Income Inequality in Malawi: Does the farm Input Subsidy Play a Role?

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Introduction

Income inequality in developing countries has received a lot of attention in the literature but little is known about the role of large scale farm input subsidy programs in promoting equity in income distribution. We fill this knowledge gap by analyzing the impact of Malawi's farm input subsidy program (FISP) on income inequality. Specifically, we test the hypothesis that *FISP has no effect on income inequality in Malawi*.

In terms of scope and coverage, FISP is perhaps the most well-known agricultural input subsidy program in Africa. It currently provides inorganic fertilizers and improved maize and legume seeds to over 50% of rural, smallholder farmers at hugely subsidized prices (about 95% subsidy). Each beneficiary is entitled to 50kg of Urea; 50kg of NPK 23:21:0; 5kg of improved maize seed or 10kg of open pollinated variety maize seed; and a kilogram of legume seed (Kilic et al., 2014). Officially, FISP has two main objectives: 1) ensuring household food security and national food sufficiency through increased food production; and 2) reducing poverty by increasing the income levels of beneficiaries (Chirwa and Dorward, 2010). Although FISP is not designed to directly promote equity in income distribution, the pro-poor focus of the program suggests that with effective targeting of the inputs income inequality can be curtailed. This analysis will complement other papers that focused on the impacts of FISP on agricultural production and household welfare indicators in promoting the effectiveness of large scale farm input subsidy programs in Africa and other developing countries.

Measurement of key variables

Income Inequality: Income inequality is measured with the relative deprivation index developed by Stark and Taylor (1989). The index is given by:

$$RD_i = AD(Y_i) * P(Y_i)$$

Where Y_i is the consumption expenditure of household i; $AD(Y_i)$ is the mean consumption expenditure of households richer than household i, and $P(Y_i)$ is the proportion of households that are richer than household i. This index is chosen over popular indices such as the Decile Dispersion Ratio, Gini Coefficient of Inequality, Generalized Entropy Measures, Atkinson's Inequality Measures because it is amenable for use in regressions with household data (Mason and Smale, 2013).

The subsidy (treatment) variable: The subsidy variable is measured as the urea equivalent of the total kilograms of subsidized inputs that a household receives. It is given by:

$$T = \frac{\sum_c Q_c * P_c}{P_{urea}}$$

Where c represent the components of the subsidy package - urea, NPK (23:21:0), improved maize seed, open pollinated variety maize seed and legume seed - and P_{urea} is the price of urea. Measuring the subsidy variable this way allows for the consideration of both subsidized fertilizer and hybrid seeds, thereby ensuring the treatment variable represents the subsidy program in its entirety. To the best of our knowledge, no study has measured the full package of a farm input subsidy program in a single variable; previous studies concentrates on either subsidized fertilizer or subsidized hybrid seed.

Identification Strategy and Data

The identification strategy used in this study follows Cerulli (2014). The author proposes a procedure that estimates treatment effect (ATE, ATET, ATENT and a dose function of the treatment) when treatment is continuous and endogenous. Compared to the Generalized Propensity Score matching method (GPS) proposed by Hirano and Imbens (2004), the full normality assumption is not needed in this model; "it is well-suited when many individuals have a zero-level of treatment"; and it also takes accounts of possible treatment endogeneity by incorporating an Instrumental-Variables (IV) estimation in a continuous treatment context (Cerulli, 2014).

The proposed identification strategy by Cerulli (2014) is appropriate in the context of this study because treatment, kilograms of subsidized inputs that a household receives, is continuous and endogenous.

Let m_i be the program participation (henceforth treatment) indicator, taking the value of 1 when household *i* participated in the program (henceforth treated) and 0 when the household did not participate in the program (henceforth untreated); $\boldsymbol{X}_{ji} = (x_{1ji}, x_{2ji}, x_{3ji}, \ldots x_{Kji})$ be a row of *K* observable, exogenous characteristics of household *i*, and other factors such as access to off-farm income that are likely to affect income inequality ; S_{ji} be the continuous-treatment indicator, measuring the kilograms of subsidized inputs that household *i* received; y_{1ji} *and* y_{0ji} be the income inequality of household *j* when treated and untreated respectively.

Household *j*'s responses to the $\boldsymbol{X}_{ji}$ vector of confounders when it is treated and when it is untreated are presented by $g_1(\boldsymbol{X}_{ji})$ and $g_0(\boldsymbol{X}_{ji})$ respectively; and the general deliverable function of s_i is given by $h(S_{ji})$. Finally, let μ_1 *and* μ_2 be two scalars and e_1 *and* e_2 be two random variables having constant variance and zero unconditional mean.

Income inequality is expressed as follows:

$$\begin{cases} m_i = 1: \; y_{1ji} = \mu_1 + g_1(\boldsymbol{X}_{ji}) + h(s_{ji}) + e_1 \\ m_i = 0: \; y_{0ji} = \mu_0 + g_0(\boldsymbol{X}_{ji}) + e_0 \end{cases} \quad (1)$$

where $h(s_{ji})$ is different from zero only in the treatment status. Given equation (1), the causal parameters of interest conditional on X and S - Average Treatment Effect (ATE), Average Treatment Effect on the Treated (ATET), and Average Treatment Effect on the Non-Treated (ATENT) - can be defined as:

$$\begin{cases} ATE(\boldsymbol{X}; S) = E(y_1 - y_0 | X, s) \\ ATET(\boldsymbol{X}; S > 0) = E(y_1 - y_0 | X, s > 0) \\ ATENT(\boldsymbol{X}; S = 0) = E(y_1 - y_0 | X, s = 0) \end{cases} \quad (2)$$

The study will use the two waves of the Malawi Integrated Household Panel Survey (IHPS) dataset that was collected by the National Statistical Office (NSO) of Malawi with support from the World Bank Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) program. The first wave of the survey was conducted from March 2010 through March 2011, and covered 3246 households in 204 enumeration areas; and the second survey was conducted in 2013. The dataset provides comprehensive information on the households, their agricultural and fisheries activities, and information about the community in which they live.

Results

Income inequality in 2010

		Region		
	Pooled	Northern	Central	Southern
Relative mean deviation	0.30056	0.27836	0.31412	0.28715
Coefficient of variation	1.29123	0.88752	1.4956	0.99901
Standard deviation of logs	0.71067	0.67835	0.71786	0.69726
Gini coefficient	0.41961	0.38777	0.4386	0.40079
Mehran measure	0.53361	0.50615	0.54779	0.51636
Piesch measure	0.36261	0.32858	0.38401	0.343
Kakwani measure	0.15363	0.13117	0.16823	0.14045
Theil index	0.36397	0.27077	0.42757	0.30506
Mean Log Deviation	0.29734	0.24953	0.3256	0.27022
Entropy index	0.34869	0.29428	0.36939	0.32366
Half	0.83332	0.39322	1.11727	0.49854

Income inequality in 2013

		Region		
	Pooled	Northern	Central	Southern
Relative mean deviation	0.28144	0.24766	0.30175	0.27241
Coefficient of variation	1.04916	0.75659	1.18855	0.94621
Standard deviation of logs	0.66917	0.60831	0.70605	0.65821
Gini coefficient	0.39343	0.34717	0.42124	0.38107
Mehran measure	0.50527	0.45945	0.53319	0.49349
Piesch measure	0.33751	0.29103	0.36526	0.32486
Kakwani measure	0.13613	0.10656	0.15509	0.12786
Theil index	0.30452	0.21179	0.3633	0.27373
Mean Log Deviation	0.25824	0.19775	0.29798	0.24156
Entropy index	0.29532	0.22504	0.3431	0.28005
Half	0.55019	0.28578	0.70573	0.44731

Results

Percentage change in income inequality

		Regions		
	Pooled	Northern	Central	Southern
Relative mean deviation	-6.35983	-11.0293	-3.93726	-5.13322
Coefficient of variation	-18.7471	-14.752	-20.5303	-5.28595
Standard deviation of logs	-5.839	-10.3241	-1.6456	-5.59981
Gini coefficient	-6.23926	-10.4695	-3.95935	-4.91991
Mehran measure	-5.31145	-9.22628	-2.66486	-4.43031
Piesch measure	-6.92194	-11.427	-4.88265	-5.28845
Kakwani measure	-11.39	-18.7593	-7.81461	-8.96528
Theil index	-16.3355	-21.7829	-15.0316	-10.2712
Mean log deviation	-13.1472	-20.7494	-8.48174	-10.6062
Entropy_index	-15.3073	-23.5289	-7.1173	-13.4723
Half	-33.9759	-27.3236	-36.8341	-10.2759

Conclusions

1. Income inequality (as measured by eleven measures) declined between 2010 and 2013
2. The farm input subsidy program might have played a role in the reduction in income inequality
3. Other factors such as farmers participation in off-farm income generating activities might be important factors too.

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