Poverty in Egypt: Modeling and Policy Simulations

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I. Introduction

Poverty profiles are a useful way of summarizing information on the levels of poverty and the characteristics of the poor in a society. They also provide us with important clues to the underlying determinants of poverty. However, important as they are, poverty profiles are limited by the bivariate nature of their informational content. The bivariate associations typical in a poverty profile can be misleading because of their unconditional nature; they beg the obvious question of the effect of a particular variable conditional on the other potential determinants. While there may be certain contexts where unconditional poverty profiles are relevant to a policy decision (e.g., in the context of indicator targeting; see Ravallion [1996]), often one is interested in the "conditional" poverty effects of proposed policy interventions. It is not surprising, therefore, that empirical poverty assessments in recent years have seen a number of attempts at going beyond the poverty profile tabulations to engage in a multivariate analysis of living standards and poverty.[1] This study of Egypt has a similar motivation.

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[1] See, e.g., Glewwe (1991), World Bank (1994, 1995a, 1995b, 1995c, 1996), and Grootaert (1997), to mention just a few.

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Several poverty profiles with descriptive analysis of the characteristics of the poor have been produced for Egypt. See, for example, Ali, El-Laithy, and Hamza (1994), Korayem (1994), El-Laithy and Osman (1996), Cardiff (1997), and Datt, Jolliffe, and Sharma (2001). Haddad and Ahmed (2003) extend the poverty profile analysis by looking at transitions in and out of poverty in Egypt between 1997 and 1999. Adams (2000), Ahmed and Bouis (2002), and Gutner (2002) examine the interaction between the food subsidy system in Egypt and poverty, providing a discussion of the feasibility of reforming the food subsidy system and its potential impact on the poor.[2] To our knowledge, though, there is no precursor to a multivariate modeling of the determinants of poverty for Egypt that allows for an analysis of the effect of some policy variable on poverty while controlling for other potential determinants.

This article is organized as follows. The next section describes our approach to modeling the determinants of poverty. Section III describes the data, discusses our consumption-based measure of poverty, and introduces the explanatory variables used in our analysis. Section IV presents the regression results. Estimates for two versions of a model of living standards are presented, and, based on these regression estimates, Section V provides results for several policy simulations of antipoverty interventions. Some concluding remarks are offered in the final section.

II. Modeling Determinants of Poverty

There can be a number of different approaches to modeling the determinants of poverty. In this section, we distinguish between two main approaches and discuss our reasons for preferring one of them for the analysis undertaken in this study.

A. Poverty versus Consumption Models

We begin with our preferred approach to modeling the determinants of poverty, which can be described as a two-step procedure. In the first step, we model c_j, the determinants of per capita consumption at the household level. The simplest form of such a model could be as follows:

$$\ln c_j = \beta' x_j + \eta_j, \tag{1}$$

where x_j is a set of household (or community) characteristics and η_j is a random

[2] See Assaad and Rouchdy (1998) for a general overview of the state of poverty research in Egypt.

error term. In the second step, a household's poverty measure is defined in terms of its consumption level:

$$p_{\alpha j} = \{\max[(1 - c_j/z), 0]\}\alpha \geq 0, \tag{2}$$

where z denotes the poverty line and α is a nonnegative parameter. The household equivalents of the head-count index, the poverty gap index, and the squared poverty gap index are obtained when $\alpha = 0, 1$, and 2, respectively. While equation (2) is a definitional relationship, combined with the model shown in equation (1) it yields a relationship between poverty levels and household/community characteristics.[3] Some recent examples of the use of this approach include Bigman et al. (2000), Hentschel et al. (2000), Minot (2000), and Elbers, Lanjouw, and Lanjouw (2001).

This approach contrasts with directly modeling household-level poverty measures as

$$p_{\alpha j} = \beta_{\alpha'} x_j + \eta_{\alpha j}. \tag{3}$$

This direct approach has often been used in the literature (see, e.g., Bardhan 1984; Gaiha 1988; World Bank 1994, 1995a, 1995c, 1996; Grootaert 1997). Despite the popularity of this approach, there are reasons why modeling household consumption may be considered preferable to modeling household poverty levels.

First, using data on only $p_{\alpha j}$ is inefficient because information on the household living standards above the poverty line is deliberately suppressed in the estimation of the regression parameters. All nonpoor households are treated alike, as censored data. Thus, equation (1) has greater informational content than equation (3); given household consumption, c_j, the household's poverty level, $p_{\alpha j}$, is completely determined, but not vice versa.[4]

Second, there is an inherent arbitrariness about the level of the absolute poverty line, even if the relative cost of living as established by the regional poverty lines is considered robust. However, different poverty lines imply that household consumption data would be censored at different levels. The esti-

[3] Aggregate poverty for a population with n households is simply the mean of this measure across all households weighted by household size (h_j), giving

$$P_\alpha = \left(\sum_{j=1}^{n} h_j p_{\alpha,j}\right)\left(\sum_{j=1}^{n} h_j\right)^{-1}.$$

[4] A related issue has to do with the number of noncensored observations available for direct modeling of poverty measures. This number is directly determined by the observed head-count index for the sample. A low head-count index means that the number of noncensored observations for estimation could be very small.

mated parameter of the poverty model would therefore change with the level of poverty line used. This can generate an internal (logical) inconsistency, as Pudney (1999) demonstrates. The logical inconsistency with modeling poverty as a binary outcome arises because there will be some combinations of household characteristics such that for a range of poverty lines the probability of being poor need not be increasing in the poverty line (i.e., the implied cumulative density function is not monotonic).[5] Modeling consumption directly has the attractive feature that the consumption model estimates are invariant to the choice of the poverty line. The link with household poverty level is established in a subsequent step.

Hence, in this study, we model consumption as in equation (1) and then use equation (2) to infer implications about levels of poverty. In estimating models such as equation (1), we express consumption in real terms, that is, nominal per capita consumption normalized by a spatial cost of living index, where this index is derived as the ratio of a region's poverty line to a reference region's line (see Sec. III). This is justified because the class of poverty measures we use is homogeneous of degree zero in mean consumption and the poverty line; in other words, the poverty measure $p_{\alpha j}$ depends on the ratio of c_j to z.

B. Basic and Augmented Models

We refer to the consumption model discussed above as the basic model. It has the feature that the marginal effects of determinants of consumption are constant across households. It is, however, arguable that there is heterogeneity across households, and the marginal effects themselves depend on household characteristics. This concern leads us to consider the following augmented version of the model that allows for a range of interaction effects and individual-specific marginal effects (β_j):

$$\ln c_j = \beta_j' x_j + \eta_j, \tag{4}$$

where

$$\beta_j = \beta + \gamma' x_j + \varepsilon_j, \tag{5}$$

and, hence,

$$\ln c_j = \beta' x_j + x_j' \gamma x_j + \eta_j^*. \tag{6}$$

This delivers a model with heteroskedastic errors, $\eta_j^* = \eta_j + \varepsilon_j' x_j$, which is easily allowed for in estimating the variance matrix of the model parameters.

[5] The same point also applies when poverty is modeled as a censored variable.

Equation (6) can also be motivated as a flexible functional form generalization of equation (1). The model has a generalized quadratic form, which is a numerically equivalent second-order approximation to any arbitrary twice-differentiable function (Lau 1974).

III. Data and Empirical Implementation

The primary data used in this article are from the 1997 Egypt Integrated Household Survey (EIHS), a nationwide, multiple-topic household survey carried out by the International Food Policy Research Institute in coordination with the Ministry of Agriculture and Land Reclamation and the Ministry of Trade and Supply. The questionnaire was administered to 2,500 households from 20 governorates using a two-stage, stratified selection process. For more information on the EIHS, including more details on the sample design, strata weights, and fieldwork, see Datt, Jolliffe, and Sharma (1998).

A. Welfare Metric and Poverty Lines

The measure of consumption used in this article is the sum of total food consumption; total nonfood, non-durable-good expenses; estimated use value of durable goods; and an actual or imputed rental value of housing. Each of these components of consumption is documented in more detail in Datt et al. (1998). Per capita consumption is used as the basic measure of individual welfare. The use of per capita consumption imposes the dubious assumptions that there are no economies of household size in consumption and that household composition does not matter, and, therefore, the estimated parameters on household size and composition have to be interpreted with caution.

We follow the cost of basic needs methodology to construct region-specific poverty lines (Ravallion 1994). Using this approach, the total poverty line (z) is constructed as the sum of a food (z^F) and a nonfood poverty line (z^N). The food poverty line is based on the estimated cost of obtaining minimum caloric requirements (World Health Organization 1985). The nonfood poverty line is a weighted average of the expenditure levels on nonfood items by those households whose food expenditure is equal to the food poverty line. The motivation for this method is that the households who can just purchase the minimum food requirements are likely to also be consuming a minimum bundle of nonfood items.

The reference poverty line varies for each of the five regions: metropolitan, lower urban, lower rural, upper urban, and upper rural. Differences in the poverty lines reflect variations in the food and nonfood prices across the five regions. They also incorporate regional differences in the size and age composition of the relatively poor households and in their food and nonfood consumption patterns. The use of a fixed bundle is typically justified by the argument that an unchanging bundle is necessary to assure that regional poverty lines represent equal levels of welfare or standard of living. However, if relative prices or tastes vary regionally, the comparability of welfare levels across regions is illusory, and the fixed bundle method can generate inconsistent poverty comparisons, as shown in Tarp et al. (2002). Region-specific bundles can accommodate differences both in prices or preferences.

The differences in the region-specific poverty lines reflect the different costs of meeting basic needs in the five regions, and thus the ratio of poverty lines can be interpreted as spatial price differences. In this article, the poverty line for the metropolitan region is treated as a baseline, and the spatial price index is the ratio of each region's poverty line to the poverty line for the metropolitan region. (See Datt et al. 1998 for details.)

B. Data on Determinants of Living Standards

In modeling the determinants of consumption, we estimate separate models for urban and rural sectors. This decision is based on two considerations. First, we argue that the rural and urban sectors of Egypt are sufficiently different from each other so as to warrant different models. Second, a number of community-level variables are available only for the rural sector, and by modeling the sectors separately, we can exploit these data.

In selecting among potential determinants of living standards, a key consideration for us has been selecting variables that are arguably exogenous to current consumption. Thus, for instance, we do not include dwelling characteristics, as these are likely to be determined by household living standards; these characteristics also determine the actual and imputed rents that directly enter into aggregate consumption for the household.

The selected determinants can be grouped broadly into household and community-level variables. At the household level, we first include a set of demographic variables: household size (a linear and quadratic term allowing for nonlinearities), the proportion of elderly (above age 60) household members, linear and quadratic terms in the age of the household head to capture possible life cycle effects, and a binary variable for female head of household. We also include a set of education variables. First, the household average of completed school years for household members above the age of 15 is included. We also include measures of parental education, in particular, a binary variable for whether either parent of the household head had primary schooling and anal-

TABLE 1
DESCRIPTIVE STATISTICS

	Rural (N = 1,326)		Urban (N = 1,123)	
	Mean	SD	Mean	SD
Log: monthly, real per capita expenditure	5.24	.031	5.46	.043
Upper Egypt	.42	.004	.27	.012
Household characteristics:				
Size	6.65	.195	4.98	.103
Size, squared	57.50	3.885	29.55	1.246
Household head: age (years)*	45.12	.552	46.86	.762
Household head: age, squared*	2,336.36	47.934	2,469.60	68.459
Dummy: female-headed household = 1	.16	.011	.14	.012
Average: years of schooling*	4.66	.192	7.97	.256
Log: owned, cultivated land	1.08	.109	.10	.028
Dummy: household head's parents' primary schooling*	.22	.024	.63	.057
Dummy: spouse's parents' primary schooling*	.18	.019	.58	.050
Community characteristics:				
Distance to secondary school	3.71	.244	2.33	.255
Distance to health post/hospital	1.39	.212	1.57	.283
Distance to bazaar	2.60	.271	1.54	.280
Distance to market	4.92	.247	2.97	.343
Distance to agricultural co-op/extension	1.73	.273	5.05	.320
Distance to commercial/village bank	3.13	.241	3.31	.289
Missing data:				
Age	.01	.003	.01	.004
Age, household head	.05	.007	.05	.008
School, household average	.02	.004	.02	.004
Zero: cultivated, owned land	.76	.023	.98	.007

* Missing values for these variables have been set to zero. Estimates are corrected for complex sample design.

ogously a binary variable for whether either parent of the spouse of the household head had primary schooling.

We include one variable related to household assets, namely, the area of cultivated land that is owned by the household. Owned land could arguably be considered exogenous, given the relatively thin land markets in Egypt. A separate binary variable for households that do not own any land is also included.

At the community level, we include six variables measuring access to facilities. We have data on mode of transit and travel time to the nearest secondary school, health post or hospital, bazaar, market, agricultural cooperative or extension center, and to a village or commercial bank. For each variable, we estimate a measure of equivalent time to the facility by foot. (See Datt et al. 1998 for details.) Finally, we include in both the rural and urban models a dummy variable for whether the household lives in upper Egypt. Descriptive statistics for the model variables for the rural and urban sectors are shown in table 1.

C. Further Specification and Estimation Issues

For several of the explanatory variables, there are missing data for some households. We include these observations with missing data and have constructed dummy variables that take the value of one if the household is missing data for a particular variable (while the value of that variable itself is set to zero). In this way we reduce the potential of sample selection bias, and we do not miss out on useful information from households with some valid data for most variables.

There may also be some concerns of potential bias in parameter estimates due to endogeneity or omitted variables. For instance, it could be argued that regional agroecological factors that determine the productivity of land are omitted from the regression and hence implicitly included in the error term of the model. If these factors are a significant determinant of living standards, the error term will not converge to zero in probability limit, and the parameter estimates for the included explanatory variables will be inconsistent. To control for this type of omitted-variable bias, we include governorate-level fixed effects in our estimation model.

While the augmented equation (6) offers a fairly general approach to modeling living standards, this generality comes at the potential cost of overparameterizing the model. With the full set of interaction terms, there is an explosion of parameters. Beginning with a k-parameter basic model, there are $2k + k(k - 1)/2$ parameters in the augmented equation (6); thus, for instance, if the basic model has 20 parameters, the extended model would have 230 parameters. A model with numerous parameters is likely to suffer from multicollinearity and therefore provide imprecisely estimated parameters (even though the model as a whole may fit the data well). This issue becomes particularly troublesome when the model is used for simulations, which typically involve changing one or two variables at a time. If the parameters for the selected variables are imprecisely estimated, then the simulated effects will also be imprecisely estimated.

In view of these difficulties, we use a selective specification strategy for introducing interaction terms into the basic equation (1). Aiming for a more parsimonious specification, we limit the interaction terms to only those variables that appear significantly in the model by themselves. Thus, prior to the introduction of interaction terms, we first strip the model down to only statistically significant variables. This is shown in the first set of columns in table 2. We then introduce interaction terms between all these variables and then further delete all statistically insignificant variables in their inter-

TABLE 2

BASIC AND AUGMENTED MODELS, LOG PER CAPITA CONSUMPTION—OLS, GOVERNORATE-LEVEL FIXED EFFECTS

		Rural Model (N = 1,326)				Urban Model (N = 1,122)			
		Basic Model		Augmented Model		Basic Model		Augmented Model	
Variable	Description	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio	Coefficient	*t*-Ratio
Upper	Upper Egypt	.147	2.91	.045	.43	−.145	−2.65	−.082	−1.82
Household characteristics:									
Hhsize	Household size	−.142	−8.83	−.156	−9.54	−.306	−12.51	−.245	−9.05
Hhsize2	Household size, squared	.004	5.23	.004	5.63	.015	9.98	.014	9.84
Hhage	Household head: age in years	.015	2.58	.012	1.97	.019	2.31	.010	3.91
Hhage2	Household head: age+ squared	.000	−1.95	.000	−1.69	.000	−1.65		
Femhead	Dummy: female-headed household	−.069	−1.77			−.114	−2.13	−.113	−2.11
Avgsch	Household average years of schooling	.041	10.51			.053	10.7	.054	10.73
Hhpedu	Household head's parent: primary school	.052	2.11	.068	2.61	.080	3.33	.079	3.27
Sppedu	Spouse's parent: primary school	.056	2.04						
Lowned	Log: owned cultivated land	.146	5.22	.253	6.98	.090	1.67		
Secsch	Distance to secondary school	.032	2.29						
H_post	Distance to hospital post/hospital	−.036	−3.06	−.022	−1.56				
Interaction effects:									
Hhsize × avgsch				.004	3.18				
Hhsize × sppedu				−.020	−2.47				
Hhsize × hhage								−.001	−2.38
Hhsize × lowned								.010	2.38
Hhage × avgsch				.000	2.82				
Hhage × sppedu				.005	4.25				
Hhage × lowned				−.001	−3.15			.001	1.92
Avgsch × lowned				−.006	−2.84				
Hhpedu × sppedu				−.041	−2.04				
Sppedu × h_post				.024	1.46				
Lowned × h_post				−.007	−1.52				
Intercept		4.876	23.88	5.196	23.79	5.352	15.35	5.246	23.68
R^2		.37		.38		.48		.48	

Note. Dummies for governorates and missing observations are suppressed from the output. The urban sample consists of 57 primary sampling units (PSUs); the rural sample has 68 PSUs. OLS = ordinary least squares.

acted or noninteracted form.[6] The resulting estimates are shown in the second set of columns in table 2.

IV. The Estimated Models

Table 2 presents estimates for both the basic and the augmented models. The null hypothesis that interaction terms in the augmented model are jointly equal to zero is convincingly rejected for both rural and urban areas.[7] Thus, there is no support for the hypothesis that the marginal effects of the determinants on living standards are uniform across households. The following points about the estimates in table 2 are notable.

1. *Demographic factors*. In both rural and urban areas, household size has a significant negative (though nonlinear) effect on living standards, as measured by consumption per person. This inverse relation between household size and per capita consumption, and by implication the positive relation between household size and poverty, is a common finding in the literature (see, e.g., Lanjouw and Ravallion 1995; and Lipton and Ravallion 1995) but, as argued above, is critically dependent on the underlying assumptions regarding economies of household size and equivalent scales. In light of this, too much should not be read into this result.

The age of the household head shows the expected life cycle effects in both rural and urban areas. In the basic models, household living standards increase with the age of the head up to 66 years (89th percentile) in rural areas and 73 years (95th percentile) in urban areas, and decline thereafter (although the quadratic term in urban areas is significant only at the 10% level). These results are consistent with life cycle phenomena of higher earning capacity with greater experience and smoothing of consumption over the life cycle.

2. *Education*. Educational variables emerge as a strong determinant of living standards in the results for both the rural and urban areas. In the basic models, average years of schooling specified on its own has a significant positive effect on per capita consumption. However, once the models are augmented with interaction terms, several interaction terms in schooling are found to be significant in rural areas. For example, the marginal return on years of schooling is found to be increasing in household size, as well as the age of the head of the household, but decreasing in the amount of

[6] With the exception of governorate fixed effects and variables to control for missing values; see discussion below.

[7] The *F*-statistics for joint significance of the interaction terms in the rural and urban models both have *P*-values of less than .001.

land owned.[8] This suggests some complementarity between greater average years of education and household size and also complementarity with experience of the head of the household but some substitutability with land ownership. The different interaction effects make it difficult to infer the rate of return of an extra year of schooling directly, and we return to this issue later in the discussion of the policy simulations below. Indeed, a key motivation for simulations is precisely to evaluate the implicit rates of return on different policy instruments.

3. *Intergenerational effects*. We find strong positive intergenerational effects in education. Parental education has a strong positive effect on household welfare in both rural and urban areas. The basic model for rural areas indicates that either parent of the household head having completed primary schooling has a strong positive effect on household welfare. A similar positive effect (of similar magnitude) also holds for the parents of the spouse of the household head. The augmented model for rural areas further indicates that the marginal effects of parental education vary across households. In contrast, in urban areas only the parental education for the household head seems to matter, and the data do not indicate any significant variation in the marginal effect across households.

4. *Household assets and community characteristics*. We find that owned land (for cultivation) has a significant positive effect on per capita consumption of the household. The effect holds for rural as well as urban areas even though less than 3% of the urban sample households are owner-cultivators. The results also indicate that the marginal effects vary across households. The only community characteristic that turns out to be important in the augmented model is distance to a health post or hospital and that too only for the rural sector, where greater proximity to health facilities promotes higher living standards.

V. Poverty Simulations

A. Methodology

Having estimated the consumption models above, we now generate predictions of poverty. The key steps of the procedure for the head-count index are illustrated below; derivations of the analytical formulas for other poverty measures can be found in the appendix and in Datt (2004). Using the estimated parameters ($\hat{\beta}$) of the preferred model and assuming (conditional) log normality

[8] This effect appears robust to economies of household size; the effect remains positive and significant with a size economy parameter of 0.5 (relative to the value of one implicit in the use of per capita consumption as the measure of welfare).

of consumption, we first estimate consumption per capita, $E(c_j)$, for every household j as

$$E(c_j) = e^{\hat{\beta}' x_j + \hat{\sigma}^2/2}. \tag{7}$$

The term $\hat{\sigma}^2/2$, where $\hat{\sigma}$ is the estimated standard error of the regression, is required because of the lognormal transformation of the dependent variable. We test for the normality of residuals from the consumption models, and although normality is statistically rejected, the residual plots in figure 1 show that it is not much off the mark.

Corresponding to every predicted consumption level, there is a probability of the household being poor (P_{0j}), which is given by

$$\begin{aligned}\hat{P}_{0j} &= \Pr(\ln \hat{c}_j < \ln z) = \Pr\left(\eta_j < \ln z - \hat{\beta}' x_j\right) \\ &= \Phi\left[\left(\ln z - \hat{\beta}' x_j\right)/\hat{\sigma}\right],\end{aligned} \tag{8}$$

$$\begin{aligned}\hat{P}_{0j} &= \Pr(\ln \hat{c}_j < \ln z) = \Pr\left(\eta_j < \ln z - \hat{\beta}' x_j\right) \\ &= \Phi\left[\left(\ln z - \hat{\beta}' x_j\right)/\hat{\sigma}\right],\end{aligned} \tag{9}$$

where Φ is the standard normal distribution function, σ is the standard error of the regression, and the circumflex ($\wedge$) indicates estimated values.

Based on predicted consumption, one could construct a binary variable to classify a household as poor or nonpoor. But predicted consumption is only a point estimate, which comes with its own prediction or forecast error. Thus, for example, even if predicted consumption were above the poverty line for a given household, there is a nonzero probability that the true value of that household's predicted consumption is below the poverty line. It is therefore appropriate to treat predicted consumption as a stochastic variable, and, hence, we go on to compute the probability of being poor associated with any given level of predicted consumption.

Finally, a weighted average of the household probabilities of being poor gives the predicted national head-count index, with the weight for each household being the product of the survey sample weight and the number of members in the household. Predicted measures of the depth and severity of poverty can be derived similarly (Datt 2004). The appendix presents the relevant formulas.

The poverty simulations we consider below are based on the augmented model estimates of table 2. The usual caveat applies to the results of this simulation analysis. The simulations assume that the considered changes in

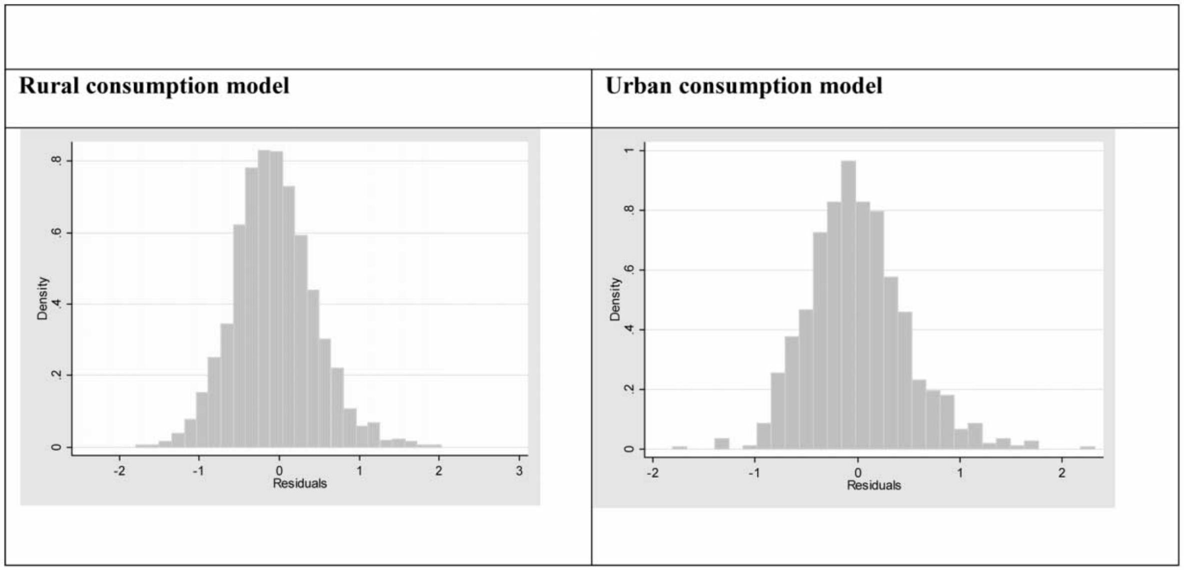

Figure 1. Residual plots for rural and urban consumption models

the determinant variables do not affect the model parameters or other exogenous variables. While this is a plausible assumption for incremental changes, it warrants a more cautious interpretation for simulations involving "large" policy changes. We comment below on the direction of bias in the case of some of these large changes.

B. Results

Table 3 presents simulation results for seven policy experiments. The first two involve increasing the average level of schooling within the household by 1 and 2 years, respectively. Such increases in schooling induce large welfare improvements. For instance, an extra year of schooling for household members increases average consumption by 5%; it reduces the proportion of poor by 10%. The effects are not limited to those near the poverty lines but run deeper: the policy simulation induces a 13% decline in the depth of poverty and a 15% decline in the severity of poverty. It is notable that the magnitude of effects across rural and urban areas is very similar.

A 2-year increase in average schooling tends to more or less double the above effects, with nearly 20% decline in the national head-count index. A uniform 2-year increase in everyone's schooling is, however, a large policy change. It is possible that the returns to education may not remain the same with such a "large" change on the supply side. Thus, there could be a degree of overestimation in the poverty impact of such an intervention insofar as it could induce some decline in the rates of return to education. Another factor that could also contribute to some overestimation is that the measured returns to education may also include an element attributable to innate (unobserved) abilities of household members.

The next two simulations explore the impact of parental education. The first of these considers an improvement in the schooling attainment of the parents of household heads to ensure that they all at least complete primary schooling. The second considers the same improvement for the parents of the spouses of household heads; this is relevant only for rural households (since parental education for the spouses turned out to be insignificant for urban households; see table 2). We compare the results of the two interventions for rural areas. Note that since the vast majority of households are male headed, the spouses are typically the wives of household heads.

For both household heads and their spouses in rural areas, an increase in parental education to the primary level decreases the incidence of poverty by about 23%. However, in the case of spouses there is a larger return in terms of mean consumption with a 19% increase, while mean consumption for the household head simulation increases by 12%. Despite the smaller increase in

TABLE 3

POVERTY SIMULATIONS (PERCENT CHANGE OVER BASE SIMULATION)

		Rural Egypt				Urban Egypt				Egypt			
No.	Description of Simulation	Mean Cons.	P0	P1	P2	Mean Cons.	P0	P1	P2	Mean Cons.	P0	P1	P2
1	Increase average household schooling by 1 year	4.7	−9.7	−13.0	−15.3	5.5	−11.0	−13.7	−15.7	5.1	−10.1	−13.2	−15.4
2	Increase average household schooling by 2 years	9.6	−19.0	−24.7	−28.8	11.4	−21.3	−26.0	−29.3	10.5	−19.8	−25.2	−29.0
3	Increase household head's parents' schooling to at least primary schooling	11.9	−22.9	−28.8	−32.8	11.0	−26.6	−33.0	−37.3	11.5	−24.2	−30.3	−34.4
4	Increase spouse's parents' schooling to at least primary schooling	18.7	−22.7	−22.7	−21.1					6.2	−14.7	−18.7	−21.5
5	Land redistribution	2.3	−6.1	−8.8	−10.7					1.2	−3.9	−5.7	−7.0
6	Extra 2 years of schooling instead of land	1.3	−4.0	−6.3	−8.1					.7	−2.6	−4.1	−5.3
7	Decrease distance to health post/hospital to no more than 20 minutes	5.0	−8.9	−11.0	−12.4					2.6	−5.7	−7.1	−8.1

Note. The figures provide an estimate of the percentage change in real per capita consumption (cons.); P0, P1, and P2 resulting from the change are shown in the "Description of Simulation" column. The head-count index is P0, P1 is the poverty-gap index, and P2 is the squared poverty-gap index. Change is measured as the difference between predicted values from the simulation less predicted values from the base simulation. See text for details.

mean consumption, increasing parental education of the household heads has a greater impact on reducing the depth and severity of poverty than the same simulation for spouses. For household heads, the poverty gap declines by 29% (compared to 23% for spouses), and the squared poverty gap declines by 33% (compared to 21% for spouses). Thus, in the case of the spouses, the increments to consumption on account of better parental education appear to be relatively more concentrated among the nonpoor and those who are the least poor. This is largely explained by the interaction effects. For instance, the marginal effects of spouses' parental education increase with the age of the household head and decrease with household size (even allowing for fairly high economies of household size), where the former is positively and the latter is negatively correlated with per capita consumption.

Simulation 5 deals with land redistribution in rural areas. In this policy simulation, cultivatable land is redistributed from owners who have more than the 75th percentile (among landowners) within the governorate to a group of eligible households within the same governorate. Half of the excess above the 75th percentile is earmarked for redistribution. The eligible households are determined to be those that have low levels of schooling and no or only a limited amount of land; in particular, households that have less than 1 year of average schooling and who either own no land or own an amount of land that is at least 50 *feddan* short of the 75th percentile for the governorate. (A *feddan* equals approx. 4,200.83 square meters or 1.038 acres; the median amount of land owned by rural landowners is 100 *feddan*.) The eligible households are given up to a maximum of 50 *feddan* or less if the surplus land per eligible household falls below 50 *feddan*. Altogether, 13.6% of all land is redistributed. Table 3 shows moderate effects of such land redistribution. The incidence of rural poverty declines by about 6%. However, since the poorest gain relatively more, the severity of poverty declines by nearly 11%.

How does land redistribution compare with extra education? Simulation 6 explores this question by asking what if the same households who benefited from land redistribution were instead given two extra years of schooling. The results indicate slightly less benefit from the schooling. Rural poverty incidence would decline by 4%, while the severity of poverty would decline by 8%. Hence, in terms of poverty reduction, the extra land for these households is worth more than two additional years of schooling for their members.

The final simulation looks at the effect of greater accessibility of health facilities. In this particular instance, access is improved such that the rural population is assured of availability of a health post or a hospital within 20 minutes from where they live. This intervention induces significant welfare improvement. The proportion of the rural poor declines by 9%, while the poverty gap and the squared poverty gap indices decline by about 11% and 12%, respectively. Overall, the effects are similar, though slightly less in magnitude, to an increase in average household schooling by 1 year.

VI. Conclusion

This article extends the descriptive analysis of poverty in Egypt presented in Datt et al. (2001) by modeling the determinants of poverty, using data from the 1997 Egypt Integrated Household Survey. We use a two-step approach, where we first model the determinants of individual welfare and then use the model predictions to estimate poverty measures. Individual welfare is measured by consumption per person, but we explore the sensitivity of our results to alternative treatments of household size and composition in defining a measure of individual welfare.

We estimate separate models for the urban and rural sectors. Both models introduce governorate-level fixed effects, and in both cases we allow marginal effects on welfare to vary across households by augmenting the models to incorporate interaction terms. For both rural and urban areas, we clearly reject the hypothesis of uniform marginal effects of determinants.

The results indicate that education is an important determinant of living standards. This holds for both rural and urban areas, and in this regard the experience of Egypt is not surprising. The article also identifies the importance of intergenerational effects in improving levels of living. Parental education is thus found to be important, over and above the positive effects of the current education levels of household members.

An innovation of the article is that we use the estimated model parameters to predict per capita consumption and expected poverty for each household. This approach readily lends itself to simulating the effects of a variety of policy changes on poverty levels in rural and urban areas, and nationally. The article considers a handful of policy simulations. Qualitatively, they confirm for poverty measures some of the results observed in the models of per capita consumption, but they also help to quantify the magnitude of poverty impacts associated with different policies.

Appendix

Formulas for Simulating Poverty Measures from Regression Models of Household Consumption

The following equations are the analytical formulas for simulating poverty measures within the Foster-Greer-Thorbecke class (in particular, the head count, the poverty gap, and the squared poverty gap measures), starting from a model of household consumption, such as equation (A1) (Datt 2004).

Consumption model:

$$\ln c_j = \beta' x_j + \varepsilon_j, \text{ where } u_j = \varepsilon_j/\sigma \sim N(0, 1). \tag{A1}$$

Predictions:

Consumption for household *j*:

$$\hat{c}_j = e^{(\hat{\beta}' x_j + \hat{\sigma}^2/2)}. \tag{A2}$$

Head-count index for household *j*:

$$\hat{P}_{0j} = \Phi\left[1\hat{\sigma}\left(\ln z - \hat{\beta}' x_j\right)\right]. \tag{A3}$$

Poverty gap index for household *j*:

$$\hat{P}_{1j} = \hat{\sigma} e^{(\hat{\beta}' x_j + \hat{\sigma}^2/2)} \Phi\left[1\hat{\sigma}\left(\ln z - \hat{\beta}' x_j\right) - \hat{\sigma}\right]$$

$$- \hat{\sigma} e^{(2\hat{\beta}' x_j - \ln z + 2\hat{\sigma}^2)} \Phi\left[1\hat{\sigma}\left(\ln z - \hat{\beta}' x_j\right) - 2\hat{\sigma}\right]. \tag{A4}$$

Squared poverty gap index for household *j*:

$$\hat{P}_{2j} = \hat{P}_{1j} - \hat{\sigma} e^{(2\hat{\beta}' x_j - \ln z + 2\hat{\sigma}^2)} \Phi\left[1\hat{\sigma}\left(\ln z - \hat{\beta}' x_j\right) - 2\hat{\sigma}\right]$$

$$+ \hat{\sigma} e^{(3\hat{\beta}' x_j - 2\ln z + 9\hat{\sigma}^2/2)} \Phi\left[1\hat{\sigma}\left(\ln z - \hat{\beta}' x_j\right) - 3\hat{\sigma}\right]. \tag{A5}$$

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