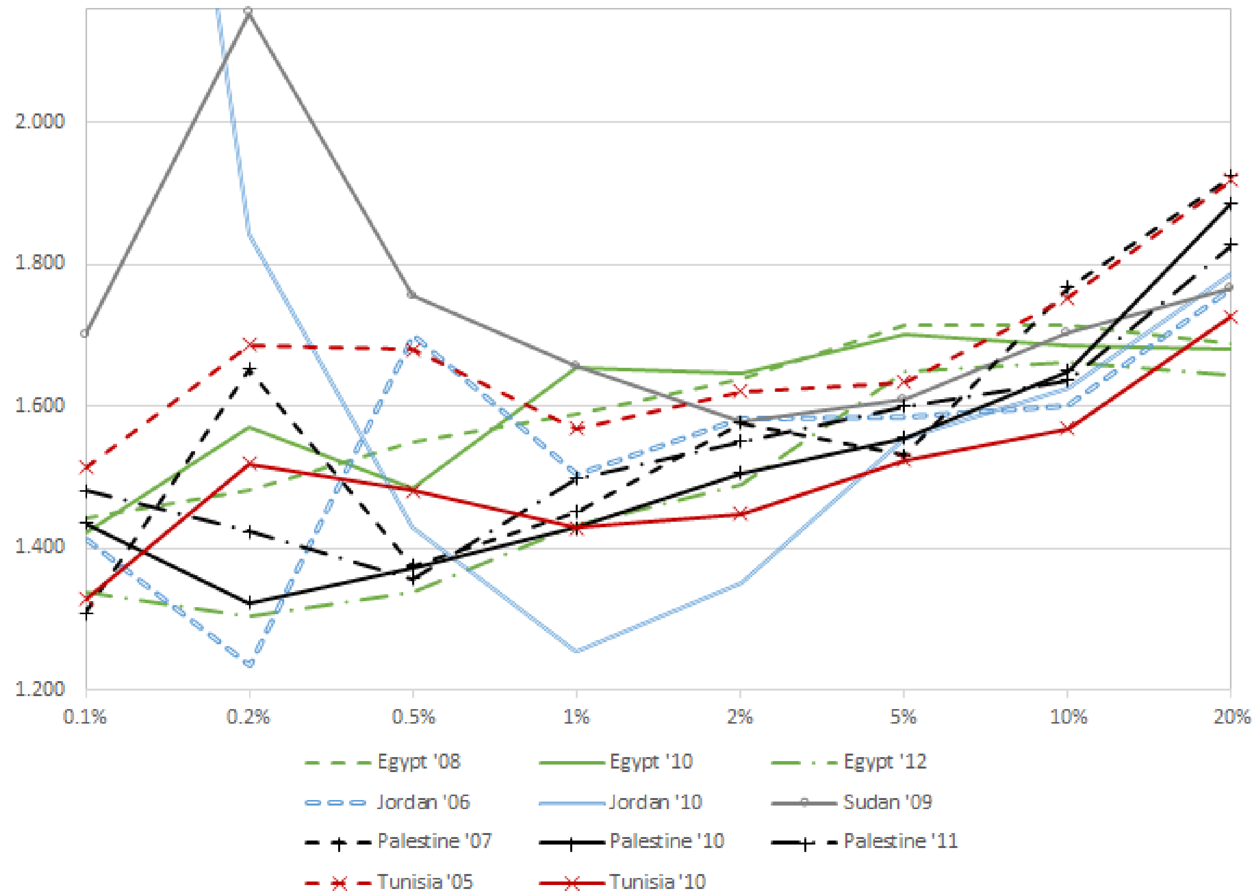
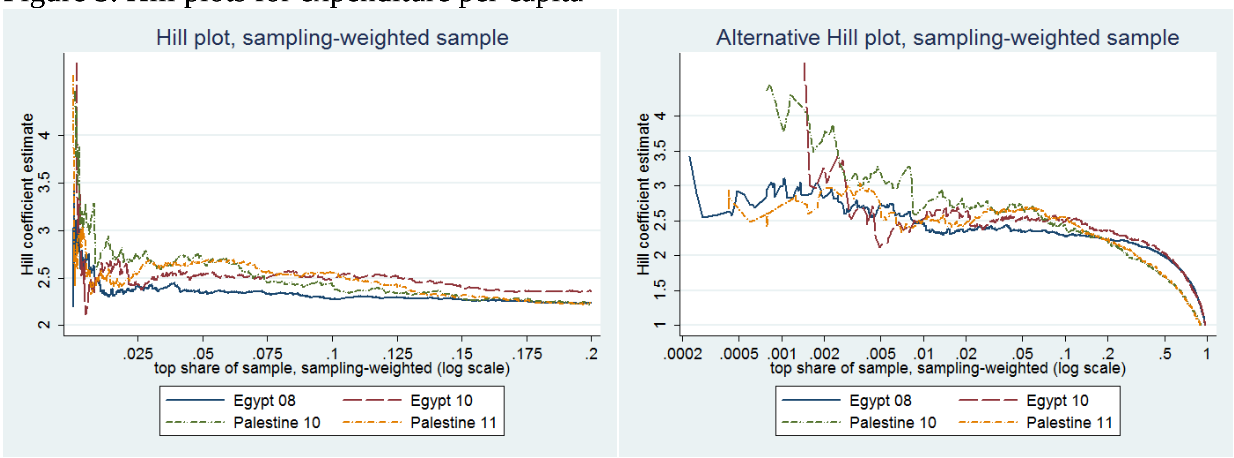
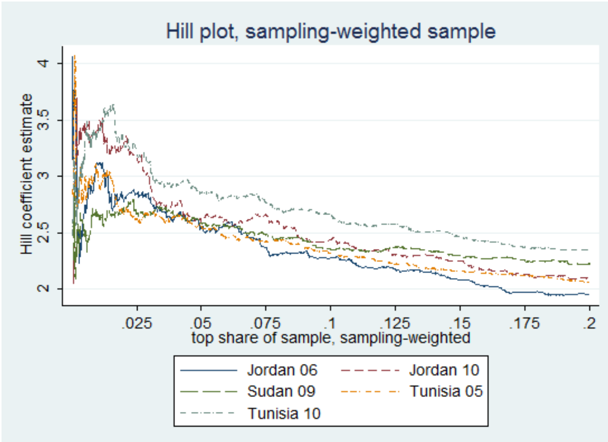


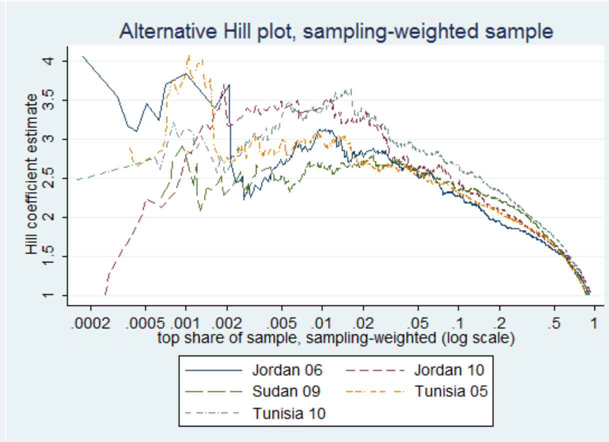
Figure 3. Hill plots for expenditure per capita



(a) Hill plots: Egypt and Palestine (b) Alternative Hill plots: Egypt and Palestine



(c) Hill plots: Jordan, Sudan and Tunisia

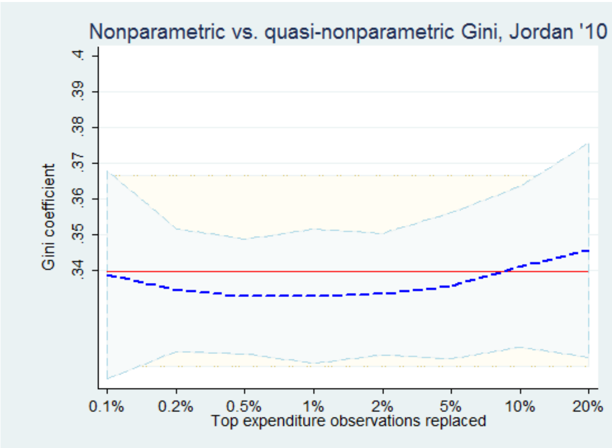


(d) Alternative Hill plots: Jordan, Sudan and Tunisia

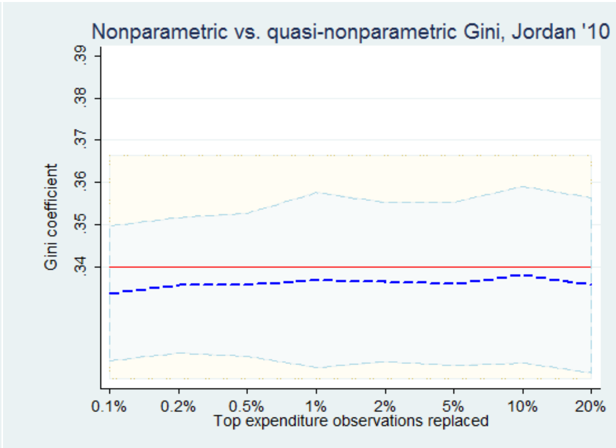
Notes: Sample size in all eleven surveys is normalized to 100% and the Hill plots truncated at top 20% of sample to facilitate comparison. The alternative Hill plots use a logarithmic scale for sample size (Drees *et al.* 2000).

Appendix

Figure A1. Uncorrected vs. corrected Ginis using an alternative adult-equivalent household-size scale



a. Pareto distribution correction, Jordan '10



b. GB2 distribution correction, Jordan '10

Note: Expenditure per capita is computed using a modified OECD adult-equivalence scale with household size taken as $[1 + 0.7\ (N_{adults}-1) + 0.3\ N_{children} + 0.3\ N_{elderly}]$ to account for a lesser role played by children under the age of 14 and the elderly aged 65+ years (Glewwe and Twum-Baah, 1991, as cited in Haughton and Khandker 2009:29).