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"Smart" Targeting of Fertilizer Subsidies in Kenya: Productivity, Welfare, and Soil Health *

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Abstract

Fertilizer subsidy programs in the Global South often juggle competing policy objectives of maximizing aggregate production and providing social protection for the poorest households. Using 2026 survey data from 3105 Kenyan households paired with parcel-level soil tests, this paper evaluates the targeting performance of Kenya's National Fertilizer Subsidy Program (NFSP). Specifically, we analyze the extent to which the current "de facto" targeting—driven by digital registration and e-vouchers—aligns with these possibly conflicting policy goals. We find that the subsidy recipient populations who would maximize productivity do not tend to include the poorest and most vulnerable farmers. Furthermore, the current pool of NFSP beneficiaries shows limited overlap with the ideal beneficiaries for either policy objective. Among those who we would ideally target, we find that factors such as mobile phone ownership and knowledge of fertilizer recommendations may help predict which households actually receive benefits. We conclude that integrating soil testing into subsidy frameworks could significantly reduce these inefficiencies and improve the alignment between program delivery and national agricultural goals.

1 Introduction

Many countries in the Global South have large scale fertilizer subsidy programs that aim to increase overall fertilizer usage, in turn bolstering farmers' incomes and national production levels. Many of these subsidy programs are universal or near universal, meaning that nearly anyone interested in purchasing subsidized fertilizer can potentially do so [Trachtman and Hill, 2025]. While this approach may decrease the administrative costs associated with targeting, it may lead to inefficiencies if purchases of subsidized fertilizer crowd out purchases of non-subsidized fertilizer rather than increasing overall fertilizer use [Ricker-Gilbert

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et al., 2011, Mather and Jayne, 2018]. In the extreme, the lack of explicit targeting can even lead non-farmers to buy up the (often scarce) supply of subsidized fertilizer to resell at higher prices [Gautam et al., 2022, Holden and Lunduka, 2013].

As such, there is growing interest in the development policy community in making the targeting of fertilizer subsidies "smarter," that is, more finely targeted to a smaller set of beneficiaries in order to meet policy objectives most efficiently [International Fertilizer Development Center, 2020, Amaglobeli et al., 2024]. However, fertilizer subsidy programs often have multiple policy objectives, which can include both increasing agricultural production and serving as social protection for the poorest or most vulnerable farmers. These objectives imply different ideal pools of beneficiaries. To increase production, the ideal population would be the farmers with the highest marginal production returns to additional fertilizer application. On the other hand, increasing the welfare of poor or vulnerable farmers would imply targeting these poor farmers, who may or may not have high production returns to fertilizer. Hence, with a limited pool of resources, a critical question is whether it is possible to satisfy both of these policy objectives at once; that is, to what extent might the ideal targeted populations for each policy objective overlap?

A central challenge in the design of agricultural subsidy programs is that alternative policy objectives imply fundamentally different targeting rules. Maximizing aggregate agricultural production requires directing scarce subsidy resources toward farmers with the highest marginal returns to fertilizer use, whereas poverty reduction objectives prioritize transfers toward poorer and more vulnerable households regardless of their production potential. Because public resources are limited, these objectives may not be simultaneously achievable, creating an inherent trade-off between efficiency and equity. Despite the prominence of fertilizer subsidies across Sub-Saharan Africa, little empirical evidence exists on the extent to which productivity-maximizing and welfare-maximizing beneficiary populations overlap, particularly in settings characterized by substantial heterogeneity in soil fertility conditions. Understanding the magnitude of this trade-off is critical for designing subsidy programs that align scarce public resources with national development objectives.

This study leverages the case of Kenya's National Fertilizer Subsidy Program (NFSP). According to Kenya's 2026 Budget Policy Statement, the fertilizer subsidy program "addresses persistent soil fertility constraints while making critical inputs affordable to resource-constrained farmers, thereby boosting productivity and food security" [The National Treasury and Economic Planning, 2026]. Budget statements in the recent past have also mentioned goals like to "reduce the cost of living" [The National Treasury and Economic Planning, 2025], "revamp underperforming/collapsed export crops" [The National Treasury and Economic Planning, 2025], and "[enable] farmers to earn more incomes" [The National Treasury and Economic Planning, 2021]. Hence, this program is intended to meet multiple policy objectives, and thus the ideal population to target is not clear. Perhaps accordingly, the NFSP generally sidesteps the question of targeting, with no explicit eligibility criteria [Ricker-Gilbert et al., 2024]. Farmers simply have to register with a centralized digital farmer registry called the Kenya Integrated Agricultural Management Information System (KIAMIS), in which fertilizer allotments are based on self-reported land area cultivated. Farmers receive an e-voucher via SMS message and can then retrieve their allotment from the nearest government depot. However, in practice, the demand for subsidized fertilizer exceeds the supply, resulting in de facto targeting; for instance, survey evidence suggests only 25% of households received subsidized fertilizer during the long rains season of 2023 [Ricker-Gilbert et al., 2024].

Given that the subsidy is not truly universal, a critical question is whether the current de facto targeting is optimal for meeting the government's policy goals. The current system, which requires farmers to register in a digital system and to collect fertilizer from government depots upon receipt of an e-voucher, could induce self-targeting in a way that aligns with policy objectives. For instance, it is possible that under the current regime, farmers who have the highest marginal returns to fertilizer are most willing to seek out and collect the subsidized fertilizer, which would be conducive to increasing domestic production. Alternatively, it could be possible that the poorest farmers who truly cannot afford to purchase fertilizer at prevailing market prices are most willing to seek out and collect the subsidized fertilizer, which would be conducive to increasing the incomes of the poorest farmers. Yet, the current system could also induce self-targeting among individuals who would not necessarily be ideal for reaching policy objectives, such as farmers who happen to live closest to fertilizer distribution points, individuals with government connections, or those who have regular access to a cell phone and signal. Moreover, there is some apparent randomness in which farmers end up receiving e-vouchers, which may induce additional targeting [Ayalew et al., 2025].

To explore these questions, we use data from a 2026 survey of 3105 Kenyan maize farmers, paired with soil test results from their farms. The survey asks detailed questions about fertilizer purchased and sources, which allows us to identify fertilizer subsidy beneficiaries. Because it is challenging to identify using non-experimental data which farmers truly have the highest marginal returns to fertilizer or the lowest welfare level, we use a series of proxies to identify the farmers who would be ideal beneficiaries under each targeting objective. Specifically, to identify the least well-off farmers, we consider farmers with the lowest per capita consumption expenditures, lowest asset index values, lowest food security index values, and a composite index of all of these indicators. To identify farmers that would most increase production and food supply in response to additional subsidized fertilizer, we introduce a novel measure of the marginal returns to fertilizer which is based on soil test data. Namely, we generate an index which identifies the farmers whose soil likely has the highest productivity returns to the additional soil nutrients introduced by the subsidized fertilizer (including nitrogen, phosphorus, potassium, and calcium). While we use this as our preferred productivity-based targeting measure, given that improved soil nutrition is the direct mechanism through which subsidized fertilizer will increase production, we also consider more traditional proxies for productivity/marginal returns to fertilizer, such as the value cost ratio of fertilizer, the output price to input price ratio, and the value of marketed surplus. Holding the quantity of subsidized fertilizer fixed, we determine which beneficiaries would be targeted under schemes based on each targeting objective, and calculate the rates in which these populations overlap.

We find that 43% of surveyed maize farmers are currently receiving subsidized fertilizer through the NFSP, suggesting that in practice, the subsidy is not universal. Subsidy recipients come from wealthier households with larger cultivation areas. Recipients also tend to have better soil nutrition on average and experience higher agricultural yields. Further, we find that the current beneficiary pool does not significantly overlap with the ideal beneficiary pool targeted by either of these policy objectives. Under welfare-related targeting, 30-34% of the sample are incorrectly included, and 11-26% of farmers are incorrectly excluded. Similarly, under productivity-related targeting criteria, 31-34% of farmers in the sample are incorrectly included as subsidy recipients, and 8-20% are incorrectly excluded. The higher exclusion errors under the welfare-based criteria may be due to the fact that the current subsidy program provides a minimum package size based on cultivating 0.5 acres of land, which is more than some farmers in the sample cultivate. Critically, the ideal beneficiaries under schemes that target productivity and welfare have little overlap, with only 6.7% of farmers in the same being chosen by both schemes, meaning that it may be challenging in practice to simultaneously target both objectives. Finally, we explore mechanisms that help to explain the poor targeting outcomes. We find that factors such as awareness of fertilizer recommendations for one's land and access to a phone both may help explain which households that should be targeted under our algorithms actually do receive benefits. These results suggest that policymakers face a significant trade-off between targeting based on production-based and social welfare-based policy objectives, but that targeting could potentially be improved by informing farmers about fertilizer recommendations for their land using soil test results, and reducing the reliance on mobile phone access in obtaining subsidy benefits.

This study contributes to three strands of literature. First, it contributes to the literature on agricultural input subsidy targeting by evaluating whether actual subsidy beneficiaries align with alternative policy objectives, including both productivity enhancement and welfare improvement. Second, it contributes to the broader literature on equity-efficiency trade-offs in public policy by quantifying the extent to which households selected under welfare-based targeting criteria overlap with those selected under productivity-based targeting criteria. While previous studies have examined targeting performance in fertilizer subsidy programs, little evidence exists on whether these competing policy objectives identify similar beneficiary populations. Third, we introduce a novel soil-diagnostic approach for identifying farmers with potentially high marginal returns to fertilizer use. By combining household survey data with plot-level soil diagnostics, we demonstrate how agronomic information can inform subsidy allocation decisions and potentially improve the productive efficiency of public expenditure. Various studies have looked at targeting of fertilizer subsidies from a social protection standpoint, asking whether benefits actually accrue to poor, smallholder farmers. Trachtman and Hill [2025] review existing fertilizer subsidies programs in the Global South, and find that while most fertilizer subsidies are generally pro-poor, this result seems to mostly be driven by the fact that agricultural households tend to be poorer on average. Case studies from countries such as Ghana and Kenya show that benefits in "universal" fertilizer subsidy programs tend to be captured by wealthier households with larger landholdings [Houssou et al., 2019, Ricker-Gilbert et al., 2024]. However, this benefit capture by wealthy households has even been shown to occur in programs that are explicitly targeted at worse-off households, such as in the cases of Malawi's Farm Input Subsidy Programme (FISP) [Holden and Lunduka, 2013], Zambia's Farm Input Support Program (FISP) [Mason et al., 2013], and Kenya's National Accelerated Agricultural Inputs Access Program (NAAIAP), a predecessor to the NFSP Mather and Jayne [2018].

A smaller body of work has explored the question of whether subsidized inputs are targeted in ways that serve other policy objectives around increasing overall production or food supply. To achieve is goal, subsidies must target farmers who will both purchase additional fertilizer in response to the subsidy (rather than simply substituting non-subsidized fertilizer for subsidized fertilizer) and have high yield returns to this fertilizer. Evidence about whether fertilizer subsidy benefits currently accrue to farmers who will increase their total fertilizer usage is mixed, but various literature suggests that much of subsidized fertilizer is inframarginal [Jayne et al., 2013, Liverpool-Tasie and Takeshima, 2013]. Mather and Jayne [2018] show that 98% of NAAIAP beneficiaries had purchased at least some non-subsidized fertilizer in the previous year, suggesting little crowd in of new fertilizer users at the extensive margin. Ricker-Gilbert et al. [2024] find partial crowd out amount NFSP beneficiaries; for every kilogram of subsidized fertilizer purchased, a farmer purchases around 0.22 kilograms less of non-subsidized fertilizer. Hence, there likely remains scope for better targeting of subsidized fertilizer to farmers who truly would have not used it otherwise. There is significantly less evidence on whether those targeted for fertilizer are also those with the highest marginal benefits of using additional fertilizer. One key exception is Basurto et al. [2020], finding that local leaders in Malawi target fertilizer subsidies toward households with higher self-reported returns to fertilizer. Overall, the literature instead points to political connections [Mason et al., 2017, Takeshima and Liverpool-Tasie, 2015] and distances to fertilizer distribution points [Ricker-Gilbert et al., 2024] as key factors influencing subsidized fertilizer receipt.

We contribute to this existing literature not only by comparing the population of NFSP beneficiaries to the ideal targeted populations for policy objectives other than reaching the poorest, but also by assessing to what extent the ideal beneficiary populations under different policy objectives overlap. While the potential for trade-offs between targeting the most needy and the most affected by program receipt has been explored empirically in the context of social protection programs [Haushofer et al., 2025], this has not been done in the context of fertilizer subsidies to our knowledge. Additionally, we contribute to this literature by using soil nutrition based indicators to assess a farmer's marginal returns to additional fertilizer. The NFSP, along with other subsidy programs, has been increasingly cognizant of soil health declines, which limits the marginal yield returns of subsidized fertilizer [Marenya and Barrett, 2009]. For instance, in 2026, the NFSP introduced subsidized lime to the NFSP to deal with soil acidity concerns. Soil nutrient contents provide an indication of farmer's marginal returns to fertilizer, as the explicit purpose of applying fertilizer is to improve a soil's nutrient contents. Moreover, soil nutrient contents can be measured fairly objectively with a soil test kit. This is unlike other measures of the marginal returns to fertilizer, which tend to rely on farmer's often error-ridden self-reports of inputs used, outputs produced, and prices, and somewhat arbitrary econometric modeling decisions. Our ability to link household survey data with soil test results allows us to explore how information on soil nutrition could inform subsidy targeting decisions.

The rest of the paper proceeds as follows. Section 2 presents additional context on the NFSP, and describes the data sources used in this analysis. Section 3 describes our empirical methods and Section 4 presents the main results on the NFSP's targeting performance compared to various objectives. Section 5 explores some additional mechanisms contextualizing the NFSP's targeting performance. Section 6 concludes.

2 Context and Data

2.1 Kenya's National Fertilizer Subsidy Program

Agricultural input subsidy programs have remained central to agricultural policy across Sub-Saharan Africa for several decades, reflecting persistent concerns regarding low fertilizer adoption, declining soil fertility, and food insecurity. In Kenya, fertilizer subsidy interventions have evolved considerably over time, shifting from relatively centralized government-led distribution systems toward increasingly digitized and market-oriented delivery mechanisms. Kenya's first major fertilizer support intervention, the National Accelerated Agricultural Inputs Access Program (NAAIAP), was launched in 2007 with the objective of improving smallholder access to improved seed and fertilizer technologies. The program primarily targeted resource-constrained maize farmers cultivating less than one hectare and relied on voucher-based systems redeemable through accredited agro-dealers. Although NAAIAP contributed to expanding access to agricultural inputs, implementation challenges quickly emerged, including leakage, delayed reimbursements, limited geographic coverage, and concerns regarding fiscal sustainability. Subsequent subsidy initiatives increasingly incorporated digital registration systems, electronic voucher platforms, and greater private-sector participation. Programs such as the Kenya Cereal Enhancement Programme–Climate Resilient Agricultural Livelihoods Window (KCEP-CRAL) and the National Value Chain Support Program (NVSP) expanded the use of electronic subsidy delivery systems while strengthening partnerships with agro-dealers to improve distribution efficiency and reduce administrative costs.

The most recent and largest intervention, the National Fertilizer Subsidy Program (NFSP), was introduced in 2022 following sharp increases in global fertilizer prices and growing food security concerns associated with the Russia–Ukraine conflict. Unlike earlier programs that bundled fertilizer and seed packages, the NFSP focuses primarily on fertilizer distribution. The program operates through the Kenya Integrated Agricultural Management Information System (KIAMIS), a centralized digital farmer registry through which registered farmers receive electronic fertilizer vouchers via SMS. Farmers redeem subsidized fertilizer through National Cereals and Produce Board (NCPB) depots and selected agro-dealers, with allocations nominally linked to cultivated acreage reported during registration. The program currently subsidizes a range of fertilizer products, including NPK blends for basal application and nitrogen-based fertilizers for top dressing, such as CAN and urea, with product availability varying across seasons and agroecological zones. During the study period, registered farmers purchased subsidized fertilizer at a fixed price of KES 2,500 per 50-kg bag, while the remaining cost was financed by the government subsidy. This represented a substantial discount relative to prevailing market prices and significantly reduced the cost of fertilizer acquisition for participating farmers. In practice, however, fertilizer demand substantially exceeds available subsidized supply, implying that subsidy receipt remains effectively rationed despite broad registration eligibility. As a result, the NFSP functions as an implicitly targeted subsidy system even in the absence of explicit eligibility criteria beyond farmer registration. The program simultaneously pursues multiple policy objectives, including increasing agricultural productivity, improving fertilizer affordability, strengthening food security, stabilizing food prices, and restoring soil fertility. More recent policy discussions have additionally emphasized the importance of integrating digital delivery systems, private-sector participation, and site-specific soil fertility management into subsidy implementation.

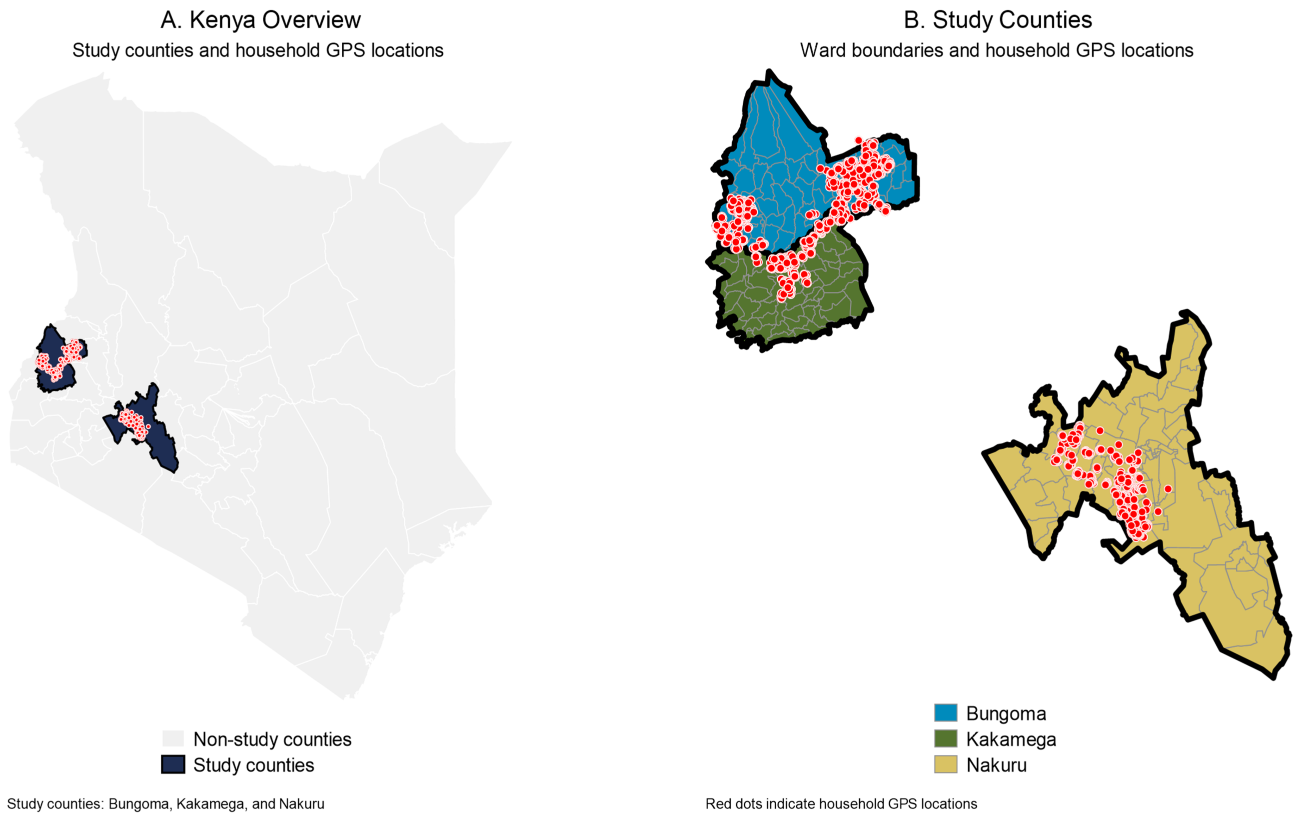
Despite the scale of public resources devoted to fertilizer subsidies, important concerns remain regarding targeting efficiency, logistical bottlenecks, and the extent to which current subsidy allocation aligns with underlying agronomic conditions and broader development objectives. Existing evidence suggests that subsidy access is strongly associated with factors such as distance to distribution centers, digital connectivity, and administrative capacity.

2.2 Study Areas and Sampling Design

The analysis draws on household- and plot-level data collected from three major maize-producing counties in Kenya: Bungoma, Kakamega, and Nakuru. These counties were purposively selected because of their strategic importance in national maize production and their representation of heterogeneous agroecological conditions across Kenya's high-potential agricultural zones. Bungoma and Kakamega counties, located in western Kenya, are characterized by high population density, intensive maize cultivation, and widespread soil nutrient depletion. In contrast, Nakuru county, located in Kenya's Rift Valley region, is characterized by relatively larger farm sizes, higher levels of commercialization, and comparatively more favorable soil conditions. The inclusion of these counties therefore captures substantial variation in agricultural production systems, market integration, and soil fertility conditions, providing a suitable setting for examining fertilizer use and productivity dynamics among smallholder farmers. To capture within-county geographic and agroecological heterogeneity, two sub-counties were selected from each county. Subsequently, 207 villages were randomly sampled across the six sub-counties. A comprehensive household listing exercise identified approximately 17,802 maize-producing households within the sampled villages. From these village rosters, 15 households were randomly selected for participation in the baseline survey, yielding a final sample of 3,105 households. The sampling strategy was designed to ensure broad geographic representation while maintaining sufficient statistical power for subsequent empirical analysis.

Figure 1 presents the geographic distribution of the study areas and sampled households. Panel A illustrates the location of Bungoma, Kakamega, and Nakuru counties within Kenya, while Panel B presents ward boundaries alongside the GPS distribution of sampled households across the study sites. The spatial distribution indicates broad coverage across heterogeneous agroecological and maize-producing regions, thereby strengthening the external validity of the analysis within Kenya's high-potential agricultural systems.

Figure 1: Study Areas and Spatial Distribution of Sampled Households



Notes: Panel A presents the location of the three study counties—Bungoma, Kakamega, and Nakuru—within Kenya. Panel B shows ward boundaries and the GPS distribution of sampled households across the study areas. The sampled households are broadly distributed across heterogeneous agroecological zones and maize-producing regions, capturing substantial variation in production systems, market access, and soil fertility conditions. *Source*: Authors' illustration based on household GPS coordinates and GADM administrative boundary data.

Table 1 presents the distribution of sampled households across counties.

Table 1: Overview of Baseline Sample by County

County	**Number of Villages**	**Households per Village**	**Total Households**
Bungoma	69	15	1,035
Kakamega	69	15	1,035
Nakuru	69	15	1,035
Total	207	15	3,105

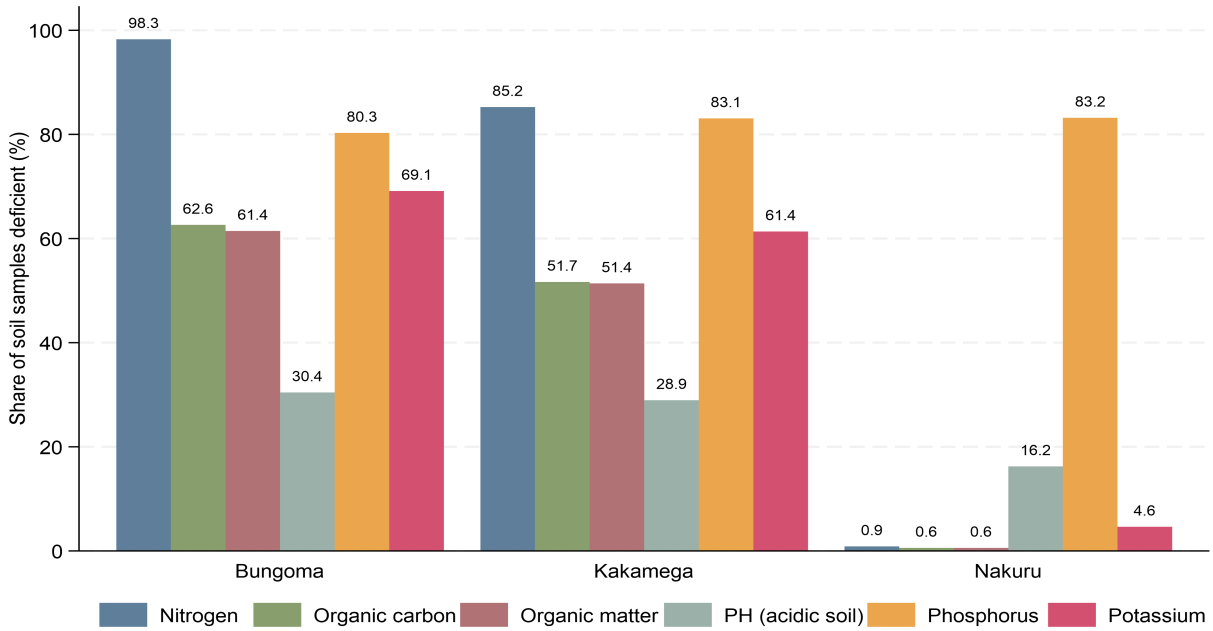
2.3 Household Survey Data

The household survey was conducted between January and February 2026 and collected detailed information on household demographics, agricultural production systems, fertilizer use, crop management practices, market participation, consumption expenditure, food security, financial inclusion, and gender dynamics. The agricultural production module collected detailed plot-level information on fertilizer application, seed use, pesticide adoption, crop management practices, and maize production outcomes for the long rains season of 2025 (around March to August). The survey additionally captured detailed information regarding participation in the National Fertilizer Subsidy Program, including farmer registration, subsidy receipt, redemption experiences, fertilizer acquisition channels, and transportation costs associated with fertilizer collection. Additional modules captured information on household assets, livestock ownership, labor allocation, access to credit and insurance, savings behavior, dietary diversity, and household food security. The survey further incorporated indicators from the Women's Empowerment in Agriculture Index (WEAI) to measure intra-household decision-making and gender dynamics. Collectively, the survey provides a rich characterization of rural livelihoods, agricultural production systems, and welfare conditions among maize-producing households in Kenya.

2.4 Soil Diagnostic Data

A unique feature of the study is the integration of detailed plot-level soil diagnostic information with household survey data. Soil samples were collected from sampled households and analyzed using a combination of wet- and dry-chemistry methods in February 2026. Wet chemistry analysis was conducted for 2,070 households, while dry chemistry analysis was implemented for a randomly selected subsample of 1,035 households. The soil test results describe soil conditions after the application of fertilizers recalled in the household survey. The soil diagnostics generated detailed information on key indicators of soil fertility, including soil pH, nitrogen, phosphorus, potassium, calcium, organic matter, and cation exchange capacity (CEC). These measures provide objective indicators of soil fertility constraints and allow direct assessment of whether fertilizer subsidy allocation aligns with underlying agronomic conditions. The results reveal widespread nutrient deficiencies across the study areas. Phosphorus deficiency affects more than 80 percent of sampled plots, while approximately 61 percent exhibit nitrogen deficiency. Deficiencies in calcium and low cation exchange capacity are also highly prevalent, indicating broader soil degradation concerns. Importantly, substantial heterogeneity exists across counties. Bungoma and Kakamega exhibit considerably higher rates of nutrient deficiencies relative to Nakuru. Nitrogen deficiency, for example, is nearly universal in several parts of Bungoma but substantially lower in Nakuru. Similarly, composite soil deficiency indices indicate the presence of multiple simultaneous nutrient constraints in western Kenya. Figure 2 presents the prevalence of major soil nutrient deficiencies across counties. The figure highlights substantial spatial heterogeneity in soil fertility conditions, particularly for nitrogen and phosphorus deficiencies. Bungoma and Kakamega consistently exhibit higher deficiency rates across most indicators relative to Nakuru, suggesting that fertilizer response potential and soil restoration needs vary considerably across regions. These patterns underscore the importance of site-specific fertilizer recommendations and highlight the potential inefficiencies associated with uniform fertilizer subsidy allocation systems that do not account for local agronomic conditions.

Figure 2: Prevalence of Soil Nutrient Deficiencies by County



Notes: The figure presents the proportion of sampled plots exhibiting nutrient deficiencies across Bungoma, Kakamega, and Nakuru counties based on plot-level soil diagnostic data. Deficiency thresholds are based on agronomic standards for maize production systems in Kenya. *Source*: Authors' calculations based on soil diagnostic data.

2.5 Summary Statistics

Table 2 presents descriptive statistics for the 3,105 households included in the baseline survey across Bungoma, Kakamega, and Nakuru counties. The sample is composed primarily of smallholder maize-producing households characterized by limited landholdings and modest input use. Households average 5.4 members, while household heads have approximately 28 years of farming experience and 10 years of formal education. Average landholdings are 1.9 acres, of which less than one acre is allocated to maize production. Participation in the NFSP is incomplete, with only 43 percent of households reporting receipt of subsidized fertilizer. Welfare indicators suggest substantial economic vulnerability: only one-third of households are classified as food secure despite moderate levels of financial inclusion through savings, credit, and insurance.

Table 2: Baseline Data: Summary Statistics

	Mean	SD	Min	Max
Household Characteristics				
Household size	5.36	2.35	1	19
Years of farming experience	28.15	17.71	0	94
Household head age	51.36	15.13	3	95
Male-headed household (=1)	0.74	0.44	0	1
Primary occupation crop farming (=1)	0.60	0.49	0	1
Years of education	10.09	5.26	0	23
Married household head (=1)	0.74	0.44	0	1
Total landholding (acres)	1.89	2.64	0	89
Maize area cultivated (acres)	0.78	0.96	0	16
Soil-tested parcel size (acres)	0.57	0.62	0	10
Financial Inclusion and Welfare				
Participated in NFSP (=1)	0.43	0.49	0	1
Formal savings account (=1)	0.59	0.49	0	1
Credit take-up (=1)	0.34	0.47	0	1
Any insurance (=1)	0.57	0.50	0	1
Total food expenditure (KES)	8,516	16,795	576	582,614
Per capita food consumption expenditure (KES)	1,968	4,433	60	119,084
Per capita total consumption expenditure (KES)	115,478	237,731	4,244	6,473,532
Total asset value (KES)	141,314	263,455	0	2,447,000
Food secure household (=1)	0.34	0.47	0	1
Food gap	2.09	1.99	0	12
Soil Fertility Conditions				
Acidic soils (=1)	0.25	0.43	0	1
Phosphorus deficient soils (=1)	0.82	0.38	0	1
Potassium deficient soils (=1)	0.45	0.50	0	1
Calcium deficient soils (=1)	0.60	0.49	0	1
Nitrogen deficient soils (=1)	0.61	0.49	0	1
Carbon deficient soils (=1)	0.38	0.49	0	1
Organic matter deficient soils (=1)	0.38	0.49	0	1
CEC deficient soils (=1)	0.62	0.49	0	1
Composite soil deficiency index	5.02	2.47	0	10
Input Use and Agricultural Production				
Nitrogen use (kg/acre)	20.39	17.76	0	91
Phosphorus use (kg/acre)	22.45	18.27	0	92
Potassium use (kg/acre)	1.36	3.15	0	16
Subsidized nitrogen use (kg/acre)	10.11	16.46	0	76
Subsidized phosphorus use (kg/acre)	11.22	18.87	0	92
Subsidized potassium use (kg/acre)	1.09	2.80	0	15
Organic fertilizer use (kg/acre)	886	2,484	0	40,741
Household maize yield (kg/acre)	1,318	868	0	10,286
Yield on soil-tested parcel (kg/acre)	1,275	852.39	0	3,600
Total maize production (kg)	973	1,605	0	37,800
Price ratio	0.78	3.13	0	89
Value-cost ratio	2.56	12.29	-0	368
Total Maize sold(kg)	422.60	1085.84	0	7560

Notes: The table reports summary statistics for sampled maize-producing households across Bungoma, Kakamega, and Nakuru counties in Kenya. NFSP refers to participation in the National Fertilizer Subsidy Program. Input use variables are measured on a per-acre basis. Food insecurity indicators are based on household food security classifications collected during the baseline survey. *Source*: Authors' calculations based on baseline household survey data.

A striking feature of the sample is the prevalence of soil fertility constraints. More than 80 percent of sampled plots are deficient in phosphorus, while deficiencies in nitrogen, calcium, and cation exchange capacity affect more than half of households. On average, households face five distinct soil constraints, highlighting the widespread nature of soil degradation in the study area. Consistent with these constraints, fertilizer application rates remain relatively low and maize yields average approximately 1.3 tons per acre, well below attainable yields in Kenya's high-potential maize-growing regions. Taken together, the descriptive statistics depict a population of resource-constrained smallholders facing significant soil fertility challenges, low agricultural productivity, and persistent welfare deficits, providing a strong rationale for interventions aimed at improving fertilizer access and soil nutrient management.

3 Methods

3.1 Proxies for Welfare and Productivity

Deciding which farmers are worst off and which farmers have the highest marginal returns to fertilizer is challenging to do in practice, as farmers' utility functions and production functions are not directly observable. Hence, we use a series of proxies to categorize farmers' welfare and productivity. For welfare, we first consider per capita household expenditures, which is often used as a proxy for welfare in settings where incomes may not be well-documented, such as is the case of smallholder agriculture [Deaton, 2003]. We construct this measure using information on reported expenditures on 99 food items in the past 7 days, as well as on 38 non-food items over differing recall periods of either 3 months, or 1 year, depending on the typical purchasing frequency of the good. As survey-elicited consumption indicators tend to be measured with noise, we also consider two additional welfare proxies. The first is an asset index constructed using the first principal component of survey-based variables about household ownership of 42 types of assets. [Filmer and Pritchett, 2001] The second is a food insecurity score based on the 8-question food insecurity experience scale (FIES) [Cafiero et al., 2018]. The FIES questions address whether households have skipped meals or modified their diets due to a lack of money or resources. While both asset and food insecurity indices may be less prone to measurement error than consumption aggregates, they also capture slightly different notions of welfare; an asset index likely picks up longer term accumulated wealth, while the FIES picks up episodes of acute vulnerability. As such, we also estimate a composite index based on all three of these metrics. Specifically, each indicator is standardized to have a mean of zero and a standard deviation of one, after which the composite index is calculated as the equally weighted average of the standardized indicators, This approach assigns equal importance to each welfare dimension.

In order to assess each farmer's marginal returns to fertilizer, we also use multiple proxies. As our main proxy we use is a soil productivity index. Soil health is multidimensional, and hence identifying the soil with the highest potential returns to fertilizer is not necessarily straightforward, even with soil test data. Previous research suggests that certain soil health parameters are particularly critical fertilizer's ability to increase yields. Notably, soils with very low percentages of soil organic matter (SOM) have virtually zero returns to using chemical fertilizer, including the NPK blends and urea top dressings that the government currently subsidizes [Marenya and Barrett, 2009, Chamberlin et al., 2021]. Similarly, pH plays a significant role in determining fertilizer returns; and at extreme pH levels, chemical fertilizer is also ineffective at increasing yields [Burke et al., 2019, Miller, 2016]. However, in soil above the minimum SOM threshold and within a suitable pH range, there are diminishing marginal production returns to additional soil nutrients like nitrogen

[Marenya and Barrett, 2009, Dhakal and Lange, 2021]. So to maximize the returns to fertilizer, we would want to give fertilizer to the farmers with the most nutrient-depleted soils, conditional on satisfying SOM and pH thresholds. Hence, in order to estimate marginal returns to additional fertilizer, we first generate a index using principal components analysis with data on soil nutrient contents for the nutrients that are included in the subsidized fertilizers subsidized by the government, which include nitrogen, phosphorous, potassium, magnesium and calcium. This measures the extent of the nutrient depletion which can be improved by applying additional fertilizer. However, we then still need to adjust for the fact that some of these soils with low nutrient levels will not meet the SOM and pH thresholds needed for chemical fertilizers to have positive returns. The effective thresholds for SOM and pH can vary a bit over space, depending on agro-ecological factors [Lal, 2020]. The soil test results data we use provides parcel-specific guide levels of the appropriate minimum and maximum ideal values for each soil attribute. As the value of these parameters are generally in line with threshold estimates in the literature, we use these farmer specific guides to decide whether a farmer's soil is in the SOM and pH range that would have any positive returns to fertilizer. If a farmer's soil is outside of this range, we essentially replace their soil index value with a negative value, such that the farmer would not get selected under any targeting regime based on targeting farmers with the highest marginal returns to fertilizer given their soil quality.

Second, we estimate the fertilizer value-cost ratio (VCR), a measure of the economic returns to fertilizer use. To do so, we construct a farmer-specific VCR based on estimated yield responses to fertilizer. Specifically, we first estimate a Cobb-Douglas maize production function in which yield is modeled as a function of fertilizer use and other observed production inputs, using ordinary least squares. Using the estimated production function, we predict each farmer's maize yield under observed fertilizer application and under a counterfactual scenario of zero fertilizer use, holding all other inputs constant. The difference between these two predictions provides an estimate of the marginal yield gain attributable to fertilizer. We then compute the VCR as the monetary value of this predicted yield gain, evaluated at local maize prices, divided by the farmer's fertilizer expenditure. Formally,

$$VCR_i = \frac{P_y\left[\hat{Y}_i(F_i) - \hat{Y}_i(0)\right]}{P_f F_i}, \tag{1}$$

where $\hat{Y}_i(F_i)$ denotes the predicted yield for farmer i under observed fertilizer use F_i, $\hat{Y}_i(0)$ denotes the corresponding counterfactual yield prediction in the absence of fertilizer, P_y is the maize output price, and $P_f F_i$ is fertilizer expenditure. This measure captures the estimated value of output attributable to fertilizer per unit of fertilizer cost, with higher values indicating greater productivity of fertilizer use.

Third, we examine output-to-input price ratios, which provide a complementary measure of economic productivity by capturing the value of crop output relative to the cost of purchased inputs. We calculate this based on survey self-reports of the price an individual receives for their maize and pays for fertilizer. This gives us some idea of the relative profitability of using fertilizer for a given farmer. Finally, we consider the amount of surplus maize that a farmer sells on the market. The rationale behind this is beyond simply increasing production, the government also aims to increase the domestic food supply and decrease food prices, which likely requires increasing the marketed supply of the commodity in particular. In that sense, the government may want to target the subsidy at more market-oriented farmers, who are likely to sell any additional production resulting from increased fertilizer use on the market.

3.2 Simulating targeting under alternative regimes

In order to compare the government's current targeting regime to optimal targeting, we need to determine how we map the values of the proxies that we calculate for each farmer to ideal targeting decisions. One option could be to choose a threshold (such as a poverty line or a minimum productivity level), and indicate that every person surpassing the threshold should get the subsidy. However, in such cases, the error rates can be highly sensitive to these arbitrarily chosen thresholds, and can lead to large variation in the size of the ideal beneficiary pool. Hence, we choose instead to take a pragmatic approach, where we fix the amount of subsidized fertilizer available, and then re-allocate this fertilizer based on which beneficiaries are deemed most ideal by our proxies. To do this we need to make a few assumptions. First we assume that the total amount of fertilizer available to be allocated among subsidy recipients in a given county is the amount of subsidized fertilizer that survey respondents in that county report receiving. Of course, this means that the "supply" of fertilizer is dependent on which farmers happen to be in our sample. Given that the sampling in each county is random, this choice shouldn't induce any type of systematic bias, though there may be measurement error. We also round up to the nearest "full bag" as subsidized fertilizer is only sold in 50kg bags. So if farmer reports using less than 50 kg of subsidized fertilizer, we assume the rest was saved or given to a neighbor. Next, we assume that if a farmer is considered an ideal recipient based on the value of a calculated proxy, that they will purchase subsidized fertilizer for their entire cultivated maize area. We do this for two reasons: first, most of our proxies are not plot specific, and second, under the current NFSP, the fertilizer a farmer is eligible to receive depends on their cultivated land area, which will allow a fairer comparison of alternative targeting regimes to "optimal" targeting. Third, we assume that fertilizer is allocated in units of full bags only, and that quantities per acre are allocated in line with current program rules. That is, a targeted farmer will be assigned 4 bags of fertilizer per acre (2 for planting, and 2 for top dressing). To assign a number of bags, we round the farmers' cultivated maize area to the nearest 0.5 acre. The rationale for this again is to be in line with logistical constraints that the government may face in allocating partial bags of fertilizer to farmers, and because these quantities of fertilizer per acre are aligned with agricultural best practices. To see the extent to which this last assumption affects our results, we also calculate an alternative targeting scenario, in which we allow for distribution of partial bags based on actual land quantities. Such a distribution mechanism may be possible under a fertilizer distribution system that is led by private sector for example, who can repackage and sell fertilizer in smaller quantities [Freeman and Omiti, 2003].

With these assumptions, our process to choose optimal beneficiaries under different targeting objectives is as follows. In each county, we add up the rounded number of bags received by farmers in that county, which we take as the total supply. Then we order farmers in each county from most to least preferable to receive fertilizer, as indicated by the proxy. For instance, if the proxy is per capita consumption, since we want to target the poorest farmers, we order them from lowest per capita expenditure to highest. Starting at the most preferable farmer, we allocate fertilizer to each farmer in quantities of 4 bags per cultivated acre, rounding to the nearest half acre as described. We go down the list giving fertilizer in to appropriate quantities to each farmer in the county in order of preference, until the total quantity of fertilizer supplied is exhausted. If individuals would have part of their allocation covered (because they are at the end of the list as the supply is being exhausted) we exclude them as beneficiaries.

3.3 Characterizing targeting performance and concordance between proxies

Once we've used the process described to determine the ideal beneficiaries according to different proxies, we can then assess how NFSP's current de facto targeting compares. To do this, for each proxy, we partition the sample into 4 groups: those targeted by our algorithm who also receive any subsidized fertilizer from the NFSP (correctly included), those not targeted by our algorithm who do not receive any fertilizer from the NFSP (correctly excluded), those who are not targeted by our algorithm but do receive fertilizer from the NFSP (inclusion errors), and those who are targeted by our algorithm, but do not receive fertilizer from the NFSP (exclusion errors). If the NFSP's current de facto targeting outcomes are generally in agreement with our targeting algorithm for a given proxy, most farmers will either be correctly included or correctly excluded. The higher the error rates are, the more discrepancies there are between the targeting under NFSP currently and our proxy-based algorithms.

We also explore the extent to which welfare-based targeting and productivity-based targeting are able to be achieved simultaneously. To do so, we perform a similar exercise, but instead of comparing the beneficiaries chosen under one of our proxy-based metrics to current targeting, we compare the beneficiaries chosen by a welfare based proxy to those chosen by a production based proxy. Specifically, we compare those targeted by our preferred proxy in each category: the combined welfare index (incorporating consumption, assets, and food security) and the soil productivity index.

4 Results

4.1 Comparison of NFSP Benefeciaries and non-beneficiaries

Table 3 compares characteristics between recipients and non-recipients of subsidized fertilizer from the NFSP. The results reveal substantial differences across the two groups in household resource endowments, agricultural production systems, soil fertility conditions, and welfare outcomes. We note that this analysis is purely descriptive and tells us about who currently selects into program participation (in part through self-selection). It does not tell us anything about the impact of NFSP receipt on any outcomes. From a policy perspective, these differences provide insight into the implicit selection mechanisms embedded within the current subsidy system. Because access to subsidized fertilizer requires registration within a digital platform, receipt of SMS notifications, and collection from designated distribution centers, participation may depend not only on agronomic need but also on factors such as information access, liquidity, administrative capacity, and market integration. Consequently, observed beneficiary characteristics provide important evidence regarding the extent to which the current allocation mechanism aligns with broader productivity and welfare objectives.

Subsidy recipients are significantly more likely to live in male-headed households, more likely to be married, have more education, and cultivate larger landholdings and maize areas than non-recipients. Recipients also exhibit stronger engagement with formal financial services, including higher rates of savings account ownership, credit access, and insurance membership. These differences are mirrored in agricultural production and input use patterns. Subsidy recipients apply significantly larger quantities of nitrogen, phosphorus, and potassium fertilizers and achieve substantially higher maize yields at both the household and (soil-tested) plot levels. Recipients additionally report better food security outcomes relative to non-recipients, although differences in annual per capita consumption expenditure remain comparatively modest. These findings are generally in line with previous literature on fertilizer subsidy programs, which suggests that in programs that are not formally targeted, beneficiaries come from wealthier households, and cultivate larger land areas [Houssou et al., 2019, Ricker-Gilbert et al., 2011].

What we are able to document, in addition, is that NFSP recipients also have less depleted soil on average. Non-recipient households exhibit significantly higher rates of nitrogen deficiency, lower cation exchange capacity, and poorer soil fertility conditions relative to subsidy recipients. The evidence therefore suggests that participation in the current subsidy system is disproportionately concentrated among relatively better-resourced households with stronger financial access and market integration, but that this may not be efficient given that these farmers already have less depleted soils, which may have lower returns to additional fertilizer use. These patterns raise important questions regarding the extent to which current subsidy allocation aligns with agronomic need, productivity potential, and broader welfare objectives.

Table 3: Characteristics of NFSP Participants and Non-Participants

Variable	**Non-Recipients**	**Subsidy Recipients**	**Difference**
Household Characteristics			
Household size	5.21	5.55	0.34***
Years of farming experience	27.94	28.43	0.49
Household head age	51.06	51.76	0.70
Male-headed household (=1)	0.71	0.78	0.07***
Primary occupation crop farming (=1)	0.59	0.62	0.03
Years of education	9.27	11.18	1.91***
Married household head (=1)	0.71	0.78	0.07***
Total landholding (acres)	1.45	2.47	1.02***
Maize area cultivated (acres)	0.58	1.05	0.47***
Soil-tested parcel size (acres)	0.45	0.74	0.29***
Financial Inclusion and Welfare			
Formal savings account (=1)	0.55	0.65	0.10***
Credit take-up (=1)	0.31	0.38	0.07***
Any insurance (=1)	0.51	0.64	0.13***
Total food expenditure (KES)	8,349	8,737	388
Per capita food consumption expenditure (KES)	2,042	1,870	-172
Per capita total consumption expenditure (KES)	117,784	112,401	-5,383
Total asset value (KES)	90,729	208,824	118,096***
Food secure household (=1)	0.27	0.42	0.15***
Food gap	2.38	1.70	-0.68***
Soil Fertility Conditions			
Acidic soils (=1)	0.24	0.27	0.03
Phosphorus deficient soils (=1)	0.82	0.83	0.01
Potassium deficient soils (=1)	0.48	0.41	-0.07***
Calcium deficient soils (=1)	0.60	0.60	0.00
Nitrogen deficient soils (=1)	0.66	0.56	-0.10***
Carbon deficient soils (=1)	0.42	0.34	-0.08***
Organic matter deficient soils (=1)	0.41	0.33	-0.08***
CEC deficient soils (=1)	0.65	0.58	-0.07**
Composite soil deficiency index	5.17	4.82	-0.35**
Input Use and Agricultural Production			
Nitrogen use (kg/acre)	17.37	24.42	7.05***
Phosphorus use (kg/acre)	19.68	26.15	6.47***
Potassium use (kg/acre)	0.48	2.54	2.06***
Subsidized nitrogen use (kg/acre)	0.90	22.39	21.49***
Subsidized phosphorus use (kg/acre)	0.95	24.93	23.98***
Subsidized potassium use (kg/acre)	0.09	2.43	2.34***
Organic fertilizer use (kg/acre)	888	884	-4
Seed use per acre	29.87	28.51	0.10*
Household maize yield (kg/acre)	1,182	1,499	318***
Yield on soil-tested parcel (kg/acre)	1,161	1,427	265***
Total maize production (kg)	615	1,449	834***
Price ratio	0.52	1.16	0.64***
Value-cost ratio	1.78	3.69	1.91**
Total Maize sold (kg)	238.38	668.46	0.00***
Observations	1,775	1,330	3,105

Notes: Columns (1) and (2) report mean values for NFSP non-participants and participants, respectively. Column (3) reports pairwise mean comparison tests between the two groups. Variables include household demographic characteristics, soil fertility indicators, fertilizer use, agricultural production outcomes, financial inclusion indicators, and welfare measures. Standard errors are clustered at the village level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source*: Authors' calculations based on baseline household survey and soil diagnostic data.

4.2 Comparison of current NFSP recipients to ideal recipients based on welfare criteria

Table 4 shows the comparison between individuals who get subsidized fertilizer from the NFSP and those who would optimally get it under welfare proxy-based targeting regimes. Inclusion and exclusion errors have distinct policy implications. Inclusion errors arise when scarce subsidy resources are allocated to households that would not be prioritized under a given targeting objective, thereby reducing the efficiency of public expenditure. Exclusion errors occur when households that should receive support under a particular targeting criterion fail to receive benefits. The relative importance of these errors depends on the policy objective under consideration, but both represent departures from an allocation that would maximize either welfare gains or agricultural productivity. Regardless of the welfare proxy used, a significant portion of the sample consists of incorrectly targeted households, which are cases in which the farmers reached by NFSP are not considered the optimal recipients under our algorithms (inclusion and exclusion errors): 50% for the combined welfare index, 44% for consumption expenditures, 50% for the asset index, and 47% for the FIES score. In most cases the number of inclusion errors is greater than the number of exclusion errors; that is, the error rate is driven more so by individuals who receive NFSP benefits in practice who are not the poorest according to the proxies. This is perhaps unsurprising given the previous results in Table 3, which suggest that NFSP recipients are wealthier on average.

Table 4: Targeting Accuracy of NFSP Beneficiaries Based on Welfare Proxies

Indicator	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	Observation
Combined welfare index	9.44	40.77	33.40	16.39	3105
Per capita expenditure	10.89	45.19	31.95	11.98	3105
Asset index	9.05	40.84	33.78	16.33	3105
Food security	9.79	42.87	33.04	14.30	3105

Notes: This table reports the performance of the targeting mechanism under the full bag allocation scenario. Targeting outcomes are evaluated across four welfare dimensions: combined welfare index, per capita expenditure, asset index and food security. Households are categorized as correctly included, correctly excluded, inclusion errors, or exclusion errors based on the comparison between predicted eligibility and actual program participation. Source: Authors' calculations based on the baseline household survey.

However, at the same time, we note that the total percentage of the sample that is chosen by our welfare-based algorithm is lower than the percentage of farmers that receive NFSP benefits in reality. Our welfare-based algorithms assign 22-26% of the sample to be subsidy recipients (the sum of the correctly included and exclusion error columns) compared to the approximately 43% of the sample that actually receives the subsidy. This may be in part due to the assumption in our algorithm that the amount of fertilizer should cover a farmer's entire land holdings, which is not always the case in practice. This could in part be responsible for the fairly high inclusion error rates. Yet it is worth noting that out of all of the individuals targeted by our algorithms, only about 36-48% are subsidy recipients in practice, suggesting that this inaccuracy is not only driven by the difference in the overall inclusion rate. At the same time, around 40-45% of households under each metric are correctly excluded. These might be households towards the center of the distribution who are not the absolute poorest, but still face high costs to obtaining fertilizer subsidies in practice.

For robustness, we also see the extent to which these targeting errors might be driven by the fact that our algorithm only allocated fertilizer in full bags, which could, for instance, exclude some smallholders with limited landholdings. Hence, instead of rounding up or down to the nearest number of bags, we simply allocate fertilizer based on actual landholdings. Table 5 shows the results. We indeed find that more households are included overall under this algorithm (30-37%, which is a bit closer to the 43% in the actual sample). Yet, only 29-40% of those chosen by our algorithms to be beneficiaries actually receive benefits under NFSP. As a result, the overall targeting error rates increase slightly under this regime, driven mostly by increased exclusion errors. Hence, it is possible that some of the targeting errors under the current NFSP program are driven by the fact that the government only provides fertilizer in full 50kg bags, as when we compare NFSP beneficiaries to an algorithm that allows for bag splitting, the government's targeting seems to perform even worse. This suggests that the government may want to consider a more robust distribution model that allows for individuals to purchase partial bags.

Table 5: Targeting Accuracy of NFSP Beneficiaries Based on Welfare Indicators–Allowing for spliting of bags

Indicator	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	Observations
Combined welfare index	10.72	31.72	32.11	25.44	3105
Per capita expenditure	11.95	39.10	30.89	18.07	3105
Asset index	10.47	32.50	32.37	24.67	3105
Food security	11.76	35.10	31.08	22.06	3105

Notes: This table presents the targeting performance that allows splitting of bags mechanism. Targeting outcomes are assessed across four welfare dimensions: combined welfare index, per capita expenditure, asset index, and food security. Households are classified into four groups: correctly included, correctly excluded, inclusion error, and exclusion error. Source: Authors' calculations based on the baseline household survey.

4.3 Comparison of current NFSP recipients to ideal recipients based on returns to fertilizer

Table 6 shows the comparison between individuals who get subsidized fertilizer from the NFSP and those who would optimally get it under productivity proxy-based targeting regimes that targets farmers with high marginal returns to fertilizer. For these indicators, the overall instances of targeting errors are still relatively high, but slightly lower than those of the welfare based proxies, at 45% for the soil health indicator, 43% for the VCR, 42% for the output/input price ratio, and 46% for the maize marketing surplus. Hence, in line with the findings about NFSP recipients being higher productivity farmers on average, it does seem that targeting based on productivity objectives is more aligned with the current regime than the targeting based on welfare objectives.

However, for this set of indicators, the number of farmers chosen by our algorithm is 17-26%, which is much less than the 43% of farmers in the sample that are currently receiving NFSP, and slightly less than the 22-26% of farmers chosen by the welfare proxy-based regimes. The fact that these shares are much lower than 43% could again be due to the fact that farmers do not tend to receive subsidized fertilizer for all of their cultivated area in reality, even though they do in our algorithm. However, this discrepancy could also reflect farmers with larger land holdings being more productive in general, which would mean that the total supply of fertilizer is exhausted by fewer farmers with larger landholdings. In that sense, the lower rate of inclusion under this scheme may reflect a true difference in the optimal number of beneficiaries under productivity-based targeting objectives, rather than a faulty assumption in our algorithm. That being said, some of likely high return farmers that are chosen by our algorithms are not currently getting NFSP benefits. The percentage of farmers chosen by our algorithm that are receiving NFSP range from 47-52%, which is again not an overwhelming majority. Of course, this doesn't necessarily mean that the way that the NFSP is currently operating is not increasing production as much as possible; a limitation here is that it's hard to know which farmers are inframarginal. Subsidizing very high productivity farmers is not ideal if the subsidy will crowd out purchases of unsubsidized fertilizer. However, for the case of the soil health indicator, individuals chosen likely have high marginal returns to fertilizer, and may not be purchasing a lot of fertilizer otherwise (otherwise their soil nutrient levels would likely be higher). Hence, policymakers make want to pay special attention to targeting these individuals, many of whom are not currently being benefited by the NFSP. Similarly to before, Table 7 also reconstructs the analysis while removing the constraint that farmers must purchase complete bags. This again increases inclusion rates based on our algorithm slightly (up to 19-35%), and similarly decreases overall targeting accuracy (0-8% more of the total sample are targeting errors). Hence, there may be some small targeting gains even when considering productivity-based objectives in allowing subsidized fertilizer to be sold in split up bags.

Table 6: Targeting Accuracy of NFSP Recipients Based on Productivity Indicators

Indicator	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	Observations
Soil health	12.70	42.73	30.66	13.91	2071
Value cost ratio (VCR)	9.34	47.25	33.49	9.92	3105
Output/Input price ratio	8.82	48.86	34.01	8.31	3105
Total Maize sold (kg)	7.38	54.01	35.46	3.16	3105

Notes: This table reports the performance of the targeting mechanism under the full bag allocation scenario. Outcomes are presented across three productivity dimensions: Soil health, Value-Cost Ratio (VCR), Output/Input Price Ratio, and maize Sold (kg). Households are classified as correctly included, correctly excluded, inclusion error, or exclusion error. Source: Authors' calculations based on the baseline household survey.

Table 7: Targeting Accuracy of NFSP Recipients Based on Productivity Indicators–Allowing for Splitting of Bags

Indicator	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	Observation
Soil health	14.53	35.25	28.83	21.39	2071
Value cost ratio (VCR)	10.43	44.67	32.40	12.50	3105
Output/Input price ratio	9.57	47.76	33.27	9.40	3105
Total Maize sold (kg)	7.31	54.04	35.52	3.12	3105

Notes:This table reports the targeting performance of the bags splitting allocation mechanism. Targeting outcomes are evaluated using three productivity-based indicators: soil health, the Value-Cost Ratio (VCR), and output-to-input price ratio, and maize sold (kg). Households are classified into four categories: correctly included, correctly excluded, inclusion error, and exclusion error. Source: Authors' calculations based on the baseline household survey.

4.4 Overlap between targeting objectives

To understand the extent to which the welfare- and productivity-based criteria overlap, we also compare the sets of individuals chosen under each targeting objective, using the combined welfare index for the welfare-based objective and soil health for the production-based objective. The results are displayed in Table 8. Critically, only 10% of the sample is targeted under both of these categories, with another 15% of the sample being targeted under welfare criteria only and 17% under productivity criteria only. Hence, in practice, it may be challenging to simultaneously reach farmers that are not well off but potentially have high returns to fertilizer. The limited overlap between productivity-based and welfare-based targeting criteria highlights a fundamental challenge in fertilizer subsidy design. Fertilizer subsidy programs are frequently expected to achieve multiple objectives simultaneously, including increasing agricultural productivity, improving food security, and supporting vulnerable households. However, our results suggest that these objectives may identify substantially different beneficiary populations. The finding that only ten percent of households are selected under both targeting approaches implies that a single allocation rule may be unable to maximize both objectives simultaneously. Consequently, policymakers face an explicit equity-efficiency trade-off in determining how fertilizer subsidies should be targeted.

These findings further suggest that debates surrounding subsidy reform should extend beyond administrative efficiency and beneficiary identification mechanisms. Even a perfectly administered targeting system would still require policymakers to determine whether maximizing agricultural production or improving household welfare should receive greater priority. In this sense, targeting is not merely a technical problem but also a policy choice involving competing development objectives. Our results show a major trade-off between the two targeting objectives, where achieving one objective likely implies sacrificing the other. However, at the same time, the overlap is still greater than 0, meaning that there is some set of individuals who should almost certainly be targeted by NFSP, regardless of which of these two objectives is more important.

Table 8: Comparison of households targeted by welfare and productivity metrics

Targeting Category	Percent	Observations
Both (welfare and productivity)	10.00	2071
Welfare only	15.11	2071
Productivity only	16.61	2071
Neither	58.28	2071

Notes: Households are classified according to whether they are selected under the welfare based targeting criteria and the productivity based targeting criterion. "Both" refers to households selected by both targeting approaches, "Welfare only" to households selected exclusively by the welfare criteria, "Productivity only" to households selected exclusively by the productivity criterion, and "Neither" to households selected by neither approach.

Source: Authors' calculations based on baseline household survey data.

5 Mechanisms/Supplemental Results

5.1 Mechanisms based on welfare targeting criteria

To help us understand the source of the targeting errors we uncovered in the previous section, and the mechanisms that explain who gets NFSP in practice, we further explore differences between individuals that are correctly vs. incorrectly targeted by NFSP. Table 9 presents descriptive statistics of key household characteristics across four targeting outcome categories: correctly included, correctly excluded, inclusion errors (incorrectly included), and exclusion errors (incorrectly excluded), under welfare-based targeting criteria. We again use the targeting algorithm of our preferred proxy, which is the combined welfare index. The analysis focuses on comparing correctly included (excluded) to incorrectly excluded (included) households, as these households form the entire group of households that should be included (excluded). In other words, holding our algorithms' classification of each household fixed, we compared those who actually do versus do not receive NFSP benefits. These comparisons are explored in the last two columns of Table 9, which display the p-values associated with a difference of means.

Table 9: Household characteristics by targeting outcome groups under a welfare-based targeting objective

Variable	Correctly Included (CI)	Correctly Excluded (CE)	Inclusion Error (IE)	Exclusion Error (EE)	p-value CI vs EE	p-value CE vs IE
Household Size	6.04	5.02	5.42	5.68	0.037**	0.000***
Years of farming experience	28.65	27.22	28.37	29.73	0.398	0.123
Household head age	50.75	50.33	52.04	52.88	0.053*	0.007***
Household head gender (Male=1)	0.74	0.73	0.79	0.66	0.027**	0.004***
Head maximum years of education	9.89	10.26	12.18	9.10	0.007***	0.000***
Head marital status (Married=1)	0.75	0.73	0.79	0.67	0.025**	0.000***
Primary occupation (Crop=1)	0.64	0.57	0.61	0.64	0.905	0.052*
Formal saving account (Yes=1)	0.55	0.57	0.68	0.50	0.157	0.000***
Credit take-up (Yes=1)	0.32	0.32	0.40	0.30	0.523	0.000***
Have any insurance membership (Yes=1)	0.56	0.51	0.67	0.49	0.050**	0.000***
Monthly per capita food expenditure (KES)	6422.61	9341.41	9390.83	5880.76	0.023**	0.951
Per capita annual consumption expenditure (KES)	377396.75	493750.41	546592.25	342767.44	0.009***	0.044**
Total asset value (KES)	74886.24	105626.30	246667.75	53674.42	0.000***	0.000***
Food secure (Yes=1)	0.04	0.37	0.53	0.04	0.902	0.000***
Frequency of Food Insecurity (Months)	2.83	2.08	1.38	3.11	0.047**	0.000***
Maize area (acres)	0.86	0.53	1.09	0.68	0.000***	0.000***
Awareness of fertilizer recommendation	0.33	0.29	0.43	0.28	0.076*	0.000***
Phone Ownership (Yes=1)	0.94	0.94	0.98	0.88	0.006***	0.000***
% of Maize Sold	0.22	0.17	0.25	0.19	0.115	0.000***
Distance to road (km)	3.18	2.97	3.20	3.18	0.998	0.711
Self reported soil quality	2.83	2.86	3.00	2.73	0.088*	0.000***
Observations	3105					

Notes: The table compares mean differences across targeting groups to assess systematic differences in observable characteristics associated with the welfare based targeting criteria outcomes. The first four columns report group means.The last two columns report p-values from two-sample t-tests comparing the correctly included group with the exclusion error group, and the correctly excluded group with the inclusion error group. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. *Source*: Authors' calculations based on baseline household survey data.

In looking at the farmers that our welfare algorithm chooses to include (correctly included and exclusion error farmers), we see that those who actually do receive NFSP benefits differ from those who do not in systematic ways. Those who do receive NFSP come from larger households, with younger, more educated household heads. They also cultivate larger maize areas, and are better off in terms of consumption expenditure, asset ownership and food security. This indicates that even among the set of poor households we would ideally target, current beneficiaries are on the richer side of the distribution. Hence, those who are missed under NFSP are indeed likely the poorest of the poor. When looking at those households which are better off, and hence not chosen as recipients by our welfare algorithm (correctly excluded and exclusion error), we observe a similar pattern. While those households excluded by our algorithm are richer than those included by construction, even among those excluded, we see that those who do get NFSP in practice come from larger households with more educated heads, and cultivate larger maize areas. This suggests that while NFSP recipients are wealthier than non-recipients on average, there is overlap in the income distributions of recipients and non-recipients.

In this sense, there are some additional factors that can help explain who receives subsidized fertilizer in practice. For instance, farmers were asked in the survey whether they know the recommended amount of fertilizer to apply to their land. Among both the poorer, algorithm-selected households and the wealthier, non-selected households, we see that NFSP recipients are significantly more likely to say that they know what is recommended. Hence, farmers with greater knowledge of recommended practices may be more likely to seek out subsidized fertilizer. Additionally, as mentioned previously, being able to access a mobile phone is critical to participating in NFSP. In line with this, in both sets of algorithm-selected and non-selected farmers, farmers who access NFSP are significantly more likely to own a cell phone. Hence, it is possible that this programmatic feature plays a de facto role in determining access to subsidized fertilizer.

5.2 Mechanisms under soil health/ productivity targeting criteria

Table 10: Household characteristics by targeting outcome groups under the productivity-based targeting objective

Variable	Correctly Included (CI)	Correctly Excluded (CE)	Inclusion Error (IE)	Exclusion Error (EE)	p-value CI vs EE	p-value CE vs IE
Household size	5.64	5.23	5.52	5.28	0.076*	0.018**
Years of farming experience	31.88	27.63	27.40	28.68	0.034**	0.800
Household head age	53.57	50.90	51.34	52.22	0.286	0.576
Household head gender (Male=1)	0.79	0.71	0.79	0.73	0.114	0.001***
Head maximum years of education	11.92	9.78	11.54	10.32	0.000***	0.000***
Head marital status (Married=1)	0.78	0.71	0.80	0.73	0.167	0.000***
Primary occupation (Crop=1)	0.63	0.59	0.61	0.58	0.219	0.536
Formal saving account (Yes=1)	0.69	0.53	0.63	0.60	0.040**	0.000***
Credit take-up (Yes=1)	0.39	0.31	0.36	0.32	0.112	0.023**
Have any Insurance membership (Yes=1)	0.70	0.48	0.64	0.53	0.000***	0.000***
Monthly per capita food expenditure (KES)	8025.32	8622.01	8471.35	7883.23	0.862	0.827
Per capita annual consumption (KES)	483748.56	471320.00	510505.16	451004.38	0.425	0.182
Total asset value (KES)	218711.91	91592.18	207539.38	88902.76	0.000***	0.000***
Food secure (Yes=1)	0.40	0.26	0.43	0.25	0.000***	0.000***
Food gap (months)	1.81	2.37	1.68	2.44	0.000***	0.000***
Maize area (acres)	1.11	0.54	1.01	0.76	0.000***	0.000***
Awareness of fertilizer recommendation	0.41	0.27	0.42	0.32	0.026**	0.000***
Phone ownership (Yes=1)	0.97	0.93	0.98	0.91	0.010**	0.000***
Commercial rate	0.25	0.17	0.23	0.23	0.356	0.000***
Distance to road (km)	3.16	3.38	3.19	3.23	0.945	0.791
Self-reported soil quality	2.88	2.88	2.97	2.75	0.044**	0.040
Observations	2071					

Notes:The table compares mean differences across targeting groups to assess systematic differences in observable characteristics associated with the productivity based targeting criteria outcomes. The first four columns report group means.The last two columns report p-values from two-sample t-tests comparing the correctly included group with the exclusion error group, and the correctly excluded group with the inclusion error group. Significance levels are denoted as follows: *** p < 0.01, ** p < 0.05, and * p < 0.10. *Source*: Authors' calculations based on baseline household survey data.

We now consider targeting based on a productivity objective, using our preferred soil health proxy for the marginal returns to additional fertilizer. The results are shown in Table 10 (and the results using alternative productivity proxies are in the Appendix Tables A1 through A3). Again, even when focusing on only the households chosen by our algorithm as having the highest returns to fertilizer, we observe systematic differences between those who do versus do not currently receive NFSP benefits. High return farmers who do receive benefits come from larger, better off households with more educated household heads and more years of farming experience. Similar to the welfare-based analysis, we also see that among the farmers we target based on the productivity objective, those who actually get NFSP benefits are more likely to be aware of the ideal fertilizer recommendation for their plot, and more likely to own a cell phone. When we instead focus on those farmers who are not chosen by the algorithm as having high returns to fertilizer, we see broadly similar patterns, where recipients differ from non-recipients in similar systematic ways.

Taken together, we see that even after "controlling" in some sense for differences in welfare status and differences in marginal returns to fertilizer by just comparing NFSP receipt among individual who are (are not) chosen by our targeting algorithm, systematic differences between recipients and non-recipients remain. Hence, factors like land holdings, knowledge of fertilizer recommendations, and mobile phone ownership may play critical roles in determining who accesses subsidized fertilizer. Hence, even in the absence of the government of Kenya instating a formal targeting regime for NFSP, they may want to consider what policy interventions, such as subsidizing split bags of fertilizer (which may exclude fewer farmers with small land-holdings), educating farmers about recommended fertilizer application, or developing pathways to purchase subsidized fertilizer which do not require mobile phone access, could play in aligning the targeting of NFSP with the government's policy goals.

6 Conclusion

In this paper, we examine the targeting of Kenya's NFSP program that subsidizes chemical fertilizer for Kenyan farmers. Despite the purportedly universal nature of the NFSP program, we find that in practice, only 43% of farmers report receiving benefits. This means there is de facto targeting, and we can assess how this targeting aligns with various policy objectives. We find that, in general, the least well off farmers do not seem to be targeted by the program, and generally, beneficiaries are wealthier than non-beneficiaries. However, it also does not seem to be the case that the benefits are targeted at farmers with the highest marginal returns to fertilizer, which means that the current targeting regime is likely not maximizing the production gains that result from the use of additional fertilizer induced by the subsidy. At the same time, we show that simultaneously satisfying both targeting objectives is likely not possible. Hence, in potentially rethinking targeting or distribution mechanisms during the process of subsidy reform, one goal may need to be prioritized over the other. More broadly, our findings highlight a fundamental equity-efficiency trade-off in fertilizer subsidy design. While fertilizer subsidy programs are frequently expected to simultaneously increase agricultural productivity, improve food security, and support poorer households, the populations identified under productivity-based and welfare-based targeting criteria overlap only minimally. Ten percent of households are selected under both objectives, suggesting that a single targeting mechanism is unlikely to maximize both outcomes simultaneously. Consequently, subsidy reform is not merely an administrative challenge of improving beneficiary identification, but also a policy choice regarding which objectives should receive priority when public resources are limited. This contribution extends the existing literature beyond assessing targeting errors by quantifying the extent to which alternative policy objectives identify different beneficiary populations.

However, there are caveats that should be kept in mind when interpreting our results. First, as noted above, choosing ideal program beneficiaries under various objectives requires us to make assumptions, which may affect our results. Second, our analysis depends on proxies for both welfare and productivity, which are imperfect. This could also introduce additional measurement error, affecting the results. Third, since the soil testing was conducted at a similar time to the household survey, the soil test results reflect conditions *after* the long rains (around March to August) application of fertilizer and participation in NFSP reported in the survey. There was also a short rains season (around October to January) before the data collection, and the on-farm activities during the short rains may also affect the soil test results. The extent to which the application of fertilizer in the long rains and the activities conducted in the short rains affect the soil test is unknown, which is a limitation of the study. Finally, our analysis does not allow us to say anything about the marginality of a given farmer, and maximizing production/food supply through a fertilizer subsidy is only achieved if farmers use more fertilizer than they otherwise would have. Moreover, this fertilizer use must have positive returns, which might not be the case if soil health is very degraded or too much fertilizer is applied.

In terms of what this means for policy, if the Kenyan government decides to engage in "smart" targeting of their subsidy program, they may want to take a more intentional approach to identifying beneficiaries. The current program is not universal in practice, and the current targeting may not satisfy policy objectives. Notably, soil test data may be a tool that could help with smart targeting. If farmers have soil test data for their plots, the government could subsidize fertilizer for farmers whose plots would have the highest returns, or at least target the type of fertilizer offered based on this information. While getting soil test data for each farmer might be challenging, soil quality seems to be correlated geographically. Hence, perhaps ward-level soil testing could even be used to target the types of fertilizer offered to farmers. In any case, policymakers may consider which policy objectives are most important to satisfy with the NFSP, given the inherent tradeoffs between them.

As governments across Africa increasingly transition toward digital subsidy delivery systems, integrating agronomic information into farmer registries may provide an opportunity to improve both the efficiency and effectiveness of public agricultural expenditures. Future research should examine the operational feasibility and cost-effectiveness of implementing soil-informed targeting systems at scale, as well as their implications for agricultural productivity, household welfare, and the long-run sustainability of fertilizer subsidy programs.

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A Appendix

Table A1: Household characteristics by targeting outcome groups under the VCR based targeting mechanism

Variable	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	p-value CI vs EE	p-value CE vs IE
Household Size	5.70	5.19	5.51	5.29	0.027**	0.001***
Years of farming experience	29.02	27.90	28.27	28.15	0.529	0.610
Household head age	50.47	51.08	52.12	50.98	0.648	0.097*
Household head gender (Male=1)	0.81	0.72	0.77	0.70	0.004***	0.004***
Head maximum years of education	12.08	9.87	11.55	10.21	0.000***	0.000***
Head marital status (Married=1)	0.82	0.71	0.77	0.73	0.013**	0.000***
Primary occupation (Crop=1)	0.61	0.59	0.62	0.61	0.950	0.119
Formal saving account (Yes=1)	0.66	0.54	0.65	0.60	0.130	0.000***
Credit take-up (Yes=1)	0.41	0.30	0.37	0.36	0.201	0.000***
Have any insurance membership (Yes=1)	0.68	0.50	0.63	0.53	0.000***	0.000***
Monthly per capita food expenditure (KES)	8438.38	7797.50	8821.29	11017.83	0.234	0.062*
Per capita annual consumption expenditure (KES)	513170.63	434781.47	508229.91	526293.06	0.777	0.001***
Total asset value (KES)	211975.17	85262.47	207933.84	117177.91	0.000***	0.000***
Food secure (Yes=1)	0.46	0.27	0.41	0.32	0.001***	0.000***
Food gap (Months)	1.46	2.44	1.76	2.08	0.000***	0.000***
Maize area (acres)	1.24	0.52	0.98	0.83	0.000***	0.000***
Awareness of fertilizer recommendation	0.44	0.26	0.40	0.39	0.228	0.000***
Phone (Yes=1)	0.97	0.92	0.97	0.92	0.008***	0.000***
Commercial rate	0.43	0.12	0.19	0.44	0.636	0.000***
Distance to road	2.92	3.01	3.28	3.14	0.828	0.645
Self reported soil quality	3.07	2.80	2.93	2.95	0.056*	0.000***
Observations	3105					

Notes: The table compares mean differences across targeting groups to assess systematic differences in observable characteristics associated with the VCR targeting criteria outcomes. The first four columns report group means.The last two columns report p-values from two-sample t-tests comparing the correctly included group with the exclusion error group, and the correctly excluded group with the inclusion error group. Significance levels are denoted as follows: *** p < 0.01, ** p < 0.05, and * p < 0.10. *Source*: Authors' calculations based on baseline household survey data.

Table A2: Household characteristics by targeting outcome groups under the Output-input Price Ratio criteria based targeting mechanism

Variable	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	p-value CI vs EE	p-value CE vs IE
Household Size	5.61	5.21	5.54	5.21	0.040**	0.000***
Years of farming experience	28.67	27.81	28.37	28.75	0.952	0.425
Household head age	50.98	51.02	51.96	51.33	0.771	0.125
Household head gender (Male=1)	0.79	0.72	0.77	0.70	0.012**	0.002***
Head maximum years of education	11.94	9.88	11.60	10.23	0.000***	0.000***
Head marital status (Married=1)	0.79	0.71	0.78	0.73	0.088*	0.000***
Primary occupation (Crop=1)	0.61	0.59	0.62	0.62	0.910	0.106
Formal saving account (Yes=1)	0.65	0.54	0.65	0.58	0.096*	0.000***
Credit take-up (Yes=1)	0.39	0.30	0.38	0.36	0.507	0.000***
Have any insurance membership (Yes=1)	0.65	0.50	0.64	0.53	0.004***	0.000***
Monthly per capita food expenditure (KES)	8522.26	7920.19	8792.89	10905.26	0.321	0.108
Per capita annual consumption expenditure (KES)	511764.56	440527.78	508680.69	509625.22	0.966	0.002***
Total asset value (KES)	201513.95	87680.31	210729.66	108898.41	0.000***	0.000***
Food secure (Yes=1)	0.45	0.27	0.41	0.31	0.001***	0.000***
Food gap (Months)	1.47	2.44	1.75	2.03	0.000***	0.000***
Maize area (acres)	1.40	0.52	0.94	0.90	0.000***	0.000***
Awareness of fertilizer recommendation	0.44	0.27	0.40	0.38	0.167	0.000***
Phone (Yes=1)	0.97	0.92	0.97	0.93	0.032**	0.000***
Commercial rate	0.43	0.13	0.19	0.44	0.704	0.000***
Distance to road	2.88	2.97	3.28	3.37	0.671	0.592
Self reported soil quality	3.07	2.81	2.94	2.94	0.056*	0.000***
Observations	3105					

Notes: The table compares mean differences across targeting groups to assess systematic differences in observable characteristics associated with the Output/input price ratio targeting criteria outcomes. The first four columns report group means.The last two columns report p-values from two-sample t-tests comparing the correctly included group with the exclusion error group, and the correctly excluded group with the inclusion error group. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. *Source*: Authors' calculations based on baseline household survey data.

Table A3: Household characteristics by targeting outcome groups under maize sold (kg) targeting mechanism

Variable	Correctly Included	Correctly Excluded	Inclusion Error	Exclusion Error	p-value CI vs EE	p-value CE vs IE
Household Size	5.73	5.20	5.52	5.40	0.239	0.000***
Years of farming experience	29.85	27.92	28.13	28.35	0.471	0.753
Household head age	51.43	51.11	51.83	50.24	0.462	0.227
Household head gender (Male=1)	0.82	0.71	0.77	0.77	0.340	0.000***
Head maximum years of education	13.46	9.81	11.28	11.97	0.022***	0.000***
Head marital status (Married=1)	0.84	0.71	0.77	0.79	0.309	0.000***
Primary occupation (Crop=1)	0.66	0.59	0.61	0.62	0.528	0.302
Formal saving account (Yes=1)	0.70	0.54	0.64	0.66	0.446	0.000***
Credit take-up (Yes=1)	0.40	0.32	0.38	0.27	0.127**	0.000***
Have any insurance membership (Yes=1)	0.65	0.50	0.64	0.62	0.631	0.000***
Monthly per capita food expenditure (KES)	8982.30	8282.55	8685.09	9499.07	0.698	0.550
Per capita annual consumption expenditure (KES)	554537.19	445459.31	499763.91	536865.19	0.782	0.011**
Total asset value (KES)	363733.88	85250.18	176092.77	185498.75	0.003***	0.000***
Food secure (Yes=1)	0.09	0.32	0.20	0.14	0.191	0.000***
Food gap (Months)	1.09	2.41	1.82	1.80	0.000***	0.000***
Maize area (acres)	2.06	0.52	0.82	1.39	0.004***	0.000***
Awareness of fertilizer recommendation	0.48	0.28	0.39	0.42	0.321	0.000***
Phone (Yes=1)	0.97	0.92	0.97	0.97	0.798***	0.000***
Commercial rate	0.51	0.16	0.19	0.53	0.451	0.000***
Distance to road	3.55	3.00	3.12	3.57	0.991	0.821
Self reported soil quality	3.07	2.81	2.94	3.15	0.381	0.000***
Observations	3105					

Notes:The table compares mean differences across targeting groups to assess systematic differences in observable characteristics associated with maize sold(kg) targeting criteria outcomes. The first four columns report group means.The last two columns report p-values from two-sample t-tests comparing the correctly included group with the exclusion error group, and the correctly excluded group with the inclusion error group. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. *Source*: Authors' calculations based on baseline household survey data.