

Targeting social programs at the margin: when scale-up dominates selection

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Abstract

We develop a framework to assess when social programs should prioritize expanding coverage rather than improving targeting. Instead of treating universalism and targeting as a binary choice, we derive three operational rules: a data-light binary rule using only poverty and coverage rates; a cost-adjusted ternary rule incorporating administrative costs; and a fully specified continuous optimum. Applying the framework to Mozambique's social pension, we find that zero targeting effort may be optimal in roughly half of administrative posts. Reallocating existing resources using only the binary rule could increase welfare by about 20%, achieving two-thirds of the gains from full optimization.

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1 Introduction

Social policy always operates under second-best conditions. The theoretical ideal of perfectly efficient, lump-sum transfers conditioned on individual ability is precluded by pervasive information, administrative and financial constraints ([Mirrlees, 1971](#); [Kanbur, 1987](#)). These challenges are typically more severe in low- and middle-income contexts, where state capabilities and information infrastructures are comparatively weak. As such, the fundamental question of the extent to which social programs should be targeted remains open ([Galtier, 2026](#)).

Existing academic literature has generally framed the answer to this question in all-or-nothing terms. A sceptical view of targeting draws on a range of ethical, practical and political economy considerations in favour of universalism ([Besley and Kanbur, 1991](#); [Sen, 1995](#); [Mkandawire, 2005](#); [Schüring and Gassmann, 2016](#); [Banerjee et al., 2019](#)). Scholars have contended that narrowly-targeted programs are often politically fragile, lacking a broad base of social and political support necessary for effective performance and sustainability. Targeting can be administratively complex and expensive to implement, potentially diverting resources away from benefit payments toward overheads. Evidence also suggests that targeting can perform poorly in practice, generating material errors (e.g., [Brown et al., 2018](#)), as well as social divisions and stigma (e.g., [Ellis, 2012](#)). And, as per [Banerjee \(1997\)](#), the finer the targeting, the greater the scope for contestation and corruption in delivery.

An opposite view holds that targeting is not only technically feasible but also frequently cost-effective ([Hanna and Olken, 2018](#)). A key argument here is that universal programs in resource-constrained settings are likely to involve (at best) moderate transfers to those in need. At the same time, targeting can be a fairly low-cost and sufficiently accurate tool, at least to exclude a considerable swathe of the ineligible. Consistent with this perspective, a large literature investigates *how* best to target, developing and testing methods such as proxy means tests and community targeting (see for instance [Devereux et al., 2017](#); [Hanna and Karlan, 2017](#)). Taking stock of this literature, [Banerjee et al. \(2024\)](#) argue that targeting is generally worthwhile across a range of contexts despite its imperfections.

From a practical standpoint, the predominant binary framing of targeting is not necessarily helpful. Whilst universalism may be a long-run aspiration, social programs are rarely established at scale from scratch. Rather, they often evolve from (collections of) smaller or pilot programs that are gradually adjusted as resources, political priorities, and administrative capacities change (see [Slater, 2023](#)). For instance, as [Lindert et al. \(2007\)](#) describe, Brazil's

flagship *Bolsa Família* program was formed from the consolidation and harmonization of four separate cash transfer schemes, the aim being to reduce what were ‘considerable gaps and duplications in coverage’. Thus, a key question for policymakers is not the binary one of whether or not to target across the population as whole, but a pragmatic one of resource allocation. Given existing funds and capacities, the relevant challenge is: *when* is it more effective to invest in improving the accuracy of existing targeting schemes, versus scaling-up to reach more people?

This study seeks to answer this question. We develop a simple analytical framework to clarify the trade-off between scaling-up program coverage (quantity expansion) and improving targeting accuracy (quality enhancement). Throughout, we work with a flexible welfare function in which the planner places a weight on leakage relative to correct inclusion. As we show, under a fixed uniform transfer this single parameter is sufficient to characterise the welfare trade-off: exclusion errors are mechanically linked to correct inclusion through the targeting identity, and so do not require a separate weight to be identified.

We present four propositions that link observed rates of poverty and program quotas to the welfare effectiveness of alternative social program designs. First, we show that targeting metrics, such as the share of eligible beneficiaries and coverage of the eligible, are interdependent. Second, we introduce a diagnostic rule-of-thumb, denoted the Relative Effectiveness of Scale-up (RES), which quantifies the marginal welfare gain from expanding coverage relative to improving targeting accuracy. Third, we derive analytical bounds on targeting performance metrics, which tighten under minimal assumptions about non-regressive targeting. Critically, these make the RES metric computable when detailed targeting data is unavailable, as is often the case in practice. Fourth, we extend the analysis to a stylized budget-constrained optimization problem, where targeting effort is costly and potentially subject to diminishing returns.

The propositions show that optimal targeting effort is decreasing in both the unit cost of effort and the poverty rate. We also show that a cost-adjusted version of the simple RES rule recovers exactly the corner conditions of the formal optimisation problem. This delivers a hierarchy of three operational rules of increasing sophistication: a binary rule based on the data-light RES; a ternary rule based on the cost-adjusted RES, evaluated at both the zero-effort and full-effort corners; and the continuous optimum from the full optimisation. Crucially, the cost-adjusted rule requires only a rough sense of the maximum relative cost of targeting, not granular cost data. Overall, the model predicts that zero targeting effort, such as that achieved by random selection among the presumed eligible, may well be optimal in high-poverty, low-capacity (high targeting cost) contexts.

We apply this framework to Mozambique’s national social pension, the elderly component of the *Programa de Subsídio Social Básico* (PSSB). Combining administrative beneficiary data and 100% census micro-data at the sub-district level, we compute poverty and quota rates for each administrative post. Our empirical results reveal substantial geographic variation, with around 50% of the elderly population residing in locations where the neutral RES rule-of-thumb exceeds unity – an indication that for a non-trivial share of the target population, expansion of program coverage may yield higher welfare returns than improving targeting accuracy.

Further interrogating these results, we estimate the optimal amount of targeting (by location) under alternative assumptions as regards its maximum cost share. At reference values, which reflect an optimistic assessment of the status quo, application of the simple binary RES rule, which uses only observed poverty and coverage rates, raises welfare per dollar spent by almost 20%, recovering over two-thirds of the optimum’s gains. The cost-adjusted ternary RES rule, which additionally uses an upper-bound estimate of targeting costs, effectively closes all of the remaining gap. Together, the results suggest that simple rules-of-thumb can provide valuable guidance to policymakers in information-constrained environments.

Our main contribution is to offer practical decision-making tools to guide how targeting effort can be adapted across contexts. This builds on various strands of existing literature, including models of targeting under imperfect information (e.g., [Ravallion and Chao, 1989](#); [Besley and Coate, 1992](#); [Lanjouw and Ravallion, 1999](#)), debates on the political and operational feasibility of effective large-scale social programs (e.g., [Gelbach and Pritchett, 2001](#); [Asri et al., 2022](#)), and estimates of the initial and recurrent costs of targeting ([Coady et al., 2004](#); [White et al., 2015](#)). Relative to the recent synthesis in [Banerjee et al. \(2024\)](#), who suggest that targeting is generally worthwhile, our framework provides a principled basis to identify the sub-set of contexts in which that conclusion may be less certain – namely, those with high poverty incidence and tight quotas, where the mechanical arithmetic of coverage can dominate the welfare gains from improved selection.

Our framework also connects to the literature on spatial or geographic targeting ([Baker and Grosh, 1994](#); [Schady, 2002](#); [Elbers et al., 2007](#)), which has established that allocating program resources at disaggregated spatial units often improves overall targeting performance. In practice, many social programs embed this insight in a two-stage allocation architecture: a central authority sets geographic budgets (such as at the province or district level), and local administrators spend these budgets through some beneficiary selection mechanism. This two-stage architecture is itself a middle position between pure universalism and blanket individual targeting: budgets embed coarse geographic targeting, while within-location decisions reflect the trade-off between accurate selection and coverage. The spatial targeting

literature has largely focused on the first stage. We focus on the second and ask: given the geographic allocation that exists, how should local targeting efforts be calibrated?

Throughout, our focus is on the merits of targeting at the margin. This reflects a constraint that beneficiaries of many existing schemes, such as social pensions, cannot be easily or quickly removed; and geographic program budgets are often as much political as technical. Indeed, in the empirical case examined here, it is clear that a counterfactual exercise that simply reallocated the existing quota of beneficiaries across locations could yield large notional welfare gains. But this is not operationally informative because such a reallocation is not on the table. Our analysis therefore characterises the marginal problem, which is how to direct future program growth across heterogeneous locations.

2 The arithmetic of targeting

2.1 Environment

The environment in which the problem of interest arises is one in which a planner seeks to direct transfers to a target population. Membership in this group, referred to as the poor for convenience, may be defined by low permanent income, multidimensional deprivation, or some other policy-relevant notion of need, but one that is not directly observable without error. Instead, eligibility is determined using imperfect indicators, such as proxy-means scores or community assessments. Investment in targeting improves the precision of these indicators and therefore the accuracy of selection. We assume that individuals do not strategically manipulate the information used for targeting. The central challenge is thus the state's imperfect measurement of need, rather than private information or hidden actions on the part of beneficiaries. This corresponds closely to the tagging framework of [Akerlof \(1978\)](#), in which transfers are conditioned on imperfectly observed correlates of type.

In this setting, an eligible individual may be excluded for two reasons. First, programme coverage may be insufficient to reach all members of the target population, so that some remain uncovered even under perfect classification. Second, targeting errors may allocate benefits to non-target individuals, reducing the number of places available for those intended to receive support. The first is a budget constraint; the second is an informational problem. As shown by the targeting identity below, however, the two are closely related.

We abstract from an alternative environment in which eligibility is private information that cannot be verified and must therefore be elicited through incentive-compatible mechanisms

such as ordeals, self-selection, or asset tests (Nichols and Zeckhauser, 1982; Besley and Coate, 1992; Golosov and Tsyvinski, 2006). In such settings, the costs of targeting are borne primarily by beneficiaries rather than the programme. For the elderly social pension studied here, however, this framework is less relevant. In particular, deprivation is largely a persistent rather than manipulable characteristic, and ordeal-based screening may exclude precisely the frail and isolated individuals the programme is intended to reach.

To describe this more formally, consider a poverty-targeted program that allocates fixed per capita transfers of value t within a population of size N . Among these, Q^* individuals are deemed eligible (hereafter “the poor”), and Q are selected as actual beneficiaries by some (possibly costly) administrative mechanism. The coverage rate or quota thus is $q = Q/N$, and the poverty rate is $q^* = Q^*/N$. Both are assumed to be known or estimated with reasonable accuracy at an aggregate spatial level (e.g., by administrative localities).

The probability of being selected as a beneficiary can be defined in two complementary ways. First we have:

$$\begin{aligned}
 P(\text{Beneficiary}) &= P(\text{Beneficiary \& Eligible}) + P(\text{Beneficiary \& Non-eligible}) \\
 &= P(\text{Eligible} \mid \text{Beneficiary}) \cdot P(\text{Beneficiary}) \\
 &\quad + P(\text{Non-eligible} \mid \text{Beneficiary}) \cdot P(\text{Beneficiary}) \\
 &= \alpha \cdot q + (1 - \alpha) \cdot q
 \end{aligned} \tag{1}$$

This is just a weighted average of the unconditional selection probability, $P(\text{Beneficiary}) = q$, with weights given by the targeting success rate: $\alpha = P(\text{Eligible} \mid \text{Beneficiary})$, and the respective leakage or Type I error rate: $1 - \alpha$. In working with a reduced-form accuracy statistic (α) our results remains agnostic as to the source of classification errors, be it due to measurement noise, elite capture, or eligibility misreporting. In turn, the marginal trade-off between coverage and accuracy depends only on the cost of reducing inaccuracy, not the particular mechanism by which it is generated.

The second definition of the same selection probability is:

$$\begin{aligned}
 P(\text{Beneficiary}) &= P(\text{Beneficiary} \mid \text{Eligible}) \cdot P(\text{Eligible}) \\
 &\quad + P(\text{Beneficiary} \mid \text{Non-eligible}) \cdot P(\text{Non-Eligible}) \\
 &= \lambda \cdot q^* + \gamma \cdot (1 - q^*)
 \end{aligned} \tag{2}$$

Here, λ captures the probability that a given eligible individual is a beneficiary (responding to the question: ‘of all the poor, what share actually receives benefits?’), while γ captures the share of the non-eligible group incorrectly covered by the program.

2.2 Planner's objective

Now consider an objective function facing policymakers, posed in a form that admits operational analysis. We value a marginal unit of transfer to beneficiary i at ω_i , its social marginal welfare weight (Saez and Stantcheva, 2016). We adopt the money-metric convention in which ω_i is expressed in units of social value per unit of transfer, so that it already embeds both the planner's distributional preferences and the recipient's marginal utility of income. Welfare from a uniform transfer t paid to the set of beneficiaries B is then:

$$W = \sum_{i \in B} \omega_i t \quad (3)$$

where, for a transfer that is small relative to baseline consumption, ω_i is approximately constant over $[c_i, c_i + t]$.

We require only that the weights take a two-type form: $\omega_E = 1$ for eligible (correctly-included) individuals, a natural normalisation; and $\omega_N = -\beta_L$ for the non-eligible, so that $\beta_L \equiv -\omega_N/\omega_E$ captures the planner's relative leakage aversion. Splitting beneficiaries into the share of eligibles, αq , and non-eligibles, $(1 - \alpha)q$, and dividing (3) by the constant tN yields the normalised maximand:¹

$$Z = \alpha q - \beta_L(1 - \alpha)q, \quad (4)$$

which is the primary operational object we use throughout. In what follows, let $k \equiv 1 + \beta_L$ denote the sum of welfare weights with correct inclusion normalised to unity, and define the composite parameter:

$$\theta_L \equiv \frac{\beta_L}{k} = \frac{\beta_L}{1 + \beta_L} \in (-\infty, 1). \quad (5)$$

As we show below, θ_L is a sufficient statistic for all subsequent welfare-weight-sensitive results. It also admits a transparent interpretation in terms of the ratio of social marginal welfare weights on non-eligible and eligible recipients, ω_N/ω_E . Specifically, $\theta_L = -\omega_N/(\omega_E - \omega_N)$, such that θ_L is increasing in the planner's relative aversion to leakage.

Three reference cases delimit the empirically relevant range. First, when $\omega_N/\omega_E \in (0, 1]$,

¹ The money-metric formulation is also practical because it requires no observation of utility or its proxies (income, consumption) across the population, which is rarely available. In many low-income contexts, for instance, informal economic activities are predominant, relevant data on these proxies are missing, outdated or subject to large measurement error, and incomes contain a material stochastic component (e.g., Beuermann et al., 2025).

leakage carries positive but diminished welfare value, which is the case obtained under a CRRA social welfare function of the form $U = \sum_i (c_i + b_i)^{1-\rho}/(1-\rho)$, as used by [Hanna and Olken \(2018\)](#), where the money-metric weight is the marginal utility of income, so that: $\omega_N/\omega_E = u'(c_N)/u'(c_E) = (c_E/c_N)^\rho$. Standard inequality-aversion parameters such as $\rho \in [1, 3]$ and plausible income ratios, $c_N/c_E \in [3, 6]$, generate $\theta_L \in [-0.5, 0)$. Second, $\theta_L = 0$ recovers the [Coady and Skoufias \(2004\)](#) case in which leakage is welfare-neutral and only correct inclusion is valued. Third, positive values $\theta_L > 0$ correspond to a planner who treats leakage as directly welfare-reducing, motivated either by a shadow price on fiscal resources reflecting the opportunity cost of public funds ([Auriol and Warlters, 2012](#)) or by political-economy concerns about programme capture ([Banerjee, 1997](#); [Gelbach and Pritchett, 2001](#)).

To interpret these magnitudes, consider the welfare value of a leaked unit relative to a correctly delivered one. At $\theta_L = 0.5$ (equivalently $\beta_L = 1$), a leaked unit imposes a welfare cost exactly equal in magnitude to the gain from a correct one; at $\theta_L = -0.5$ ($\beta_L = -1/3$), a leaked unit instead yields a welfare gain equal to one third of that from a correct one. The two cases are symmetric in θ_L , being equidistant from the reference $\theta_L = 0$, but not in the underlying weight β_L , which is a consequence of the nonlinearity of the map $\theta_L = \beta_L/(1 + \beta_L)$. We therefore state our main analytical results in terms of θ_L , taking $\theta_L = 0$ as the reference, and report sensitivity across the symmetric interval $[-0.5, 0.5]$ in the empirical application.

A final question is whether the welfare specification should include a separate weight on exclusion errors, capturing rights-based or Sen-type concerns about failing to reach the poor. Under a fixed uniform transfer, however, exclusion is not an independent dimension of welfare in equation (4): the targeting identity (Proposition 2.1 below) implies that exclusion equals $q^*(1 - \lambda) = q^* - \alpha q$, so any increase in correct inclusion at fixed q mechanically reduces exclusion one-for-one. So, a planner who places greater value on reaching the poor need only scale up the existing program (raise q). As shown in Appendix B.1, a separate exclusion weight β_E would enter the marginal conditions only by rescaling the correct-inclusion coefficient, but is not separately identified given the targeting identity.

2.3 Quantity expansion vs. quality enhancement

This subsection presents three propositions speaking to the trade-off between quantity expansion and targeting quality in social program design. Throughout, we maintain two assumptions: (i) rates of program coverage (q) and formal eligibility (q^*) in the population are known at meaningful levels of spatial (dis)aggregation, perhaps reflecting some prior

allocation of program budgets across geographic locations (e.g., [Elbers et al., 2007](#)); but (ii) the policy-maker does not have accurate information on local targeting performance. Our view is that in such circumstances of imperfect information that robust operational guidance on the direction of social program reform can be most helpful.

Proposition 2.1. *The targeting identity*

In any targeting scheme, the number of beneficiaries who are eligible must equal the number of eligibles who are beneficiaries: $q^ \lambda \equiv q \alpha$.*

Reflecting the equivalence between the first terms on the RHS of equations (1) and (2), this says that the product of the poverty rate and eligibility coverage rate is equal to the product of the quota and the targeting success rate.² An immediate corollary is that the ratio of targeting success to eligibility coverage (a ratio of two unknowns) equals the ratio of two knowns, namely that of the poverty rate and the quota:

$$\frac{\alpha}{\lambda} \equiv \frac{q^*}{q} \quad (6)$$

The implication is that targeting errors are mechanically interdependent: if coverage is below the poverty rate ($q < q^*$), under-coverage necessarily exceeds leakage.

As an aside, note that the Coady-Grosh-Hoddinott (CGH) index ([Coady et al., 2004](#)) provides an alternative perspective on the targeting identity (equation 6). Proposed as a general measure of the extent to which a program targets the poorest (progressiveness), it compares a metric of the share of benefits going to the poorest (the eligible) versus the share expected under a distribution-neutral benchmark. While this measure ideally defines coverage in terms of the total value of transfers, if program benefits do not vary substantially across individuals (e.g., cash transfers are uniform) then the index can be approximated by the ratio of targeting success to the poverty rate:

$$\text{CGH} \approx \frac{\alpha}{q^*} = \frac{\lambda}{q} \quad (7)$$

Echoing analysis to come, this ratio equals unity under a benchmark assumption that selection is non-regressive and also suggests that absolute improvements in targeting performance will be valued in inverse proportion to the poverty rate.³

□

² See Appendix Table A1 for illustration.

³ For instance: $\frac{\alpha + \Delta}{q_1^*} > \frac{\alpha + \Delta}{q_2^*}$ if $q_1^* < q_2^*$.

The welfare function (4) depends on two primary levers available to policymakers: changes to the targeting success rate (α), which effectively proxies for the welfare impact of the program given a fixed set of beneficiaries; and changes to the quota (q), which refers to the size of the set of beneficiaries. The relevant question is when one of these levers should be prioritized over the other. A preliminary answer comes from the marginal rate of technical substitution between the two.

Proposition 2.2. *Relative Effectiveness of Scale-up*

Given the welfare maximand Z (equation 4), the relative effectiveness of expanding program coverage versus improving targeting accuracy is given by:

$$\text{RES} \equiv \frac{\partial Z / \partial q}{\partial Z / \partial \alpha} = \frac{\alpha - \theta_L}{q} \quad (8)$$

where θ_L is as defined in equation (5). When $\text{RES} > 1$, marginal welfare gains from coverage expansion are expected to outweigh gains from improvements in targeting.

In the baseline case $\theta_L = 0$, the RES reduces to the simple ratio α/q , a practical rule-of-thumb. More generally, the $-\theta_L/q$ adjustment term lends to an increasingly conservative evaluation of pure scale-up as leakage aversion rises: higher β_L raises θ_L , tilting the RES away from favouring scale-up. Intuitively, scale-up mechanically expands the pool of beneficiaries and thus the absolute volume of leakage, so a planner more averse to leakage is more reluctant to expand coverage at the margin. Appendix B.1 extends the RES to incorporate welfare weights on excluded eligibles, showing this only modifies the denominator of θ_L , such that Sen-type aversion to exclusion translates to lower values of this parameter holding other weights fixed.

□

The RES formula in equation (8) depends on the targeting success rate α , which we have assumed the policymaker does not fully observe. To operationalize the RES, we derive analytical bounds on α (and its counterpart λ) that depend only on the known parameters q and q^* .

Proposition 2.3. *Bounds on targeting performance*

For any feasible allocation of program benefits across eligible and non-eligible groups, the

targeting performance metrics must satisfy:

$$\max \left(0, \frac{q + q^* - 1}{q} \right) \leq \alpha \leq \min \left(1, \frac{q^*}{q} \right) \quad (9)$$

$$\max \left(0, \frac{q + q^* - 1}{q^*} \right) \leq \lambda \leq \min \left(1, \frac{q}{q^*} \right) \quad (10)$$

These bounds, summarized in Appendix Table A2, are derived by fixing $\gamma \in (0, 1)$ at either of its extremes, and solving for the remaining unknown parameters in equations (1) or (2). The expressions show that upper bounds on the success rate (eligibility coverage) are inversely proportional to the quota (poverty rate) – i.e., for $q < q^*$ the higher the poverty rate, the lower the upper bound on the coverage of the eligible. Substituting these bounds for α into the RES formula (8) provides strict lower and upper bounds on the RES that are now computable from observable parameters and given welfare weights alone.

By way of extension, note that if targeting is minimally non-regressive, requiring that selection of beneficiaries is no worse than random (see also Lastunen et al., 2025), then the targeting success metrics will satisfy tighter lower bounds:

$$\alpha \geq q^*; \quad \lambda \geq q \quad (11)$$

Applying these yields a practical lower bound, which we refer to as the *neutral* RES (RES_n), representing a simple rule-of-thumb for decision-makers:

$$\text{RES}_n \equiv \frac{q^* - \theta_L}{q} \quad (12)$$

In the baseline case $\theta_L = 0$, this simplifies to the ratio: q^*/q (also equation 6).

To build intuition, Table 1 sets out a range of combinations for what are assumed to be two known inputs (q, q^*), and derives corresponding bounds on the targeting success rate, eligibility coverage rate and the baseline RES under $\theta_L = 0$. As might be expected, while the interval between the upper and lower bounds on the targeting parameters often can be large, they are far from uninformative and tighten considerably if we assume targeting is minimally non-regressive. For instance, in the first row, where the quota far exceeds the poverty rate, the upper bound on the share of beneficiaries who are eligible is at best 0.28 while a neutral (lower) bound is 0.24. The RES provides unambiguous guidance as to the expected relative gains from program expansion versus improved targeting.

□

Table 1: Numerical examples of targeting performance bounds

Inputs		α		λ		RES ($\theta_L = 0$)	
q^*	q	Lower	Upper	Lower	Upper	Neutral	Upper
0.20	0.85	0.06	0.24	0.25	1.00	0.24	0.28
0.35	0.70	0.07	0.50	0.14	1.00	0.50	0.71
0.20	0.33	0.00	0.62	0.00	1.00	0.62	1.89
0.60	0.75	0.47	0.80	0.58	1.00	0.80	1.07
0.50	0.55	0.09	0.91	0.10	1.00	0.91	1.65
0.25	0.20	0.00	1.00	0.00	0.80	1.25	5.00
0.80	0.50	0.60	1.00	0.38	0.63	1.60	2.00
0.65	0.40	0.13	1.00	0.08	0.62	1.63	2.50
0.80	0.25	0.20	1.00	0.06	0.31	3.20	4.00

Source: own derivations.

Notes: table shows illustrative combinations taking poverty and coverage rates as inputs (q^* and q), then calculating resulting (lower, upper or neutral) bounds on the targeting success rate (α), eligibility coverage rate (λ), and the Relative Effectiveness of Scale-up (RES) under $\theta_L = 0$; when the RES exceeds unity then marginal gains from expanding program coverage are expected to exceed gains from improving targeting accuracy.

2.4 Optimal targeting effort

While the preceding analysis offered practical tools to assess targeting quality in the absence of direct measures of leakage or under-coverage, it was silent on costs. We now make the trade-off between program expansion and selection explicit via a budget constraint: $B = tQ + cN$, where B is the variable portion of the overall budget allocated to the program. We assume the policy variable here is c , which captures the cost of screening per individual in the population, while transfers are fixed at a value of t per beneficiary. Defining $c = x \cdot (\mu B/N)$ re-expresses the former targeting cost as the product of two terms: $\mu B/N$, the share $\mu \in [0, 1]$ of the total per population budget required to achieve maximal targeting success; and $x \in [0, 1]$, a decision parameter representing how much of this maximum cost the policymaker chooses to bear. This constraint can be rearranged to express the quota as a function of the budget and other parameters:

$$\begin{aligned}
 Q &= B(1 - x \cdot \mu)/t \\
 \implies q &= (b/t)(1 - x \cdot \mu)
 \end{aligned} \tag{13}$$

We interpret μ as a technology parameter reflecting the share of variable program costs required to achieve the maximum feasible targeting precision in a given context. It is equivalent to the slope of the trade-off between x and q , or the price of targeting effort. Plausibly, it

varies across contexts due to differences such as capacity constraints, infrastructure quality, and registry digitisation. This includes not only direct expenditures on data collection, verification, and eligibility scoring systems (e.g., implementing and maintaining a proxy means test), but also indirect or hidden costs (see also Slater, 2023). In turn, x represents the policy lever determining how much of this maximum is actually deployed. A setting with high μ is one where fully-implemented targeting is relatively expensive. The product $x \cdot \mu \leq \mu$ thus gives the share of the program budget actually devoted to targeting.

Next, we require a behavioural equation linking costly effort to the targeting success rate. For ease of analysis, we assume this is an increasing concave function in q^* and x :

$$\alpha = f(q^*, x) \quad (14)$$

meaning that $\partial\alpha/\partial x = f'_x \geq 0$, etc. We also assume bounds on $0 \leq \alpha \leq 1$ are always satisfied and $f(q^*, x = 0) = q^*$, implying that if no effort is allocated to targeting then $\alpha = q^*$, as per the benchmark non-regressive scenario of (11).⁴

Pulling this together, the policy maximand of equation (4) is a non-linear function of x :

$$Z(x) = k \cdot \frac{b(1 - x\mu)}{t} [f(q^*, x) - \theta_L] \quad (15)$$

where $b = B/N$ is the per capita variable budget.

Solving the relevant first-order condition and applying the constraints $0 \leq x \leq 1$ yields our final proposition:

Proposition 2.4. *Optimal targeting effort*

Optimal targeting effort, $x^ \in [0, 1]$, satisfies:*

$$x^* = \begin{cases} 0, & \text{if } \mu \geq \frac{f'_x}{q^* - \theta_L} \\ 1, & \text{if } \mu \leq \frac{f'_x}{f'_x + \bar{\alpha} - \theta_L} \\ \frac{f'_x - \mu[f(q^*, x^*) - \theta_L]}{f'_x \mu}, & \text{otherwise} \end{cases} \quad (16)$$

where $\bar{\alpha} = f(q^*, 1)$ and we assume $q^* > \theta_L$ (the program is non-regressive in welfare terms at random targeting). For proof see Appendix B.2.

⁴ A more complete model would recognize that targeting is expected to be more difficult as the standard deviation of the underlying but unobserved target variable – say, permanent income – increases.

In the baseline case $\theta_L = 0$, the threshold on μ for zero effort reduces to f'_x/q^* , and that for full effort to $f'_x/(f'_x + \bar{\alpha})$. Raising θ_L (via higher β_L) shrinks the zero-effort region: more weight on leakage justifies incurring targeting costs to reduce it.

While generic, Proposition 2.4 raises the possibility that optimal targeting effort may be located at or close to its zero lower bound. This would occur where additional targeting effort induces a relatively large budgetary cost, where the poverty rate is already high, or where marginal gains in the success rate from higher effort are low. Minimally, it follows that in contexts with heterogeneous rates of poverty, a one-size-fits-all targeting effort is likely to be sub-optimal, and zero effort may indeed be optimal in some cases.

Application. To make the trade-off implicit in equation (16) concrete, consider a minimal specification for the targeting technology:

$$\alpha = q^* + x(1 - q^*)^\phi \quad (17)$$

which says that maximum targeting effort closes the gap between the non-regressive benchmark by $(1 - q^*)^\phi$. Here, $\phi \geq 1$ governs concavity in the targeting technology, capturing the idea that in higher poverty locations it is more difficult to distinguish between the poor and the non-poor.⁵ At $\phi = 1$ the gap is fully closed and full effort delivers perfect targeting $\alpha = 1$; at $\phi > 1$ a residual gap remains even at $x = 1$, reflecting irreducible errors in any practical selection process. We choose $\phi = 1$ as our base case as it represents the upper envelope of admissible concave targeting technologies. That is, any concave f satisfying the non-regressive floor and bounded above by one has $f'_x(q^*, 0) \leq 1 - q^*$; the linear form attains this upper bound with equality and so delivers the most optimistic estimate of the marginal returns to targeting at the benchmark.⁶ Nonetheless, we also report sensitivity to alternative values for ϕ .

Under (17) the optimal effort function (16) admits a simple closed form solution (see Appendix B.3):

$$x^* = \begin{cases} 0, & \text{if } \mu \geq \frac{(1 - q^*)^\phi}{q^* - \theta_L} \\ 1, & \text{if } \mu \leq \frac{(1 - q^*)^\phi}{2(1 - q^*)^\phi + q^* - \theta_L} \\ \frac{(1 - q^*)^\phi - \mu(q^* - \theta_L)}{2\mu(1 - q^*)^\phi}, & \text{otherwise} \end{cases} \quad (18)$$

⁵ An alternative is to allow for concavity in x , but this does not allow for closed form solutions to the optimization problem.

⁶ The upper-envelope interpretation means that if targeting does not pay under this most optimistic assumption (with a concave technology), it does not pay under any less optimistic one.

The criterion $\mu(q^* - \theta_L) \geq (1 - q^*)^\phi$ has an intuitive reading: zero effort is optimal when the cost of targeting (scaled by the adjusted poverty rate) exceeds the scope for improvement relative to the non-regressive benchmark. At $\phi = 1$, the share of locations satisfying this criterion provides a conservative lower bound on the zero-effort share under any concave f compatible with (11). Admittedly, the notion of a zero-effort corner may appear strong; but it just says that even the smallest investment in targeting is expected to reduce welfare relative to pure random selection given the price of targeting effort (μ). The intuition follows directly from the opportunity cost of targeting: as μ rises, each unit of effort consumes a larger share of the program budget, reducing the quota q .

Figure 1 visualises the full x^* map in (q^*, μ) space under the linear specification with $\theta_L = 0$. The zero-effort region (red) dominates at combinations of high μ and high q^* ; the full-effort region (green) appears when both are low. Relaxing $\theta_L = 0$ would shift the zero-effort frontier horizontally via $q^* \rightarrow q^* - \theta_L$, while increasing ϕ shifts it rightward; but in both cases the qualitative picture remains unchanged. To take one example, consider a location with a poverty rate of $q^* = 0.6$ (and $\theta_L = 0$). Under the linear specification, zero effort is optimal when $\mu \geq 0.67$ and full effort is optimal when $\mu \leq 0.29$, with intermediate values of x^* in between. However, setting $\phi = 1.5$ implies zero effort becomes optimal when $\mu \geq 0.42$.

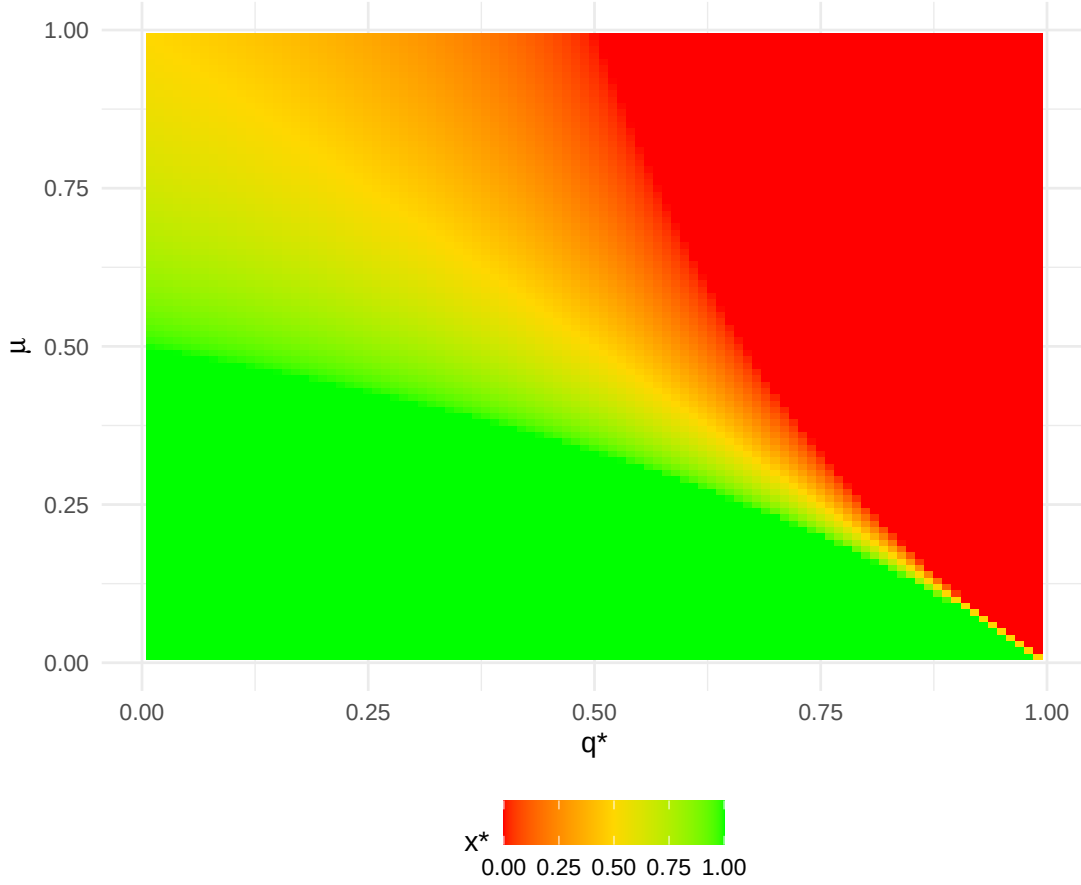
2.5 Cost-adjusted RES and a ternary rule

The RES rule of equation (8) and the optimal-effort criterion of Proposition 2.4 have so far been presented as distinct tools: the former a data-light marginal-rate comparison, the latter a fully specified budget-constrained optimum. In fact, they are two routes to the same destination. To see this, observe that the RES compares marginal welfare gains in output space, treating a unit of q and a unit of α as comparable. The budget structure of Section 2.4 makes clear that the two levers likely carry different marginal costs: expanding coverage requires paying an additional transfer of t per beneficiary, while raising targeting accuracy requires a per-capita expenditure on effort. A genuine bang-per-buck comparison normalises each derivative by its marginal cost:

$$\text{RES}^c \equiv \frac{\partial Z / \partial q}{\partial Z / \partial \alpha} \cdot \frac{MC_\alpha}{MC_q} \quad (19)$$

From the budget constraint (13), total per-capita program spending decomposes into a transfer component tq and a targeting component $x\mu b$. The marginal cost of increased coverage is therefore $MC_q = t$, while the marginal cost of improved accuracy is the per-

Figure 1: Simulated optimal levels of targeting (x^*) given alternative poverty rates (q^*) and maximum costs (μ), under a linear targeting response function ($\phi = 1$)



Source: own elaboration.

Note: the heatmap plots optimal values for the level of targeting, ranging from zero to one, obtained from equation (18) applying a systematic combination of different input values (for q^* , μ) and setting $\theta_L = 0$.

capita cost of effort divided by the marginal return: $MC_\alpha = \mu b / f'_x$, since $\partial\alpha/\partial x = f'_x$. Substituting into (19) and using $\partial Z/\partial q$, $\partial Z/\partial\alpha$ from (8):

$$\text{RES}^c = \frac{\alpha - \theta_L}{q} \cdot \frac{\mu b}{t f'_x} \quad (20)$$

Assuming our simple linear technology, such that $f'_x = (1 - q^*)^\phi$, and evaluating at zero effort such that $\alpha = q^*$ and $q = b/t$ (by equation 13), yields:

$$\text{RES}_0^c = \frac{(q^* - \theta_L) \mu}{(1 - q^*)^\phi} \quad (21)$$

The same cost-adjusted logic applies symmetrically at the opposite corner. At full effort we

have $\alpha = q^* + (1 - q^*)^\phi$ and coverage is $q = (b/t)(1 - \mu)$, yielding:⁷

$$\text{RES}_1^c = \frac{(q^* + (1 - q^*)^\phi - \theta_L) \mu}{(1 - q^*)^\phi (1 - \mu)} \quad (22)$$

Combined, this motivates a practical ternary rule:

$$x^c = \begin{cases} 0, & \text{if } \text{RES}_0^c \geq 1 \\ 1, & \text{if } \text{RES}_1^c \leq 1 \\ 0.5, & \text{otherwise} \end{cases} \quad (23)$$

This rule sits between the two methods for establishing x presented above. The simpler binary rule of equation (12) is least data (assumption) intensive, being broadly agnostic as to the technology of targeting effort, but nonetheless treats every ‘non-zero effort’ location identically. The continuous optimal rule of Proposition 2.4 (equation 18) is fully cost-aware but requires committing to a specific functional form and a precise value of μ . The ternary rule preserves cost-awareness at the corners, where the decision is unambiguous, but otherwise defaults to a fixed intermediate interior value. Its decisions, like the continuous rule, depend on $(q^*, \mu, \theta_L, \phi)$, but the discreteness makes it operationally easier to deploy and explain.

Note that the first condition, $\text{RES}_0^c \geq 1$, is identical to the zero-effort criterion $\mu(q^* - \theta_L) \geq (1 - q^*)^\phi$ from Proposition 2.4. For $\phi = 1$, this represents a lower bound on the zero-effort share. Similarly, condition $\text{RES}_1^c \leq 1$ rearranges to $\mu \leq (1 - q^*)^\phi / (q^* + 2(1 - q^*)^\phi - \theta_L)$, which is exactly the full-effort corner condition of Proposition 2.4. Thus, the only difference between the ternary and the optimum rule is how interior solutions are handled.

Several implications follow. First, the data-light RES of equation (8) is just a special case of the cost-adjusted criterion, valid under the implicit assumption that the cost ratio $MC_\alpha/MC_q = \mu b/(t f'_x)$ is approximately unity. The simple binary RES rule is therefore most informative when targeting costs and marginal returns to effort are not extreme. Second, although precise cost data are rarely available at sub-national resolution, a policymaker need not abandon the cost-adjusted criteria. The primary additional parameter is μ , the share of the program budget required to deliver maximum targeting success in a given context. Plausibly, a planner has an informed view of this ceiling – if only as an upper

⁷ Under the upper-envelope argument of Section 2.4 the linear case provides the most optimistic assessment of the marginal returns to targeting, so $\text{RES}_1^c(\phi = 1)$ delivers a conservative (i.e., upper-bound) recommendation for staying at full effort.

bound – even when granular spending data are absent. Equations (21) and (22) can then be evaluated under a plausible-maximum assumption (or range) for μ , providing defensible diagnostics that incorporate cost considerations without requiring detailed administrative cost accounts. In Section 3 we illustrate this by anchoring μ from the headline program-wide administrative cost share, and then reporting sensitivity across a plausible range. Third, the welfare consequences of using simpler rules in place of full optimisation are empirically quantifiable. As we show below, the binary rule captures roughly two thirds of the welfare gains achievable under full cost-aware optimisation; the ternary rule closes most of the remaining gap by adapting to local cost conditions at the corners.

3 Mozambique case

The previous section provided a practical framework for analysis of targeting performance, highlighting the critical relationship between the poverty rate, the price of targeting effort, and optimal targeting choices. Our results formalize the intuition that the optimal choice of targeting technology will vary across contexts in line with differences in various factors, primarily poverty rates and targeting costs. Naturally, this implies there is no single ‘best’ dosage of targeting across all contexts. The framework also points to the kind of empirical information that is critical to guide decisions in this domain – namely, data on program coverage (q), eligibility rates (q^*), and targeting costs (μ). Under the linear specification (17), additional calibration of the targeting-success function $f(q^*, x)$ is not required since, by the upper-envelope argument, any zero-effort finding obtained under this specification is robust to admissible alternative concave forms.

We now apply this framework to guide an analysis of Mozambique’s largest social protection scheme, the elderly component of the *Programa de Subsídio Social Básico* (PSSB), implemented by the National Institute for Social Action (*Instituto Nacional de Acção Social*, INAS).

3.1 Context and data

The PSSB is a social pension for the vulnerable elderly, covering around half of all persons aged 60+ in the country (for details see Almeida et al., 2025). To conduct our analysis we combine two main data sources: first, administrative data consisting of the complete register of all program beneficiaries over the period 2020–2023 (yielding data on Q); and, second, granular population and poverty data based on the full records of the 2017 Population and

Housing Census (yielding data on N, Q^*). For current purposes, poverty among the elderly is defined using a multi-dimensional index based on assets and living conditions, which closely mirrors the methodology adopted under the government’s national poverty assessment, also used to determine provincial budgets.⁸ Since individual records are anonymised, data from both sources is aggregated and then merged at the *postto administrativo* level, which is the third administrative tier, allowing for a highly localized analysis of targeting performance.⁹

It merits comment that the estimated poverty rate (q^*) applied here, despite having the advantage of full spatial coverage and broad consistency with national poverty assessment criteria, is not without limitations. First, the choice of poverty definition matters. Multi-dimensional metrics, while normatively appealing and generally stable over time, do not necessarily align with the implicit targeting criteria used in practice, such as community judgments or proxy means scores.¹⁰ Second, measurement error in q^* is plausible given the data was collected in 2017, since when population pressures and various shocks (e.g., COVID-19) appear to have aggravated socio-economic conditions in many areas of the country (Salvucci and Tarp, 2024), potentially biasing estimates of the RES metric as well as the inferred optimal effort level. Indeed, comparing the census-based estimates of poverty with a comparable metric collected from a bespoke survey of households in selected locations across the country undertaken in 2024 (described further below), we find the former estimates are around 20% lower than the most recent estimates (despite a rank correlation of 0.89; see Table A3). This would suggest the proceeding analysis likely underestimates the relative welfare importance of program scale-up in high poverty locations.

3.2 Insights from the neutral RES

Notwithstanding the above caveats, Table 2 summarises key information derived from the merged data sources by province, reporting bounds on the targeting metrics as per our

⁸ The poverty measure applied here is an Alkire-Foster multidimensional poverty headcount index covering indicators across three main dimensions: education, housing conditions, and asset ownership. Households are classified as poor if deprived in at least five of six indicators.

⁹ In theory, aggregation of the registry and census data to lower levels is possible, but in practical terms this is problematic due to the use of differing (incompatible) geographical codes and naming conventions in the datasets.

¹⁰ According to the program’s operational manual (INAS, 2022), eligibility for the elderly component of the PSSB is determined based on three criteria: (i) age – applicants must be 60 or older; (ii) residency – living for at least three months in the local community; (iii) poverty – household income is below a first-tier threshold, assessed via a Proxy Means Test (PMT). In practice, no PMT is performed and community-based targeting is used to identify the vulnerable persons without sources of income.

earlier numerical examples.¹¹ At the national level, we observe the poverty rate among the elderly ($q^* = 0.50$) and the program quota ($q = 0.48$) are closely matched, suggesting the program is reasonably scaled on aggregate. However, national averages mask profound sub-national differences, including under-coverage ($q^* > q$) in the higher poverty regions of Zambézia and Nampula, compared to significant over-coverage in the far south (e.g., Maputo Province and Maputo City). These patterns are reflected in the estimated bounds on the targeting success rate, as well as in the neutral RES metric, which ranges from 0.03 in Maputo City to 1.57 in Zambézia, with a national mean of 1.09.

The high degree of spatial heterogeneity is illustrated in Appendix Figures A1 to A3, where the latter confirms significant dispersion in the neutral RES metric. Figure 2(a), which plots population-weighted cumulative distributions of the RES metrics (corresponding to bounds on α), shows that almost 50% of the elderly population reside in locations where the neutral RES measure is greater than one; and this proportion would exceed 60% if we assume poverty rates are now 20% higher than those estimated from the 2017 census. Put differently, only in the three most southerly provinces of the country (Gaza, Maputo City and Maputo Province) can we reject a null hypothesis that the provincial average neutral RES is below unity.

Before presenting further results, it is important to be explicit about the locus of decision-making to which our framework speaks. The PSSB, like social pension programs elsewhere, operates under a strong political constraint: in practice, existing beneficiaries cannot be removed from the rolls. The cross-provincial misalignment observed between q and q^* is therefore not a policy choice to be undone, but a feature of the system.¹² The operational question facing INAS and its partners is forward-looking: how should additional local budgets, as they become available, be allocated and selected? Within this constraint, the relevant trade-off is precisely the one our framework characterises: in any given location, should additional resources be directed toward scaling up coverage (reaching more people) or toward improving selection accuracy (targeting better among entrants)?

3.3 Optimal effort and welfare

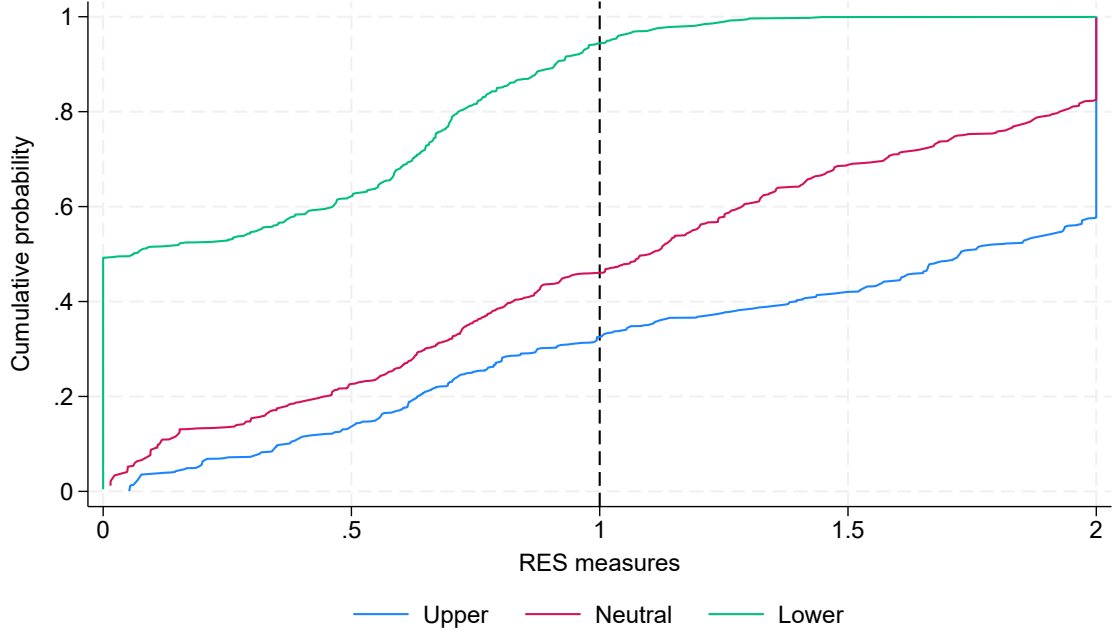
Turning to the question of optimal effort, operationalising our model demands an estimate of μ , the budget share corresponding to maximum targeting success. Although μ is not directly

¹¹ We focus here only on the *de jure* coverage of the program, abstracting from issues of delayed payments that are material but nevertheless a subject of separate research. See [MGCAS \(2022\)](#) and [IGM \(2025\)](#) for further discussion.

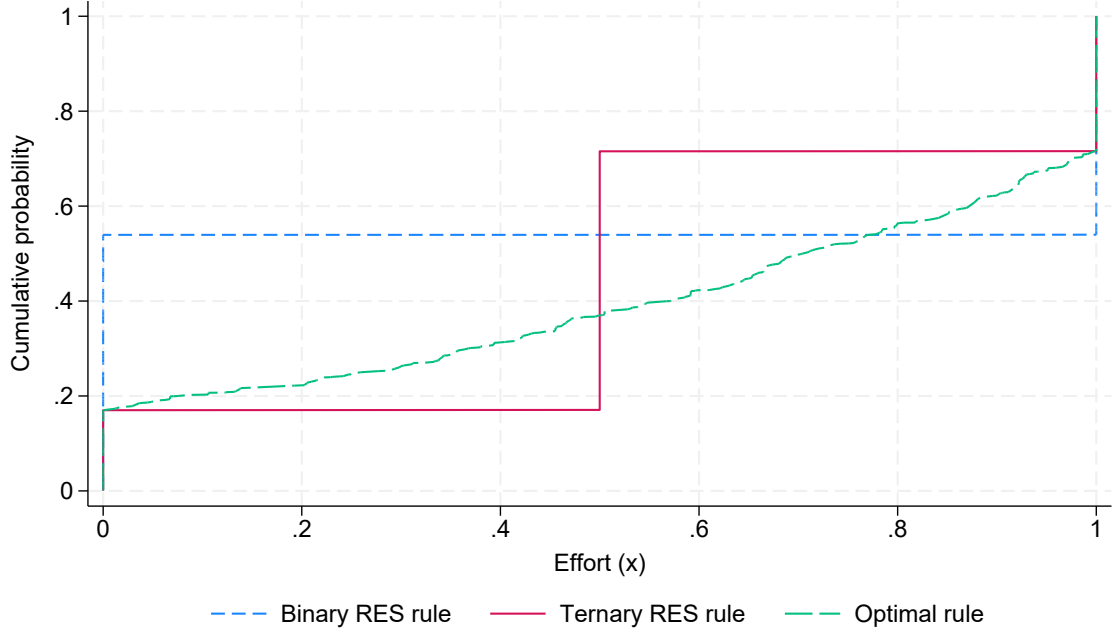
¹² This feature is only reinforced when external partners allocate funds to social program expansion in specific areas, as has been the case in Mozambique.

Figure 2: Cumulative distribution plots

(a) Estimates of bounds on RES:



(b) Rule-based estimates of targeting effort:



Source: own estimates.

Notes: figure (a) shows the cumulative distribution functions (CDFs) of upper, neutral, and lower bound estimates of the simple RES metric (under $\theta_L = 0$) across all administrative posts, weighted by population aged 60+, and winsorized at 2 for visual symmetry; figure (b) plots the CDFs of the estimated levels of targeting effort under three rules at reference parameter values ($\theta_L = 0, \phi = 1, \mu = \bar{\mu}_{a,1}$): the simple (binary) RES rule, the cost-adjusted (ternary) RES rule, and continuous optimal effort.

Table 2: *De jure* coverage of PSSB-Elderly program, 2023

Province	q^*	q	α		λ		RES_n
			LB	UB	LB	UB	
Niassa	0.55	0.70	0.36	0.76	0.54	0.89	0.88
Cabo Delgado	0.62	0.48	0.27	0.92	0.24	0.69	1.42
Nampula	0.67	0.50	0.35	0.91	0.31	0.70	1.37
Zambezia	0.63	0.40	0.22	0.92	0.21	0.54	1.57
Tete	0.51	0.53	0.19	0.85	0.23	0.86	1.06
Manica	0.50	0.60	0.23	0.71	0.32	0.86	0.93
Sofala	0.45	0.46	0.17	0.73	0.19	0.79	1.00
Inhambane	0.50	0.43	0.14	0.90	0.15	0.74	1.34
Gaza	0.37	0.62	0.17	0.60	0.30	0.97	0.65
Maputo Prov.	0.12	0.40	0.04	0.23	0.09	0.99	0.24
Maputo City	0.01	0.26	0.00	0.03	0.04	1.00	0.03
National	0.50	0.48	0.21	0.76	0.24	0.77	1.09

Source: own estimates.

Notes: table summarizes merged estimates from administrative records and census data, showing average poverty rates (q^*), program quotas (q), and derived bounds on targeting metrics (α , λ) for each province ordered North to South; UB, LB refer to upper and lower bounds respectively; the RES_n column reports the mean neutral Relative Effectiveness of Scale-up (RES) metric, under $\theta_L = 0$, highlighting where program expansion is expected to yield greater welfare returns versus improving targeting accuracy.

observed, it can be anchored from two pieces of information: the share of the (variable) program budget currently absorbed by targeting-related spending, and an estimate of the *de facto* level of targeting effort. According to INAS, the administrative costs of the PSSB, excluding fixed central and regional overheads, is set at 12% of the total program budget (MGCAS, 2022), implying: $\hat{x}\hat{\mu} = 0.12$ should hold on aggregate.¹³ In turn, using equation (17) to estimate x on the assumption that α is at its upper-bound, suggests a lower-bound: $\bar{\mu}_{\alpha, \phi=1} \approx 0.38$,¹⁴ meaning highly accurate targeting would require around triple the current budget share. In other words, current targeting effort is likely to be below its maximum in many locations (see Table 2).

More granular (location-specific) estimates of μ are not credibly identified from the available data. INAS's reported 12% administrative share is a program-wide accounting figure, not a local measurement. Relying on local estimates of effort via $\hat{\mu}_i = 0.12/\hat{x}_i$ would amount to a heroic assumption, and the resulting estimates would inherit substantial measurement

¹³ This compares to the estimate of 16.9% given by Lastunen et al. (2025) for the same program, but which encompasses both fixed and variable administrative costs. Cost estimates of this magnitude (and higher) are reported for a range of other low income contexts.

¹⁴ Calculated as the population-weighted mean of $\hat{\mu}_i = \min(0.12/\hat{x}_i, 1)$ across administrative posts indexed by i .

error from $\hat{x}_i$. Thus, we treat μ as a single (national) parameter and report the sensitivity of our results across a plausible range of values.

To complement this, a valuable preliminary insight concerning where optimal effort may lie comes from the implicit thresholds for μ associated with zero and full effort respectively, calculated for each administrative post. Appendix Figure A4 plots their means by province, setting $\phi = \{1, 2\}$ and $\theta_L = 0$. Two main insights emerge. First, again reflecting the large variation in poverty rates across the country, the (zero effort) thresholds vary materially between provinces. For instance, non-zero targeting is almost always justified in Maputo City and Maputo Province, with full effort being recommended as long as the maximal budget share remains below around 0.5. In contrast, zero effort is recommended (on average) in Nampula, where the budget share exceeds 0.46. Second, there is significant sensitivity to the assumed degree of concavity in the targeting technology. For the linear specification ($\phi = 1$), around 20% of the population reside in locations where zero effort is recommended at the anchor $\bar{\mu}_{a,\phi}$. But for moderate concavity ($\phi = 2$), this jumps to 52%.

Focussing on a baseline scenario ($\phi = 1, \mu = \bar{\mu}_{a,1}, \theta_L = 0$), Figure 2(b) plots the estimated cumulative distributions of effort under three rules. The first is the simple binary RES rule, which sets $x = (\text{RES}_n < 1)$ and is invariant to both the budget and concavity parameters; the second is the cost-adjusted (ternary) RES rule; and the third is the continuous optimal effort from equation (18). The main takeaway is that even under this minimal set of parameter assumptions, which are optimistic about the targeting technology and its costs, investing the maximum budget share on targeting is recommended only in a minority of locations (covering 26% of the elderly population), most of which are found in the far south of the country where poverty is low.

Figure 2(b) also indicates that the simple (binary) RES rule tends to recommend lower levels of targeting than the optimization procedure, the national means being 0.46 and 0.61 respectively; and the cost-adjusted (ternary) RES rule lies between the two (0.56). However, these gaps vary with different parameter assumptions, as shown in Figures A5 to A7. For instance, where the planner tolerates some leakage ($\theta = -0.5$), the binary RES rule almost unanimously leans toward zero targeting effort, while the other rules nuance this recommendation depending on the budget share (see also below). However, at $\theta_L = 0, \phi = 2$ the mean estimate for x^* falls to 0.35 (below the simple-rule mean) with over 50% of the population residing in zero effort locations, which is highly consistent with both the corresponding binary and ternary RES shares.

As a final exercise we estimate the welfare implications of these rules under different parameter assumptions. To do so, we focus on welfare per budget spend, which abstracts

from the absolute size of the total budget as well as its allocation across locations. Thus, the absolute welfare metric of interest is given by:

$$\tilde{Z}(x; \mu, \theta_L, \phi) = (1 - x\mu) [q^* + x(1 - q^*)^\phi - \theta_L]$$

which differs from equation (15) in two main respects. First, b is factored out, corresponding to the focus on welfare per unit of spending; and, second, k/t is excluded since it serves only as a (nuisance) scalar that cancels out once we consider relative changes:

$$\Delta = \frac{\tilde{Z}(x; \mu, \theta_L, \phi)}{\tilde{Z}(x'; \mu, \theta_L, \phi)} - 1 \quad (24)$$

This gives the percentage change in normalized welfare for different choices of x at given parameter values; and where we set x' to the upper bound estimate described above, reflecting an optimistic assessment of the status quo.

Figure 3 illustrates these results comparing the three rules for setting targeting effort and reporting relative welfare changes versus the status quo. We focus primarily on sensitivity to variation in μ (on the horizontal axis), considering values in the range $[\mu_{a,1}/3, 3\mu_{a,1}]$. We also consider contrasting extreme assumptions for the two other parameters, namely: $\phi \in \{1, 2\}$ and $\theta_L \in \{-0.5, 0, 0.5\}$. To complement this, Figure A8 plots the average level of optimal effort under different combinations of μ and ϕ for $\theta_L = 0$. The selected parameter ranges are not *ad hoc*. Recent comparative work (Lastunen et al., 2025) compiles administrative cost share estimates for social protection programs across sub-Saharan Africa and Latin America, reporting a median of approximately 17% of total costs for means-tested programs in SSA, with individual estimates ranging from roughly 3% to 28%. Critically, these are *realised* cost shares under prevailing targeting effort, not the shares associated with maximum targetting success – i.e., in our notation, they correspond to $x\mu$. Inverting through plausible values for x yields a range for μ in line with our choices. Similarly, the upper value $\phi = 2$ approaches the level of concavity in returns to effort also assumed by the same authors, underlining the optimistic nature of our reference assumptions.

Four findings stand out. First, as may be expected, the estimates reveal a substantial degree of sensitivity to the parameters. Across scenarios we find that increases in μ are associated with higher welfare gains. This may appear counter-intuitive, but reflects the fact that the level of targeting effort under the status quo is fixed (regardless of cost), while the RES-based rules and the optimal rule all adapt by reducing effort as μ rises. So, as targeting becomes more expensive, the welfare cost of failing to adjust grows: each unit of targeting effort sustained at the status quo level consumes a larger share of the budget, crowding out transfers and reducing coverage. The gains from switching to an adaptive rule therefore

widen with μ , not because targeting becomes more valuable, but because the cost of *not* responding to expensive targeting becomes larger.

We also observe that larger values for θ_L tend to significantly raise the estimated magnitude of welfare gains across all rules, reflecting the larger welfare costs of failing to target when leakage is penalized. Indeed, at $\theta_L = 0.5$, the simple (binary) RES rule suggests a mean value for x equal to 0.95, implying most locations are recommended to be at full effort. Where the planner tolerates some leakage, such as at $\theta_L = -0.5$, welfare gains remain moderate especially when targeting is cheap, suggesting the scope for welfare gains from targeting reforms is limited.

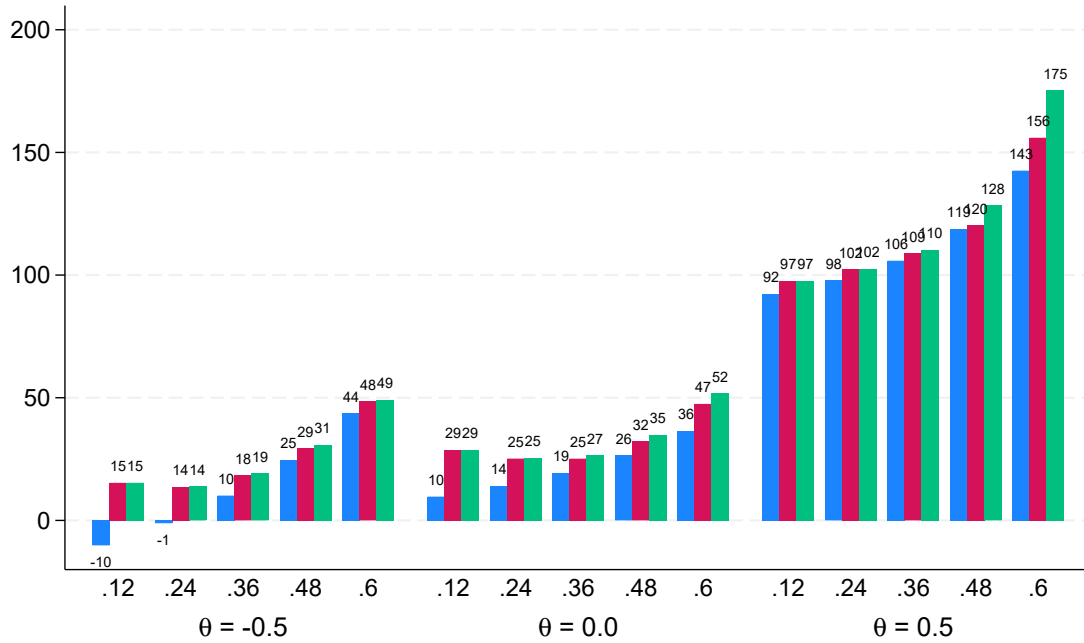
Second, estimated welfare often declines as ϕ increases (*ceteris paribus*), except for high values of μ . This reflects the structure of the targeting technology. Higher ϕ implies that the marginal return to targeting effort declines more sharply as q^* rises – i.e., the productivity factor $(1 - q^*)^\phi$ shrinks faster. Consequently, there is less scope for α to improve through investments in targeting, especially in high-poverty locations. In turn, welfare becomes less responsive to changes in effort and a larger share of locations are allocated to the zero effort regime, where: $\tilde{Z}(0; \mu, \theta_L, \phi) = q^* - \theta_L$.

Third, there is a very high degree of association in the welfare change estimates across the three rules, indicated by a pairwise rank correlation of over 0.96 covering a wide range (N=630) of parameter combinations within the limits illustrated in the same figure. And while the continuous optimal rule necessarily delivers the highest expected welfare gains (by construction), the simple (binary) RES rule — which depends *only* on (q^*, q, θ_L) — achieves 0.65 of the maximum gains on average (and median of 0.74). The cost-adjusted (ternary) RES rule sits between the two: by adapting to local cost conditions at the corners, it closes almost all of the gap between the binary rule and the continuous optimum, achieving 96% of the maximum welfare gains on average.

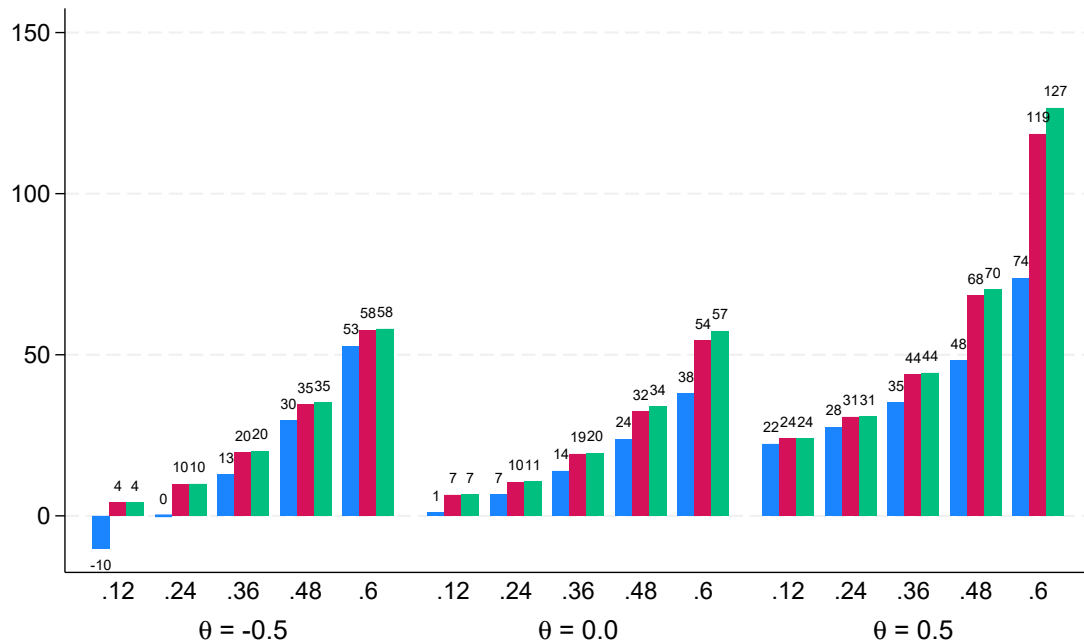
Fourth, echoing previous comments, the robustness of decision rules to the welfare specification interacts in a substantive way with targeting costs. The cost-adjusted ternary rule and the continuous optimum deliver positive welfare gains across the full range of (θ_L, μ) , since both incorporate targeting costs directly. The binary rule, which depends only on (q^*, q, θ_L) , performs well across the μ range for $\theta_L \geq 0$, and continues to perform well for $\theta_L < 0$ when targeting is at least moderately costly, including at our reference value. But the same rule can deliver negative welfare gains for $\theta_L < 0$ at (very) low μ . The logic here remains intuitive: when the planner places positive welfare value on leaked transfers ($\theta_L < 0$) and the targeting machine is cheap (low μ), abandoning targeting in favour of pure coverage expansion yields negligible cost savings while sacrificing welfare gains from

Figure 3: Estimates of welfare gains from changed targeting effort at alternative parameter choices

(a) For $\phi = 1$:



(b) For $\phi = 2$:



Source: own estimates.

Notes: figure shows national average estimates of welfare gains relative to status quo under different decision rules regarding targeting effort across alternative scenarios defined by combinations of maximal targeting costs shares (μ , x-axis), targeting technologies (ϕ), and leakage aversion (denoted θ).

existing targeting efforts. The binary RES rule therefore is best understood as a diagnostic tool that requires either a lower tolerance of leakage or moderate-to-high targeting costs. The cost-adjusted ternary rule, by adapting at both corners of the μ range, is robust across the full welfare specification range.

Fifth, and perhaps most critically, at reference parameter values the welfare gains from employing differentiated targeting methods are likely to be significant in Mozambique. Concretely, at the anchor maximal budget share with $\phi = 1, \theta_L = 0$, the simple (binary) RES rule delivers around a 19% gain in welfare, versus 25% and 27% under the ternary rule and continuous optimal effort respectively. However, these gains vary by location. The largest relative welfare gains appear to come from raising targeting in lower poverty locations, such as in the southern region (where welfare increases 59% under the simple RES rule); but smaller welfare gains (under 15%) are found in higher poverty locations, where it is reasonably assumed that a large share of the poor are already covered. The relevant policy implication is that adapting targeting to context is essential – i.e., given scarce resources, applying the same targeting technology in all contexts is likely to be suboptimal. And while crude, the binary RES rule can go a long way to indicating where investments in better targeting should be prioritised, versus where the status quo or even lighter touch selection approaches are recommended.

It is important to emphasise that, by virtue of our analytical set-up, the welfare gains reported here arise primarily from one direction: tightening targeting in low-poverty over-covered locations, where reduced leakage outweighs the coverage contraction. In high-poverty locations where any of the rules loosens targeting, the welfare contribution is smaller because current accuracy is already high, leaving little scope for material variation in α – i.e., per budget spending cannot significantly shift welfare. As such, our framework implicitly holds the spatial allocation of the program budget fixed, meaning that the welfare change estimates do not capture any potential improvements that could be achieved by cross-locational budget reallocation. The reported estimates therefore are conservative with respect to the full welfare potential of targeting reform.

A further structural feature of these results merits attention. In severely over-covered locations, the targeting identity (Proposition 2.1) implies that high α requires q to fall toward q^* , which can be achieved either through more expensive selection or through a lower local budget allocation (b). The welfare gains reported above hold b fixed at observed levels and so capture only the selection-cost side of this lever. They are correspondingly conservative with respect to the joint reallocation that the framework would recommend if b were also adjustable. In the PSSB case, however, reducing b without removing existing beneficiaries is only operationally feasible through natural attrition — as current beneficiaries exit the

program, q presumably falls and b can be redirected to under-covered locations. Recommendations of higher targeting effort in over-covered locations should thus be read as advice on selecting new entrants more accurately, while the budget side of the joint lever unwinds gradually through attrition. The combination of these two adjustments delivers the long-run achievable gains reported in our results.

4 Conclusion

In contrast to existing literature that tends to offer general prescriptions either for or against targeting, this paper proposed a framework to evaluate *when* investments in more accurate targeting justify their costs. We showed that the trade-off between targeting precision and program coverage is usefully summarized by the marginal rate of technical substitution, the Relative Effectiveness of Scale-up (RES). Extended to take account of the cost of targeting, the framework delivers a hierarchy of three operational rules. The data-light binary rule, based on observed poverty and coverage rates alone, asks whether scale-up dominates selection at the margin. The ternary rule extends this by cost-adjusting the criterion at both the zero-effort and full-effort corners, requiring only a plausible-maximum estimate of the budget share devoted to targeting. The continuous rule solves the full budget-constrained welfare optimisation, requiring a stronger commitment to specific functional forms and parameter values. The framework accommodates leakage aversion via a single welfare-weight parameter, θ_L , with feasible values ranging from tolerance to leakage ($\theta_L \rightarrow -\infty$) to pure leakage aversion ($\theta_L \rightarrow 1$).

We applied this framework to Mozambique’s national social pension program (the elderly component of the PSSB). Reflecting large inequalities in coverage, we found that zero targeting effort — assumed equivalent to random selection of beneficiaries — is indicated in around half of all locations under the binary RES rule, or in 20% of all locations according to continuous optimal effort estimates at reference parameter values. Conversely, full effort is only recommended in a quarter of locations. Welfare gains of around 20% per budget spend are associated with the binary RES rule, rising significantly to the degree that leakage is penalized in the welfare function. We also found that while the binary RES rule delivers about two-thirds of the welfare gains of the optimum across a wide range of parameter combinations on average, the cost-adjusted ternary rule closes almost all of the gap.

Beyond providing a specific diagnosis of the PSSB, three broader implications follow. First is the basic point that blanket application of costly targeting schemes is unlikely to be optimal, especially where there is high spatial variation in poverty rates. Targeting efforts

should be adapted to local conditions, not only via geographic (budget) quotas, but also in the choice of local targeting technologies. Simply put, where rates of poverty are high, costly targeting schemes may be redundant.

Second, our finding that simple rules-of-thumb recover most of the welfare gains from continuous-effort optimisation suggests that operationally feasible decision rules can approximate sophisticated welfare calculations with limited loss. For practitioners without access to effort-optimisation machinery, a binary RES rule based on observable poverty and coverage rates alone can be defensible where (maximal) targeting costs are non-trivial. Where the policymaker has a rough sense of the share of program spending that maximally-effective targeting could absorb, the cost-adjusted ternary rule is recommended. In other words, targeting can be calibrated in information-poor environments.

Third, while our analysis is framed around administered targeting schemes — where the state pays to identify eligible beneficiaries through proxy means tests, community-based selection, or registry verification — the framework speaks to a broader menu of targeting mechanisms. Our central finding that administered targeting is least worthwhile in high-poverty, high-cost contexts, raises the question of what else to do in these settings, especially when budgets bind. Self-targeting schemes, (e.g., ordeals, workfare, etc.; see [Besley and Coate, 1992](#); [Alatas et al., 2016](#)) offer one answer, but they do not eliminate the cost of selection so much as shift it from the state to potential beneficiaries, achieving improved targeting financed by a separate welfare cost our maximand does not price. This caveat is material for an elderly target population: an ordeal that induces self-selection may screen out the most frail and isolated applicants, defeating the purpose. Categorical schemes, where eligibility follows from observable attributes such as age, can likewise be read within our framework as setting $\alpha = q^*$ at minimal cost. Extending not only the framework but also empirical analysis to price the beneficiary-borne costs of self-targeting, and to characterise when shifting selection costs away from the state improves on administered targeting, is a promising direction for future work, as is collecting further evidence on the cost-effectiveness of different targeting technologies in different settings.

In sum, these findings offer a pathway beyond what is often a polarized debate between universalism and targeting. Focussing on the reality of contexts such as Mozambique where financial resources are limited, poverty is high, and many eligible individuals are not yet covered, a key challenge lies in determining when and where to focus on program scale-up relative to making investments in targeting, which can be both costly and disruptive. The tools set out here can provide guidance to policymakers without extensive information requirements. At the same time, it merits emphasis that for guidance taken from the (neutral) RES metric to be informative, low-cost selection schemes that are minimally non-regressive

remain essential. Thus, a relevant challenge is not just where to focus targeting efforts, but also how to avoid distortions associated with program capture.

References

- Akerlof, G. A. (1978). The economics of “tagging” as applied to the optimal income tax, welfare programs, and manpower planning. *American Economic Review*, 68(1):8–19.
- Alatas, V., Purnamasari, R., Wai-Poi, M., Banerjee, A., Olken, B. A., and Hanna, R. (2016). Self-targeting: Evidence from a field experiment in Indonesia. *Journal of Political Economy*, 124(2):371–427.
- Almeida, S., Berkel, H., Jones, S., Justino, P., and Massingue, T. (2025). Social protection for Mozambique’s elderly: History, structure, and potential effectiveness. WIDER Working Paper 12/2025, UNU-WIDER, Helsinki.
- Asri, V., Michaelowa, K., Panda, S., and Paul, S. B. (2022). The pursuit of simplicity: Can simplifying eligibility criteria improve social pension targeting? *Journal of Economic Behavior & Organization*, 200:820–846.
- Auriol, E. and Warlters, M. (2012). The marginal cost of public funds and tax reform in Africa. *Journal of Development Economics*, 97(1):58–72.
- Baker, J. L. and Grosh, M. E. (1994). Poverty reduction through geographic targeting: How well does it work? *World Development*, 22(7):983–995.
- Banerjee, A., Hanna, R., Olken, B. A., and Lisker, D. S. (2024). Social protection in the developing world. *Journal of Economic Literature*, 62(4):1349–1421.
- Banerjee, A., Niehaus, P., and Suri, T. (2019). Universal basic income in the developing world. *Annual Review of Economics*, 11(1):959–983.
- Banerjee, A. V. (1997). A theory of misgovernance. *The Quarterly Journal of Economics*, 112(4):1289–1332.
- Besley, T. and Coate, S. (1992). Workfare versus welfare: Incentive arguments for work requirements in poverty-alleviation programs. *The American Economic Review*, 82(1):249–261.
- Besley, T. and Kanbur, R. (1991). The principles of targeting. In Balasubramanyam, V. N. and Lall, S., editors, *Current Issues in Development Economics*, pages 69–90. Macmillan Education UK, London.
- Beuermann, D. W., Hoffmann, B., Stampini, M., Vargas, D. L., and Vera-Cossio, D. (2025). Shooting a moving target: Evaluating targeting tools for social programs when income fluctuates. *Journal of Development Economics*, 172:103395.
- Brown, C., Ravallion, M., and Van de Walle, D. (2018). A poor means test? Econometric targeting in Africa. *Journal of Development Economics*, 134:109–124.

- Coady, D., Grosh, M., and Hoddinott, J. (2004). Targeting outcomes redux. *The World Bank Research Observer*, 19(1):61–85.
- Coady, D. and Skoufias, E. (2004). On the targeting and redistributive efficiencies of alternative transfer instruments. *Review of Income and Wealth*, 50(1):11–27.
- Devereux, S., Masset, E., Sabates-Wheeler, R., Samson, M., Rivas, A.-M., and Te Lintelo, D. (2017). The targeting effectiveness of social transfers. *Journal of Development Effectiveness*, 9(2):162–211.
- Elbers, C., Fujii, T., Lanjouw, P., Özler, B., and Yin, W. (2007). Poverty alleviation through geographic targeting: How much does disaggregation help? *Journal of Development Economics*, 83(1):198–213.
- Ellis, F. (2012). ‘We are all poor here’: economic difference, social divisiveness and targeting cash transfers in Sub-Saharan Africa. *Journal of Development Studies*, 48(2):201–214.
- Galtier, F. (2026). Do good but do it right. An ethical assessment of the targeting of food aid and antipoverty transfers. *Food Ethics*, 11(1):39.
- Gelbach, J. B. and Pritchett, L. H. (2001). Indicator targeting in a political economy: Leakier can be better. *The Journal of Policy Reform*, 4(2):113–145.
- Golosov, M. and Tsyvinski, A. (2006). Designing optimal disability insurance: A case for asset testing. *Journal of Political Economy*, 114(2):257–279.
- Hanna, R. and Karlan, D. (2017). Designing social protection programs: using theory and experimentation to understand how to help combat poverty. In *Handbook of economic field experiments*, volume 2, pages 515–553. Elsevier.
- Hanna, R. and Olken, B. A. (2018). Universal basic incomes versus targeted transfers: Anti-poverty programs in developing countries. *Journal of Economic Perspectives*, 32(4):201–226.
- IGM (2025). Evaluating the impact of the basic social subsidy programme on elderly well-being in Mozambique. IGM Report, Inclusive Growth in Mozambique, Maputo.
- INAS (2022). Manual de procedimentos do Programa Subsídio Social Básico. Internal procedures manual, Instituto Nacional de Acção Social, Ministério do Género, Criança e Acção Social, Matola.
- Kanbur, S. R. (1987). Measurement and alleviation of poverty: With an application to the effects of macroeconomic adjustment. *Staff Papers-International Monetary Fund*, 34(1):60–85.
- Lanjouw, P. and Ravallion, M. (1999). Benefit incidence, public spending reforms, and the timing of program capture. *The World Bank Economic Review*, 13(2):257–273.
- Lastunen, J., Zasova, A., and Rattenhuber, P. (2025). Administrative costs of social protection in sub-Saharan Africa and Latin America: A microsimulation study. Working paper, UNU-WIDER, Helsinki. Version: 21 February 2025.

- Lindert, K., Linder, A., Hobbs, J., and De la Brière, B. (2007). The nuts and bolts of Brazil's Bolsa Família program: implementing conditional cash transfers in a decentralized context. Social Protection Discussion Paper 709, World Bank, Washington DC.
- MGCAS (2022). Relatório de avaliação intermédia da estratégia nacional de segurança social básica (2016-2024). Technical report, MGCAS.
- Mirrlees, J. A. (1971). An exploration in the theory of optimum income taxation. *The Review of Economic Studies*, 38(2):175–208.
- Mkandawire, T. (2005). Targeting and universalism in poverty reduction. Social Policy and Development Programme Paper 23, United Nations Research Institute for Social Development (UNRISD).
- Nichols, A. L. and Zeckhauser, R. J. (1982). Targeting transfers through restrictions on recipients. *American Economic Review*, 72(2):372–377.
- Ravallion, M. and Chao, K. (1989). Targeted policies for poverty alleviation under imperfect information: algorithms and applications. *Journal of Policy modeling*, 11(2):213–224.
- Saez, E. and Stantcheva, S. (2016). Generalized social marginal welfare weights for optimal tax theory. *American Economic Review*, 106(01):24–45.
- Salvucci, V. and Tarp, F. (2024). Crises, prices, and poverty—an analysis based on the mozambican household budget surveys 1996/97–2019/20. *Food Policy*, 125:102651.
- Schady, N. R. (2002). Picking the poor: Indicators for geographic targeting in Peru. *Review of Income and Wealth*, 48(3):417–433.
- Schüring, E. and Gassmann, F. (2016). The political economy of targeting – a critical review. *Development Policy Review*, 34(6):809–829.
- Sen, A. (1995). The political economy of targeting. In Van De Walle, D. and Nead, K., editors, *Public Spending and the Poor: Theory and Evidence*, pages 245–260. Johns Hopkins University Press, Baltimore.
- Slater, R. (2023). Universal, categorical and targeted social protection: issues, debates and solutions. In Patel, L., Plagerson, S., and Chinyoka, I., editors, *Handbook on Social Protection and Social Development in the Global South*, chapter 10, pages 180–204. Edward Elgar Publishing Ltd., Cheltenham, UK.
- White, P., Hodges, A., and Greenslade, M. (2015). Measuring and maximising value for money in social protection systems. Technical report, Department for International Development (DFID), United Kingdom, London, UK.

A Appendix: Additional tables and figures

Table A1: Classification of population by beneficiary and eligibility status

		Beneficiary?		
		No	Yes	
Eligible?	No	a	b	$1 - q^*$
	Yes	c	d	q^*
		$1 - q$	q	1

Source: own elaboration.

Notes: population is normalized to size one, such that $a + b + c + d = 1$; table indicates that the group of beneficiaries (q) can be expressed in two ways: $q = d + b = \alpha q + (1 - \alpha)q$, where $\alpha = d/(b+d)$; or $q = \lambda q^* + \gamma(1 - q^*)$, where $\lambda = d/(c+d)$ and $\gamma = b/(a+b)$.

Table A2: Bounds on targeting success and error rates under alternative scenarios

	Targeting (α)	Elig. coverage (λ)
Upper	$\min(1, q^*/q)$	$\min(1, q/q^*)$
Neutral	q^*	q
Lower	$\max(0, (q + q^* - 1)/q)$	$\max(0, (q + q^* - 1)/q^*)$

Source: own derivations.

Notes: this table summarizes the theoretical bounds for two key targeting performance metrics – the targeting success rate (α) and the eligibility coverage rate (λ), as well as their corresponding error rates (leakage and under-coverage); the bounds are derived from algebraic identities that hold between observed program coverage (q) and poverty rates (q^*); neutral values correspond to random assignment or non-regressive targeting.

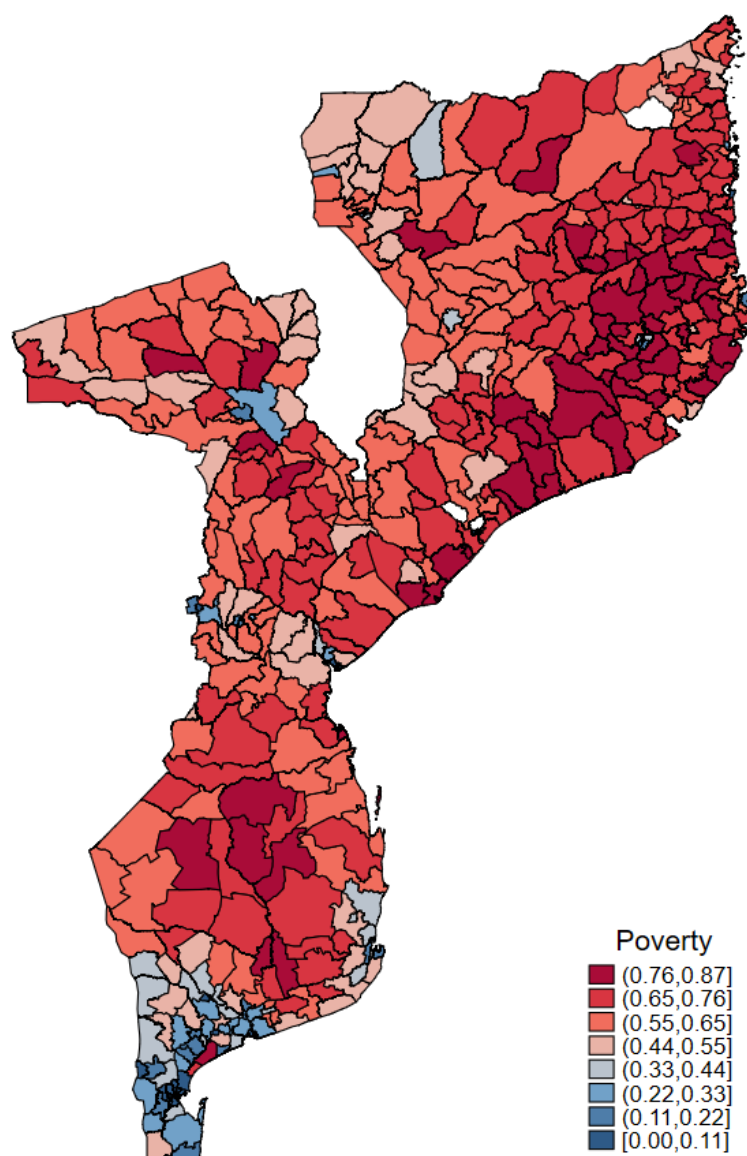
Table A3: Comparison of poverty estimates from Census and Vulnerable Lives Survey (individuals aged 60+)

Region	Admin.post	VLS (2024)		Census (2017)	
		Poverty	$\hat{\alpha}$	Poverty	$\hat{\alpha}$
North	Namialo	0.70	0.81	0.49	0.49
	Monapo Sede	0.82	0.82	0.67	0.68
Center	Luabo Sede	0.83	0.81	0.65	0.65
	Vila de Marromeu	0.65	0.62	0.47	0.86
South	Xinavane	0.18	0.30	0.15	0.23
	Manhiça	0.19	0.31	0.15	0.34
Mean		0.55	0.59	0.43	0.58

Source: own estimates.

Notes: the table shows multi-dimensional poverty headcount estimates for elderly persons (aged 60+) in six administrative posts, based on the 2024 Vulnerable Lives Survey ([IGM, 2025](#)) and the 2017 census, alongside estimates of the PSSB targeting success rate.

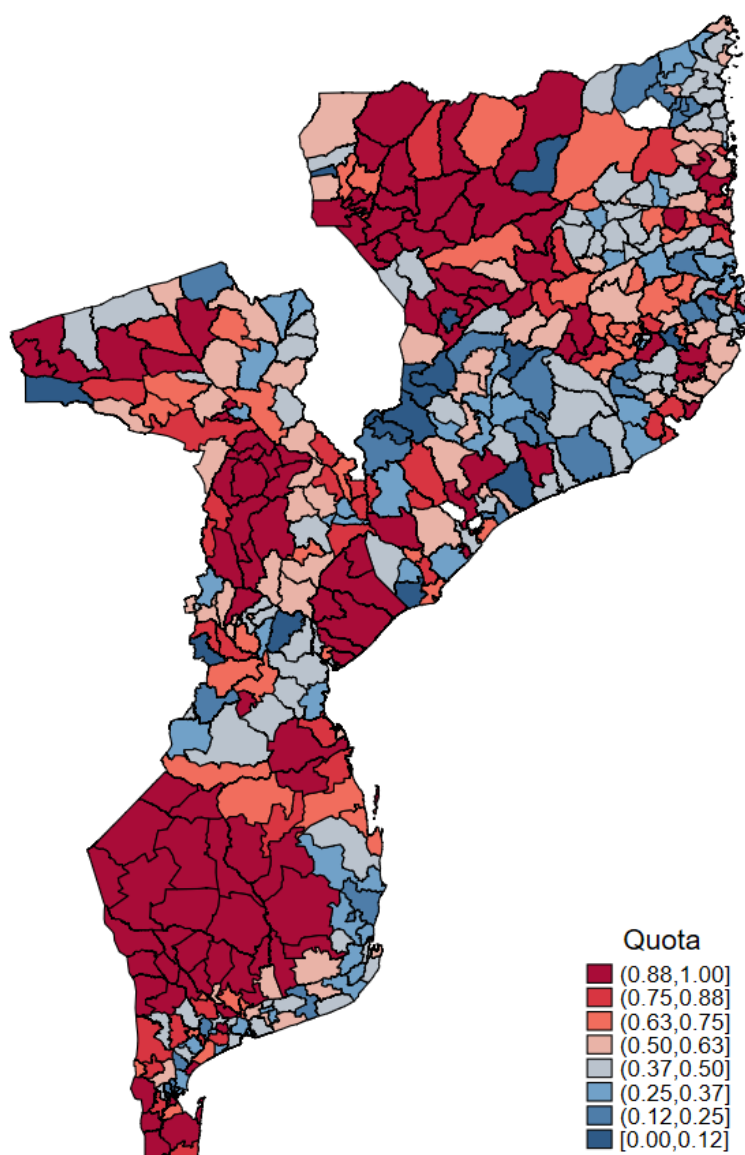
Figure A1: Estimated elderly poverty rates by administrative post



Source: own elaboration.

Notes: the map shows estimated poverty rates among elderly individuals (aged 60+) across Mozambique's administrative posts; poverty is defined using a composite index incorporating indicators across health, education, and living standards dimensions, in line with official multidimensional poverty estimation methodologies.

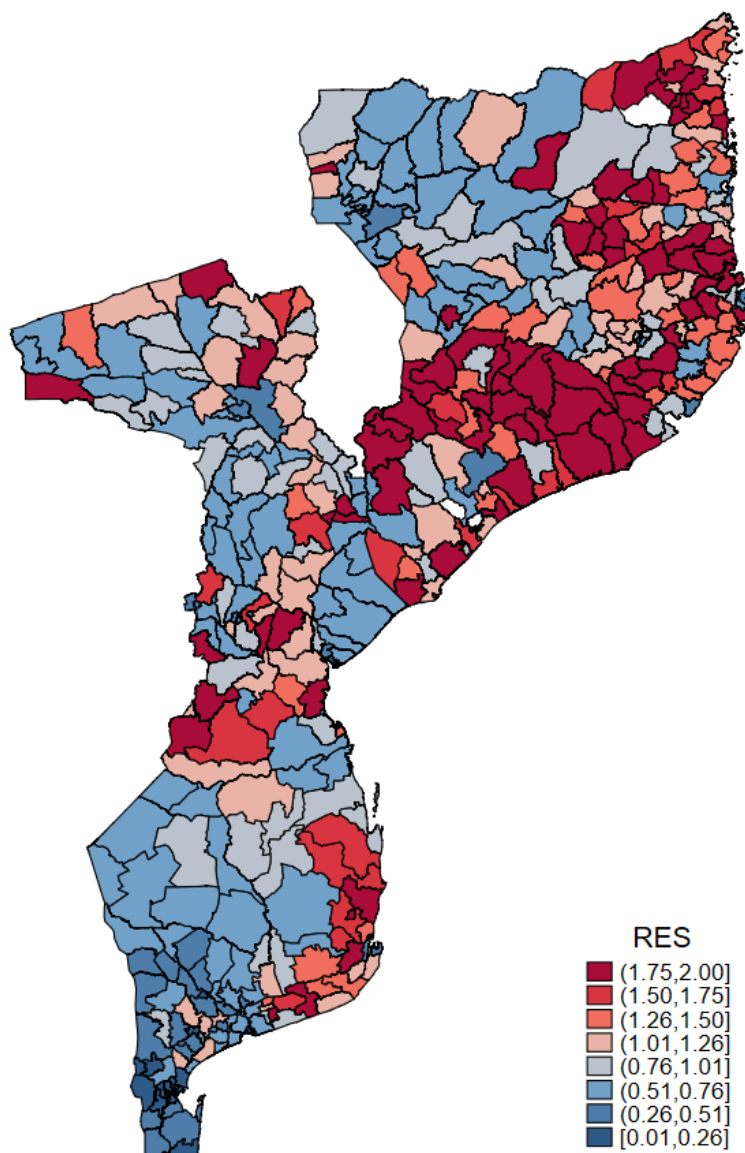
Figure A2: PSSB-Elderly quotas, by administrative post



Source: own elaboration.

Notes: the map illustrates the *de jure* coverage of the PSSB-Elderly program across administrative posts in Mozambique, measured as the ratio of enrolled program beneficiaries to the estimated total elderly population (60+) in each location as of November 2023.

Figure A3: Estimates of the neutral RES, by administrative post

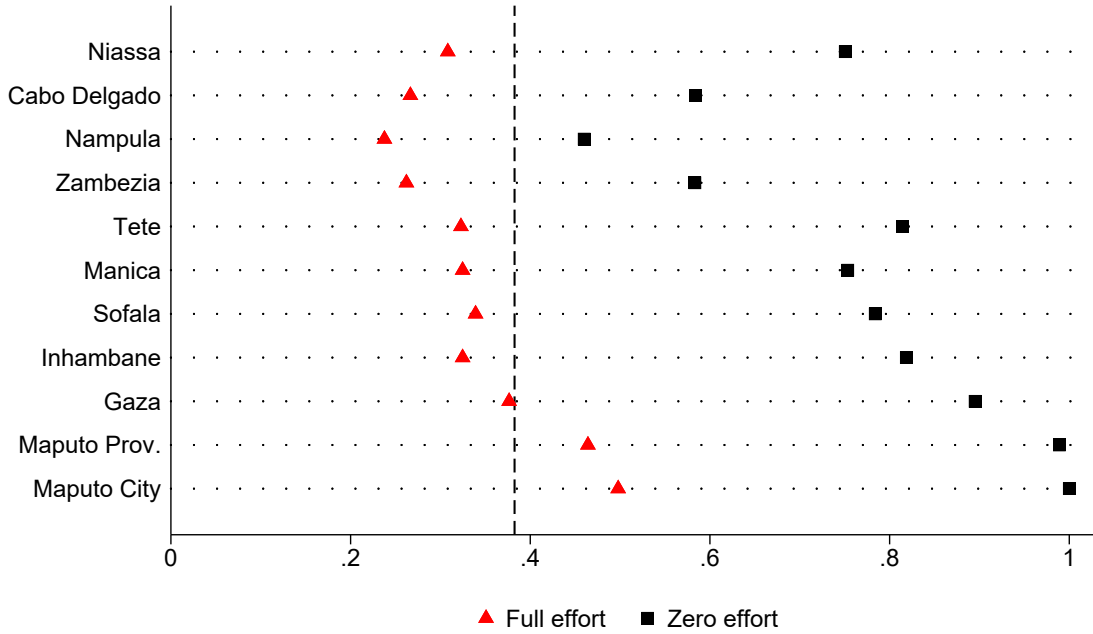


Source: own elaboration.

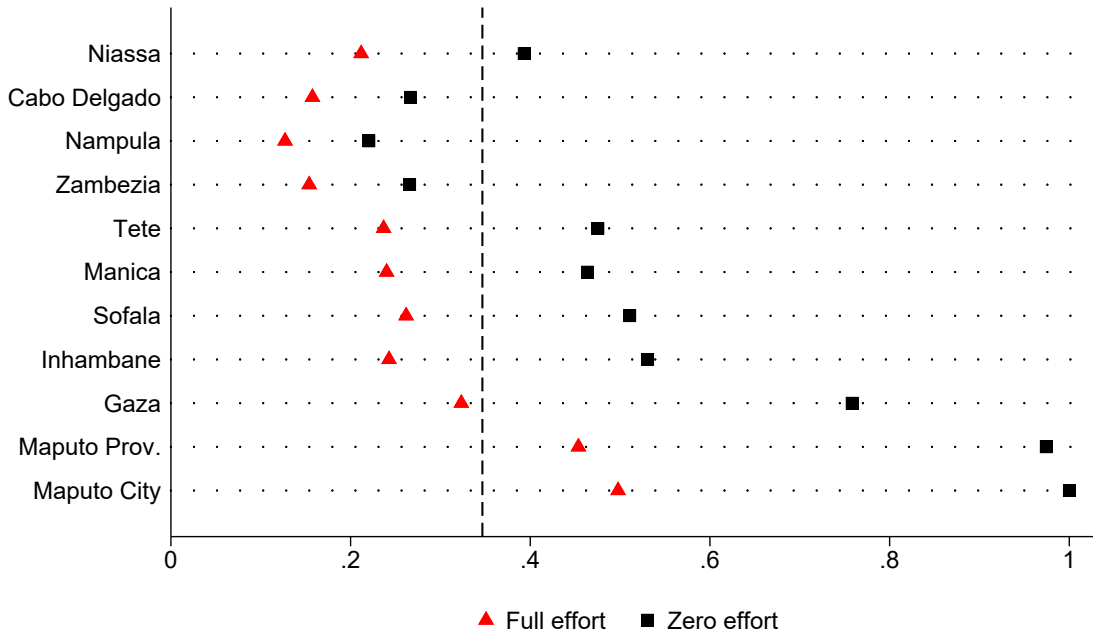
Notes: the map shows estimates of the neutral Relative Effectiveness of Scale-up (RES) metric across administrative posts in Mozambique for $\theta_L = 0$; the RES index compares the marginal welfare gain from expanding program coverage relative to improving targeting accuracy, using a benchmark assumption of non-regressive targeting.

Figure A4: Average thresholds on zero and full effort maximal budget shares, for chosen values of ϕ at $\theta_L = 0$

(a) Thresholds for $\phi = 1$:



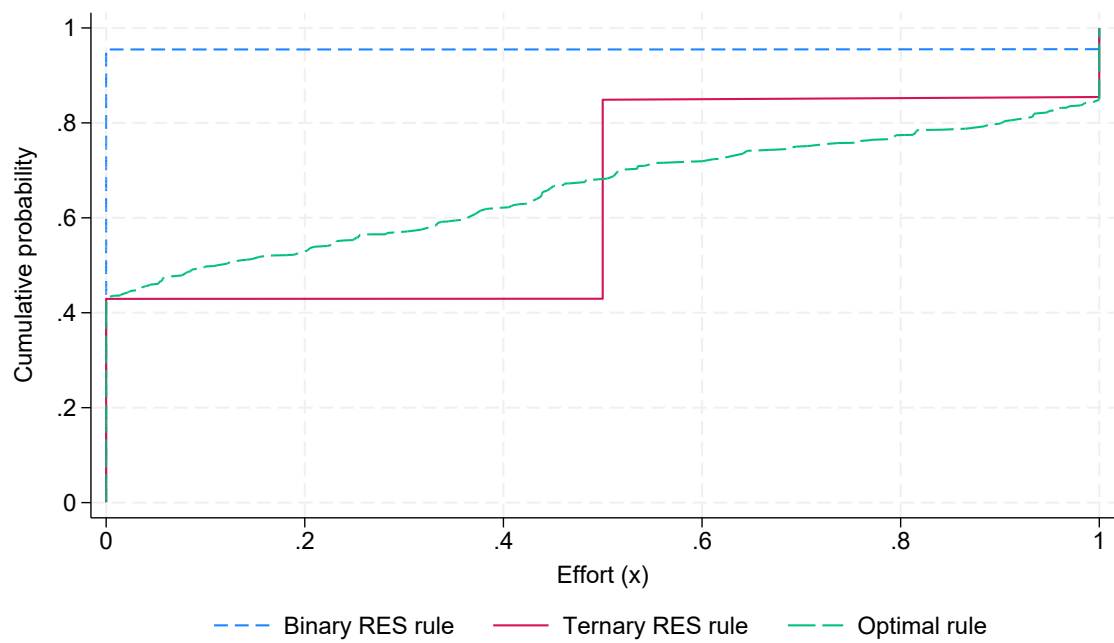
(b) Thresholds for $\phi = 2$:



Source: own elaboration.

Notes: figure shows mean budget thresholds (x-axis) associated with zero or full targeting effort by province; if the actual maximum budget (μ) is greater than the higher threshold, then zero effort is recommended; if the maximum budget falls below the lower threshold, then full effort is recommended; vertical line indicates the (lower bound) anchor on the maximal budget share, $\bar{\mu}_{a,\phi}$; leakage aversion, θ_L , is fixed at zero.

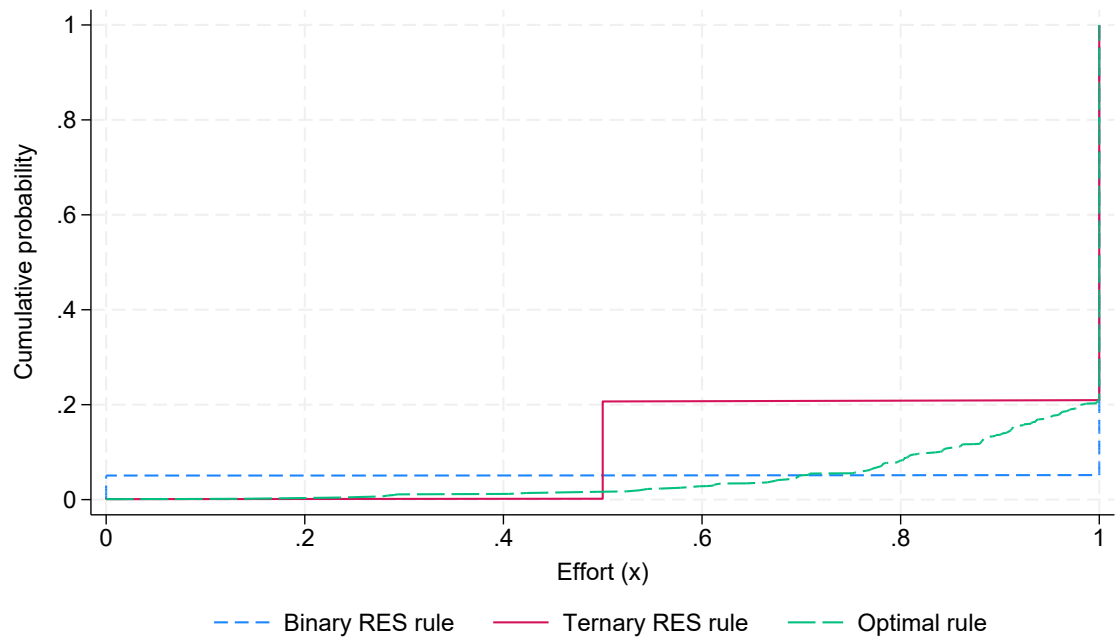
Figure A5: Cumulative distributions of recommended effort under alternative rules,
 $\theta_L = -0.5, \phi = 1$



Source: own elaboration.

Notes: this figure replicates Figure 2(b) setting $\theta_L = -0.5, \phi = 1, \mu = \bar{\mu}_{a,1}$.

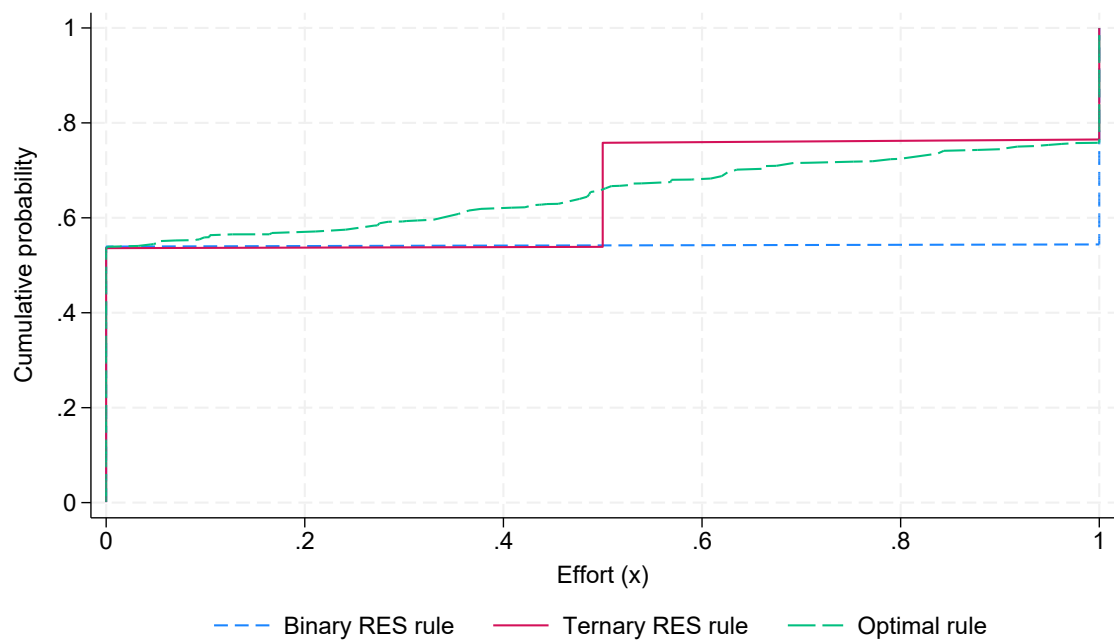
Figure A6: Cumulative distributions of recommended effort under alternative rules,
 $\theta_L = 0.5, \phi = 1$



Source: own elaboration.

Notes: this figure replicates Figure 2(b) setting $\theta_L = 0.5, \phi = 1, \mu = \bar{\mu}_{a,1}$.

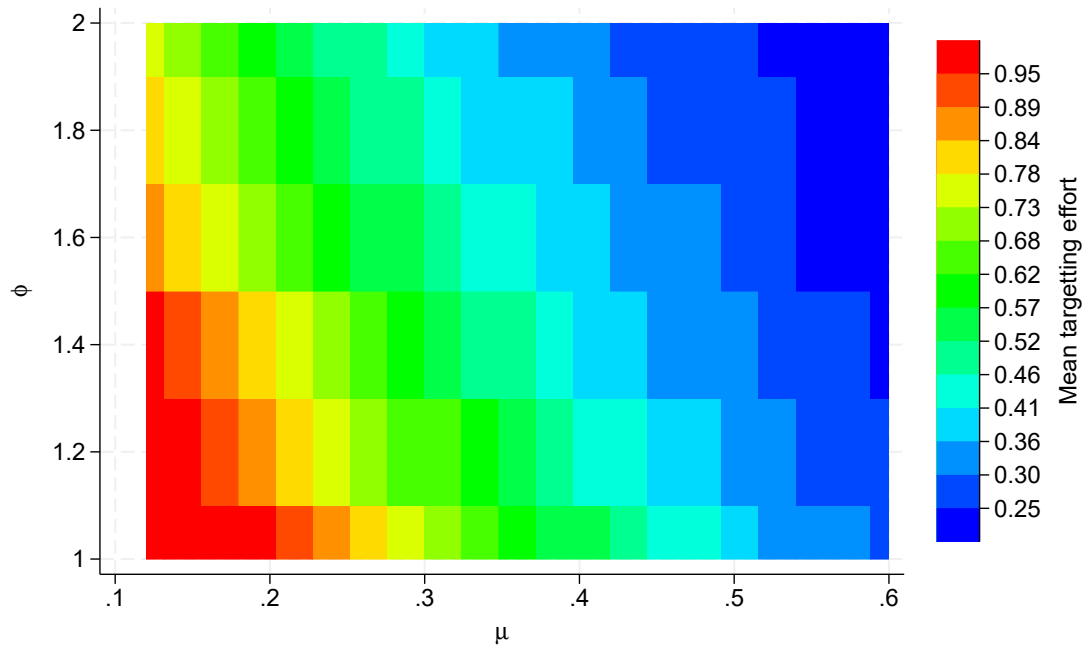
Figure A7: Cumulative distributions of recommended effort under alternative rules,
 $\theta_L = 0, \phi = 2$



Source: own elaboration.

Notes: this figure replicates Figure 2(b) setting $\theta_L = 0, \phi = 2, \mu = \bar{\mu}_{a,1}$.

Figure A8: Heat map of county-wide average optimal targeting effort for alternative values of ϕ and μ , with $\theta_L = 0$



Source: own elaboration.

Notes: figure displays a heat map of the population-weighted mean optimal targeting effort under equation (18) with $\theta_L = 0$; estimates are based on simulations using alternative values for the targeting return parameter (ϕ) and the cost share parameter (μ); warmer colors (red/yellow) indicate higher effort, while cooler colors (blue) represent lower effort.

B Appendix: Theoretical extensions and derivations

B.1 Extension of RES to exclusion aversion

Consider augmenting the operational welfare maximand to $Z' = \alpha q - \beta_L(1 - \alpha)q - \beta_E(q^* - \alpha q)$, where $\beta_E \geq 0$ is now an additional weight on exclusion. This simplifies to:

$$Z' = (1 + \beta_E)\alpha q - \beta_L(1 - \alpha)q - \beta_E q^* \quad (\text{B1})$$

The final term $-\beta_E q^*$ is a constant from the planner's perspective once q^* is fixed, and so plays no role in the marginal trade-off between q and α . The exclusion weight β_E therefore enters only by rescaling the correct-inclusion coefficient from unity to $(1 + \beta_E)$.

Working through the marginal rate of substitution thus yields a modified RES:

$$\text{RES}' = \frac{(1 + \beta_E)\alpha - \beta_L}{(1 + \beta_E)q} = \frac{\alpha - \theta'_L}{q}, \quad (\text{B2})$$

where $\theta'_L \equiv \beta_L/(1 + \beta_E + \beta_L) \in [-\infty, 1)$ is a rescaled composite parameter.

This demonstrates that under exclusion aversion the structural form of the RES is preserved; the exclusion weight β_E acts only through the denominator of θ'_L , thereby dampening the effective leakage aversion. Hence, a planner who places greater value on reaching the poor (higher β_E) is observationally equivalent to one with lower leakage aversion (lower effective θ_L), in the sense that both shift the RES criterion toward favouring coverage expansion. Without independent information distinguishing the two motives, β_E and β_L are not separately identified from the targeting decision alone; so, the composite θ_L remains the relevant sufficient statistic. A planner who places strict ethical priority on exclusion can equivalently be represented by a planner with a low effective θ_L in our framework.

B.2 General case for optimal effort

We derive the optimal targeting effort $x^* \in [0, 1]$ by maximizing the welfare objective function of equation (15) in the main text:

$$Z(x) = k \cdot \frac{b(1 - x\mu)}{t} \left[f(q^*, x) - \theta_L \right], \quad (\text{B3})$$

where $\alpha = f(q^*, x)$ is a concave function increasing in x , with $f(q^*, 0) = q^*$; $\mu \in (0, 1)$ is the maximum fraction of the total budget per capita of population that can be allocated to targeting effort; $x \in [0, 1]$ is the policymaker's decision on what share of that maximum is used; $b = B/N$ is the per capita variable budget; t is the uniform transfer amount per beneficiary; $k = 1 + \beta_L$; and $\theta_L = \beta_L/k \in [0, 1)$ is the composite welfare-weight parameter defined in equation (5).

Step 1: First-Order Condition

Differentiating $Z(x)$ with respect to x , and denoting the partial derivative $f'_x = \partial f(q^*, x)/\partial x$, we obtain:

$$\frac{\partial Z}{\partial x} = \frac{b k}{t} \{f'_x(1 - x\mu) - \mu [f(q^*, x) - \theta_L]\}$$

Setting $\partial Z/\partial x = 0$ gives the interior first-order condition (FOC):

$$f'_x(1 - x\mu) = \mu [f(q^*, x) - \theta_L] \quad (\text{B4})$$

Solving equation (B4) for the optimum $x = x^*$:

$$x^* = \frac{f'_x - \mu [f(q^*, x^*) - \theta_L]}{f'_x \mu}$$

Note that because f'_x and $f(q^*, x^*)$ are both functions of x , this expression is implicit and may require numerical solution methods. However, it is informative for establishing bounds and sufficiency conditions.

Step 2: Corner Solutions and Bounds

We now explore when the optimal x^* lies at the boundary of the feasible interval. Throughout, we maintain the regularity condition $q^* > \theta_L$, which ensures the program delivers positive welfare per beneficiary at the neutral (random-selection) benchmark. When this condition fails, the program is net-regressive in welfare terms under any feasible targeting accuracy and a degenerate corner obtains in which the planner allocates as much as possible to targeting.

Case 1: Zero effort is optimal ($x^ = 0$).*

Substitute $x = 0$ into the first-order condition (B4):

$$f'_x = \mu [f(q^*, 0) - \theta_L] = \mu(q^* - \theta_L)$$

Hence, $x^* = 0$ is optimal if:

$$f'_x \leq \mu(q^* - \theta_L) \quad \Rightarrow \quad \mu \geq \frac{f'_x}{q^* - \theta_L}$$

Case 2: Full effort is optimal ($x^ = 1$).*

Substitute $x = 1$ into the same first-order condition:

$$f'_x(1 - \mu) = \mu [f(q^*, 1) - \theta_L] = \mu(\bar{\alpha} - \theta_L),$$

where $\bar{\alpha} = f(q^*, 1)$. Rearranging:

$$f'_x = \mu(f'_x + \bar{\alpha} - \theta_L) \quad \Rightarrow \quad \mu \leq \frac{f'_x}{f'_x + \bar{\alpha} - \theta_L}$$

Thus, $x^* = 1$ is optimal if the cost share is small relative to the marginal and maximum adjusted benefits of targeting.

Step 3: Interior Solution

If neither corner condition holds, the solution must lie in the interior $x^* \in (0, 1)$, and is defined implicitly by equation (B4), with:

$$x^* = \frac{f'_x - \mu[f(q^*, x^*) - \theta_L]}{f'_x \mu}$$

Hence, the optimal effort level x^* satisfies equation (16) in the main text. This general formulation allows for application across a wide class of concave targeting functions, and provides a rigorous foundation for policy-relevant simulations.

B.3 Specific example for optimal effort

For completeness, we now present the derivation for the general parametric form $\alpha = q^* + x(1 - q^*)^\phi$ as used in the main text (equation 17), where $\phi = 1$ represents the linear reference case. Substituting into the FOC (B4):

$$(1 - q^*)^\phi(1 - x\mu) = \mu[q^* + x(1 - q^*)^\phi - \theta_L]$$

Expanding:

$$(1 - q^*)^\phi - x\mu(1 - q^*)^\phi = \mu q^* + x\mu(1 - q^*)^\phi - \mu\theta_L$$

Rearranging:

$$(1 - q^*)^\phi - \mu(q^* - \theta_L) = 2x\mu(1 - q^*)^\phi$$

Solving for x yields the interior solution:

$$x^* = \frac{(1 - q^*)^\phi - \mu(q^* - \theta_L)}{2\mu(1 - q^*)^\phi}$$

Applying the constraints $0 \leq x \leq 1$, the lower-bound solution ($x^* \geq 0$) obtains when:

$$\frac{(1 - q^*)^\phi - \mu(q^* - \theta_L)}{2\mu(1 - q^*)^\phi} \geq 0$$

Since the denominator is positive for $\mu > 0$ and $q^* < 1$, we require the numerator to be

non-negative:

$$(1 - q^*)^\phi - \mu(q^* - \theta_L) \geq 0,$$

which, solving for μ , yields:

$$\mu \leq \frac{(1 - q^*)^\phi}{q^* - \theta_L}$$

Hence, if $\mu > (1 - q^*)^\phi / (q^* - \theta_L)$, then $x^* = 0$

Similarly, the upper-bound solution ($x^* \leq 1$) obtains when:

$$\frac{(1 - q^*)^\phi - \mu(q^* - \theta_L)}{2\mu(1 - q^*)^\phi} \leq 1$$

Multiplying both sides by $2\mu(1 - q^*)^\phi$:

$$(1 - q^*)^\phi - \mu(q^* - \theta_L) \leq 2\mu(1 - q^*)^\phi$$

Rearranging:

$$(1 - 2\mu)(1 - q^*)^\phi \leq \mu(q^* - \theta_L)$$

Solving for μ :

$$\mu \geq \frac{(1 - q^*)^\phi}{2(1 - q^*)^\phi + q^* - \theta_L}$$

So, if $\mu < (1 - q^*)^\phi / [2(1 - q^*)^\phi + q^* - \theta_L]$, then $x^* = 1$.