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Measurement of Multidimensional Poverty in Egypt

Shaimaa Hussien* and Bokyeong Park**

Measuring poverty and targeting the poor is still challenging in many developing countries due to the absence of an agreed definition of poverty and the limited availability of data. Poor measurement and mal-targeting in anti-poverty policies makes those policies less effective. Egypt suffers from the problems because only a single dimension of poverty such as income is considered to measure and target poverty, while real poverty is multidimensional. Further, the access to those data is limited. This paper suggests a method of poverty measurement that enables us to consider the multi-dimensionality of poverty and circumvent the inaccessibility of household-level income data. First, we measure Multidimensional Poverty Index (MPI) for Egypt using a publicized dataset to show that the MPI gives a closer estimate of actual poverty. Second, we identify the characteristics of poor households by using the probit model to use the results for better targeting.

Key Words: poverty measurement, poverty targeting, Multidimensional Poverty Index, Egypt

INTRODUCTION

Poverty has been one of the chronic socio-economic challenges facing the Egyptian policy-makers during the last decades. Despite the government's efforts to reduce poverty by providing cash and in-kind transfer to the poor, the population under the national poverty line has increased from 16.7 percent in 1999/2000 to 32.5 percent in 2017/2018. Poverty is concentrated in rural areas, especially Upper Egypt, i.e. the southern part, which has a poverty rate of 51.9 percent.

The government started the economic structural adjustment program in 1991 after the economic crises of the 1980s. While the program stabilized its macro-economic conditions and promoted economic growth, the poverty rate and the size of the poor has continued to increase. To cope with a rise in poverty, the government implements various anti-poverty policies including in-kind transfer programs, but it has no clear eligibility criteria for the subsidies. These weak targeting mechanisms allow the non-poor to get more benefits and more access to the public subsidies and social safety nets than the poor. Moreover, subsidy policies have caused price distortion, excessive consumption, and the creation of black market (Helmy 2005).

Reducing poverty requires a reliable measurement of poverty, and a good targeting mechanism based on detailed information on household. However, measuring poverty is not an easy task. Orshansky (1969) emphasizes that "poverty, like beauty, lies in the eyes of the beholder". The concept of poverty changes over time as well. A change in its concept or definition requires some socio-economic variables to be added to differentiate between the poor and non-poor. Economic or institutional underdevelopment makes it difficult for

* Graduate School of Pan-Pacific International Studies, Kyung Hee University, shaimaa.hussien@gmail.com

** Graduate School of Pan-Pacific International Studies, Kyung Hee University, bokyeong23@khu.ac.kr

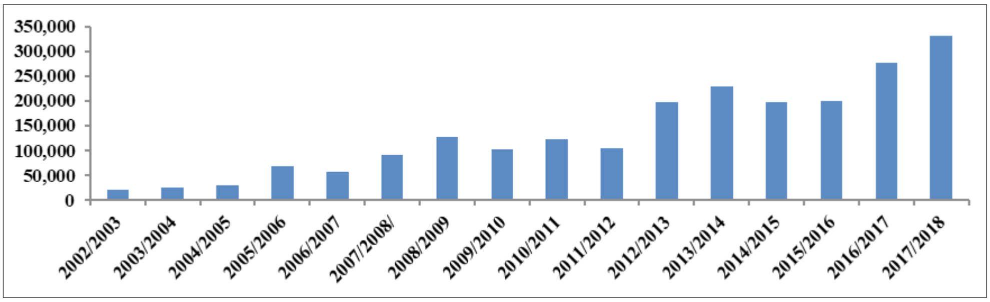
a government to obtain necessary information on true household conditions. For instance, in Egypt even the taxation office does not have reliable information on household income because of large informal sectors accounting for around 35% of the total economic activity (Schneider 2010). Besides, the household survey dataset with the most detailed information is not open to the public, which prevents an in-depth analysis on poverty in Egypt.

Motivated by those situations, this paper aims to explore a method of poverty measurement that will encompass the multiple dimensions of poverty and circumvent the inaccessibility of household-level income or consumption data. This paper shows that the Multidimensional Poverty Index (MPI) calculated from non-monetary information on households can be a qualified alternative poverty measurement. To calculate alternative poverty indices, we use open data sources to circumvent the problem of limited data availability. Based on the newly constructed poverty measurement, the paper identifies also the characteristics of households in poverty by using the probit model.

MAL-TARGETING PROBLEMS IN EGYPT

Reducing poverty has been one of priority policy goals for the Egyptian government in the latest decades. For this purpose, the government has been implementing in-kind and cash transfer programs. The government has tried to reduce the negative impacts of the economic reform program since the devaluation of the Egyptian pound (EGP) in January 2003 and expanded government subsidies by more than 15 times in 2002-2017 (see Figure 1).

Figure 1. Subsidies, Grants and Social Benefits

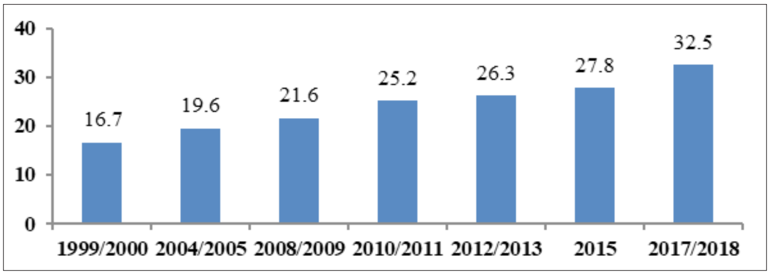


Unit: Million EGP
Source: Ministry of Finance, Egypt.

Despite the increased subsidies, the percentage of the population under the national poverty line[1] increased from 16.7 percent in 1999/2000 to 32.5 percent in 2017/2018 (See Figure 2). The poverty is concentrated mainly in rural areas, especially rural Upper Egypt. In rural Upper Egypt with 25.2 percent of total population, the national poverty rate is as high as 51.9 percent (See Figure 3). The poverty rate in rural Lower Egypt jumped from 19.7 percent in 2015 to 27.3 percent in 2017/2018 (CAPMAS 2019).

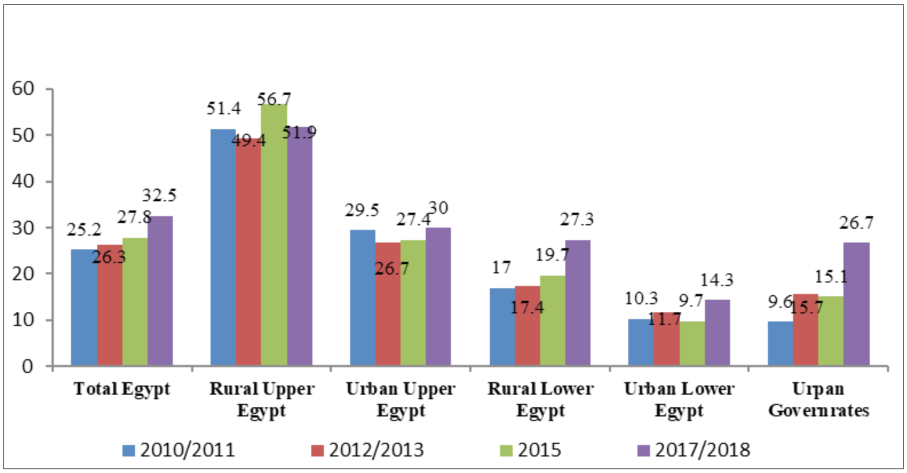
[1] Egypt's national poverty line consists of two main components, food and non-food items. Population under food poverty line is classified as 'extreme poor', while population under the summation of food and nonfood poverty lines is classified as 'poor'.

Figure 2. Percentage of Population under National Poverty Line



Source: CAPMAS (2019).

Figure 3. National Poverty Rate by Region



Source: CAPMAS (2019).

Mal-targeting in In-kind Transfer Programs

In fact they suppose that the Egyptian government manages the subsidy system to ensure political stability rather than to reduce poverty. The way of providing the in-kind transfer supports such supposition. The government provides subsidized goods and services without targeting specific groups. For example, the food subsidies program has two components, i.e. *baladi* bread and ration card. The first is the program to provide the *baladi* bread, a basic foodstuff, at a lower price to whoever wants to buy it without any restrictions. Although most of the poor are concentrated in rural areas, the sale outlets of the *baladi* bread are usually located in urban areas. This geographical mismatch causes large leakage in the system by giving access to the non-poor. The second program, ration card, provides registered households with fixed quota of subsidized food items such as cooking oil, sugar, and rice at a lower price. According to the World Bank (2010), this program also has a mal-targeting problem. Another in-kind transfer program, the fossil fuel subsidies, also was found to make budget leakage by not targeting a specific group. After the Arab spring in Egypt, therefore, the World Bank required the government to reduce the fuel subsides drastically (ESMAP 2017).[2]

The weak targeting mechanism explains in part the poor effectiveness of poverty reduction programs. Helmy (2005) shows that those policies are biased to the non-poor at the expense of the poor. The richest 60 percent received two thirds of the food subsidies and the poorest 40 percent only one third. Moreover, people in urban areas have better access to subsidies than those in rural. While most of the poor households live in rural areas, the urban population gets 70 percent of the food subsidies. More, the subsidy policies are reported to cause price distortion, excessive consumption and the creation of black market.

Mal-targeting in Cash Transfer Programs

In 2015 the Ministry of Social Solidarity (MOSS) started a new program targeting the poor, titled "*Takaful* and *Karama*" (Solidarity and Dignity). The first part, "*Takaful*", is a conditional cash transfer that targets poor households with kids. The eligible household receives monthly payment of EGP 325~625 depending on the number of kids and their education level. The payment is terminated if the kids enrolled in the program attend less than 80 percent of the school days. At the same time, the mothers are required to attend health awareness sessions and get all kids immunized to maintain the eligibility (MOSS 2019, Socialprotection.org 2019). The second part, "*Karama*", represents unconditional cash transfers to households with old or severely disabled persons. The selected households can receive the monthly payment of EGP 350 for each old or disabled person.

MOSS (2019) explains that it uses a targeting method to combines proxy means test, geographical targeting, and self-targeting. That is, the MOSS selects 6 out of 27 governorates as candidate target regions using the latest household dataset, i.e. the Household Income, Expenditure and Consumption Survey (HIECS) 2015 (geographical targeting). Then, households have to apply for the program by submitting the required documents (self-targeting). Each household reports its own household characteristics and living conditions. This information is used to determine the eligibility of the programs (proxy means test). As of June 2019, more than 1.6 million households are registered in *Takaful* program and more than 0.2 households in *Karama* program[3].

However, the targeting method remains as black box because of no official or published documentation about how the governorates and households are selected.[4] Breisinger *et al* (2018) reports that only 20 percent of the poorest quintile benefits from *Takaful* program, implying the need of improvement in the program coverage. The assessment finds no significant impact of the program on school enrolment or health. These all suggest an inefficient use or leakage of social assistance expenditure due to a poor targeting mechanism and limited use of household information. In this regard, the next part explores an alternative poverty measurement which can be used to improve a targeting mechanism, circumventing the problem of limited availability of the household data.

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[2] The World Bank and the Egyptian government agreed to reduce the subsidy from 7 percent of GDP in 2013 to 0.5 percent in 2019

[3] See: http://www.moss.gov.eg/ar-eg/Pages/default.aspx

[4] The selected governorates are Souhag, Asyut, Luxur, Qena, Aswan, and Giza, while the HIECS 2015 reports Asyut, Souhag, Qena, Menia, Aswan and Bani Swif as the poorest governorates (CAPMAS 2015).

ALTERNATIVE MEASUREMENT OF POVERTY

Better targeting requires correct measurement of poverty at household level. Poverty is multi-dimensional, so it cannot be captured merely in income or consumption. Considering this, we calculate two alternative indicators of poverty, Wealth Index (WI) and Multi-Dimensional Poverty Index (MPI). WI uses the asset that households possess to identify households in poverty and MPI considers more comprehensive conditions of a household. Both WI and MPI are non-monetary measures of poverty. WI has been widely used since Filmer and Pritchett (2001) introduced it to overcome the problem of unavailability or inaccuracy of household income data. MPI is a recently developed non-monetary measure of poverty. We calculate the two indicators for Egypt and examine which one measures the real poverty better by comparing their poverty rates and the official poverty rate at region and governorate level.

As mentioned before, the data with the most detailed information on households, the HIECS, are not available to the public. As alternatives, we use two open household survey datasets, the Harmonized Household Income and Expenditure Surveys (HHIES) 2015 and the Egypt Demographic Health Survey (EDHS) 2014.[5] The HHIES 2015 covers more than 11,000 households and provides data about assets, income and consumption expenditure. This dataset helps check the differences in distribution between WI and income (or consumption). The EDHS 2014 covers more than 28,000 households and provides data about assets, education and health conditions. Table 1 summarizes the coverage and accessibility of three household surveys mentioned above.

Table 1. Coverage and Accessibility of Household Surveys

	HIECS	HHIES	EDHS
Frequency	Every 4 year	Every 4 year	Every 5 year
Income data	Available	Available	Not available
Consumption data	Available	Available	Not available
Assets owned	Available	Available	Available
Education indicators	Partially available	Partially available	Available
Health indicators	Not available	Not available	Available
Accessibility	Not accessible	Accessible	Accessible
Constructed by	Central Agency for Public Mobilization and Statistics	Open Access Micro Data Initiative - Economic Research Forum	Ministry of Health and Population, El-Zanaty and Associates, and ICF International

Source: By Authors

[5] The HHIES 2015 is composed of a half of the full sample of the HIECS 2015 for selected variables.

Wealth Index

The previous literature observes that given the unavailability of income or consumption data, WI from the household assets is an alternative criterion to determine whether or not a household is in poverty. Following Filmer and Pritchett (2001) who introduced a simple technique of constructing a composite index from household assets, we estimate WI using the principal component factor analysis.[6] WI is constructed as follows (O'Donnell, e*t al* (2007) and McKenzie (2005)):

$$A_i = \sum_k [f_k \frac{a_{ik} - \bar{a}_k}{s_k}] \quad \text{(Eq.1)}$$

where A_i is WI for individual household i, f_k the weights associated or the "scoring factors" for the k asset determined by the procedure,[7] a_{ik} the value of asset k for household i, $\bar{a}_k$ the sample mean for asset k, and s_k the sample standard deviation for asset k.

The appendix shows the lists of assets included in the calculation of the WI and the results of the factor analysis from the HHIES 2015. Based on the computed eigenvalue, we calculate WI using the first five components. The quintile distribution of WI from the HHIES is shown in Table 2. When the rule in Filmer and Pritchett (2001) is applied that defines households in the first quintile as in poverty, the WI-based poverty rate is 24.8%. To examine whether the WI can be a reliable substitute for income or consumption expenditure indicators, we calculate the correlation between the quintiles of the WI and those of income or consumption. The quintiles of income and consumption are computed also from the same HHIES 2015. Table 3 shows the Pearson correlation coefficients between them. The

Table 2. WI Quintiles

WI Quintiles	Freq.	Percent	Cum.
Q1	2,975	24.8	24.8
Q2	2,006	16.7	41.6
Q3	2,371	19.8	61.3
Q4	2,351	19.6	80.9
Q5	2,285	19.1	100.0
Total	11,988	100.0	

Source: calculated by authors using the HHIES 2015

6 It is a mathematical tool used to reduce a large set of indicators into a smaller set of indicators. The first principle component is supposed to capture most of the variability.

7 Usually the first component captures most of the variation. Every component is calculated for the full list of assets included in the analysis. The criterion for choosing the number of components to calculate the scoring factor f_k is that the minimum eigenvalue equals 1.

Table 3. Pearson Correlation between WI, Income and Consumption Quintiles

	WI Quintiles
Income Quintiles	0.51 (0.00)
Consumption Quintiles	0.54 (0.00)

Note: significance level in parenthesis.
Source: calculated by authors using the HHIES 2015

coefficients are approximately 50% which means a medium significant relationship.[8] This medium correlation does not ensure that the WI will produce outcomes similar to those from income or consumption index. Therefore, we turn to explore a more comprehensive index, MPI, in the next part.

Multidimensional Poverty Index and its Modification

Sen (1994) adopts "capabilities approach" to poverty, stating that a person is poor if he or she lacks the most basic capabilities that lead to reasonable life. This approach expands the definition of poverty beyond the inability to satisfy the nutritional basket or the basic needs. In this strand Alkire and Foster (2011a) argue that a poverty indicator merely based on income or consumption cannot differentiate the poor and the non-poor correctly. They underscore the multidimensionality of poverty. Afterwards, the Oxford University and the United Nations Development Programme (UNDP) develop a measurement that takes into account various dimensions of poverty, i.e. Multidimensional Poverty Index.

The MPI is calculated as a weighted deprivation score after determining whether a person is deprived of selected dimensions. The MPI is constructed using three categories of indicators representing education, health, and standard of living, which are the same scopes of the Human Development Index (Alkire and Kanagaratnam 2018). The three categories have equal weights and the indicators used in each category are shown in Table 4. According to Alkire and Foster (2011b), the MPI is constructed as follows,

$$C_i = W_1 I_{i1} + W_2 I_{i2} + \cdots + W_d I_{id}, \text{ s. t. } \Sigma W_k = 1 \qquad \text{(Eq. 2)}$$

The score C_i ranged from 0 to 1 rises as the household increases the number of indicators that it is deprived of. Thus, $C_i = 0$ means that the household is not deprived at all, and $C_i = 1$ means that the household is deprived of all indicators. A household is considered to be in poverty if its deprivation score is 0.333 or more.[9] The multidimensional headcount ratio (H)

8 We calculate correlations with WI quintiles from the EDHS 2014 which covers more assets than the HHIES 2015. The coefficients are similar to those from the HHIES 2015, though not reported because of limited space.

9 For checking the robustness of the MPI to the changes in poverty cutoff point k, Alkire and Foster (2014) use bootstrapping for testing poverty orderings among countries. Their database covers 104 countries. They tested the robustness for country ranking to the selection of k-cutoff that ranges

Table 4. Indicators for Multidimensional Poverty Index (MPI)

Dimension	Indicator	Deprived if	Related to	Weight
Education	Years of Schooling	No household member has completed five years of schooling	MDG2	16.7%
	Child School Attendance	Any school-aged child is not attending school in years 1 to 8	MDG2	16.7%
Health	Mortality	Any child has died in the family	MDG4	16.7%
	Nutrition	Any adult or child for whom there is nutritional information is malnourished	MDG1	16.7%
Standard of Living	Electricity	The household has no electricity	MDG7	5.6%
	Sanitation	The household´s sanitation facility is not improved (according to the MDG guidelines), or it is improved but shared with other households	MDG7	5.6%
	Water	The household does not have access to clean drinking water (according to the MDG guidelines) or clean water is more than 30 minutes walking from home.	MDG7	5.6%
	Floor	The household has dirt, sand or dung floor	MDG7	5.6%
	Cooking Fuel	The household cooks with dung, wood or charcoal.	MDG7	5.6%
	Assets	The household does not own more than one of: radio, TV, telephone, bike, motorbike or refrigerator, and does not own a car or truck.	MDG7	5.6%

Note: MDG is millennium development goal
Source : Alkire and Santos (2010)

is calculated as the percentage of population in poverty. Alkire and Foster (2011b) provide a modified multidimensional headcount ratio (M_0) that equals $H \times A$, where A is the average intensity measured as average proportion of indicators of which a household in poverty are deprived.

The UNDP calculated the multi-dimensional headcount ratio H and the modified multidimensional headcount ratio M_0 for Egypt. However, the figures of H (3.6 %) and M_0(0.014) in 2014 seem not realistic, when considering that the national headcount ratio (NH), i.e. the percentage of population under the national poverty line, is 26.3% and

between 20~40 percent. The results reveal that for the 104 countries, 91.2 percent of the comparisons are robust. Therefore, they conclude that the selection of one third (0.333) cutoff detects “the acutely poor”, i.e. households who do not satisfy the minimum standard of multiple indicators of basic life functions agreed internationally.

27.8% in 2012/2013 and 2015 respectively (UNDP 2018, CAPMAS 2019). That is, the multidimensional headcount ratio *H* is abnormally discrepant from the national headcount ratio *NH* which is a common poverty indicator measured with income.[10]

We suppose that this discrepancy stems from loosely coined definitions of deprivation, particularly in education dimension. Thus, we modify the definition of the first indicator of education dimension. This indicator defines that the family is deprived of education if there is no household member who has completed five year schooling. This definition underestimates the level of deprivation in education, because a household is classified as non-deprived even when only one person has completed five year schooling in a large family. In the EDHS 2014, among household members aged over 10 years, 23.6% did not complete five year schooling. This ratio exceeds 40% in 22.2% of the total households. Moreover, it exceeds 50% in 13.4% of the households. The average household size in Egypt is 4.04 individuals in the latest census of 2017. We assume that when all kids take at least primary education in an average-sized family with illiterate parents, the family is not deprived of education. Therefore, we raise the threshold of deprivation in education to 50 % of the household members.[11]

With this adjusted definition, we recalculate the MPI in Egypt, using the EDHS 2014 which comprises various social and demographical dimensions besides asset.[12] Next, we examine which one of the WI-based[13] and MPI-based poverty rates is more comparable to national headcount ratio NH.[14] For that, we need to aggregate the MPI and WI calculated at household level into the regional level, because *NH* calculated from the HIECS is available only at regional level as explained before.

Figures 4 and 5 portray the headcount poverty ratios calculated from three measurements of poverty. The first is our adjusted MPI-based headcount ratio *H* and the second the WI-based poverty rate. Both are calculated from the EDHS 2014. The third is *NH* published by CAPMAS. They are compared at regional level in Figure 4 and at governorate level in Figure 5.[15] The comparison shows that the adjusted MPI is closer to *NH* estimates than the WI at regional and governorate level. The latter exhibits wide gap especially in urban governorates. In conclusion, the adjusted MPI is better than the WI in identifying whether or not a household is in poverty under the unavailability of income or consumption data at household level. Aggregated data can serve only in simple descriptive analysis, while household data allow a deeper analysis using econometrics models. By using the MPIs of individual households calculated from accessible dataset, we can investigate, for instance, the relationship between the poverty status of a household and school attainment, health inequalities, child mortality, child nutrition, and schooling inequalities.

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[10] Because M_0 represents the severity of poverty, it is not comparable to headcount ratios such as *NH*.

[11] The adjustment is made only in the definition of the education variables but other variables representing health and standard of living are exactly same as Alkire and Foster (2011a).

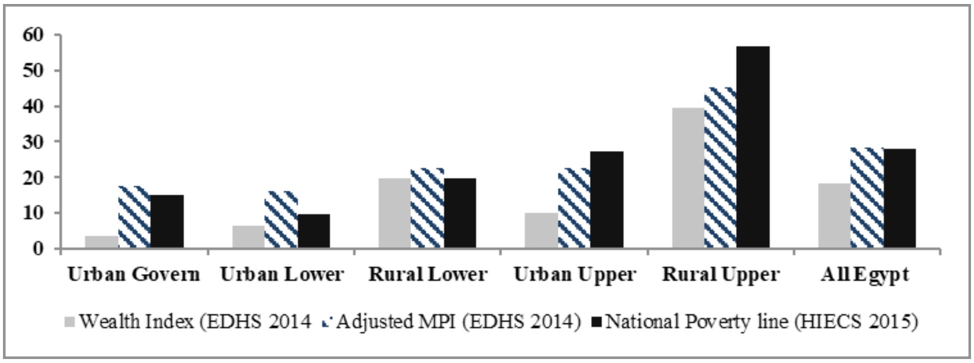
[12] The EDHS is mainly concerned about health and family planning issues, but provides also the characteristics of the household and the dwelling.

[13] WI here is calculated using EDHS 2014 so that we can compare the MPI and WI for the same households.

[14] As the HHIES 2015 does not provide data about the sub-indicators of MPI, we calculate the WI again using the EDHS 2014 and compare the results of WI and MPI for the same household.

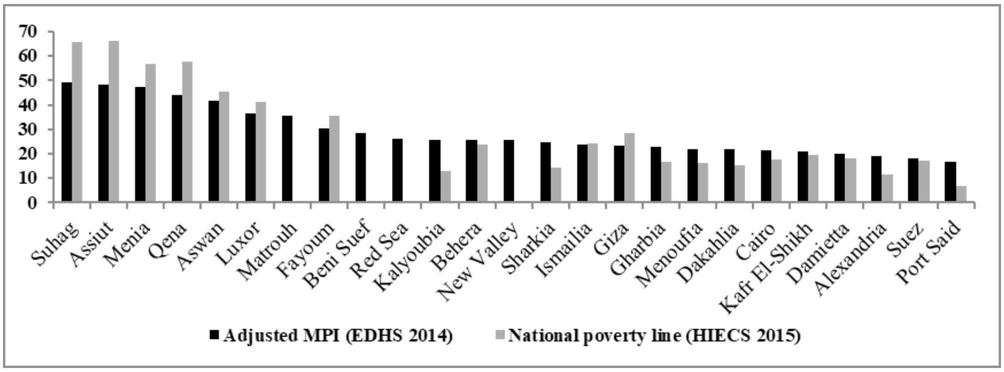
[15] Egypt is divided into five main regions (rural Upper Egypt-, urban Upper Egypt-, rural Lower Egypt-, urban Lower Egypt-, urban Governorates)

Figure 4. Comparison among Poverty Rates by Region



Source: Calculated by authors and from CAPMAS (2015)

Figure 5. Comparison among Poverty Rates by Governorates



Source: Calculated by authors and from CAPMAS (2015)

THE CHARACTERISTICS OF THE POOR

As explained before, the Egyptian government has used obscure and combined targeting methods for social assistance programs, causing inefficient allocations. For instance, subsidies are allocated based on the method of self-targeting or self-report by applicants, which is prone to a false report on their household conditions. Even though the report is correct, it is difficult to determine whether or not a household is in poverty if many indicators should be considered as eligibility criteria. An analysis on the characteristics of households in poverty and its utilization for the identification of a household in poverty can help overcome those problems.

Therefore, this section analyzes the probability for a household to be in poverty using its characteristics. We identify whether or not a household is in poverty by using the MPI, and construct the binary dependent variable of the probit model that takes the value of 1 if $C_i \geq 0.333$ and the value of zero otherwise. By estimating the model, we can find out covariates that are strongly associated with poverty in Egypt. Those covariates or characteristics of a household can be used to predict the probability of a household being in poverty. The probit model is expressed as follows:

$$Pr(Y=1\,|\,X)=\phi(X^T\beta)=\int_{-\infty}^{X'\beta}\phi(Z)dZ \qquad \text{(Eq. 3)}$$

where Pr is the probability, ϕ the cumulative distribution function of the standard normal distribution, X^T a set of explanatory variables (household characteristics), and β the parameters to be estimated.

The set of explanatory variables is divided into three categories: household head characteristics (sex, age, marital status, and sector of work), family characteristics (family size, number of kids less than 6 years, number of kids between 6-14 years, and number of elderly aged over 64), and housing characteristics (type of toilet facility, toilet share, ownership of arable land, and location of residence[16]).

Table 5 displays the results of the estimation and the marginal effects (*dy/dx*) of the three samples (all Egypt, urban Egypt, and rural Egypt). The produced coefficients by the probit model provide the change in the Z (standard normal) value due to one unit change in the explanatory variables. Thus, while the sign of the probit coefficients is simple to interpret, but the magnitude of the coefficients is not. To interpret the magnitude, the marginal effects (*dy/dx*) are calculated as follows:

$$\frac{\partial E[Y\,|\,X]}{\partial X}=\left\{\frac{dF(X'\beta)}{d(X'\beta)}\right\}\beta=f(X'\beta)\beta \qquad \text{(Eq. 4)}$$

Then, one unit increase in variable x will increase (decrease) the probability that the dependent variable equals 1 by the value of the marginal effects in percentage.[17]

The results of all Egypt sample reveal that living in rural Egypt increases the probability of being in poverty. The sub-samples for rural and urban Egypt show that living in Upper Egypt increases the probability of being in poverty. This result emphasizes the importance of geographical targeting. Especially, the result shows that rural Upper Egypt suffers the highest poverty headcount ratio. Other results are mostly consistent with the previous literature on poverty characteristics. All models reveal that a female-headed household increases the probability. It may be because a female is less likely to be paid than a male. The job opportunities available to a female are few compared with a male, especially in rural areas where most females are not working. Concerning house conditions, the connection to piped sewer and the existence of a separate toilet decrease the probability of being in poverty. This sheds lights on possible areas that the government can intervene effectively in rural areas. The results also show that the age of a household head is positively associated with the probability. To have a job decreases poverty and, particularly, working at professional, technical, managerial and clerical, or service sector significantly decreases the probability of being in poverty. In contrast, an agricultural job has the lowest impact on the probability of being in poverty.

[16] Location of residence in the probit model of all Egypt is a binary variable (urban=0 and rural=1), while in the urban and rural Egypt samples it is another binary (lower=0 and upper=1).

[17] For example, if the marginal effect of the age of a household head is 0.04, it means that with each additional year in age, the household is more likely to be in poverty by 4 percent.

Table 5. Analysis of Poor Households' Characteristics in Egypt Using MPI

	All Egypt		Urban		Rural	
VARIABLES	Probit model	marginal effects	Probit model	marginal effects	Probit model	marginal effects
Age of household head	0.018**	0.005**	0.016	0.003	0.021**	0.006**
	(0.008)	(0.002)	(0.011)	(0.002)	(0.010)	(0.003)
Age squared	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex of household head	0.087**	0.022**	0.203***	0.043***	-0.013	-0.003
	(0.041)	(0.011)	(0.057)	(0.012)	(0.059)	(0.016)
Married	-0.695***	-0.178***	-0.462***	-0.098***	-1.129***	-0.309***
	(0.098)	(0.025)	(0.136)	(0.028)	(0.155)	(0.042)
Work: professional	-1.055***	-0.270***	-0.952***	-0.201***	-1.168***	-0.320***
	(0.041)	(0.010)	(0.057)	(0.013)	(0.055)	(0.015)
Work: agriculture	-0.376***	-0.096***	-0.171	-0.036	-0.455***	-0.125***
	(0.051)	(0.013)	(0.107)	(0.023)	(0.059)	(0.016)
Work: manual	-0.693***	-0.178***	-0.650***	-0.137***	-0.760***	-0.208***
	(0.038)	(0.009)	(0.058)	(0.012)	(0.048)	(0.013)
Work: service	-0.817***	-0.209***	-0.661***	-0.140***	-0.921***	-0.252***
	(0.058)	(0.014)	(0.090)	(0.019)	(0.071)	(0.019)
Family size	-0.154***	-0.039***	-0.212***	-0.045***	-0.140***	-0.038***
	(0.014)	(0.004)	(0.022)	(0.004)	(0.016)	(0.005)
No. of children under 6	0.641***	0.164***	0.791***	0.167***	0.584***	0.160***
	(0.019)	(0.004)	(0.034)	(0.006)	(0.023)	(0.005)
No. of children aged 6-14	0.303***	0.078***	0.372***	0.079***	0.261***	0.072***
	(0.017)	(0.004)	(0.028)	(0.006)	(0.020)	(0.005)
No. of the elderly	0.247***	0.063***	0.255***	0.054***	0.292***	0.080***
	(0.036)	(0.009)	(0.056)	(0.012)	(0.048)	(0.013)
Share toilet with others	0.908***	0.233***	0.485***	0.103***	0.944***	0.258***
	(0.082)	(0.021)	(0.164)	(0.035)	(0.099)	(0.027)
Piped sewer	-0.491***	-0.126***	-0.502***	-0.106***	-0.304***	-0.083***
	(0.034)	(0.009)	(0.067)	(0.014)	(0.051)	(0.014)
Owns arable land	0.014	0.004	-0.041	-0.009	0.022	0.006
	(0.041)	(0.011)	(0.109)	(0.023)	(0.044)	(0.012)
Location of residence	0.131***	0.034***	0.066	0.014	0.449***	0.123***
	(0.036)	(0.009)	(0.044)	(0.009)	(0.050)	(0.013)
Constant	-0.766***		-0.937***		-0.228	
	(0.192)		(0.285)		(0.251)	
Observations	28,131	28,131	13,958	13,958	14,116	14,116

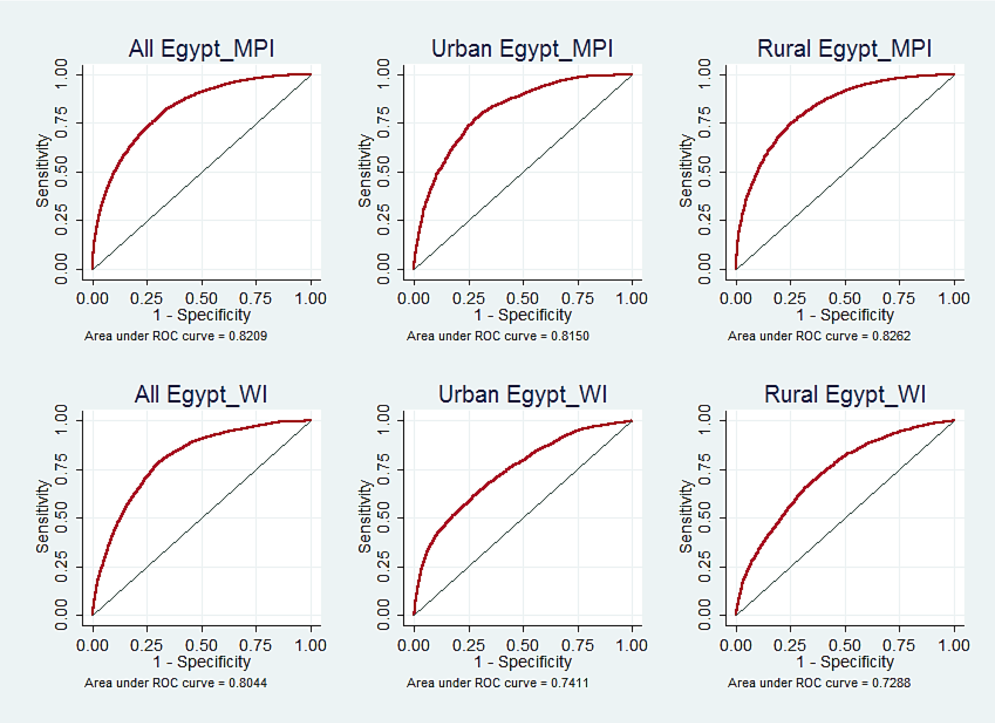
Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6. Analysis of Poor Households' Characteristics in Egypt Using WI

VARIABLES	All Egypt		Urban		Rural	
	Probit model	marginal Effects	Probit model	marginal Effects	Probit model	marginal Effects
Age of household head	-0.014*	-0.003*	-0.030***	-0.007***	-0.021**	-0.005**
	(0.008)	(0.002)	(0.011)	(0.003)	(0.010)	(0.003)
Age squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex of household head	0.289***	0.066***	0.315***	0.076***	0.291***	0.073***
	(0.044)	(0.010)	(0.053)	(0.013)	(0.058)	(0.014)
Married	-0.252**	-0.057**	-0.234**	-0.056**	-0.321**	-0.081**
	(0.101)	(0.023)	(0.117)	(0.028)	(0.140)	(0.035)
Work: professional	-0.743***	-0.169***	-0.846***	-0.203***	-0.776***	-0.195***
	(0.044)	(0.010)	(0.057)	(0.015)	(0.064)	(0.016)
Work: agriculture	0.362***	0.082***	0.626***	0.151***	0.166***	0.042***
	(0.045)	(0.010)	(0.115)	(0.027)	(0.048)	(0.012)
Work: manual	0.022	0.005	0.161***	0.039***	-0.052	-0.013
	(0.039)	(0.009)	(0.059)	(0.014)	(0.050)	(0.013)
Work: service	-0.201***	-0.046***	-0.103	-0.025	-0.329***	-0.083***
	(0.049)	(0.011)	(0.083)	(0.020)	(0.060)	(0.015)
Family size	0.011	0.002	0.019	0.005	-0.021	-0.005
	(0.010)	(0.002)	(0.018)	(0.004)	(0.014)	(0.003)
No. of children under 6	0.009	0.002	0.043	0.010	0.022	0.006
	(0.019)	(0.004)	(0.030)	(0.007)	(0.022)	(0.006)
No. of children aged 6-14	0.070***	0.016***	0.103***	0.025***	0.080***	0.020***
	(0.016)	(0.004)	(0.024)	(0.006)	(0.019)	(0.005)
No. of the elderly	0.035	0.008	0.021	0.005	0.096**	0.024**
	(0.039)	(0.009)	(0.049)	(0.012)	(0.048)	(0.012)
Share toilet with others	0.866***	0.197***	1.152***	0.277***	0.654***	0.164***
	(0.075)	(0.017)	(0.182)	(0.044)	(0.078)	(0.019)
Piped sewer	-0.656***	-0.149***	-0.879***	-0.212***	-0.377***	-0.095***
	(0.051)	(0.011)	(0.084)	(0.018)	(0.071)	(0.017)
Owns arable land	-0.062	-0.014	0.088	0.021	-0.158***	-0.040***
	(0.039)	(0.009)	(0.133)	(0.032)	(0.046)	(0.012)
Location of residence	0.504***	0.115***	0.108	0.026	0.303***	0.076***
	(0.060)	(0.014)	(0.076)	(0.018)	(0.061)	(0.015)
Constant	-1.390***		0.299		-0.425*	
	(0.211)		(0.287)		(0.248)	
Observations	28,131	28,131	13,958	13,958	14,116	14,116

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figure 6. Receiver Operating Characteristic Curve (ROC)



Source: by Authors

Overall, family size is negatively associated with the probability of being in poverty. This may be because a family with more members has higher probability to earn income if they are of working age. All models agree that the more dependent members there are in a family, the higher the probability of being in poverty. The marginal effects show that the children aged 6-14 have a smaller slope than those below 6 years or over 64 as children at this age group may participate in income activities in developing countries.

The analysis suggests that Egypt exhibits uneven distribution of poverty across regions, implying that geographical targeting is highly recommendable. Table 6 displays the results of the estimation using the WI. The results of Tables 5 and 6 show that the MPI has more significance in analyzing the characteristics of poor households compared with the WI. Besides, the results of ROC curves in Figure 6 reveal that the estimations using the adjusted MPI have higher predictive efficiency in all the samples than using the WI.[18]

The detailed data of the MPI and household characteristics can help government target households in poverty more correctly, which make intervention policies more effective and efficient. The information will help minimize distortions from the self-targeting, and enable

[18] The vertical axis of the ROC curve represents the true positive rate (sensitivity) (i.e. the probability that poor household are classified as poor), while the horizontal axis represents false positive rate (100-specificity) (i.e. the probability of non-poor households classified as poor). The greater the area under the ROC curve, the better the sensitivity and specificity of the model.

the combination of the geographical targeting and the self-targeting, as well. That is, when a household in a targeted area applies for the social assistance program, the government agency can determine the eligibility of the household by calculating its MPI on basis of household characteristics.

CONCLUSION

Many developing economies suffer from the prevalence of poverty. Some adopt various social assistance programs to combat against it, but frequently fail to obtain expected impacts because of the mal-targeting of beneficiaries. Among the common causes is the failure in correct identification of household in poverty, due to unavailability or inaccessibility of detailed information on household conditions. Poverty targeting is a policy tool designed to transfer resources to the targeted poor groups. The main types of poverty targeting are means testing, proxy means testing, categorical targeting, geographical targeting, self-targeting and community-based targeting. There is a trade-off between the accuracy and the cost for each type of poverty targeting methodologies. The most accurate targeting methodologies are means testing and proxy means testing. Those two methodologies cannot be used without having household data.

As a means to overcome the limited availability of income or consumption data, this paper explores two alternative measurements, i.e. WI and MPI. We find that in Egypt the MPI can be a good substitute for the income or consumption criterion and, further, is superior in terms of comprehensiveness. In addition, we conduct the analysis on the characteristics of households in poverty, the results of which demonstrate highly uneven distribution of poverty across regions in Egypt. Moreover, the MPI can be used in constructing poverty maps for geographical targeting on the district level which helps policy makers to understand the nature and differences of each locality and determine the candidate locations for government intervention.

In conclusion, the combination of geographical targeting and self-targeting is recommendable as a poverty targeting method in Egypt, when its distribution of poverty, the administrative capacity, and data availability are all considered. In addition, the estimation results suggest that the location of a household, the sex and age of a house head, family size, and the demography of a family can provide useful information to supplement the self-targeting method.

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APPENDIX: THE COMPUTATION OF WEALTH INDEX USING THE HHIES 2015

Table A1. List of Assets Used in Measuring the WI

Variable	Obs	Mean	Std.Dev	Min	Max
Has a car, van, taxi, cart, etc …	11988	0.076	0.265	0	1
Has bicycle, scooter, motorcycle, etc…	11988	0.170	0.376	0	1
Has a TV, LCD, LED, etc...	11988	0.955	0.206	0	1
Has satellite dish, receiver, etc...	11988	0.926	0.262	0	1
Has DVD, VCR, CD player, audio player, etc…	11988	0.203	0.402	0	1
Has photo or video camera	11988	0.018	0.132	0	1
Has telephone, cell phone, etc...	11988	0.955	0.207	0	1
Has computer or laptop connected or not to an internet line	11988	0.313	0.464	0	1
Has internet line and related equipment (router, USB, etc ...)	11988	0.172	0.377	0	1
Has refrigerator, freezer, water cooler, etc…	11988	0.956	0.205	0	1
Has cooker, stove, oven, etc...	11988	0.979	0.144	0	1
Has microwave, grill, fryer etc...	11988	0.050	0.218	0	1
Has food processor, kitchen	11988	0.896	0.305	0	1
Has washing machine	11988	0.939	0.239	0	1
Has a dishwasher	11988	0.013	0.112	0	1
Has an air conditioner	11988	0.129	0.335	0	1
Has an electric fan	11988	0.928	0.258	0	1
Has a heater	11988	0.076	0.264	0	1
Has a water heater	11988	0.533	0.499	0	1
Has a sewing machine	11988	0.042	0.201	0	1
Has a vacuum cleaner	11988	0.216	0.411	0	1
Has an iron	11988	0.670	0.470	0	1
Has other durables	11988	0.093	0.290	0	1

Table A2. Principal Component Factors

Factor analysis/correlation			Number of obs =	11988
Method: principal-component factors			Retained factors =	5
Rotation: (unrotated)			Number of params =	105
Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.185	1.674	0.182	0.182
Factor2	2.510	1.298	0.109	0.291
Factor3	1.212	0.102	0.053	0.344
Factor4	1.110	0.098	0.048	0.392
Factor5	1.013	0.030	0.044	0.436
Factor6	0.983	0.052	0.043	0.479
Factor7	0.931	0.018	0.041	0.519
Factor8	0.913	0.037	0.040	0.559
Factor9	0.876	0.020	0.038	0.597
Factor10	0.856	0.026	0.037	0.634
Factor11	0.830	0.038	0.036	0.670
Factor12	0.792	0.025	0.035	0.705
Factor13	0.768	0.019	0.033	0.738
Factor14	0.749	0.019	0.033	0.771
Factor15	0.730	0.016	0.032	0.803
Factor16	0.714	0.061	0.031	0.834
Factor17	0.653	0.019	0.028	0.862
Factor18	0.634	0.033	0.028	0.890
Factor19	0.601	0.035	0.026	0.916
Factor20	0.566	0.040	0.025	0.940
Factor21	0.526	0.078	0.023	0.963
Factor22	0.448	0.051	0.020	0.983
Factor23	0.397	.	0.017	1.000

LR test: independent vs. saturated: chi2(253) = 4.5e+04 Prob>chi2 = 0.0000

Table A3. Factor Loadings and Unique Variances (using 5 factors)

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Uniqueness
Has a car, van, taxi, cart, etc	0.490	-0.334	0.167	-0.196	-0.047	0.581
Has bicycle, scooter, motorcycle, etc	0.090	0.118	-0.215	0.390	0.369	0.644
Has a TV, LCD, LED, etc.	0.334	0.547	0.286	-0.340	0.244	0.333
Has satellite dish, receiver, etc.	0.371	0.527	0.271	-0.310	0.185	0.380
Has DVD, VCR, CD player, audio player, etc	0.287	-0.152	-0.124	0.426	0.229	0.645
Has photo or video camera	0.326	-0.310	0.407	0.170	0.199	0.564
Has telephone, cell phone, etc.	0.364	0.324	-0.007	0.247	-0.199	0.662
Has computer or laptop connected or not to an internet line	0.647	-0.204	-0.323	-0.164	0.024	0.408
Has internet line and related equipment (router, USB, etc.)	0.575	-0.275	-0.229	-0.226	0.077	0.485
Has refrigerator, freezer, water cooler, etc.	0.411	0.478	0.137	0.179	-0.127	0.536
Has cooker, stove, oven, etc.	0.224	0.330	0.112	0.066	0.116	0.811
Has microwave, grill, fryer etc.	0.367	-0.348	0.344	0.009	0.030	0.625
Has food processor, kitchen	0.480	0.440	0.031	0.182	-0.151	0.519
Has washing machine	0.424	0.489	0.018	0.189	-0.203	0.504
Has a dishwasher	0.218	-0.314	0.516	0.243	-0.042	0.527
Has an air conditioner	0.487	-0.332	0.129	-0.078	-0.115	0.617
Has an electric fan	0.276	0.345	-0.035	-0.110	0.213	0.747
Has a heater	0.326	-0.280	0.128	0.286	-0.218	0.669
Has a water heater	0.645	-0.024	-0.284	-0.089	-0.108	0.483
Has a sewing machine	0.199	-0.085	-0.119	0.190	0.621	0.518
Has a vacuum cleaner	0.623	-0.263	-0.121	-0.107	-0.047	0.515
Has an iron	0.585	0.127	-0.290	0.127	-0.172	0.512
Has other durables	0.448	-0.274	0.005	-0.152	0.112	0.688

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Shaimaa Hussien, PhD Candidate, Graduate School of Pan-Pacific International Studies, Kyung Hee University, 1732 Deogyeong-daero, Giheung-gu, Yongin-Si, Gyunggi-do, Suwon South Korea, 17104, Tel. +82 010 51998613

Bokyeong Park, Professor, Graduate School of Pan-Pacific International Studies, Kyung Hee University, 1732 Deogyeong-daero, Giheung-gu, Yongin-Si, Gyunggi-do, Suwon South Korea, 17104,Tel. +82 31-201-2334