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Improving the Targeting of Fertilizer Subsidy Programs in Africa South of the Sahara

Perspectives from the Ghanaian Experience

Nazaire Houssou

Collins Asante-Addo

Kwaw S. Andam

Development Strategy and Governance Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

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AUTHORS

Nazaire Houssou (n.houssou@cgiar.org) is a research coordinator in the Development Strategy and Governance Division of the International Food Policy Research Institute (IFPRI), Accra, Ghana.

Collins Asante-Addo is a scientific assistant and PhD candidate at the Department for Market Analysis, Johann Heinrich von Thünen Institute, Braunschweig, Germany.

Kwaw S. Andam is a research fellow in the Development Strategy and Governance Division of IFPRI, Accra, Ghana.

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ABSTRACT

This paper assesses whether fertilizer subsidy programs can be better targeted to resource-poor farmers using the case of Ghana and proxy means test approaches. Past fertilizer subsidy programs in the country have not been particularly targeted to the poor, even as targeting poor and smallholder farmers has become key in the program implementation guidelines. As a result, many poor farmers have not benefited from past programs. Our results show that targeting approaches based on proxy means tests that use the correlates of poverty to select beneficiary farmers can potentially improve the poverty outreach and cost-effectiveness of Ghana's fertilizer subsidy programs. Therefore, we propose that the proxy means test approach should be considered for implementing Ghana's fertilizer subsidy programs, first in a pilot project involving a few communities, and later, if found successful, in a full-scale program.

Keywords: targeting, poverty, smallholder farmers, fertilizer subsidy, proxy means tests, community-based targeting, Ghana, Africa south of the Sahara

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1. INTRODUCTION

Targeting of development interventions has been recognized as more equitable and progressive than universal policies that transfer resources equally to all members of society (Coady, Grosh, and Hoddinott 2004; Dutrey 2007). In theory, limited resources meant for social transfers would be used in the most efficient manner when distributed to a selected subgroup of the population, generally eliminating those who are not in need and focusing resources on the poor (Dutrey 2007). The motivations for targeting have been extensively discussed by Coady, Grosh, and Hoddinott (2004). They include maximizing poverty reduction, or more generally, increasing social welfare, budget constraint, and minimizing opportunity cost (that is, the trade-off between the number of beneficiaries covered by the intervention and the level of transfers). Furthermore, the question of more accurately targeting resource-poor smallholder farmers has become critical for input subsidy programs that have reemerged recently in many countries in Africa south of the Sahara (SSA). Many scholars have suggested that the achievement of the full benefits of fertilizer subsidy programs (FSPs) is generally supported by pro-poor targeting (see, for example, Dorward and Chirwa 2013; Mansuri and Rao 2012). While policy makers are increasingly acknowledging the contribution of targeting in improving the effectiveness of subsidy programs, recent experience shows that these subsidy programs are not sufficiently targeted to the poor. Yet many scholars have indicated that better coverage of poor farmers will increase program efficiency while reducing leakage to nonpoor farmers who could afford unsubsidized inputs, thereby reducing the crowding-out effect on commercial inputs in the private markets (Chibwana, Fisher, and Shively 2012; Ricker-Gilbert, Jayne, and Chirwa 2011; Jayne et al. 2011; Holden and Lunduka 2010; Dorward et al. 2008). In short, four main reasons can be advanced to support the targeting of input subsidies to the poor: (1) budget constraints, (2) efficiency grounds (benefits are enhanced by pro-poor targeting), (3) equity reasons, and (4) reduction of crowding out of the private sector.

In Ghana, the case studied in this paper, past FSPs had not been aimed particularly at any specific group until 2013, when policy makers decided to target specific groups, such as smallholder farmers, vulnerable farmers, and women farmers, among others. But these changes did not go far. While the central administration still set targeting criteria, the selection of beneficiary farming households was left to district agricultural staff under the assumption that they would know better those who meet targeting criteria at the local level. But the evidence in this paper suggests that most of the subsidies were captured by well-off farmers. Other social programs on education, electricity, health, and tariff subsidies, among others, are also poorly targeted in the country (Wodon 2012). Meanwhile, a major cash transfer program in Ghana, the Livelihood Empowerment Against Poverty (LEAP), essentially combines the use of a proxy means test (PMT), which relies on a set of poverty correlates, and community-based targeting (CBT), involving the use of local authorities and community leaders, to successfully target poor and vulnerable households, suggesting that it is feasible to better target fertilizer subsidies as well in the country.

This research intends to move the debate on decentralized targeting to assessing whether use of a PMT is a realistic approach that SSA countries should seriously consider. Would the PMT approach be more effective than CBT? For how long can the same PMT be used without diminishing performance? What implementation issues might arise with the application of a PMT given the local context? We focus on these critical questions in order to inform policy makers about whether to consider (for example, at least to pilot) or disregard the approach altogether, especially in the SSA region, where it has been applied only in a few cases. The paper contributes to the literature by analyzing the applicability of PMT-based methods to target input subsidy programs as opposed to the CBT methods that are widely used in the SSA subregion despite their failures in correctly targeting the poor. We strengthen the ex ante assessment of the PMT approach by conducting validation tests using nationally representative random samples from different periods, which inform about how the PMT may actually perform when implemented in the field. We also estimate the administrative costs of targeting, which most previous research fails to consider adequately; estimating such costs is essential for deciding whether to pilot a PMT-based targeting approach.

Specifically, we assess to whom Ghana's fertilizer subsidies have been going versus to whom they should be going, based on equity and poverty grounds. We then model the factors that influence household and community participation in the programs. Third, we examine whether using a PMT can improve targeting performances compared with the current system, which is characterized by limited targeting involving use of district agricultural staff. Fourth, to assess how well and for how long a PMT would likely perform in correctly identifying the target group in the field, we conduct robustness tests using nationally representative data from three different time periods spanning 20 years. Finally, we assess whether administering a targeted version of an FSP based on the PMT approach is more cost-effective than implementing a loosely targeted FSP based on the current system.

Our results suggest that past FSPs have not been pro poor and that nonpoor farmers are disproportionally receiving subsidized fertilizer. There are also spatial inconsistencies in the way that the 2012 FSP was targeted, but some efforts seem to have been made to target remote communities. More important, the PMT-based approach performs better than the actual targeting outcome of the 2012 FSP in including a considerable share of poor farming households on the list of FSP beneficiaries. The validation and robustness tests suggest that the set of poverty indicators developed under the PMT approach can potentially be used to target poor farmers for two decades if not more without losing their predictive performance and without the need to calibrate a new PMT for targeting Ghanaian poor farmers. Estimates of the administrative costs of targeting show that using the PMT is potentially more cost-efficient than relying on CBT methods involving district agricultural staff, suggesting that concerns over the costs of administration are ungrounded, at least for the case of Ghana. We conclude that the PMT that is designed here should be considered for piloting in a few communities in an intensely monitored program that will allow useful lessons to be derived and integrated in a full-scale implementation of an FSP with the PMT-based approach, if found successful.

Section 2 of the paper reviews the trajectory of FSPs (from universal to targeted programs) in SSA, and Section 3 sets out the conceptual framework for targeting development programs. Section 4 examines the targeting of FSPs within the Ghanaian context, and Section 5 presents the data and the empirical approach used to design the PMT for Ghana. Section 6 presents the results, and Section 7 discusses the issues emerging from our findings. Section 8 concludes.

2. FERTILIZER SUBSIDY PROGRAMS IN AFRICA SOUTH OF THE SAHARA: FROM UNIVERSAL TO TARGETED PROGRAMS

In the past, many countries in SSA have tried to increase fertilizer use among their farming populations through the use of universal FSPs. But those programs were abandoned due to high fiscal costs in the wake of structural adjustment programs that were adopted by many countries in the subregion. Fertilizer subsidies resurfaced in recent years partly due to rising fertilizer prices, with countries adopting several best practices toward smarter subsidy programs. The new generation of FSPs intends to overcome some of the weaknesses emanating from universal subsidy programs and heavy state involvement in the importation and distribution of subsidized fertilizer by introducing new approaches to subsidization (Banful 2011; Pan and Christiaensen 2012; Druilhe and Barreiro-Hurlé 2012; Dorward 2009; Morris et al. 2007). As such, they have been termed "smart subsidy." Among the new approaches introduced are the use of vouchers, a stronger participation of private fertilizer importers and private retail outlets, and use of decentralized methods of fertilizer distribution to the farming population. Indeed, decentralized targeting methods have become the vehicle of choice for identifying who should receive targeting benefits and who should not (Kilic, Whitney, and Winters 2015). With the shift from universal subsidy programs in the 1970s to CBT programs, policy makers are learning the value of inclusive targeting mechanisms, in particular the use of community leaders and local government in identifying beneficiaries (Sheahan et al. 2014; Dorward and Chirwa 2013; Xu et al. 2009; Minde et al. 2008).

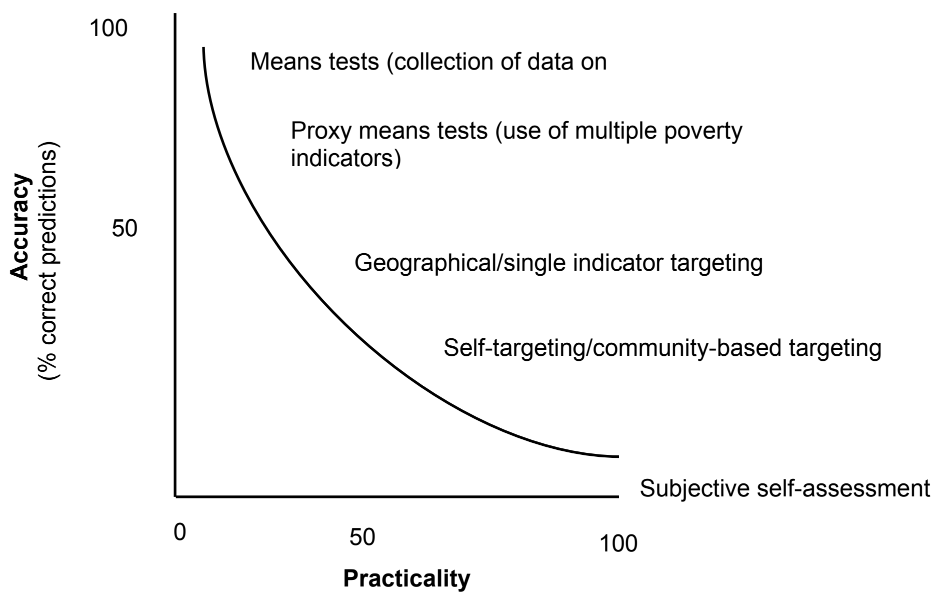
CBT methods have the advantage of tapping into local knowledge and preferences to identify intended program beneficiaries, while reducing the administrative costs of targeting. However, CBT methods have issues, such as lack of transparency, which perpetuates perceptions of unfairness (Dorward and Chirwa 2013), and elite capture, which can reduce targeting performances substantially (Kilic, Whitney, and Winters 2015; Pan and Christiaensen 2012). While it is rarely possible for central administrators to know who meets targeting criteria at the local level, the experience of many countries with CBT methods indicates that most poor and vulnerable households are not sufficiently targeted by subsidy programs (Kilic, Whitney, and Winters 2015; Chibwana, Fisher, and Shively 2012; Ricker-Gilbert, Jayne, and Chirwa 2011; Jayne et al. 2011; Holden and Lunduka 2010; Dorward et al. 2008; Morris et al. 2007; Jayne et al. 2003).

Furthermore, Alatas et al. (2012), using field experiments from 640 villages in Indonesia, show that proxy means testing performs better than either CBT or a hybrid model combining both methods, even after controlling for elite capture. For these reasons, scholars are increasingly suggesting the use of alternative methods, such as the PMT, to better target fertilizer subsidy beneficiaries in the SSA subregion (Kilic, Whitney, and Winters 2015; Dorward and Chirwa 2013; Pan and Christiaensen 2012; Houssou and Zeller 2011). The PMT method is essentially the use of a small set of easily verifiable indicators to identify and target the poor. It has been shown to be one of the most effective methods for reaching the poor in many developing countries (Stoeffler, Mills, and del Ninno 2016; Alatas et al. 2012; Houssou and Zeller 2011; Coady, Grosh, and Hoddinott 2004; Grosh and Baker 1995), even though there are concerns with administrative costs. These competing arguments for targeting FSPs to the poor frame our analysis of the Ghanaian case. Section 3 discusses in more detail the conceptual approach used in this paper.

3. TARGETING IN THEORY AND PRACTICE: A CONCEPTUAL FRAMEWORK

Targeting, essentially, is the process of increasing program efficiency by raising the benefits that the poor can get amidst budget constraints (Coady, Grosh, and Hoddinott 2004). In practice, targeting involves first defining who should receive program benefits, and second, establishing a mechanism for identifying those people in the population. Various methods have been proposed to target social interventions and input subsidy programs, including means tests, proxy means tests, community-based targeting, geographical targeting, categorical targeting, self-targeting, and subjective self-assessment (see, for example, Houssou 2013 and Coady, Grosh, and Hoddinott 2004 for fuller details on targeting methods). These methods all have the same goal, which is to correctly select out intended program beneficiaries or the poor from unintended beneficiaries or the nonpoor in the population. But none of these methods is perfect at identifying program beneficiaries and nonbeneficiaries as they exhibit trade-offs. For example, Figure 3.1 shows that the higher the method's accuracy in identifying intended and unintended program beneficiaries, the lower the practicality, and hence, the higher the cost of implementation and vice versa (for the definition of practicality, see the subsection "Identifying the Best Indicators for Selecting Poor Farming Households").

Figure 3.1 Trade-off between practicality and accuracy of targeting methods



Source: Houssou and Zeller (2011).

Although different methods are available to target transfers, CBT methods for the distribution of subsidized input vouchers have become a popular tool of choice to target input subsidies and other social interventions in SSA (Stoeffler, Mills, and del Ninno 2016; Kilic, Whitney, and Winters 2015; Robertson et al. 2014; Sheahan et al. 2014; Dorward and Chirwa 2013; Pan and Christiaensen 2012; Garcia and Moore 2012). Stoeffler, Mills, and del Ninno (2016) define CBT as involving "communities in a participatory process to select beneficiary households at the local level." But that definition can be extended to the use of intermediary agents who select or participate in the selection of program beneficiaries (Conning and Kevane 2002). Proponents of the community-based method indicate that it allows information about household wealth and vulnerability to be generated relatively quickly and cheaply (Robertson et al. 2014). Others have indicated that CBT ensures direct accountability and empowerment of communities, making it easier for communities to accept targeting choices (Robertson et al. 2014; Alatas et al. 2012). CBT is also believed to be less costly, as it taps into local knowledge (Schüring 2014; Pan and Christiaensen 2012).

While CBT takes advantage of local information, critics argue that it is characterized by favoritism and elite capture of program benefits (Alatas et al. 2012; Garcia and Moore 2012). Supporting this view, Pan and Christiaensen (2012) report that in Tanzania, members of the local elite had a higher probability of receiving input vouchers through their disproportionate membership in village voucher committees. As a result of this local elite capture, targeting performance was substantially reduced. Similarly, Dorward and Chirwa (2013) suggest that in Malawi, traditional leaders, government officials, and other members of the local elite arrogate vouchers to themselves, friends, and relatives, leading to low coverage of the poor. Another criticism is that with CBT marginalized groups risk being excluded or stigmatized, while local preferences may not be pro poor (Conning and Kevane 2002). For example, Kilic, Whitney, and Winters (2015) and Dorward and Chirwa (2013) report that under CBT, the Malawi Farm Input Subsidy Program failed to target the poor. CBT lacks standardization, which creates greater loopholes for corruption and misappropriation and makes it extremely difficult for individual community members to claim their entitlements (Schüring 2014).

Where there are tensions and disharmony among community members, the use of CBT for selecting program beneficiaries may create a more volatile situation and hamper social cohesion. Likewise, community institutions vary in terms of superior information, embeddedness in monitoring institutions, their willingness to engage in rent-seeking, and their propensity to be responsive to the poor (Stoeffler, Mills, and del Ninno 2016). Therefore, even though CBT-based methods may reduce the burden of identifying intended program beneficiaries on the central government, unconditional devolution of targeted programs to communities may be problematic (Conning and Kevane 2002) if poverty reduction is a key objective. In sum, the feasibility and effectiveness of CBT methods depend on local contexts, and outcomes may vary widely across countries, communities, or regions. The best community outcomes are likely to be achieved with systems that incorporate and implement clear rules and targeting guidelines (Conning and Kevane 2002). Meanwhile, the results on the ground is that intended beneficiaries are not sufficiently targeted with CBT methods in SSA. This outcome is critical and calls for a reexamination of CBT methods as a preferred mechanism to target social interventions, including input subsidy programs.

In theory, means testing is the best way of determining eligibility for a social transfer program. Means tests require the collection of information on income or consumption expenditures to determine whether a household qualifies for a targeted program, but the method is highly impractical given the difficulty associated with collecting and verifying income or expenditures and therefore has rarely been used in developing countries. PMTs have been shown to be more feasible and useful, especially in a developing-country context, where a high degree of informality, seasonality, and in-kind earnings makes quantifying and verifying income difficult (Castañeda et al. 2005). The PMT uses a multidimensional index of observable household characteristics, such as quality of dwelling, ownership of durable goods, education, and others, as proxies for household income or welfare level (Castañeda et al. 2005; Coady, Grosh, and Hoddinott 2004). The PMT method has a number of advantages over the CBT method. A PMT is simpler to implement and relies on objective criteria (implying credibility, fairness, and robustness to manipulation). A PMT is based on indicators that can be easily measured and verified and also are correlated with long-term well-being rather than short-term consumption (Stoeffler, Mills, and del Ninno 2016; Kidd and Wylde 2011; Coady, Grosh, and Hoddinott 2004). However, it is argued that the PMT-based method is more expensive to administer than CBT, has associated social and political costs, and often comes with targeting errors, implementation issues, and exclusion of communities from the targeting process (Kidd and Wylde 2011).

Furthermore, the choice between the CBT and PMT methods is usually framed as a trade-off between the better information that communities might have against the risk of elite capture in the community-targeting process (Alatas et al. 2012). Given these trade-offs, which method works best may be an empirical question. In SSA, the tendency has been to target cash transfer programs using PMT-based methods and to target fertilizer subsidies and other input programs using CBT methods. However, there is evidence to suggest that the PMT method may perform better than CBT or that the combination of both may be more desirable than using CBT alone (Stoeffler, Mills, and del Ninno 2016; Alatas et al. 2012; Houssou and Zeller 2011). For example, in Cameroon, Stoeffler, Mills, and del Ninno (2016) find that the PMT method outperforms CBT in selecting households with low per capita consumption. Houssou and Zeller (2011) also propose targeting by a PMT, arguing that this approach would be more target- and cost-effective than CBT, which was used to target subsidy benefits to the poor in Malawi. In Ghana, LEAP, which is the most effectively targeted social protection program in the country, uses a combination of geographical, community, and proxy means testing to target beneficiary households (Wodon 2012). In this approach, the PMT is used as a means of validating the efficacy of geographical- and community-based targeting, by ensuring that beneficiaries are indeed poor. This implies that the PMT-based method can also be used to target fertilizer subsidies to intended beneficiaries, the poor farmers who cannot afford commercial fertilizer prices.

While proxy means testing is seen as superior in terms of targeting, it also comes with implementation challenges, as with any targeting approach, that need to be considered in order to achieve a successful targeting. Coady, Grosh, and Hoddinott (2004) outline the conditions under which a PMT can be effective. These include (1) identifying variables (easily observed and that cannot be manipulated by households) that exist in the surveys that are highly associated with household income; (2) periodic recertification of beneficiaries to remove from the system those whose welfare has improved; (3) developing an information system that can reliably gather this information from many households, especially the poor; and (4) having better administrative arrangements, such as a good outreach program and home visits, which are associated with collecting and verifying information to ensure low errors of exclusion and reduce errors of inclusion. These conditions imply that costs exist that should be considered in choosing the best targeting method. We consider these costs in this research. PMTs can also gain in legitimacy if communities perceive the target group as a reflection of the local understanding of poverty. In the case of Ghana, much can be learned from the administration of the LEAP program, which has been implemented in the country since 2008 (Wodon 2012). Section 4 discusses the targeting of fertilizer subsidies within the Ghanaian context.

4. TARGETING FERTILIZER SUBSIDIES: THE GHANAIAN CONTEXT

Since 2008, Ghana has initiated successive rounds of fertilizer subsidies intended for the farming population. The FSP is intended to stimulate greater private-sector development and participation in fertilizer markets (Benin et al. 2013). Ghana's current program aims to increase the rate of fertilizer application to at least 50 kilograms per hectare, a rate that is recommended under the country's Medium Term Agriculture Sector Investment Plan and in line with the Abuja Declaration. Initially, the subsidy rate was 49 percent of the fertilizer price, but that rate declined to 26 percent in 2016, while the volume of fertilizer subsidized has quadrupled, reaching 180,000 metric tons of fertilizer in 2016 (Houssou, Andam, and Asante-Addo, 2017). Ghana Living Standards Survey (GLSS) data suggest that in 2012, 11.4 percent of fertilizer users benefited from the program, totaling 112,844 farming households (Table 4.1). But the majority of farming households acquired fertilizer from private sources, indicating that there is a well-developed private fertilizer distribution network in the country.

Table 4.1 Sources of fertilizer used in 2012

Source of fertilizer	Number of users	Share of users (%)
Private sector	840,658	84.78
Cooperative	20,121	2.03
MoFA/subsidized	112,844	11.38
NGOs	14,381	1.45
Others	3,550	0.36
Total	**991,554**	**100**

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Note: MoFA = Ministry of Food and Agriculture; NGO = nongovernmental organization.

The top-four fertilizer subsidy recipient regions are the Ashanti, Upper West, Northern, and Brong-Ahafo regions, which shared 65 percent of subsidy beneficiaries in 2012 (Table 4.2). Broadly speaking, most fertilizer subsidy beneficiaries are located in the northern parts of Ghana, indicating that the program focused on these regions.

Table 4.2 Regional distribution of actual fertilizer subsidy beneficiaries, 2012

Region	Number of beneficiaries	Share of beneficiaries (%)
Ashanti	24,521	21.73
Upper West	17,395	15.42
Northern	15,637	13.86
Brong-Ahafo	15,427	13.67
Eastern	13,570	12.03
Volta	9,637	8.54
Upper East	6,891	6.11
Central	6,217	5.51
Western	3,549	3.15
Total	**112,844**	**100**

Source: Authors' estimations based on GLSS6 data (GSS 2012).

The subsidy program was implemented through a voucher system in 2008 and 2009; that system was replaced by a waybill system that aimed at addressing some of the weaknesses of previous programs, such as high overhead and administrative costs, too much time spent by Ministry of Food and Agriculture (MoFA) officers monitoring the process, and diversion of fertilizers from intended target beneficiaries (Banful 2011; Baltzer and Hansen 2011; Benin et al. 2013). The program has also been plagued by implementation difficulties, such as late delivery of subsidized fertilizer resulting from delayed procurement process and financial challenges at various levels of government (Banful 2009; Yawson et al. 2010; Benin et al. 2013; Resnick and Mather 2016). Nonetheless, implementation issues are not peculiar to FSPs alone: almost all subsidy programs suffer from implementation deficiencies in many SSA countries.

Existing evaluations of Ghana's FSPs suggest that they have led to increased fertilizer use across the country (Bumb, Johnson, and Fuentes 2011; Benin et al. 2013; Jayne et al. 2015). These results are consistent with findings from Kenya, Malawi, Nigeria, and Zambia that suggest that the new subsidies have had some positive impact over the short to medium terms, which includes promoting input use, increasing output, and reducing poverty in the SSA subregion. However, these subsidies have not yet offered a convincing solution for sustainably raising fertilizer use in SSA, as they carry over many of the problems of the past (Druilhe and Barreiro-Hurlé 2012). For example, Banful (2011) reported that FSPs attempt to incorporate only part of the new innovations, although it is the aggregate use of innovations that is expected to avoid the downsides of the past. This suggests that Ghana's FSP can be more beneficial to Ghana's economy as a whole. The next section assesses the role that politics may have played in Ghana's fertilizer subsidies.

Is Targeting of Fertilizer Subsidies Politically Motivated at the District Level?

Elite and political capture has been a recurring issue in large-scale input subsidy programs across the SSA subregion (Banful 2011; Dorward and Chirwa 2013). For example, Banful (2011) indicates that Ghana's 2008 FSP lacked innovation to constrain political manipulation based on the evidence that district political characteristics were considered in the allocation of fertilizer vouchers, with districts where the ruling party had lost receiving more vouchers than where it had won, suggesting that the 2008 program was used in an attempt at vote-buying. The author also adds that poverty levels did not influence voucher allocation in the ways that would be expected under a purely efficiency-based distribution pattern. Nonetheless, she indicates that voucher allocations were partly influenced by economic considerations as less poor districts appeared to have received more vouchers, which are likely to increase the subsidy benefits that displace unsubsidized purchases of fertilizer. Baltzer and Hansen (2011) also draw similar conclusions, indicating that the sharing of fertilizer subsidy vouchers across regions and districts in Ghana was based on vague notions of "farmers' needs."

Our own results seem to concur with these authors' conclusions. The distribution of the 2012 FSP beneficiaries suggests that the program was mostly targeted at districts where the ruling party lost (Table 4.3). For example, the average number of the 2012 FSP beneficiaries is higher in districts where the ruling party lost in the 2008 presidential elections compared with districts where the party won. A similar pattern is also observed when we use the 2012 presidential election results to assess FSP beneficiary distribution. Although our approach is not a perfect way to determine the political biasness of the program, these results suggest that the allocation of fertilizer subsidies to districts is in part influenced by prior election outcomes. Our paper focuses on targeting at the community and household levels—that is, after vouchers have been allocated to various districts.

Table 4.3 Estimated number of fertilizer subsidy beneficiaries by political stronghold

Election	Variable	Ruling party won	Ruling party lost	Total
2008 elections	Number of districts	47	30	77
	Average number of beneficiaries	1,212	1,541	1,340
	Total number of beneficiaries	56,951	46,223	103,173
	Share of beneficiaries	55.2	44.8	100
2012 elections	Number of districts	59	24	83
	Average number of beneficiaries	1,226	1,629	1,342
	Total number of beneficiaries	72,323	39,084	111,408
	Share of beneficiaries	64.9	35.1	100

Source: Authors' estimations based on GLSS6 (GSS 2012) and 2008 and 2012 election results.

Targeting of Subsidies at the Household Level Is Poor

Initially, the FSP did not target vouchers to farmers based on their wealth status or the crop they cultivated (Table 4.4), probably because it was designed in great haste as an emergency measure to ease the adverse impacts of the extremely high fertilizer prices in 2007 (Baltzer and Hansen 2011). All crop farmers were given the opportunity to participate in the program and buy as much subsidized fertilizer as they needed. Farmers received the subsidy in the form of fertilizer-specific and region-specific vouchers distributed by agricultural extension agents within their operational areas (Benin et al. 2013). The voucher allowed farmers to purchase NPK 15:15:15, NPK 23:10:05, urea, and sulphate of ammonia in 50-kilogram bags at a subsidized rate (Banful 2009). The district agricultural staff spent much time monitoring and administering the program during implementation, and farmers had to travel back and forth to gather endorsement signatures, a situation that discourages their participation in the program (Benin et al. 2013).

Recently, implementation challenges and increasing budget constraints have compelled Ghanaian policy makers to introduce new changes to the FSP to deliver effectively to the population and adhere to a "smarter subsidy" program similar to the one implemented in other SSA countries. For example, beginning in 2013 and after several years of FSP implementation, the state introduced criteria for targeting resource-poor smallholder farmers and other vulnerable groups in the farming population. The program has therefore moved from targeting all farmers regardless of crops grown to targeting specific smallholder farmers cultivating up to 2 hectares and certain crops, with a fixed amount of subsidized fertilizer. These changes aim at ensuring better coverage of resource-poor farmers and achieving greater efficiency in fertilizer distribution, goals that were not achievable under previous FSPs, which were universal. Specifically, the 2013 program targeted the following beneficiaries (Ghana, MoFA 2015):

- smallholder farmers cultivating maize, rice, sorghum, and millet, with priority given to food crop farmers in the savannah areas of the country;
- outgrower farmers registered under recognized nucleus farmers/companies[1]—however, nucleus farmers or companies with a verifiable list of outgrowers cultivating maize, rice, sorghum, and millet must apply to MoFA to procure fertilizer at such rates;
- food crop farmers, either on their own or as a member of an outgrower scheme (entitled to not more than the fertilizer inputs for 2 hectares, amounting to 10 bags of compound fertilizer and 5 bags of sulphate of ammonia or urea); and
- women farmers, who were to be given priority as much as possible.

[1] A *nucleus farmer* is farmer who provides inputs (including technical advice) to a certain number of outgrowers, who have to repay him in kind at the end of the harvest.

Table 4.4 Characteristics of Ghana's fertilizer subsidy programs

Item\Year	2008–2009	2010–2012	2013	2015	2016
System	Coupon	Waybill	Waybill	Waybill	Waybill
Package size	No standard package (first come, first serve)	No standard package (first come, first serve)	10 bags of NPK and 5 bags of urea	10 bags of NPK and 5 bags of urea	10 bags of NPK and 5 bags of urea
Crops targeted	Food grains	Food grains	Food grains	Food grains, vegetables, and cotton crop	Food grains, vegetables, and cotton crop
Target group	Food crop farmers of all size	Food crop farmers of all size	Food crop farmers with less than 2 hectares	Food crops, vegetables, and cotton farmers with less than 2 hectares	Food crops, vegetables, and cotton farmers with less than 2 hectares
Beneficiary selection	No standard mechanism/tool, agricultural extension agents select beneficiaries	No standard mechanism/tool, agricultural extension agents select beneficiaries	No standard mechanism/tool, agricultural extension agents select beneficiaries	No standard mechanism/tool, agricultural extension agents select beneficiaries	No standard mechanism/tool, agricultural extension agents select beneficiaries

Source: Compiled from MoFA implementation guidelines (2015).
Note: The government did not provide any fertilizer subsidy in 2014.

Following financial challenges, the government could not subsidize fertilizer in 2014. The 2013 targeting criteria were continued in 2015, with smallholder vegetable farmers and cotton farmers operating under recognized nucleus farmers in the northern part of the country added to the list of beneficiaries. Qualified farmers could purchase subsidized fertilizers at any registered agent shop or the district offices of MoFA (in areas where private agents are not available) using only passbooks, provided that they are verified by extension agents (Ghana, MoFA 2015). But recurring financial challenges compelled the government to cut the subsidy budget by 50 percent and subsidize only 90,000 metric tons of fertilizer in 2015. In theory, that volume of subsidized fertilizer would have covered 120,000 smallholder farmers if targeting guidelines were followed.

On the ground, however, the changes to the FSP have produced only limited results, especially with respect to the targeting of beneficiary farmers. While a cap of 15 bags (10 bags of compound fertilizer and 5 bags of sulphate of ammonia) has been put on the quantity of fertilizer that a farmer can buy, the selection of FSP beneficiaries is left to extension agents and district staff under the assumption that they know the farmers in their operational areas and can select following FSP guidelines without a clear mechanism to do so. The absence of a standard and verifiable mechanism by which to target would not be an issue if the targeting agents distributed subsidized fertilizer to the right beneficiaries. However, recent evaluations suggest that past rounds of the FSP have been poorly targeted to the farming population, with medium-to-large-scale and well-off farmers disproportionally benefiting from the program (Imoru 2015; Jatoe 2016). Insights from the ground also suggest that district agricultural staff distributed subsidized fertilizer to farmers without considering their farm size. District agricultural staff indicated that they could know the farm size of only a few farmers in their operational areas, which cover a large number of farming communities. Hence, it is not feasible for them to target effectively smallholder farmers as stipulated in the implementation guidelines. This result can be partly explained by the low ratio of agricultural extension workers to farmers (1:1,800) in the country, resulting from restructuring in the agricultural sector.

Nonetheless, other factors related to implementation may have contributed to the low coverage of poor farmers. For example, Imoru (2015) indicates that during the implementation of the 2013 program in some northern communities, farmers were asked to present proof of country citizenship and a telephone number and must be known to the extension agents. Qualified farmers were advised to contact MoFA extension agents to obtain a voucher before going to the fertilizer retail store, while others could go with the required documents to purchase the subsidized fertilizer. However, the author indicates that some farmers acquired the subsidized fertilizer without presenting any documentation to the retail agents and did not know whether their details were taken. In sum, the reliance on district agricultural staff coupled with implementation issues has resulted in poor targeting of fertilizer subsidies on the ground. Elsewhere, in Tanzania and Malawi, CBT methods are used to target beneficiary households, but there is significant capture by the elite, which reduces targeting performance considerably (Kilic, Whitney, and Winters 2015; Pan and Christiansen 2012). A reliable and efficient mechanism for identifying subsidy beneficiaries is therefore essential if the intention of Ghanaian policy makers is to target resource-poor farmers. We look more closely at the outcomes of the 2012 FSP with respect to beneficiary targeting in the next section.

Targeting Outcomes of the 2012 FSP at the Community and Household Levels

Actual access to and use of subsidized fertilizer by a mix of farmers is the complex result of central allocations of vouchers between regions and districts, and it is a function of access to farming communities, the presence of a local fertilizer retail shop, and formal and informal targeting criteria used by the district agricultural staff in charge of distributing fertilizer vouchers at the local level. Therefore, our aim here is not to evaluate the targeting performance of the 2012 subsidy program per se, because the program was not even specifically targeted. Rather, this section intends to show how the implementation of the program has affected to whom the subsidies have been going in terms of farming communities and households versus to whom they should be going based on equity grounds.

Targeting of the Poor

Table 4.5 presents the performance of the 2012 FSP in terms of targeting of beneficiary households. At the national level, the subsidy reached only 11 percent of poor farmers, while 72 percent of nonpoor farmers captured the subsidy benefits. Leakage to nonpoor farmers is lower in the northern regions (53 percent) and higher in the southern regions (82 percent). It therefore seems reasonable to suggest that the 2012 fertilizer subsidy program has been regressive in reaching many poor farming households—the type of household to whom the subsidies should be going based on the fact that targeting such farmers would reduce displacement of commercial fertilizer, increase the efficiency of fertilizer use, and contribute to achieving the full benefits of fertilizer subsidies (Dorward and Chirwa 2013; Mansuri and Rao 2012; and Ricker-Gilbert, Jayne, and Chirwa 2011).

Table 4.5 Targeting performance of Ghana's fertilizer subsidy program (2012)

		Regional level	
Variable	**National level**	**Three northern regions**	**Southern regions**
Poverty accuracy (%)	11.1	11.4	10.8
Undercoverage (%)	88.9	88.5	89.3
Leakage (%)	71.5	52.9	81.6

Source: Own estimations based on GLSS6 data (GSS 2012).
Note: Subsidy beneficiaries were households who received fertilizer from MoFA in 2012. Poverty accuracy is defined as the total number of poor farming households that received subsidized fertilizer, expressed as a percentage of the total number of poor farming households. *Undercoverage* is defined as the number of poor farming households who did not receive fertilizer subsidy, expressed as a percentage of the total number of poor farming households. Leakage is defined as the number of nonpoor farming households who received a fertilizer subsidy, expressed as a percentage of the total number of poor farming households.

Furthermore, the distributions of farm size among FSP beneficiaries indicate that only a quarter of subsidy recipients (26 percent) were smallholder farmers cultivating less than 2 hectares, and only one-third (29 percent) were actually poor, sharing 33 percent of the subsidy benefits (Table 4.6). Regional differences do exist in terms of the number of poor farmers who received the subsidy and the share of subsidy benefits that they received. For example, the percentage of poor farmers among beneficiary households is higher (47 percent) in the North than the South (20 percent). Likewise, poor farmers in the northern regions received a higher share of subsidy benefits (61 percent) compared with their southern counterparts (17 percent).

Table 4.6 Farmland distribution, fertilizer benefits, and poverty rate among subsidy recipients

		Regional level	
Subsidy recipients	**National level**	**Three northern regions**	**Southern regions**
Number of subsidy beneficiaries	112,414	39,493	72,921
Farm size among subsidy beneficiaries (%)			
Small farmers (< 2 ha)	25.7	25.1	26.0
Medium farmers (2–5 ha)	42.0	49.3	38.0
Large farmers (> 5 ha)	32.3	25.6	36.0
Share of subsidy benefits by farm size (%)			
Small farmers (< 2 ha)	16.7	14.0	18.2
Medium farmers (2–5 ha)	29.2	29.5	28.9
Large farmers (> 5 ha)	54.2	56.5	52.8
Percentage of poor farmers among subsidy beneficiaries	29.4	46.9	19.7
Share of subsidy benefits received by poor farmers (%)	33.1	61.1	17.0

Source: Author's estimations, based on GLSS6 data (GSS 2012).
Note: Subsidy beneficiaries are households receiving fertilizer from MoFA in 2012. The shares of subsidy benefits were estimated using the official subsidy rate of 43 percent in 2012 multiplied by the beneficiary household expenditures on inorganic fertilizer purchases.

Factors Influencing Subsidy Reception

We investigate the factors that influenced farming households and community access to the 2012 FSP. The community survey of GLSS6 did not cover all of the survey household communities. Hence, we restrict the analysis to the communities that were surveyed in order to examine whether community-level factors influenced the allocation of vouchers. First, we examine the factors that determined access to and use of subsidized fertilizer in 2012 in the farming population as a whole and in northern Ghana and southern Ghana separately (Table 4.7). Second, we look at the same issue from a different perspective by examining the factors that influenced the quantity of subsidized fertilizer farming households used, approximated using the total cost of fertilizer among subsidy recipients (Table 4.8).

Table 4.7 suggests that education was not a key factor in the allocation of the 2012 FSP. Farming households with larger areas were more likely to receive fertilizer vouchers, although the relationship is significant only in the South. Likewise, poorer farming households were less likely to receive subsidized fertilizer, especially in the South, whereas poverty status was not a factor for subsidy allocations in the North. Larger farming households were less likely to receive the fertilizer subsidy, and this was more so in the North. In addition, female-headed households were less likely to receive the 2012 fertilizer subsidy in the northern regions. The emphasis placed on women farmers as a target group since 2013 could correct this result if implementation guidelines are followed in subsequent programs. Households with older heads were also less likely to receive fertilizer vouchers, especially in the southern regions.

Contrary to expectations, maize-growing households were less likely to receive fertilizer vouchers but only in the North, while those growing rice were also less likely to receive subsidized fertilizer, especially in the South. On the other hand, households growing sorghum were more likely to receive vouchers, but the relationship is significant only in the North where sorghum is predominantly produced. Finally, the higher the number of crops grown, the higher the likelihood of receiving vouchers, but this relationship is only significant in the South.

With regard to the community variables, interestingly the greater the distance to the nearest motorable roads or mobile phone network, the more likely a community received subsidized fertilizer, although these relationships were significant only in the North. This result suggests that efforts were made to target remote communities during the implementation of the 2012 FSP in the northern regions. On the other hand, communities that are poorer in terms of basic infrastructure, such as a primary school or a health facility, were less likely to receive fertilizer vouchers. More important, communities that are far from the nearest extension office were less likely to receive subsidized fertilizer, and this was more so in the North. Lastly, communities where most households use electricity were less likely to receive subsidized fertilizer in the South, while they were more likely to receive subsidies in the North.

Table 4.7 Logit estimates of factors that influence fertilizer subsidy reception, 2012

Factor	Dependent variable = 1 if household purchased MoFA/subsidized fertilizer, 0 if household purchased fertilizer from private sources: Full sample	North	South
Household head has been to school	-0.343	-0.177	-0.312
	(0.219)	(0.374)	(0.295)
Land cultivated (hectare)	0.005	-0.006	0.061**
	(0.007)	(0.020)	(0.025)
Poverty status (1 = poor)	-0.247	-0.061	-0.766*
	(0.210)	(0.246)	(0.444)
Household size	-0.071*	-0.124**	-0.029
	(0.038)	(0.040)	(0.067)
Sex of head (1 = female)	-0.636	-1.596***	-0.210
	(0.410)	(0.411)	(0.530)
Age of household head (years)	-0.020**	-0.006	-0.026**
	(0.007)	(0.006)	(0.012)
Household grew maize (1 = yes)	-0.385	-1.035**	-0.074
	(0.252)	(0.328)	(0.365)
Household grew millet (1 = yes)	0.085	0.059	0.098
	(0.224)	(0.231)	(0.739)
Household grew rice (1 = yes)	-0.565**	-0.101	-1.600*
	(0.214)	(0.246)	(0.956)
Household grew sorghum (1 = yes)	0.762**	0.935***	0.968
	(0.241)	(0.258)	(1.020)
Number of crops grown	0.136***	0.062	0.146**
	(0.041)	(0.068)	(0.057)
Village-level variables			
Distance to nearest motorable road (km)	0.049*	0.124***	-0.321
	(0.025)	(0.030)	(0.196)
Distance to nearest mobile phone network (km)	0.031	0.097***	0.002
	(0.022)	(0.023)	(0.042)
Distance to nearest periodic market (km)	0.003	-0.003	0.017
	(0.011)	(0.013)	(0.021)
Distance to nearest primary school (km)	-0.225***	-0.254***	-0.267*
	(0.055)	(0.056)	(0.138)
Distance to nearest health facility (km)	-0.030**	-0.010	-0.058**
	(0.010)	(0.009)	(0.025)
Distance to nearest extension office (km)	-0.032***	-0.045***	-0.021
	(0.009)	(0.010)	(0.018)
Living conditions are better in community (1 = yes)	0.160	-0.321	0.135
	(0.205)	(0.246)	(0.353)
Most households use electricity (1 = yes)	-0.538*	1.028**	-1.419**
	(0.302)	(0.322)	(0.477)
Number of tractors used in community	0.030	0.074	0.029
	(0.019)	(0.062)	(0.021)
Regional dummies			
North (Reference: south)	-0.319		
	(0.274)		
Observations	1,780	1,174	606
Log likelihood	-146991.163	-62122.052	-72997.928
Chi-squared	526.587***	442.673***	192.415***

Source: Authors' estimations based on GLSS6 data (GSS 2012).

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$. North includes the three northern regions: Northern, Upper East, and Upper West. South includes the remaining seven southern regions. km denotes kilometer.

Factors Influencing the Quantity of Fertilizer Received

As mentioned earlier, we run truncated least squares on the subsample of households receiving subsidized fertilizer in order to examine the factors influencing how much subsidized fertilizer a farming household received in 2012 (Table 4.8).

Table 4.8 Least squares estimates of the factors that influence the quantity of subsidized fertilizer received in 2012

	Dependent variable: Logarithm of fertilizer cost purchased by beneficiary households		
Factor	**Full sample**	**North**	**South**
Household head has been to school (1 = yes)	0.762**	0.204	0.813**
	(0.264)	(0.272)	(0.382)
Land cultivated (hectare)	0.012	-0.002	0.077*
	(0.013)	(0.008)	(0.044)
Poverty status (1 = poor)	-0.098	0.440	-0.061
	(0.280)	(0.363)	(0.472)
Household size	0.056	0.117**	-0.048
	(0.043)	(0.043)	(0.074)
Sex of head (1 = male)	-0.262	0.112	-0.228
	(0.244)	(0.359)	(0.525)
Age of household head (years)	0.032***	0.020**	0.038***
	(0.006)	(0.006)	(0.009)
Household grew maize (1 = yes)	0.909**	2.454***	0.330
	(0.424)	(0.717)	(0.494)
Household grew millet (1 = yes)	-0.461*	-0.279	-0.525
	(0.246)	(0.279)	(0.797)
Household grew rice (1 = yes)	-0.153	0.419*	0.310
	(0.240)	(0.232)	(1.508)
Household grew sorghum (1 = yes)	-0.203	0.040	0.765
	(0.270)	(0.304)	(0.969)
Number of crops grown	0.141**	0.011	0.143**
	(0.043)	(0.057)	(0.062)
Village-level variables			
Distance to nearest motorable road (km)	-0.088**	-0.061**	0.311
	(0.027)	(0.029)	(0.280)
Distance to nearest mobile phone network (km)	0.044***	0.078***	-0.025
	(0.013)	(0.021)	(0.027)
Distance to nearest periodic market (km)	0.053***	0.013	0.067**
	(0.014)	(0.017)	(0.033)
Distance to nearest primary school (km)	0.072	0.009	-0.148
	(0.078)	(0.092)	(0.205)
Distance to nearest health facility (km)	-0.004	0.008	-0.002
	(0.010)	(0.010)	(0.027)
Distance to nearest extension office (km)	-0.013	-0.019	0.049*
	(0.014)	(0.014)	(0.026)
Living conditions are better in community (1 = yes)	0.519**	0.597*	0.330
	(0.230)	(0.360)	(0.327)
Most households use electricity (1 = yes)	0.411	0.191	0.172
	(0.256)	(0.294)	(0.505)
Number of tractors in the community	0.025	0.044	0.083
	(0.038)	(0.035)	(0.062)
Regional dummies			
North (**reference:** south)	1.190***		
	(0.328)		
Observations	230	171	59
F	230.07***	234.88***	61.99***
R-square	0.95	0.95	0.97

Source: Authors' estimations based on GLSS6 data (GSS 2012).

Notes: The quantity of subsidized fertilizer approximated using the cost of subsidized fertilizer purchased by the household. km denotes kilometer. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

The results in Table 4.8 suggest that even though education played no role in the allocation of vouchers (see Table 4.7), educated households that did receive subsidized fertilizer tended to get higher quantities than noneducated heads. This was more so in the South. Consistent with the findings in Table 4.7, neither the land area cultivated nor the poverty status of a household influenced the quantity of subsidized fertilizer acquired by households, except in the South where the land area cultivated is positively and significantly associated with the quantity of subsidized fertilizer purchased. Households with larger size received more subsidized fertilizer, but this relationship was significant only in the North. Likewise, older household heads who received subsidized fertilizer tended to purchase higher quantities of the input, indicating that age did have an influence on the quantity of subsidized fertilizer received. The same pattern applies to households growing maize, especially in the northern regions. Households growing rice in the northern regions also received higher quantities of fertilizer, whereas those growing millet tended to receive less quantities of the input. Likewise, the higher the number of crops that a household grows, the higher the quantities of fertilizer received, especially in the southern regions.

Farmers in communities located far off motorable roads received less quantities of subsidized fertilizer, especially in the North. On the other hand, the proximity to a motarable road did not influence the quantity of subsidized fertilizer purchased in the South. Communities located farther away from a mobile phone network (especially in the North) and markets (especially in the South) received more quantities of subsidized fertilizer as well. Likewise, communities located farther away from an extension office also received more quantities of subsidized fertilizer, but this was more so only in the South. On the other hand, communities with higher numbers of well-off farmers received more quantities of subsidized fertilizer than those with predominantly poorer farmers, especially in the North.

Overall, the findings in Tables 4.7 and 4.8 suggest that the 2012 FSP was not particularly pro poor or pro smallholder farmers, even though efforts seem to have been made to target remote communities, especially in the North. More important, targeting outcome varies according to region. There are spatial inconsistencies in targeting the 2012 FSP, with community-level factors sometimes positively influencing participation in the program (in the northern regions) and sometimes negatively affecting program participation (in the southern regions), and vice versa. For example, while the 2012 FSP excluded farming households that are far from the extension office in the North, it provided more quantities of subsidized fertilizer to more distant households in the South. These findings are broadly consistent with Banful (2011), who reported that there was limited targeting during implementation of Ghana's FSP.

Even though the 2012 FSP targeted all food crop farmers, the fact that most of the poor and smallholder farmers were left out of the FSP raises questions about the equity of the program. Likewise, this poor performance challenges the political rhetoric that the subsidy program is meant for resource-poor smallholder farmers who cannot afford fertilizer at prevailing market prices. Nonetheless, these results cannot be attributed to poor targeting alone. They may also result from poor implementation of the program. Likewise, the dual or even contradictory goals of fertilizer subsidy programs may also make targeting objectives more difficult to achieve.

Regardless, other social programs in the country use alternative targeting methods to reach a considerable number of intended program beneficiaries. For example, LEAP is a cash transfer program that relies on a combination of CBT and proxy means testing to successfully target poor and vulnerable households. That program has been described as the most effectively targeted social protection program in Ghana (Wodon 2012), and much can be learned from its implementation to better target fertilizer subsidies. Elsewhere, in Latin America, social transfer programs have been successfully targeted with the use of a PMT (Castañeda et al. 2005; Coady, Grosh, and Hoddinott 2004; Grosh and Baker 1995). Such successful examples suggest that delivering subsidized fertilizer more effectively is feasible.

5. DATA AND EMPIRICAL APPROACH

Data

We use data from the sixth round of the Ghana Living Standards Survey (GLSS6) to estimate the proxy means tests. The GLSS6 was carried out over a period of 13 months from October 2012 to October 2013 and covered a nationally representative sample of 16,772 Ghanaian households. In addition to its representativeness, the survey covered a wide range of poverty indicators that are potentially suitable for developing PMT models. To assess the robustness of the results, we use GLSS3, GLSS4, and GLSS5 data, which were nationally representative at the household level and were collected in 1992, 1999, and 2005, respectively.

Empirical Approach

Identifying the Best Indicators for Selecting Poor Farming Households

Using GLSS6 data, we prepared two sets of 110 potential indicators that we used to design the PMT for the North and South of Ghana. These indicators were selected based on practicality considerations that consider the accuracy and ease with which information can be quickly collected on the indicators in interviews with potential program beneficiaries. Practicality essentially refers to two useful criteria for designing a PMT: the difficulty and the verifiability of an indicator (Zeller, Alcaraz, and Johannsen 2005). Difficulty can be expressed in terms of time, money, and social costs expended for obtaining information. For example, the value of total assets is very difficult and tedious to obtain, and therefore it is not really suitable for an operational PMT model. The difficulty of an indicator will also vary with the socioeconomic and cultural context, and it will depend on the skill level and quality of training of interviewers, among other things.

With regard to the verifiability criterion, the indicators selected must be objective—that is, characterized by measurement scales that can, at least in principle, be verified by consistent standards of measurement metrics. Although some subjective indicators are among the more powerful poverty indicators, they are hardly verifiable, as the scales used are subjective and not disclosed to others. In keeping with the practicality criteria, variables that do not meet these requirements were excluded from the set of potential poverty indicators in the GLSS6 survey data. Nonetheless, we agree with Zeller, Alcaraz, and Johannsen (2005) who argue that it might appear rather arbitrary to classify a particular indicator (or a group of indicators) as being more or less difficult to ask, or more or less verifiable because the difficulty and verifiability of an indicator may not be generalizable across different socioeconomic and cultural contexts.

Designing the PMT

Targeting involves two elements—first, defining who should receive benefits, and second, establishing mechanisms for identifying those people within the population. We identify program beneficiaries as poor farming households in Ghana that could not afford to purchase fertilizer at market prices. This definition is consistent with the central government's and Ghanaian policy makers' objectives to target poor smallholder farmers. On the second aspect, we examine whether the PMT is potentially a better mechanism for identifying and targeting fertilizer subsidies to Ghanaian poor farming households. The PMT uses household socioeconomic characteristics to determine whether the household is poor or not. In general, the aim of a PMT is to find a few indicators that are less costly to verify but are sufficiently correlated with poverty to be used for identifying the poor (Besley and Kanbur 1993).

In this research, we adopt the standard definition of poverty as measured by the shortfall in consumption expenditures necessary to live a decent life. We apply two estimation methods for the PMT models and assess their performances in correctly identifying the poor in the farming population: least squares and logit regressions. Previous applications of PMT methods for targeting the poor include

Braithwaite, Grootaert, and Milanovic (2000), Houssou and Zeller (2011), van Edig, Schwarze, and Zeller (2013), and Alatas et al. (2012), among others.

The least squares regression uses the continuous dependent variable logarithm of per capita daily expenditures,[2] whereas the dependent variable in the logit regression is the actual household poverty status as a dummy variable, coded 1 if the household is poor (that is, consumption expenditures are below the national poverty line) and 0 if otherwise. In other words, the logit method estimates the probability of a household being below the poverty line. Both methods seek to identify the best set of indicators for predicting household poverty status. Following previous research, we limit the number of these indicators to the best 10 in order to balance the PMT model's accuracy with its practicality and costs of implementation.

A model with a high explanatory power is a prerequisite for good predictions. Therefore, we select the best 10 regressors to use for estimating the least squares regression based on the stepwise MAXR (maximum R-square) routine of SAS (SAS Institute 2003), which seeks to maximize the method-explained variance (that is, R^2). With regard to the logit regression, we select the best 10 regressors using the stepwise score routine of SAS, which is similar to the MAXR routine, offering a method for the best subset selection of variables with logistic regressions. The stepwise score routine seeks the best set of variables that maximizes the likelihood score (chi-square) statistic.[3] Using GLSS6 data, we estimate both PMT models following Greene (2003) and Wooldridge (2006):

▪ ***Least Squares***

$$y_i = \beta_o + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i \, , \tag{1}$$

where y_i is the logarithm of daily per capita expenditures, $x_{ik}, k = 1....K \; and \; i = 1....n$ are the set of poverty predictors, including rural/urban locality as a control variable, β_o is the intercept term, $\beta_k, k = 1...K$ are the parameter estimates, ε_i is the random disturbance, and n is the total number of observations in the sample. The predicted value of y_i, $\hat{y}_i$, is estimated by

$$\hat{y}_i = \hat{\beta}_o + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_k x_{ik} \, . \tag{2}$$

▪ ***Logit***

$$\rho_i(z_i = 1 | x_i) = \frac{1}{1 + e^{-\eta_i}} \, , \tag{3}$$

where ρ_i is the probability of being poor, e is an exponential function, and z_i is the poverty status variable:

$$z_i = \begin{cases} 1 \; (poor) \; if \, \rho_i \geq cut-off \\ 0 \; (non-poor), \; otherwise \end{cases} . \tag{4}$$

η_i is the linear predictor:

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[2] The logarithm of expenditures is used instead of simple expenditures because the log function better approximates a normal distribution.

[3] See SAS Institute (2003) for further details on the score procedure.

$$\eta_i = \alpha_o + \alpha_1 x_{i1} + \alpha_2 x_{i2} + ... + \alpha_k x_{ik} + \varepsilon_i \quad (5)$$

where $x_{ik}, k = 1....K \; and \; i = 1....n$ are the set of poverty predictors, including the control variable, α_o is the intercept term, $\alpha_{1k}, k = 1...K$ are the parameter estimates, and ε_i is the random disturbance. The estimated logit or natural log ($\ln$) of the odds is given by

$$\ln\left(\frac{\hat{\rho}_i(z_i = 1|x_i)}{1 - \hat{\rho}_i(z_i = 1|x_i)}\right) = \hat{\alpha}_o + \hat{\alpha}_1 x_{i1} + \hat{\alpha}_2 x_{i2} + ... + \hat{\alpha}_k x_{ik} \quad (6)$$

We design separate PMT models for northern and southern Ghana because of substantial differences in living standards between the country's North and South. We also control for rural and urban households in the PMT models as shown above. The purpose of the PMT is to identify and use highly significant but easily measurable correlates of poverty to select out the poor in the rural population. Therefore, a causal relationship should not be inferred from our results. Likewise, the term *best indicators* simply refers to the best model fit, given the constraints on the set of available indicators and on the maximum number of indicators allowed for inclusion in the PMT models. These indicators should not be misunderstood as a value statement implying that they are best in terms of any of the measures used for assessing targeting performances (Table 5.1).

Predicting the Household Poverty Status

Having estimated the household consumption expenditures and the probability of being poor with least squares and logit regressions, the question arises as to which cutoff to use to determine whether a household is poor or not. In this paper, we use the cutoff that maximizes the balanced poverty accuracy criterion (BPAC), which is the overall performance measure of the PMT models (see definition of BPAC in Table 5.1). Different measures have been proposed in the literature to assess performance of a PMT model. In this paper, we focus on the most relevant ratios for targeting the poor: poverty accuracy, undercoverage, leakage, and the BPAC (Table 5.1).

Table 5.1 Selected accuracy ratios

Targeting ratio	Definition
Poverty accuracy	Number of farming households correctly predicted as poor, expressed as a percentage of the total number of farming households poor
Undercoverage	Error of predicting poor farming households as being nonpoor, expressed as a percentage of the total number of poor farming households
Leakage	Error of predicting nonpoor farming households as poor, expressed as a percentage of the total number of poor farming households
Balanced poverty accuracy criterion	Poverty accuracy minus the absolute difference between undercoverage and leakage, measured in percentage points

Source: Adapted from IRIS (2005).

Poverty accuracy measures the number of poor farming households correctly predicted by the method, expressed as a percentage of the total number of poor farming households. Undercoverage and leakage are errors of predictions. Whereas the former measures the number of poor farming households incorrectly identified as nonpoor, expressed as a percentage of the total number of poor farming households, the latter estimates the number of nonpoor farming households who are wrongly identified as poor, expressed as a percentage of the total number of poor farming households. The BPAC, on the other hand, is used to assess a PMT's overall targeting performance. It is calculated as the poverty accuracy minus the absolute difference between undercoverage and leakage, measured in percentage points. These three measures exhibit trade-offs. For example, minimizing leakage leads to higher undercoverage and lower poverty accuracy. Leakage and undercoverage are also equally valued in the estimation of the BPAC, but a policy maker may give higher or lower weight to undercoverage compared to leakage depending on political considerations on the ground.

Model Validations

As indicated earlier, GLSS6 data are used to calibrate the PMT models and ensure the representativeness of the results. A key concern related to the PMT, however, is whether indicator-based models are robust over time and for how long they can be used without losing their predictive power (van Edig, Schwarze, and Zeller 2013; Houssou and Zeller 2011). Most previous research fails to address that question adequately owing to lack of data. For example, van Edig, Schwarze, and Zeller (2013) could only perform validation tests on a small set of data collected two years after the model had been built. We attempt to address this concern. Specifically, after estimating the PMT models with the GLSS6 dataset, we apply the models (that is, the 10 indicators and their weights) to the validation samples consisting of GLSS3, GLSS4, and GLSS5 survey data collected in 1992, 1999, and 2005, respectively, to estimate targeting performances. Following the specifications in subsection "Designing the PMT", for any household i in the validation samples, we predict consumption expenditures and probability of being poor as follows:

$$\hat{y}_i = \hat{\beta}_o + \hat{\beta}_1 x_{i1} + \hat{\beta}_o x_{i2} + \ldots + \hat{\beta}_k x_{ik} \text{ . (least squares)}$$

$$\hat{\rho}_i(z_i = 1 | x_i) = \frac{1}{1 + e^{-(\hat{\alpha}_o + \hat{\alpha}_1 x_{i1} + \hat{\alpha}_2 x_{i2} + \ldots + \hat{\alpha}_k x_{ik})}} \text{ . (logit)}$$

Estimating the Cost of Targeting the FSP with a PMT Model

As discussed in Section 3, targeting comes at a cost, and the administrative costs of a well-targeted program are likely to be higher than those of an untargeted or loosely targeted program. Therefore, we estimate in this section the potential cost of administering a targeted version of Ghana's FSP based on the PMTs developed. Specifically, we compare the targeting efficiency of a loosely targeted program—such as the current method, which relies on district agricultural staff, especially extension agents, distributing the same amount of subsidized fertilizer to the farming population—to the performance of the program if it were to be targeted using the proxy indicators developed in this paper. This allows us to assess whether administering targeted FSPs based on poverty proxies is more cost-efficient than administering a loosely targeted program similar to the current system.

Following Besley and Kanbur (1993), we estimate the total budget required for targeting a fertilizer subsidy program as

$$T = P + NP + A + H,$$

where T is the total budget of the program; P is the value of fertilizer subsidies given to poor farmers; NP is the value of fertilizer subsidies given to nonpoor farmers; A is the administrative cost; and H is the hidden cost (private, indirect, social, and political costs).

We estimate the targeting efficiency using the measures below:

$$F = P \cdot 100/(P + NP);$$

$$F_1 = (NP + A + H)/P;$$

$$F_2 = P \cdot 100/(P + NP + A + H).$$

F is the value of fertilizer subsidies given to poor farmers as a percentage of the total cost of the fertilizer subsidy program; F_1 is the cost of transferring a cedi's worth of fertilizer subsidies to poor farmers; and F_2 is the total value of fertilizer subsidies transferred to poor farmers as a percentage of total program cost.

Following the 2016 subsidy program, which was nationwide in nature, we assume an FSP that will transfer GH¢138 million worth of subsidized fertilizer to the farming population, covering 240,000 beneficiaries who receive the same amount of fertilizer according to targeting guidelines (see Section "Targeting of Subsidies at the Household Level Is Poor"). We set the administrative cost of targeting the program at 30 percent of the total program cost, following Houssou and Zeller (2010) and Smith and Subbarao (2003). In addition, the hidden costs of targeting are set at 5 percent of program administrative cost.

More important, in separate simulations (see Table 6.7), we increase administrative cost to 50 percent to align it with the cost of administering the LEAP program, which was targeted through a combination of CBT and PMT approaches in Ghana. Wodon (2012) indicates that LEAP administrative costs may represent close to 50 percent of the program cost in the beginning. But the author also suggests that such costs are likely to be reduced when the program reaches a critical mass of beneficiaries. In fact, administrative costs can be reduced if the PMT models are shared between different social transfer programs using the same system to identify the poor or when the program reaches its maturity.

With regard to the comparative, which is a loosely targeted program, we assume the program performs as the 2012 subsidy program, which provided fertilizer subsidies to only 11 percent of poor farming households and leaked program benefits to 72 percent of the nonpoor farming households in the country (Table 4.5), totalling 240,000 beneficiaries, each receiving the same amount of fertilizer subsidies. Under this program, we set administrative costs at 15 percent of total program cost, which is consistent with the cost of administration under a universal targeting. Likewise, we assume that under a loosely targeted program, the hidden costs of targeting are negligible because every farmer is potentially qualified to receive subsidy benefits.

6. RESULTS AND DISCUSSION

Identifying the Best Indicators for Targeting Subsidy Beneficiaries

Here we present the set of best poverty indicators that were selected during the design of the PMT models for the three northern regions (Table 6.1) and the seven southern regions (Table 6.2). These proxies are objective and can be grouped into different dimensions of poverty, such as demography, education, farming characteristics, and housing conditions. Some of them are easily observable (for example, household flooring material, wall material, lighting fuel) when visiting the dwelling of a potential program beneficiary, while others are less prone to falsification (for example, household size, education level of head, whether household grows maize or rice), indicating a lower risk of underreporting during program implementation. However, the objectiveness and verifiability of these proxies should not preclude administrators from setting up an effective verification system during the administration of the program to reduce misreporting and bribery from targeting agents and potential subsidy recipients who may (intentionally) provide false information just to qualify for the program. The following subsection discusses the targeting performances of the PMT.

Table 6.1 Best 10 poverty predictors for the northern regions

Best 10 indicators for predicting expenditures per adult equivalent (least squares method)		**Best 10 indicators for predicting the probability of being poor (logit method)**	
Intercept	1.981*** (0.039)	*Intercept*	-2.353*** (0.012)
Rural/urban control variable (1 = rural)	-0.213*** (0.030)	*Rural/urban control variable (1 = rural)*	0.778*** (0.008)
1. Household size	-0.087*** (0.003)	*1. Household size*	0.237*** (0.001)
2. Main flooring material is earth/clay/mud	-0.307*** (0.032)	*2. Main flooring material is earth/clay/mud*	0.676*** (0.009)
3. Main cooking fuel is firewood, waste, residues	-0.248*** (0.031)	*3. Main cooking fuel is firewood, waste, residues*	0.589*** (0.009)
4. Main lighting fuel is electricity	0.216*** (0.025)	*4. Main lighting fuel is electricity*	-0.411*** (0.007)
5. Household garbage is collected	0.281*** (0.045)	*5. Household garbage is collected*	-0.746*** (0.013)
6. Household grows rice	0.151*** (0.022)	*6. Household grows rice*	-0.538*** (0.006)
7. Household grows sweet potato	0.306*** (0.052)	*7. Household grows kenef*	-0.983** (0.015)
8. Household grows yam	0.149*** (0.023)	*8. Household head is in a common law relationship*	-0.891*** (0.017)
9. Main water source is own pipe water, tap, private	0.393*** (0.056)	*9. Main water source is well/borehole*	0.482*** (0.006)
10. Minimum education level of head is tertiary education	0.603*** (0.060)	*10. Household head can read and write in English*	-0.729*** (0.008)
Observations	3,731	Observations	3,731
F	152.75***	Log likelihood	163,661.89***
R-square	0.311	Chi-squared	113,284.79***

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Note: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

Table 6.2 Best 10 poverty predictors for the southern regions

Best 10 indicators for predicting expenditures per adult equivalent (least squares method)		Best 10 indicators for predicting the probability of being poor (logit method)	
Intercept	2.143*** (0.029)	*Intercept*	-2.781*** (0.007)
Rural/urban control variable (1 = rural)	-0.040*** (0.019)	*Rural/urban control variable (1 = rural)*	0.074*** (0.004)
1. Household size	-0.121*** (0.003)	*1. Household size*	0.332*** (0.000)
2. Number of habitable rooms in the household	0.113*** (0.008)	*2. Number of habitable rooms in the household*	-0.297*** (0.002)
3. Household grows cocoa	0.126*** (0.016)	*3. Household grows cocoa*	-0.427*** (0.004)
4. Main cooking fuel is firewood, waste, residues	-0.274*** (0.020)	*4. Main cooking fuel is firewood, waste, residues*	0.960*** (0.006)
5. Main lighting fuel is electricity	0.124*** (0.017)	*5. Main lighting fuel is electricity*	-0.381*** (0.004)
6. Household head can read and write in English	0.124*** (0.016)	*6. Household head can read and write in English*	-0.463*** (0.004)
7. Household grows okro	0.164*** (0.020)	*7. Household grows oil palm*	-0.410*** (0.005)
8. Main wall material is concrete/cement/brick/stone	0.090*** (0.017)	*8. Household grows pepper*	-0.289*** (0.004)
9. Household garbage is buried/burned	-0.122*** (0.021)	*9. Main wall material is clay/mud*	0.467*** (0.004)
10. Highest education level is tertiary	0.363*** (0.047)	*10. Main water source is vendor/truck, neighbor*	-2.413** (0.041)
Observations	5,597	Observations	5,597
F	234.85***	Log likelihood	409,522.69***
R-squared	0.316	Chi-squared	305,518.84***

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Note: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

How Accurately Do the PMT Models Target Potential Fertilizer Subsidy Beneficiaries?

Table 6.3 presents the targeting performances of the PMT models. The results show that the northern model yields a poverty accuracy of 70.4 percent and a BPAC of 68.8 percent under the least squares method. These results indicate that the model will potentially target about 70 percent of poor farming households if used to select out potential subsidy beneficiaries in northern Ghana. The model's undercoverage is estimated at 29.6 percent, while its leakage amounts to 31.2 percent, which means that the least squares–based PMT model will leak subsidy benefits to about 31 percent of the nonpoor farming households. Under the logit method, the northern model yields a higher poverty accuracy (71.2 percent) and BPAC (69.1 percent) compared with the least squares method. Additionally, undercoverage and leakage are lower under the logit method. They were estimated at 28.8 percent and 30.9 percent, respectively.

With regard to the southern model, the BPAC and the poverty accuracy are estimated at 49 percent, while leakage and undercoverage rates amount to 51 percent under the least squares method. Likewise, the targeting performances of the southern model are slightly better under the logit compared with the least squares method. Compared with the northern model, the performances of the southern model are lower. This result can be explained by the low poverty rate in the South. Overall, the findings in Table 6.3 suggest that the logit method does somewhat better in identifying poor farming households than the least squares method. Therefore, we compare targeting performances of the PMT models under the logit to the actual performances of the 2012 FSP (Table 6.4).

Table 6.3 Model targeting performances

Region	Method	Poverty accuracy (%)	Undercoverage (%)	Leakage (%)	BPAC (%)
North	Least squares	70.4	29.6	31.2	68.8
	Logit	71.2	28.8	30.9	69.1
South	Least squares	48.7	51.3	51.3	48.6
	Logit	49.0	51.0	51.1	48.9

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Note: Poverty accuracy is defined as the number of farming households correctly predicted as poor, expressed as a percentage of the total number of poor farming households. Undercoverage is defined as the number of poor farming households who were predicted as nonpoor, expressed as a percentage of the total number of poor farming households. Leakage is defined as the number of nonpoor farming households who were predicted as poor, expressed as a percentage of the total number of poor farming households. The balance poverty accuracy criterion (BPAC) is the poverty accuracy minus the absolute difference between undercoverage and leakage.

The distribution of the 2012 FSP shows that only 11 percent of poor farming households actually received fertilizer subsidies in the North and that the subsidies were leaked to 89 percent of nonpoor farmers. On the other hand, district agricultural staff could have targeted 71 percent of the poor farmers and seen a leakage of just 31 percent to nonpoor farming households if a PMT-based model were used to select the beneficiaries of the 2012 FSP. The results with regard to the South also show that if the PMT model were used, 50 percent of poor farming households could have potentially benefited from fertilizer subsidies, versus just 11 percent under the 2012 FSP. Likewise, mistargeting or leakage would have been reduced from 81 percent to 51 percent. On the other hand, Table 6.4 shows that a universal or an untargeted subsidy program with a random distribution of fertilizer subsidies to farming households would have performed very poorly in terms of coverage of poor farming households compared with both the 2012 FSP and the PMT models, but it would have reduced leakage to nonpoor farming households considerably. These patterns indicate that targeting is key to reaching poor farming households, but it comes with trade-offs. In sum, even though the PMT approach is not perfect, the results show that it could potentially minimize leakage and undercoverage rates considerably compared with the 2012 FSP. We look at the out-of-sample validity of the PMT models in the next section.

Table 6.4 PMT-based versus actual targeting performance of 2012 FSP

Region	Performance	Poverty accuracy (%)	Undercoverage (%)	Leakage (%)
North	PMT based	71.2	28.8	30.9
	2012 FSP	11.4	88.5	89.3
	Universal (random distribution of FSP)	5.9	94.1	6.2
South	PMT based	49.0	51.0	51.1
	2012 FSP	10.8	89.3	81.6
	Universal (random distribution of FSP)	3.0	97.0	10.8

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Notes: Poverty accuracy is defined as the number of farming households correctly predicted as poor, expressed as a percentage of the total number of poor farming households. Undercoverage is defined as the number of poor farming households who were predicted as nonpoor, expressed as a percentage of the total number of poor farming households. Leakage is defined as the number of nonpoor farming households who were predicted as poor, expressed as a percentage of the total number of poor farming households.

PMT Approach Likely to Perform Well in the Field

As mentioned earlier, we validated the PMT models using data from different time periods, and we present those results in Table 6.5. We find that with the northern model, poverty accuracy has improved with increases ranging from 5 percentage points to 14 percentage points across the three rounds of data. The results indicate that the PMT model covers a higher percentage of poor farming households, but as with any PMT, there are trade-offs. For example, the leakage rate has increased by 10 percentage points when validated with the GLSS5 dataset. The results of the southern model show similar trends with poverty accuracy increasing from about 6 percentage points to about 14 percentage points. Disappointingly, the leakage associated with the GLSS5 data has increased from 51 percent to 72 percent with the southern model. Overall, the results suggest that the PMT models can perform reasonably well on the field and can be used for about 20 years without losing accuracy, and with no need to calibrate a new PMT for targeting fertilizer subsidies to poor farmers in the country.

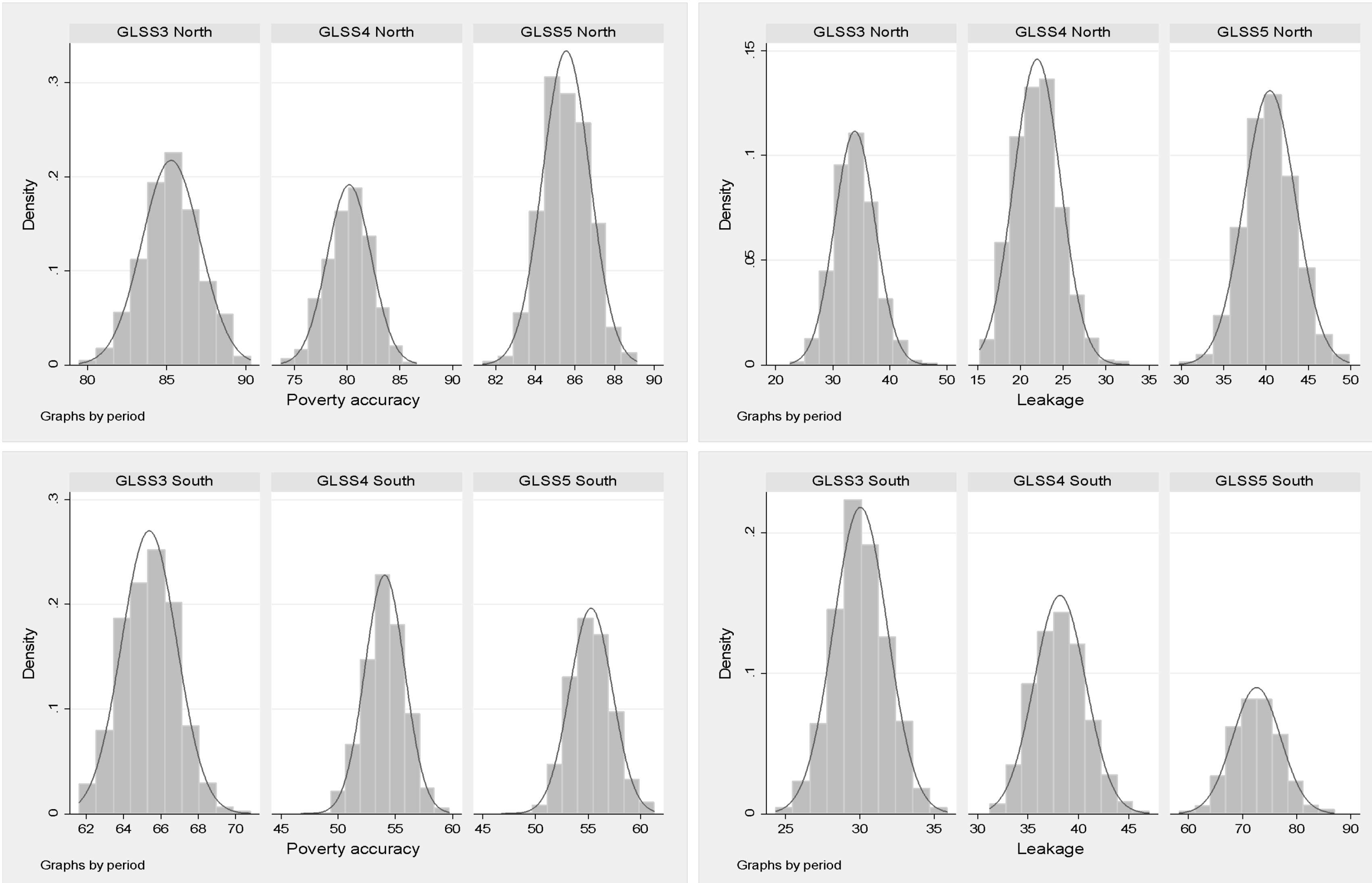
Table 6.5 Model targeting performances: backward validation tests

			Poverty accuracy (%)	Undercoverage (%)	Leakage (%)
North	Calibration sample	*GLSS6 2012*	**71.2**	**28.8**	**30.9**
	Validation samples	*GLSS5 2005*	85.5	14.5	40.3
		GLSS4 1998	80.2	19.8	21.8
		GLSS3 1992	85.3	14.7	33.7
South	Calibration sample	*GLSS6 2012*	**49.0**	**51.0**	**51.1**
	Validation samples	*GLSS5 2005*	55.3	44.7	72.3
		GLSS4 1998	54.1	45.9	38.1
		GLSS3 1992	65.3	34.7	30.0

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Note: Poverty accuracy is defined as the number of farming households correctly predicted as poor, expressed as a percentage of the total number of poor farming households. Undercoverage is defined as the number of poor farming households who were predicted as nonpoor, expressed as a percentage of the total number of poor farming households. Leakage is defined as the number of nonpoor farming households who were predicted as poor, expressed as a percentage of the total number of poor farming households.

As mentioned earlier, actual access to a subsidy program is determined by many factors, including implementation issues—hence we can expect the final list of potential beneficiaries and recipients of a targeted subsidy program to be randomly distributed. Therefore, we perform further validations using the bootstrap procedure by drawing random samples from the validation samples and assessing the targeting performance over these samples. Following Houssou and Zeller (2011), we draw 1,000 random samples of the same size (with replacement) from each of the three GLSS datasets used to validate the PMT models. Figure 6.1 presents the range of targeting performances achieved under the random samples for three periods. The results for both the North and the South show that the performances achieved follow a normal distribution with tight ranges, indicating that we can expect the PMT to perform reasonably well in the field.

Figure 6.1 Distributions of poverty accuracy and leakage rates over 1,000 random samples for three periods



Source: Authors' estimations based on GLSS3, GLSS4, and GLSS5 data (GSS 1991, 1998, 2005).

Administering Ghana's FSP with a Proxy Means Test Is Cost-Effective

Table 6.6 compares the cost-effectiveness of the 2012 FSP with that of targeting with the PMT developed. The results for northern Ghana show that a targeted FSP will transfer three times more fertilizer subsidies to poor farming households compared with the outcome of the 2012 FSP (GH¢17,253,126 versus GH¢5,395,846). In addition, the cost of leakage will be cut by 70 percent (from GH¢25,038,617 to GH¢7,491,808) if the program were targeted compared with the leakage cost under the 2012 FSP.

Estimates of the transfer efficiency measures for northern Ghana also suggest that administering the FSP with the proxy indicators would have been more efficient. For example, 18 percent of resources were transferred to poor farming households under the 2012 FSP (fertilizer equivalent), whereas a targeted FSP would have transferred close to 70 percent of resources to these poor farmers. Likewise, the results show that GH¢5.7 is spent for every cedi transferred to poor farming households under the 2012 FSP, versus GH¢1.1 under a targeted FSP using the PMT models.

The results with regard to the South also show substantial improvements in targeting efficiency. In both North and South, the average transfer per poor farming household decreases (even though the total transfer to these poor farmers increases) because a higher number of poor farming households are covered by the targeted program, while the increase in total transfer to poor farming households is not proportional to the increase in program coverage. Furthermore, the simulations based on higher administrative program costs (Table 6.7) also suggest that implementing a targeted version of the FSP using the PMT is potentially more cost-effective. Overall, the above results show that although not perfect, the proposed targeting system can potentially improve the cost and transfer efficiency of fertilizer subsidies using the PMT approach to target poor smallholder farmers. If other programs were to use the same targeting system, they could lower their administrative costs substantially.

Table 6.6 Cost and transfer efficiency of the 2012 FSP versus a targeted fertilizer subsidy program based on a PMT

Region	Scheme	Poverty accuracy	Leakage	Total transfer to the poor	Cost of leakage	Admin. and hidden costs	Total cost	*F*	F_1	F_2
North	2012 FSP	11.4	89.3	5,395,846 (575)	25,038,617	5,689,529	36,123,992	17.7	5.7	14.9
	Targeted FSP	71.2	30.9	17,253,126 (468)	7,491,808	11,379,057	36,123,992	69.7	1.1	47.8
South	2012 FSP	10.8	81.6	12,572,596 (575)	9,499,295	20,108,693	127,674,244	11.7	9.2	9.8
	Targeted FSP	49.0	51.1	42,803,022 (468)	44,653,836	40,217,387	127,674,244	48.9	2.0	33.5

Source: Authors' estimations based on GLSS6 data (GSS 2012).
Note: FSP = fertilizer subsidy program; PMT = proxy means test. Average amount of subsidy transferred to poor farming households in brackets. *F* is the transfer to poor farming households as a percentage of total transfer. F_1 is the cost of transferring one unit of program resources to poor farming households. F_2 is the transfer to poor farming households as a percentage of the total program cost. The costs of leakage are defined as the amount of transfer wrongly given to the nonpoor farming households. Administrative (admin.) costs are the costs of running the program. The hidden costs include private, indirect, social, and political costs (see Houssou and Zeller [2011] and Besley and Kanbur [1993] for further details on such costs). The cost estimates are given in Ghana cedis.

Table 6.7 Simulations of the effects of administrative cost on program efficiency

Region	scheme	Poverty accuracy	Leakage	Administrative costs as % of program cost	*F*	F_1	F_2
North	2012 FSP	11.4	89.3	15%	17.7	5.7	14.9
	Targeted FSP	71.2	30.9	50%	69.7	1.1	47.8
				60%	69.7	2.0	33.1
South	2012 FSP	10.8	81.6	15%	11.7	9.2	9.8
	Targeted FSP	49	51	50%	48.9	3.3	23.2
				60%	48.9	4.5	18.1

Source: Authors' simulations.

Note: FSP stands for fertilizer subsidy program. Administrative (admin.) costs are the costs of running the program. *F* is the transfer to poor farming households as a percentage of total transfer. F_1 is the cost of transferring one unit of program resources to poor farming households in Ghana cedis. F_2 is defined as the transfer to poor farming households as a percentage of the total program cost.

7. ROBUSTNESS OF THE RESEARCH FINDINGS

Our findings raise critical issues that need to be clarified and reflected in our conclusions. Critics could argue that the research assumes a flawless implementation of the PMT models (whereas the 2012 FSP may have been subject to deliberate and other irregularities, considering that the program was not particularly targeted). Indeed, issues such as implementation challenges, political considerations, or other reasons that may lead to adjustment in the program were not considered in our assessment. Although it is true that the outcome of the PMT overstates the performances obtained when such targeting rules are implemented in practice, we show how greatly the outcomes differ between specific targeting rules (ideally implemented) and current targeting rules (as implemented in practice), even though the benefits actually achieved would be less when subjected to the hiccups of actual implementation versus the perfect implementation as assumed by the model results. But the results indicate that the PMT-based targeting may be worth the effort and may improve targeting efficiency, a point that is also somewhat disputed in the previous literature.

Furthermore, any targeting strategy may well face implementation difficulties due to political processes and information asymmetries, so there remains a gap between modeled and actual outcomes. Actual outcomes of a newly proposed targeting methodology can be assessed only through experimental pilot research, ideally with the exact replication of the proposed targeting process with all institutions involved in distributing subsidies. That kind of research is very costly and may—after the research is done—still have weak external validity.While this is a critical issue, such action-oriented research is beyond the scope of the paper, as it would require cooperation among government agencies, pilot communities, and the actual distribution of pilot subsidies, complemented by household and other surveys. Nonetheless, the PMT indicators developed are more objective and fairly easy to verify, and hence they are likely to face less implementation challenges. Furthermore, a pilot cash transfer program in Cameroon (Stoeffler, Mills, and del Ninno 2016), a field experiment in Indonesia (Alatas et al. 2012), and an evaluation of 122 targeted programs (Coady, Grosh, and Hoddinott 2004) suggest that targeting approaches based on a PMT perform better than a CBT method in terms of targeting the poor.

Some may also argue that the multiplicity of targeting criteria makes it difficult to achieve targeting objectives. While this is critical, we agree that poverty should be the major factor in beneficiary selection, not only because it is emphasized by policy makers in nearly every subsidy program in Ghana and SSA, but also because targeting the poor matters for realizing higher efficiency gains from the programs. Scholars such as Ricker-Gilbert, Jayne, and Chirwa (2011) and Dorward et al. (2008) have indicated that there are higher incremental productivity gains from targeting more fertilizer to poorer farming households. Ensuring that more poor people get subsidized inputs for maize production should have positive benefits in promoting reduced displacement of commercial fertilizer, greater productivity and growth impacts, and greater impacts on reducing food insecurity, hunger, and poverty. Greater displacement of commercial purchases and hence less incremental fertilizer use occurred when less poor farming households received subsidized fertilizer (Dorward et al. 2008).

One could also argue that the PMT approach is theoretical. That argument would ignore the fact that the results provided were validated with data from three surveys (GLSS3, 4, and 5) other than the one used to estimate the models. Such validations are good substitutes for very costly direct field tests that to the best of our knowledge have been conducted only in a few cases. These tests show how well the models will perform in an independent sample derived from the population, but different from the sample used to estimate the models. We agree though that in-situ-type action-oriented research tests of poverty indicators have higher internal validity, but if not carefully designed and implemented, they may also have low external validity.

One could raise the point that giving fertilizer subsidies to some farmers and not to others can create tension in communities and disrupt social cohesion. That is a fair point but it also applies to CBT and other targeting methods. Our view on this point is that targeting methods are not mutually exclusive: the proposed PMT can be combined with CBT, which could integrate community views of who deserves benefits and who does not and diffuse or reduce any social tension. Some programs are already targeted within Ghana, and a combination of PMT and CBT targeting approaches is also used within the scope of the LEAP program in the country.

Furthermore, our assessment of the PMT approach did not consider the political reality that even policy makers and program managers involved in the subsidy programs at the local level may adjust targeting criteria for various reasons, including political, self-interested, administrative, budgetary, managerial, or logistical reasons. We argue that such adjustments are guided by conditions on the ground and occur only during the implementation of subsidy programs. As such, they cannot be properly evaluated ex ante.

Likewise, a related challenge is that misreporting during implementation can reduce performance of the proposed PMT approach given the stakes in subsidy programs. However, this is a rather general critique that certainly applies to all research that deals with policy evaluation not only through models but also evaluating implementation as such. Our focus is not on the evaluation of the implementation of an existing policy, but on alternative options that might be considered by policy makers for implementation (first in pilot programs, later countrywide). Such action-oriented research could be highly useful, but it is beyond the scope of this paper. However, much can be learned from LEAP to reduce misreporting and address other implementation challenges during of the implementation of a PMT-based fertilizer subsidy program in Ghana. For example, misreporting can be reduced with an effective verification system through random home visits, triangulation of the information provided by potential program beneficiaries, and introduction of bonus and malus clauses for program screening agents, among others. These strategies imply costs, which we have considered in the estimation of the administrative costs of targeting.

Finally, critics may also argue that focusing on the direct costs of a targeted versus an untargeted program distorts our comparison as it does not consider the full effects of the programs. For example, a loosely targeted program or even a universal subsidy could generate some positive effects on the poor and others as well if the nonpoor (for example, wealthy farmers) were to expand their activities (for example, by cropping more lands), demand more services offered by the poor, or invest more in the economy. So there are indirect effects of subsidy programs that benefit wealthier farmers or the society as a whole. Our conclusions should reflect this critical point. However, measuring the full effects of targeting (indirect effects such as income, nutrition, health, work productivity linkages, sectoral, and macroeconomic effects) requires entirely different methodological approaches (for example, for the latter, general equilibrium models) and additional data, which are beyond the scope of this paper. Nonetheless, research has indicated that subsidized fertilizer displaces commercial fertilizer, especially if farmers who can afford commercial fertilizer also benefit from subsidies (that is, wealthier farmers) (Mason and Jayne 2013; Ricker-Gilbert, Jayne, and Chirwa 2011; Xu et al. 2009). This suggests that these farmers do not buy additional fertilizer in the presence of subsidies, but rather substitute subsidized fertilizer for commercial fertilizer. Therefore, that an untargeted or a loosely targeted program can result in a meaningful pro-poor market effect is doubtful, especially given that most policies have tended to focus on fertilizer subsidies as the only policy instrument, while there are additional policy instruments to increasing the use of and return to fertilizer use in Ghana (Houssou, Kolavalli, and Silver 2016; Jayne et al. 2015).

8. CONCLUDING REMARKS

The paper assesses whether FSPs can be better targeted to resource-poor farmers using PMT methods and considers the case of Ghana's FSP. Currently, many SSA countries target fertilizer subsidies using CBT methods. While the rationale for targeting fertilizer subsidies at resource-poor farmers is clear, the evidence suggests that such farmers are not sufficiently targeted under CBT approaches. Therefore, this paper develops and validates PMT models for Ghana. In addition, we assess whether it is cost-effective to deliver a targeted FSP using such models. The findings in this paper point to the following conclusions.

First, past subsidy programs in Ghana have not been particularly aimed at poor farming households, even as targeting has become key in the implementation guidelines. Second, political considerations continue to play some role in the allocation of fertilizer subsidies at the central government level. Third, indicator-based targeting can potentially improve targeting at the household level because the proposed PMT produces superior outcomes than the actual targeting processes of Ghana's FSP, but those superior outcomes derive from the fact that the PMT approach assumes a flawless implementation of a targeted fertilizer subsidy scheme on the ground. Fourth, the validation tests indicate that the PMT system is equally accurate in selecting out poor farming households when applied to different samples derived from the same population. The results also suggest that the same PMT can be used for as many as two decades without losing its accuracy. Fifth, targeting fertilizer subsidies using the PMT approach is potentially cost-effective because the subsidy benefits to poor farming households increase while leakage costs are reduced substantially. Overall, since the proposed targeting system can potentially enhance the achievement of Ghana's FSP, the PMT approach should be considered for implementation, first in a pilot project involving a few communities, and later, if found successful, in a full-scale program.

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Fax: +1-202-467-4439
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CSIR Campus
Airport Residential Area, Accra
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Accra, Ghana
Tel.: +233 (0) 21 780-716
Fax: +233 (0) 21 784-752