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Targeting when Poverty is Multidimensional

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Abstract

The view of poverty as a multidimensional phenomenon has swiftly become mainstream. However, the debate remains open as to how such 'multidimensional poverty' should be assessed in practical settings, particularly when identifying the beneficiaries of poverty alleviation programmes. This paper develops a novel empirical approach that explicitly takes into account the goals and needs of the policy-maker. In particular, the paper takes up the case of a government official running a budget-constrained programme to alleviate a few dimensions of poverty, and translates her concerns into a set of desiderata which the multidimensional measure should meet. The policy-maker targeting ability and aversion to the risk of leakages play crucial roles in setting the desired properties. We illustrate our methodology in the context of a CCT programme in Peru, and show that it improves expected leaking and undercoverage relative to alternative Alkire-Foster based approaches.

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1 Introduction

The literature on poverty has welcomed the concept of multidimensionality as a timely reminder that poverty cannot be reduced to monetary shortfalls, since the latter do not fully capture the total set of dimensions in which a person may suffer from severe hardship. However, while the view of poverty as a multidimensional phenomenon has swiftly found a place within the mainstream of the field, the debate remains open as to how such 'multidimensional poverty' should be empirically assessed. This should come as no surprise, since it is a challenging task to produce a formula specifying precisely how shortfalls across a variety of dimensions compound to distress a family.

In this paper we take a different viewpoint and focus on the goals and needs of the policy-maker. Our proposed measure will not aim at greater consistency with the nature of the predicament of the household. Instead, we argue that a multidimensional measure would be of greater use to policy-makers, and of wider use among them, if their concerns and the practicalities of their work were explicitly taken into account. We propose a measure placing these needs at the root of its specification.

As pointed out elsewhere, no single value can summarise the multi-faceted nature of poverty. Any multidimensional measure is bound to miss information, and may well mislead analyses if it fails to capture those pieces of information which matter most to the questions at hand. As this paper proposes a particular measure for multidimensional poverty aiming to inform actual policy, it explicitly focuses on the questions and 'operational' needs of the policy-maker, even at the cost of overlooking the details of how hardships frustrate individual lives. In particular, the paper takes up the case of a government

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official running a budget-constrained programme to alleviate a few dimensions of poverty, and translates her concerns into a set of desiderata which the multidimensional measure should meet. Difficulties in targeting and aversion to the risk to leakages play crucial roles.

For instance, in the eyes of our policy-maker, a location where many individuals are free from poverty in every dimension will be a location with a high risk of delivering aid packages into the hands of people with no need of such packages, not even of parts of them. If her targeting ability is weak, a location where everyone suffers poverty in at least some dimension may be a safer choice. Considerations in this vein will lead us below to impose restrictions on the cross-derivatives of our multidimensional index. Likewise, its marginal rate of substitution will be required to reflect that the policy-maker will not fail to notice severe unidimensional hardship. So to speak, paying attention to multiple dimensions should not blind her to evident suffering, while on the other hand it should alert her to the risk of leaking her resources through multiple channels.

The paper embeds such concerns into our multidimensional measure from the onset, i.e. from the specification of how individual achievements in each dimension impact on the assessment of their multidimensional poverty. By this route, we come to the conclusion that a homothetic specification will suit best these concerns, and for simplicity, within the set of homothetic functions, we opt for a measure with a constant elasticity of substitution across dimensions.

Path-breaking efforts to clarify how to measure multidimensional poverty include Bourguignon & Chakravarty (2003), Tsui (2002), Deutsch & Silber (2005). They build on the properties of unidimensional poverty measures, and formulate sets of axioms transporting those properties to, and addressing the new issues raised by, the multidimensional case. This paper draws on these approaches. We however pay particular attention to the double-cutoff index developed by Alkire & Foster (2011), since it has arguably become the most common multidimensional measure among policy-makers, not least because this counting method is simple to implement and, crucially, because it easily deals with qualitative dimensions, such as access to sanitation or basic health services. Since budget constraints typically imply that staff will not be sufficiently trained to deal with complex estimations, both simplicity and conformity to data availability are attributes much appreciated by policy-makers. However, we argue below that other attributes would be just as desirable, and yet a sum of FGT unidimensional indices, such as AF, fails to secure them.

The rest of the paper is organized as follows. Section 2 lays down a set of axioms for a policy-oriented multidimensional poverty measure. Section 3 presents our preferred measure. Section 4 implements our targeting methodology in the context of a CCT programme in Peru and assesses its performance. Section 5 concludes and discusses policy implications.

2 Properties

Recall we take the viewpoint of the policy-maker, and in particular we embrace her interest to run social programmes with as much efficacy as possible. In this case, a multidimensional index serves the policy-maker chiefly by enabling her to rank all possible beneficiaries and thus select which of them should be cared for first. With such an index driving her targeting efforts, she may operate her programmes fluently. In particular, she should not halt her work when she sees that, say, Adam is severely deprived in dimension 1 but free from poverty in dimension 2, whereas Bob suffers only mild hardship in both dimensions. To negotiate such conflicts between dimensions by means of a set of socially acceptable criteria, we define axioms which we then impose on our multidimensional index.

In particular, the defining characteristic of our policy-maker will be her wariness at the possibility of wasting the resources entrusted to her, and even at the threat of being accused of such waste. She will be mindful of her own difficulties to prevent leakages of her resources into the hands of non-targeted individuals and will exhibit risk aversion.

We first lay down our notation. Imagine a budget-constrained social programme aiming to impact r dimensions, each d-th dimension characterised for each i-th individual by an outcome x_{id}. Define matrix $\mathbf{X} = [x_{id}]$, column-vector $\mathbf{x}^d = [x_{1d} \dots x_{nd}]$ and row-vector $\mathbf{x}_i = [x_{i1} \dots x_{ir}]$, where n is the number of possible beneficiaries. Row-vector $\mathbf{z} = [z_1 \dots z_r]$ contains all r unidimensional poverty lines, and let $\mathbf{1}$ denote a row-vector with all elements equal to 1. For all i and d, impose hereafter $x_{id} \geq 0$ and $z_d \geq 0$.

When $r = 1$, a number of well-accepted measures of unidimensional poverty can guide spending. When $r > 1$, targeting is less straight-forward because dimensions need not be positively correlated over the population – e.g. in the case of Adam and Bob above, $x_{A1} < x_{B1}$, but $x_{A2} > x_{B2}$.

Hereafter, to assess multidimensional poverty m_i for any i-th individual,

$$m_i = \phi(\mathbf{x}_i; \mathbf{z}) \tag{1}$$

where we assume that for any $\mathbf{x}_i$ and $\mathbf{z}$, $\phi(.)$ is continuous and differentiable in $\mathbf{x}_i$, both to simplify proofs below and to prevent small changes in x_{id} from causing abrupt changes in m_i. For later use, let $\phi_d(\mathbf{x}_i; \mathbf{z}) \equiv \frac{\partial \phi(\mathbf{x}_i;\mathbf{z})}{\partial x_{id}}$ and $\phi_{de}(\mathbf{x}_i; \mathbf{z}) \equiv \frac{\partial^2 \phi(\mathbf{x}_i;\mathbf{z})}{\partial x_{id} \partial x_{ie}}$.

As usual in the literature, we further define aggregate multidimensional poverty M as the average of individual multidimensional indices:

$$M = \frac{1}{n} \sum_{i=1}^{n} m_i \tag{2}$$

We now proceed to our axioms, which we group into three categories: properties directly drawn from the theory on unidimensional measures, properties governing how different dimensions are combined into the single multidimensional measure, and lastly properties capturing the policy-maker's efforts to use the available resources as efficiently as possible.

2.1 Basic properties

Our first four axioms are akin to the usual properties of unidimensional measures, and we state them without further discussion:

Scale invariance (ScI). $\phi(\mathbf{x}_i; \mathbf{z}) = \phi(\mathbf{x}_i \mathbf{\Lambda}; \mathbf{z}\mathbf{\Lambda})$ for any definite-positive diagonal matrix $\mathbf{\Lambda}$. Changes in measurement units for the outcome of any dimension have no bearing.

Monotonicity (Mo). $\phi_d(\mathbf{x}_i; \mathbf{z}) \leq 0$ for any x_{id}. Keeping outcomes for all other dimensions unaltered, an increase in the outcome of any dimension can never entail a rise in multidimensional poverty.

Focus (Fo). $\phi_d(\mathbf{x}_i; \mathbf{z}) = 0$ if $x_{id} > z_d$. Changes in outcomes above the unidimensional poverty line are not allowed to impact on multidimensional poverty.

Boundedness (Bo). $\text{Min}_{\mathbf{x}_i} \phi(\mathbf{x}_i; \mathbf{z}) = 0$ and $\text{Max}_{\mathbf{x}_i} \phi(\mathbf{x}_i; \mathbf{z}) = 1$. The lower- and upper-bounds are 0 and 1, respectively, and act as reference values to judge whether multidimensional poverty is 'low' or 'high'.

2.2 Substitutability properties

Our next set of properties addresses a question absent in unidimensional analyses – can high outcomes in some dimensions substitute for deprivation in some others? Should someone under severe deprivation in one dimension receive greater (or less) attention than, say, someone else facing only mild hardship, but in all dimensions? In the case of Adam and Bob above, who should be targeted first?

To our knowledge, the literature has thus far sought the answer to these questions in the nature of individual well-being, i.e. do high achievements in some aspects of Adam's life actually alleviate his sufferings in other spheres? This is no simple question. Indeed, perhaps no proper and general answer exists.

Consider instead the viewpoint of the policy-maker. When it comes to targeting decisions, failure to capture correctly the actual degree of substitutability between dimensions creates the risk of e.g. withdrawing support from individuals enduring patent, verifiable shortfalls (as Adam) in the wrong belief that other achievements in their lives will lessen their pains. The policy-maker will understandably refuse to incur in, or be accused of, such misjudgements.

To expand on this point, we note that any specification of $\phi(\mathbf{x}_i; \mathbf{z})$ implies some assumption about how dimensions substitute (or fail to substitute) for each other, and a multidimensional measure requires the policy-maker to be willing to embrace that particular guess. In particular, we hereafter use the marginal rate of substitution s^{de} to measure the ability of an additional unit of dimension d to make up for losses in dimension e:

$$s_i^{de} = \frac{\phi_d(\mathbf{x}_i; \mathbf{z})}{\phi_e(\mathbf{x}_i; \mathbf{z})} \tag{3}$$

Our focus on s_i^{de} is akin to the approach in Ravallion (2012) – there, if any "change entails that one dimension increases at the expense of another then it is the marginal rate of substitution that tells us whether human development is deemed to have risen or fallen. Only if we accept the tradeoffs built into such a composite index can we be confident that it is adequately measuring what it claims to measure" (p. 201).

To capture the concerns above, we formulate the following three axioms:

Symmetry across dimensions (Sy). $\phi(\mathbf{x}_i; \mathbf{z}) = \phi(\mathbf{x}_i\mathbf{B}; \mathbf{zB})$ for any bi-stochastic matrix B. There is no change if dimensions are relabelled, so that all dimensions receive equal treatment. Neither will some dimensions receive greater weights than others, nor will some pair of dimensions relate to each other in a particular manner (e.g. in terms of substitutability), different from the relationship between any two other dimensions. If desired, a weaker version of this symmetry could be invoked to allow for dimension-specific weights.

Sensitivity to unidimensional hardship (UH). $\frac{\partial s_i^{de}}{\partial x_{ie}} > 0$ for any d and $e \neq d$. The lower the outcome in any e-th dimension, the more difficult for any other dimension to make up for further decreases in that troubled dimension, i.e. substitutability decreases when hardship deepens in a given dimension. When this property holds, the willingness to accept that an individual facing unidimensional poverty can cope with it due to her higher achievements elsewhere weakens when that unidimensional poverty becomes more severe – the policy-maker will refuse to turn a blind eye on manifest hardship, however unidimensional it might be.

Sensitivity to severe unidimensional hardship (SUH). If $x_{ie} = 0$, then $s_i^{de} = 0$. If deprivation in one dimension is extreme, improvements in other dimensions are entirely meaningless. While this property may be read as a stronger version of UH, it is important to note that it also sets an absolute reference for the degree of concern for unidimensional hardship, which under SUH requires more than just a relative increase in s_i^{de} if hardship intensifies. Added to UH, this property secures concerns for the unidimensionally deprived will be consequential, as policy-makers plausibly wish. Alternative versions of this axiom could define severity at values other than zero, e.g. $s_i^{de} = 0$ if $x_{ie} \leq \hat{x}_e$.

2.3 Efficiency properties

Policy-makers are typically haunted by budget constraints. In particular, our policy-maker will exhibit risk aversion as she faces up to the possibility that part of her funds may prove fruitless. She will be wary of her own inability to reach her intended beneficiaries. Our next two properties are motivated by the intention to avoid leakages. While the first property will consider the case of a policy-maker with poor observation and enforcement abilities, the second one will imagine these abilities are in place. In practice, either stance will result in a specific constraint on the cross-derivative $\phi_{de}(\mathbf{x}_i; \mathbf{z})$.

Minimal leakage with weak targeting ability (WTA). For any d and e, $\phi_{de}(\mathbf{x}_i; \mathbf{z}) < 0$. A budget-constrained, risk-averse policy-maker should be wary of a positive correlation across dimensions if her targeting ability is weak, since the threat of significant leakage will loom on her.

Minimal leakage with strong targeting ability (STA). For any d and e, $\phi_{de}(\mathbf{x}_i; \mathbf{z}) > 0$. In spite of her risk aversion, a budget-constrained policy-maker with a strong targeting ability will dare to use a positive correlation across dimensions to seek a higher impact of her resources.

We now explain the rationale for these properties. Drawing first from a prior result of the literature, we recall that, since our aggregate index M in (2) follows an additive specification, the cross-derivative

$\phi_{de}(\mathbf{x}_i;\mathbf{z})$ will govern how it reacts to changes in the correlation among dimension outcomes. In particular, a greater positive correlation causes an increase in M if $\phi_{de}(\mathbf{x}_i;\mathbf{z}) > 0$.[1]

Next, to consider what a positive correlation across dimensions entails for the policy-maker, compare cases (I) and (II) below.

Table 1

	(I)		(II)	
	Dimensions		Dimensions	
	1	2	1	2
Individual 1	0.80	0.20	0.20	0.20
Individual 2	0.20	0.80	0.80	0.80

With no change in the marginal distribution of outcomes for each dimension, cases (I) and (II) differ because in the latter case individual 1 is poorer than individual 2 in both dimensions. The literature on multidimensional poverty calls this an 'increasing correlation switch', and again, efforts to pronounce judgement on it typically endeavour to understand how dimensions compound in distressing a household, e.g. how much harder is it for individual 1 above to endure a low x_{12} if now x_{11} is also low?

We take a different stance. Imagine $z_1 = z_2 = 1$ and a *risk-averse* policy-maker runs a programme to raise outcomes in *both* dimensions and with enough resources to reach only one individual. If we let (I) and (II) describe two scenarios and the policy-maker had to select one of them, then (II) provides her with an opportunity to maximise the impact of the programme, if only she can ensure individual 1 is the sole beneficiary – otherwise, the whole of her resources will go wasted. We argue that the choice of a risk-averse policy-maker will hence depend on her ability to observe individual outcomes and target accordingly.

On the one hand, if the policy-maker has sufficient trust in her targeting ability and can ensure that only individual 1 can access the programme, then M should rank (II) above (I). This is secured by $\phi_{de}(\mathbf{x}_i;\mathbf{z}) > 0$, as in STA.

On the other hand, if she realises her difficulties to target correctly are a hurdle, then the ranking may well reverse. (I) provides certainty about the amount of 'leaked' resources – regardless of which individual is chosen as beneficiary, 50% of resources will be devoted to raising an outcome which is already as 'high' as 0.80. In case (II), the expected 'leakage' is also 50%, but uncertainty haunts the policy-maker – with a 50% probability, individual 2 is selected as beneficiary and all resources are leaked. Recall our policy-maker is risk averse. Hence, with insufficient targeting ability, a positive correlation is now something to fear, and by imposing $\phi_{de}(\mathbf{x}_i;\mathbf{z}) < 0$, WTA will prioritise (I) above (II).

Adding some further structure to the example in Table 1 may illustrate further the choice between STA and WTA. Let the b-th individual be the *actual* beneficiary. Temporarily, keep $n = r = 2$, and assume that outcomes are tradable and that the programme at hand delivers (z_1, z_2) to this b-th individual, so that she escapes poverty even if $(x_{b1}, x_{b2}) = (0, 0)$. The policy-maker is mindful of other social goals beyond this programme. Hence, she will see (x_{b1}, x_{b2}) as resources that have been spent unnecessarily, since only $(z_1 - x_{b1}, z_2 - x_{b2})$ would suffice to lift the beneficiary out of his poverty.

To account for imperfect targeting ability, the *intended* beneficiary will have only a λ probability of actually having access to the programme, so that someone else gets away with the benefits with probability $(1 - \lambda)$. Assume $\lambda \geq \frac{1}{2}$ and let targeting ability be measured by a monotonically increasing function $T(\lambda)$:

$$T(\lambda) = \frac{\lambda}{1 - \lambda} \tag{4}$$

where $T(\lambda) \geq 1$ because with targeting ability at its lowest, $\lambda = \frac{1}{2}$ and the beneficiary could just as well be determined by tossing a coin.

[1]To see why, let $n = 2$, $r = 2$ and $\hat{x}_d > \check{x}_d$ for $d = 1, 2$. Note then $[\phi(\hat{x}_1, \hat{x}_2) + \phi(\check{x}_1, \check{x}_2)] - [\phi(\hat{x}_1, \check{x}_2) + \phi(\check{x}_1, \hat{x}_2)] = \int_{\check{x}_2}^{\hat{x}_2} \int_{\check{x}_1}^{\hat{x}_1} \phi_{12}(x_1, x_2) \mathrm{d}x_1 \mathrm{d}x_2$, where for simplicity we omit $\mathbf{z}$ from $\phi(\mathbf{x}_i;\mathbf{z})$.

Take a strong positive correlation as a starting point. To this end, assume individual 1 is poorer in every dimension ($x_{11} < x_{21}$ and $x_{12} < x_{22}$) and hence the intended beneficiary. In this case, the risk-averse policy-maker will seek the minimise the expected (risk-adjusted) loss of resources $\mathbb{L}$:

$$\mathbb{L}(\mathbf{x}_1, \mathbf{x}_2) = \lambda \left(x_{11} + x_{12}\right)^{\mu} + (1 - \lambda) \left(x_{21} + x_{22}\right)^{\mu} \tag{5}$$

where $\mu > 1$ to secure risk aversion.

Imagine now a correlation-reducing transfer of the outcome of either dimension from individual 2 to individual 1. The policy-maker will welcome this reduction in correlation (i.e. $\Delta\mathbb{L} < 0$) whenever her targeting ability fails to reach a threshold $\tilde{T}$:

$$\text{If } T(\lambda) \left\{ \begin{array}{c} < \\ = \\ > \end{array} \right\} \tilde{T}, \text{ then } \Delta\mathbb{L} \left\{ \begin{array}{c} < \\ = \\ > \end{array} \right\} 0 \tag{6}$$

where $\tilde{T} = \left(\frac{x_{21}+x_{22}}{x_{11}+x_{12}}\right)^{\mu-1}$.[2]

Intuitively, with limited targeting ability (below $\tilde{T}$), the policy-maker would welcome the decrease in correlation because a strong positive correlation means that poor outcomes will be concentrated in the intended beneficiary. In such a case, failure to reach her would mean that the actual beneficiary was already free from poverty in every dimension. For the policy-maker, this amounts to the daunting risk of a ruinous waste of resources if they ended up in the wrong hands. This is our WTA case. Note risk aversion plays a crucial role. Greater risk aversion (i.e. higher μ) raises the ability threshold $\tilde{T}$ further up, and few policy-makers escape this dread of waste.[3]

When targeting ability is strong enough (that is, above $\tilde{T}$), we have our STA case. $\Delta\mathbb{L} > 0$, so that when poor outcomes are concentrated in one individual, the fears described above are not forceful enough to cloud the view of a good opportunity – the policy-maker will confidently aim to turn this intended beneficiary into the actual beneficiary.

We close this section with three remarks. First, note our argument is reminiscent of the dilemma between 'risk equity' and 'catastrophe avoidance' in Keeney (1980) – the policy-maker may dislike to see all predicaments agglomerating on one individual (to the detriment of 'equity'), but the threat of widespread hardship ('catastrophe') would be a bleak alternative. As in Keeney (1980), the dilemma boils down to a decision about the cross-derivative $\phi_{de}(\mathbf{x}_i; \mathbf{z})$.

Second, this implies that targeting ability will play a very clear role in the case of geographical targeting, since the correlation of dimension outcomes *within* locations will drive the choice of the policy-maker. For instance, if cases I and II in Table 1 above describe two locations, then the policy-maker will rank them following her choice between WTA and STA.

Third, note again that as we pay attention to the target ability and the risk aversion of the policy-maker, we disregard whether the dimensions at hand are complements or substitutes in the so-called ALEP sense. We realise that our prescriptions may therefore collide with viewpoints focusing on e.g. how much individual 1 suffers under case II in Table 1 (say, because dimensions are substitutes to each other and low outcomes in both dimensions amount to unabashed hardship). With our proposal, this concern would bow to the fear of leakage under WTA. We are explicit about this departure from the literature, because as we argue above, the question about the nature of individual predicaments and whether dimensions substitute for or complement each other has in our view no cogent answer. In contrast, the policy-maker does know about her practical difficulties and about the consequences of her leakages. For this same reason, we have ignored the $\Delta\mathbb{L} = 0$ case in (6). In the absence of the answer about how dimensions behave, it may be tempting to say dimensions do not interact, as indeed any additive multidimensional measure does, but we think no policy-maker will remain indifferent to the choice between WTA and STA.

[2]To see why, note that for $\Delta x_{11} = -\Delta x_{21} > 0$, $\Delta\mathbb{L} = \mu(1-\lambda)\left(x_{11} + x_{12}\right)^{\mu-1}\left[\frac{\lambda}{1-\lambda} - \left(\frac{x_{21}+x_{22}}{x_{11}+x_{12}}\right)^{\mu-1}\right]\Delta x_{11}$

[3]Indeed, absence of risk aversion (i.e. $\mu \leq 1$) would discard $T(\lambda) < \tilde{T}$, since $T(\lambda) \geq 1$ and $\frac{x_{21}+x_{22}}{x_{11}+x_{12}} > 1$.

3 A targeting-oriented measure of multidimensional poverty

We now seek a measure conforming to the axioms above. Where a choice is in order, we opt for the path leading to a simpler specification. Since the skills of the staff running social programmes are typically heterogeneous, we see simplicity as a crucial feature of a proposal intending to suit the needs of policy-makers. After presenting our preferred measure in Subsection 3.1, we next discuss in Subsection 3.2 how it compares with the measure of widest current use, namely the Alkire-Foster double-cutoff index.

3.1 A homothetic measure of multidimensional poverty

To begin with, we note that ScI and Fo jointly imply that every piece of meaningful information in x_{id} and z_d is captured by a standardised, censored outcome $\tilde{x}_{id}$:

$$\tilde{x}_{id} \equiv \text{Min}\left[1, \frac{x_{id}}{z_d}\right] \tag{7}$$

Define accordingly $\tilde{\mathbf{X}}$, $\tilde{\mathbf{x}}^d$ and $\tilde{\mathbf{x}}_i$, so that hereafter,

$$m_i = \psi(\tilde{\mathbf{x}}_i), \text{ where } \psi(\tilde{\mathbf{x}}_i) \equiv \phi(\tilde{\mathbf{x}}_i; \mathbf{1}) \tag{8}$$

We next invoke SUH, which requires that for any $d \neq e$, no value of $\tilde{x}_{id}$ should override the fact that $s_i^{de} = 0$ if $x_{ie} = 0$. For instance, and recalling (3),

$$\frac{\psi_d(\tilde{\mathbf{x}}_i)}{\psi_e(\tilde{\mathbf{x}}_i)} = \theta^{de}(\tilde{\mathbf{x}}_{i|e})\tilde{x}_{ie}^{\rho}, \text{ with } \rho \neq 0 \tag{9}$$

where $\tilde{\mathbf{x}}_{i|e}$ is a row vector identical to $\tilde{\mathbf{x}}_i$, but omits $\tilde{x}_{ie}$, and $\theta^{de}(\tilde{\mathbf{x}}_{i|e})$ is an unrestricted function. Alternative specifications for s_i^{de} would equally secure $s_i^{de} = 0$ regardless of $\tilde{\mathbf{x}}_{i|e}$, but we opt for the simpler route.[4]

Given Sy, (9) also implies $\frac{\psi_e(\tilde{\mathbf{x}}_i)}{\psi_d(\tilde{\mathbf{x}}_i)} = \theta^{ed}(\tilde{\mathbf{x}}_{i|d})\tilde{x}_{id}^{\rho}$, so that

$$\left[\theta^{de}(\tilde{\mathbf{x}}_{i|e})\tilde{x}_{id}^{\rho}\right]\left[\theta^{ed}(\tilde{\mathbf{x}}_{i|d})\tilde{x}_{ie}^{\rho}\right] = 1 \tag{10}$$

which entails $\theta^{de}(\tilde{\mathbf{x}}_{i|e}) = \tilde{x}_{id}^{-\rho}$. Resorting again to (9), this leads to our main result:

$$s_i^{de} = \left(\frac{\tilde{x}_{ie}}{\tilde{x}_{id}}\right)^{\rho} \tag{11}$$

Hence, a simple measure of multidimensional poverty satisfying ScI, Fo, Sy and SUH must be written as follows:

$$m_i = \psi(\tilde{\mathbf{x}}_i), \text{ where } \psi(\cdot) \text{ is homothetic.} \tag{12}$$

Homotheticity restricts the set of available forms for $\psi(\cdot)$, but does not confine it to one single choice. We again invoke simplicity and opt for a specification with constant elasticity of substitution as the simplest among the set of homothetic functions (Clemout 1968):

$$\psi(\tilde{\mathbf{x}}_i) = \zeta(\mu), \text{ where } \begin{cases} \zeta(\mu) \text{ is a monotonic transformation} \\ \mu = [\sum_{d=1}^{r} x_{id}^{\gamma}]^{\frac{1}{\gamma}} \\ \gamma = 1 - \rho \neq 1, \text{ given (9)} \end{cases} \tag{13}$$

To select a specific form for $\zeta(\mu)$, it will suffice to invoke Mo and Bo.

[4] For instance, $s_i^{de} = \theta(\tilde{\mathbf{x}}_{i|e})x_{ie}^{\hat{\theta}(\tilde{\mathbf{x}}_{i|e})}$, or $s_i^{de} = \theta(\tilde{\mathbf{x}}_{i|e})\left(a^{x_{ie}} - 1\right)$ where $a > 0$, or a sum of all these choices.

In particular, given Bo and Mo, $\zeta'(\mu) < 0$, $\zeta(0) = 1$ and $\zeta(1) = 0$. To take a simple instance,

$$\zeta(\mu) = 1 - \mu^{\beta} \text{ where } \beta > 0 \tag{14}$$

Lastly, UH imposes $\gamma < 1$, and hence we can write as follows the final version of our multidimensional measure:

$$m_i = \begin{cases} 1 - [\sum_{d=1}^{r} \tilde{x}_{id}^{\gamma}]^{\frac{\beta}{\gamma}} \text{ , for } \gamma < 1 \text{ and } \gamma \neq 0 \\ 1 - (\prod_{d=1}^{r} \tilde{x}_{id})^{\beta} \text{ , for } \gamma = 0 \end{cases} \tag{15}$$

where the limiting case $\gamma = 0$ is a well-known result.

Note that in choosing values for β and γ, the policy-maker will in practice opt for either WTA or STA, in keeping with how strong she feels her ability to identify and effectively target her preferred beneficiaries. In particular, $\gamma > \beta$ is necessary for STA to hold.

Importantly, the limiting case with $\gamma = 0$ implies $\beta > \gamma$ and hence is always committed to WTA. For this reason, $m_i = 1 - (\prod_{d=1}^{r} \tilde{x}_{id})^{\beta}$ may be a convenient rule-of-thumb choice for countries with weaker targeting abilities. Risking some ambiguity, we will hereafter refer to it as the WTA index

3.2 Comparison with the double-cutoff measure

Adding an indicator function $\mathbb{I}[\cdot]$ to our notation and assuming all dimensions are equally weighted, the AF family of measures can be written as follows:

$$m_i^{AF(\alpha)} = \omega_i \left(\frac{1}{r} \sum_{d=1}^{r} (1 - \tilde{x}_{id})^{\alpha} \right) \text{, where } \omega_i = \mathbb{I}\left[\sum_{d=1}^{r} \mathbb{I}[\tilde{x}_{id} < 1] \geq k \right] \tag{16}$$

As Alkire and Foster suggest themselves, the AF specification in (16) builds on the well-known FGT(α) index for individual, dimension-specific poverty, with $\alpha \geq 0$. The key postulate in AF is that such unidimensional hardship should matter only if $\omega_i \neq 0$, i.e. if for the i-th individual the count of dimensions below their unidimensional poverty lines is at least as high as k. Most of the latest efforts to target and evaluate social spending with a multidimensional view have adopted and adapted this version of the double cutoff approach for targeting purposes. For example, Azevedo & Robles (2013) develop a version of the AF index in order to target a Conditional Cash Transfer (CCT) programme in Mexico. More recently, Diaz et al. (2015) also follow the AF principles to develop an index that first identifies deprivations at the individual level, and then aggregates them at the household level to obtain a multidimensional deprivation index.

By means of the axioms in Section 2, we now turn to examine how the AF index fares as a targeting tool.. We take the $\alpha = 0$ and $\alpha > 0$ cases in turn. First, when $\alpha = 0$, the measure boils down to the count of dimensions below their unidimensional poverty lines – to say it again, provided that count is at least as high as k:

$$m_i^{AF(0)} = \omega_i \left(\frac{1}{r} \sum_{d=1}^{r} \mathbb{I}[\tilde{x}_{id} < 1] \right) \tag{17}$$

This double-cutoff individual index thus turns into a double-counting index in its aggregate version M. First, dimensions in hardship are counted for each individual, and then the individuals with more than k such dimensions are counted within the population. This formulation of multidimensional poverty has been widely used, not least because of its simplicity and, in particular, because it easily handles qualitative outcomes, which are only observed as yes-no conditions.

Under $\alpha = 0$, AF meets all our basic properties (ScI, Mo, Fo, Bo), as well as Sy if no dimension-specific weights are imposed. UH, which requires s_i^{de} to increase in x_{ie}, is harder to assess, because the dichotomous nature of yes-no outcomes rules out successive increases in any one dimension. Nonetheless, we note first that both below and above the k-threshold, s_i^{de} remains stable (at 0 and 1, respectively), regardless of the value of x_{ie}.[5] Next, we see that in the vicinity of the threshold, s_i^{de} diminishes following a switch from $x_{ie} = 0$ to $x_{ie} = 1$.[6] If anything, we must say that AF fails to exhibit sensitivity to unidimensional hardship when $\alpha = 0$. SUH is likewise violated, since $s_i^{de} = 0$ does not necessarily follow from $x_{ie} = 0$. For instance, $s_i^{de} = 1$ in the case just said, when the number of deprived dimensions is high enough to surpass the k-threshold.

As for targeting abilities, the double-counting index sides with neither WTA nor STA, at least sufficiently away from the k-threshold, since the impact of x_{id} on $m_i^{AF(0)}$ is then constant (at either 0 or 1) and hence $\phi_{de}(\mathbf{x}_i; \mathbf{z}) = 0$. In the vicinity of the threshold, the impact is erratic.[7] Policy-makers using the double counting index should bear in mind this behaviour as a caveat, which adds to the likely unease of wielding a tool with no sensitivity to severe deprivation when it is 'only' unidimensional.

We now turn to the $\alpha > 0$ case, which pays attention to the gap between the unidimensional poverty line and the actual outcome for the relevant dimension. As compared to the double count under $\alpha = 0$, this adds valuable information to the measurement exercise. On the flipside, $\alpha > 0$ requires all dimension-specific gaps to be informative, and hence qualitative outcomes can only enter the analysis after some additional structure is imposed on them. We return to this point in our empirical exercise below.

The AF index is consistent with ScI, Mo, Fo, Bo and Sy again under $\alpha > 0$. UH also holds if $\alpha > 1$, but only if the individual is under sufficient duress due to other $k - 1$ dimensions – otherwise, deeper deprivation in any given dimension is entirely inconsequential when the number of dimensions in poverty is less than k. Moreover, under the not uncommon linear case $\alpha = 1$, s_i^{de} becomes constant and AF loses all sensitivity to unidimensional hardship, except for the limiting case when the k boundary is crossed.[8] SUH is likewise violated if $\alpha = 1$.

It will be interesting to note that AF can approach SUH for high values of α. Indeed, assuming at least k dimensions exhibit poverty,

$$\lim_{\alpha \to 0} \left(s_i^{de} \right) = \begin{cases} \infty & \text{if } x_{id} < x_{ie} \\ 1 & \text{if } x_{id} = x_{ie} \\ 0 & \text{if } x_{id} > x_{ie} \end{cases} \tag{18}$$

where $x_{id} > x_{ie}$ secures SUH if x_{id} remains above destitution levels. However, we can also see in (18) that in the case of AF, SUH comes at the cost of assuming perfect complementarity among dimensions.[9] We think that such assumption can hardly be imposed to all contexts *a priori*.

Lastly, as in the $\alpha = 0$ case, neither WTA nor STA is embraced. Altogether, we find the caveats for the double counting index (for $\alpha = 0$) remain valid under higher values of α.

[5]To see why, note that as long as the number of deprived dimensions is above the k-threshold, a rise from poverty to no-poverty in the d-dimension requires the e-th dimension to switch in the opposite direction for $m_i^{AF(0)}$ to remain unaltered. In turn, below the k-threshold a rise in x_{id} has no impact on $m_i^{AF(0)}$, and so there is no need for x_{ie} to change.

[6]Take $x_{id} = 1$ and imagine that among all other dimensions, only $z - 2$ report unidimensional hardship. If $x_{ie} = 0$, then a drop in x_{id} down to 0 would take the individual up to the k-threshold. To keep $m_i^{AF(0)}$ unchanged, a switch in x_{ie} from 0 to 1 would be necessary, and hence $s_i^{de} = 1$. However, if $x_{ie} = 1$, then $s_i^{de} = 0$, since the individual would be too far from the threshold and the initial drop in x_{id} would prove inconsequential.

[7]If among all dimensions other than d and e, only $z - 2$ report unidimensional hardship, then $x_{ie} = 0$ implies that the double-counting index will fall sharply to 0 following a rise in x_{id} from 0 to 1. With $x_{ie} = 1$, $m_i^{AF(0)}$ would remain unaltered at 0 after a similar rise in x_{id} – i.e. $\phi_{de}(\mathbf{x}_i; \mathbf{z}) > 0$ and the double-counting index would appeal to a policy-maker with strong targeting ability. However, if only $z - 1$ other dimensions were in poverty, then WTA ($\phi_{de}(\mathbf{x}_i; \mathbf{z}) < 0$) would result.

[8]See footnote 5.

[9]Graphically, (18) entails L-shaped isopoverty curves.

4 Empirical application to the Peruvian CCT programme

To illustrate our proposal, we use data on *Juntos*, a CCT programme that every two months provides poor households in Peru with 200 Peruvian Soles (about 75 USD in 2012). This transfer is conditional on school-age children attending school, as well as infants and expectant mothers in the household regularly attending health controls. Hence, $r = 3$ for this exercise, with consumption, education and health-nutrition as the dimensions of interest. We compare our WTA index to AF both for $\alpha = 0$ and $\alpha = 1$. As we pointed out in Subsection 3.1, the WTA index is the $\gamma = 0$ case of our measure, which is a convenient choice when targeting ability is expected to be weak.

4.1 Description of programme

The National Programme for the Direct Support of the Poor, *Juntos*, was created in 2005 with the goal of alleviating poverty and breaking its intergenerational transmission. The target group are poor households in rural areas, with at least one person aged between 0 and 19 years or one expectant mother. To receive aid, the household head must hold a valid ID and children must have birth certificates.

A household is eligible if its Household Targeting Index (IFH for the initials in Spanish) is below a region-specific threshold. Although a multiplicity of variables take part in its construction, the IFH is in essence an index of (unidimensional) consumption poverty, based on principal component analysis. It takes values between 0 and 100, with higher values indicating better living conditions. In online Appendix A, we show in detail how the IFH is constructed.

Beneficiaries receive 75 USD bimonthly, conditional on three requirements. First, children aged between 6 and 14 years must be enrolled in a school and attend classes. Second, those aged between 0 and 5 years must regularly visit the doctor for check-ups. Third, pregnant women must attend periodic health controls.

Official information reports that, as of December 2013, *Juntos* had 1, 570, 942 beneficiaries (1, 553, 772 young people aged up to 19 years and 17, 170 pregnant women) in more than 718, 000 households in 14 regions of the country.

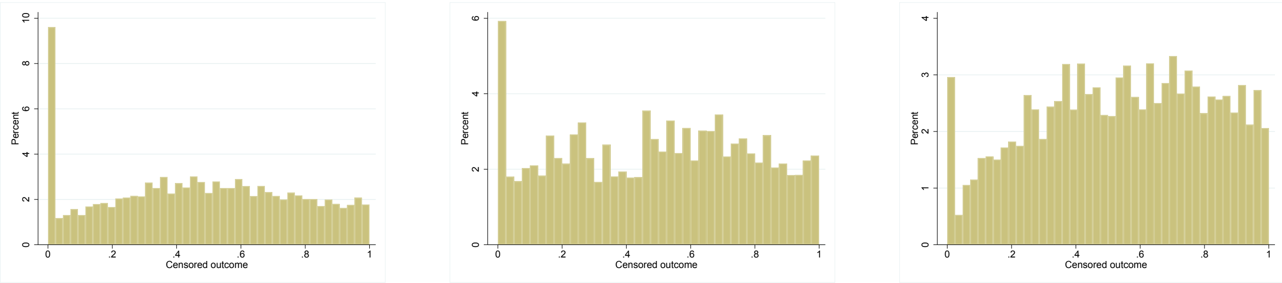
4.2 Poverty estimates

We use a 2012 LSMS (Encuesta Nacional de Hogares) to measure hardship in each of the three dimensions of interest to *Juntos*. In keeping with the rules of the programme, we focus on rural households with at least one person aged between 0 and 19 years.[10] The number of individuals in this subsample is 32, 591, which represents one third of the entire survey.

Self-reported information raises moral hazard issues which have led practitioners to rely on verifiable, unalterable indicators, rather than on dimensions outcomes as reported by applicants. This is one of the reasons why we will use predicted values for the outcomes of all our three dimensions, based on regressions we report in Appendix B – in the case of health, we resort to out-of-sample estimates from the 2012 round of the national survey on health and economic conditions, since our LSMS lacks information on infant health. A further reason is related to the smoothness of the histograms of both predicted outcomes and the corresponding poverty estimates, which we discuss next. Figure 1 reports the histogram of each (censored) predicted outcome for deprived individuals (i.e. $\tilde{x}_{id} < 1$):

[10] Unfortunately, our LSMS does not identify pregnant women.

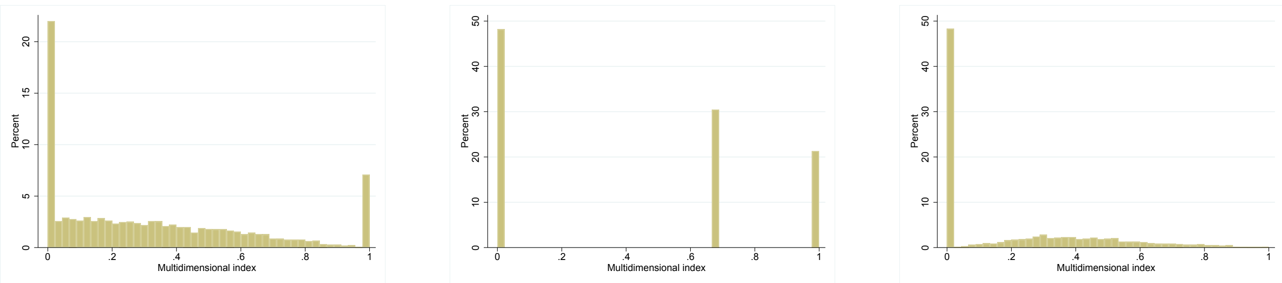
Figure 1: Poverty measures of deprived individuals by dimension



Education | Health | Consumption

We now compute the WTA index for the *Juntos* case, as well as to AF indices that will act as benchmarks for our empirical assessment: AF(0) and AF(1), with $k = 2$.[11] To compute the WTA index, we simply apply the previous censored outcomes $\tilde{x}_{id}$ in equation (15) with $\gamma = 0$ and $\beta = \frac{1}{3}$. Similarly, the AF(α) index with $\alpha = 0$, and $\alpha = 1$. Figure 2 presents histograms for the resulting indices. Each index identifies a group of individuals free from poverty, but little is comparable beyond this. Interestingly, only our WTA index and the double counting index AF(0) reach the upper limit of their range, thereby singling out individuals in severe multidimensional poverty. However, unlike AF(0) but similarly to AF(1), WTA reacts relatively smoothly to marginal changes in a potential cutoff to select beneficiaries. This smoothness is not trivial in the context of targeting, since abrupt reactions could unleash pressures (from within and without the policy-making group) to challenge the threshold and adjust it slightly so as to accommodate more beneficiaries.

Figure 2: Multidimensional poverty measures



WTA index | AF(0) index | AF(1) index

4.3 Multidimensional indices as targeting tools

We turn to assess how these indices perform as targeting tools. In the case of our proposed measure, we use the WTA version (that is, $\gamma = 0$), on the assumption that imperfect targeting ability is the right guess for Peru. Our exercise will be twofold. First, we pay attention to those who suffer evident hardship, and yet an index-based ranking discards them as beneficiaries. Second, we look into wasteful spending, as indices do signal individuals who can be hardly said to live in destitution as beneficiaries.

While our assessment thus echoes the usual concern for two types of targeting errors (*undercoverage* and *leakages*, respectively), we stress that to our knowledge, no agreed definitions of undercoverage and leakage exist when poverty is multidimensional. With a given index acting as the one rightful norm, then should-be beneficiaries and should-be non-beneficiaries could be defined as those on either side of a threshold for that index. This approach is however unwarranted since no such 'true' multidimensional

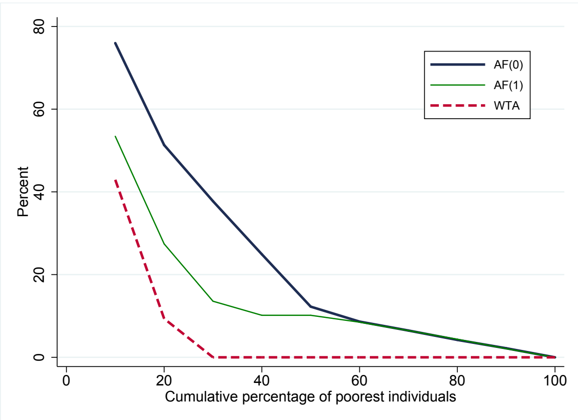
[11] We keep $k = 2$ hereafter, which given $r = 3$ ensures the second AF cutoff is meaningful ($k > 0$) but not extreme ($k = 3$).

index exists, and indeed for comparison purposes, we need WTA and AF(α) to compete on equal footing.

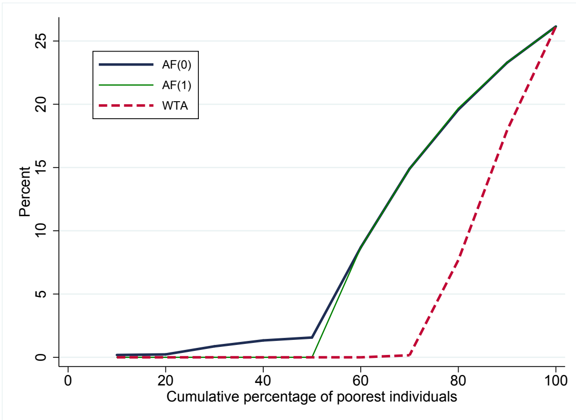
In this exercise, we define undercoverage as failure to reach individuals suffering acute deprivation in one or more dimensions – in practice, $\tilde{x}_{id} \leq w_u$ for any d, where we set $w_u = 0.15$. 5,698 individuals in our dataset (17% of the sample) endure such hardship. We keep the same parameters as in Subsection 4.2.

The first panel in Figure 3 shows the percentage of those should-be beneficiaries who are denied access when the policy-maker defines her target as a given percentage of the poorest individuals according to WTA or AF(α).[12] Assume for instance that *Juntos* aims to cater for the poorest 20% of the target population. If targeting followed the AF(α) index, then at least 30% of the 5,698 individuals in acute deprivation would be excluded. If *Juntos* used the WTA instead, only about 10% of them would be excluded. While undercoverage under AF(α) lessens as the programme increases the size of the target population and approaches universal access, this index is outperformed by our WTA measure.

Figure 3: Undercoverage and leakage under individual targeting



Undercoverage



Leakage

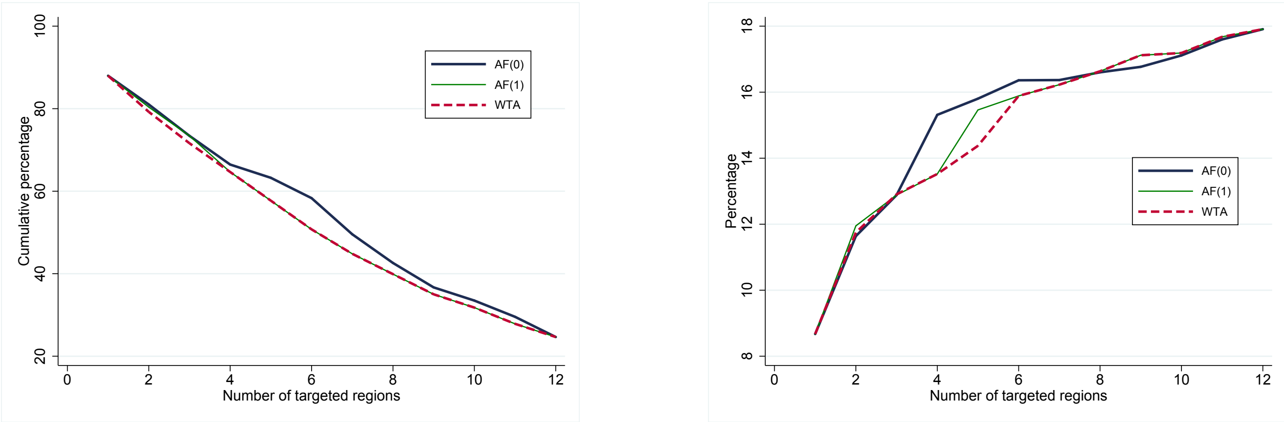
Likewise, our operational definition of leakage will be uncommitted to a particular multidimensional index. Here, the should-be non-beneficiaries will be those with (standardised) outcomes above some threshold in all three dimensions. In practice, $\tilde{x}_{id} = \frac{x_{id}}{z_d} > w_l$ for all d, and we set $w_l = 0.85$ for this exercise. The second panel of Figure 3 reports results for such leakages. Again, our WTA proposal proves more efficient. For instance, consider that *Juntos* decides to cover the poorest 60% of the target population. With AF(α), about 10% of beneficiaries would belong to our non-target group. When the scope of the programme is restricted (for these parameters, when 50% or fewer of the poorest are targeted), WTA and AF(1) are equally successful in mitigating leakage.

As we next consider geographical targeting, we keep the same operational definitions for undercoverage ($w_u = 0.15$) and leakage ($w_l = 0.85$). To assess this case, we assume that once a region is selected, no individual targeting is feasible within it, i.e. for each index, all 24 regions in the country will be ranked, then only those with the highest measure of aggregate multidimensional poverty will be selected, and lastly access will be granted randomly within each of them. The horizontal axes in Figure 4 allow for a range of choices about the number of regions where the programme will operate, taking 12 (out of 24) as the maximum number to keep the exercise realistic.

The first panel in Figure 4 reports the percentage of should-be beneficiaries who remain unaided as the scope of the programme expands to more regions, following the ranking produced by each possible index. We see that the policy-maker is never led to higher undercoverage with WTA, as compared to AF(α). In particular, WTA proves more efficient than AF(0) throughout the relevant range, and also more efficient than AF(1) when the budget constraint is tight and only allows the policy-maker to operate in less than four regions. In the second panel, we report the percentage of non-target individuals

[12] Throughout, we let a random draw choose the beneficiary when the index at hand produces a tie among individuals.

Figure 4: Undercoverage and leakage under geographical targeting



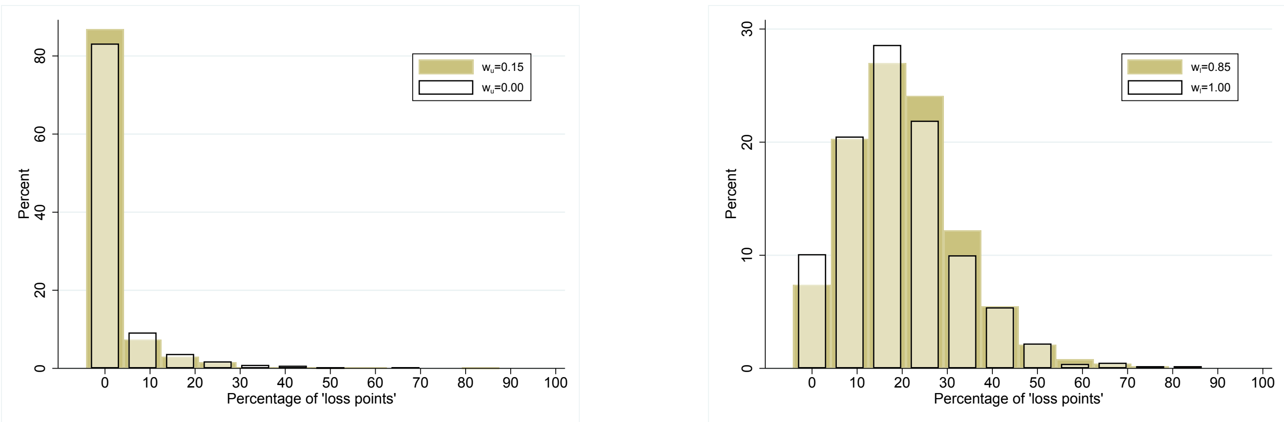
Undercoverage Leakage

in the selected regions, and again WTA largely performs at least as well as AF(α). Within the range of 12 possible choices for the scope of the programme, each AF(0) and AF(1) exhibit lower expected leakage than WTA for only one possible choice (9 targeted regions for AF(0), and 2 for AF(1)).

4.4 Simulations

Lastly, we explore whether our results for the Peruvian LSMS can be expected to obtain from other samples. In addition to the analytical arguments in Section 2, we generate to this end samples of individuals with random outcomes for each of three dimensions. Details can be found in our replication package which includes the Stata code. Figure 5 shows the histograms of WTA loss points upon producing $1,000$ graphs such as those in Figure 4, keeping their same parameter values.[13] By 'loss points', we mean that within the range of possible numbers of beneficiary regions (along the horizontal axis in Figure 4), cases exist where AF(1) leads to lower errors (undercoverage or leakage) than WTA, e.g. when targeting is geographical and two regions are selected, so that leakage is lowest under AF(1). (The histograms for the comparison of WTA to AF(0) are not qualitatively different.)

Figure 5: Performance of WTA versus AF(1) under geographic targeting



Undercoverage Leakage

We see that our index only rarely leads to greater expected than AF(1). However, loss points are more frequent in the case of leakage, as indeed Figure 4 shows for *Juntos* one such point out of 12

[13] $\gamma = 0$, $\beta = \frac{1}{3}$, $k = 2$, $w_u = 0.15$, and $w_l = 0.85$.

possible choices, i.e. 8%. Our simulations suggest we should typically expect more loss points in other samples, but the mode remains relatively low at 20%, and samples where loss points dominate are very rare. In our exercises, these results held true for every set of parameter values we tried. For instance, the panels in Figure 5 include largely similar histograms for other definitions of undercoverage ($w_u = 0$, so that there is a targeting error only if the unidimensional hardship of the unaided individual is extreme) and leakage ($w_l = 1.0$, so that an error exists only if the beneficiary is free poverty in every dimension). Histograms for the case of individual targeting are not reported, but exhibit an even greater weight near zero. As compared with AF1, the average frequencies of WTA loss points are 3.5% and 2.7% for undercoverage and leakage, respectively.

5 Conclusion

In this paper, we have developed a novel approach to the measurement of multidimensional poverty, focusing on the goals and needs of the policy-maker. We embedded the concerns of policy-makers into our measure from the onset, i.e. from the specification of how individual achievements in each dimension impact on the assessment of their multidimensional poverty. Through this axiomatisation, we have concluded that a homothetic specification will suit best theses concerns, and for simplicity, within the set of homothetic functions, we have opted for a measure with a constant elasticity of substitution across dimensions.

In particular, we have let our policy-maker be defined by two of her dominating concerns. She refuses to deny aid to individuals in severe, evident unidimensional hardship, so that the technicalities of how dimensions combine into a overall, multidimensional poverty should not thwart her efforts to cater for these individuals. Also, our policy-maker is much aware of her own practical difficulties to ensure that her targeted individuals become the actual beneficiaries of her programme. For this reason, and for her risk aversion, the index should reduce her exposure to scenarios where she may easily waste resources by allowing them to flow into the hands of non-targeted individuals. In practice, these two concerns are pinned down by restrictions on the marginal rate of substitution (s^{de}) and the cross-derivative (ϕ_{de}) of our proposed index.

As we illustrate our proposal with LSMS data from Peru and also with randomly generated samples, we have argued that this double emphasis of our approach should result in the reduction of targeting errors. In fact, as we tested our index in the context of identifying beneficiaries of a CCT in Peru, and our results suggested both undercoverage and leakage can be expected to lessen, at least as compared with alternative Alkire-Foster indices.

By no means our paper aims to provide a definitive answer to the practical problem of targeting when poverty is multidimensional, but we do intend to highlight the importance of bringing into the debate the goals and needs of those running poverty alleviation programmes. A multidimensional measure will be of greater use to policy-makers, and of wider use among them, if their concerns and the practicalities of their work are explicitly considered.

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Appendix A: Construction of the IFH index

The IFH index is a weighted sum of household characteristics, where the weights are area-specific. Tables I and II, taken from Bernal et al. (2017), present the complete list of variables, together with their mutually-exclusive categories. The table also shows the three sets of area-specific weights: Metropolitan Lima, other urban areas, and rural areas. Notice that higher weights correspond to better categories in terms of welfare. Therefore, higher values of the IFH index indicate better living conditions.

In order to obtain an index ranging from 0 to 100, the weighted sum is standardized in each cluster according to the following formula:

$$ifh_{ij} = 100 * \frac{i\tilde{f}h_{ij} - i\tilde{f}h_j^{min}}{i\tilde{f}h_j^{max} - i\tilde{f}h_j^{min}},$$

where ifh_{ij} is the standardized IFH that lies in the interval $[0, 100]$, $i\tilde{f}h_{ij}$ is the original weighted sum of household characteristics, and $i\tilde{f}h_j^{min}$ and $i\tilde{f}h_j^{max}$ are the minimum and the maximum values of the weighted sum in cluster j, respectively.

Individuals are eligible if their household index is below or equal to a cluster-specific threshold. Each cluster identifies a geographic area, not necessarily connected, with similar monetary poverty in the year 2009.

Bernal et al. (2017) and especially SISFOH (2010) provide more details on the logic and construction of the IFH index.

Table I: Variables and weights for IFH construction

Variables	Metropolitan Lima	Other urban areas	Rural areas
Fuel used to cook			
Do not cook	-0.49	-0.67	-0.76
Other	-0.40	-0.50	-0.38
Firewood	-0.37	-0.33	0.05
Carbon	-0.33	-0.22	0.36
Kerosine	-0.29	-0.19	0.37
Gas	0.02	0.12	0.52
Electricity	0.43	0.69	0.52
Water supply in the home			
Other	-0.78	-0.58	
River	-0.65	-0.42	
Well	-0.62	-0.37	
Water tanker	-0.51	-0.34	
Pipe	-0.41	-0.32	
Outside	-0.35	-0.25	
Inside	0.10	0.12	
Wall material			
Other	-0.70	-0.80	
Wood or mat	-0.48	-0.55	
Stone with mud	-0.44	-0.46	
Rushes covered with mud	-0.41	-0.43	
Clay	-0.39	-0.38	
Sun-dried brick or adobe	-0.37	-0.20	
Stones, lime or concrete	-0.33	-0.07	
Brick	0.10	0.25	
Type of drainage			
None	-0.89	-0.68	
River	-0.75	-0.49	
Sinkhole	-0.59	-0.40	
Septic tank	-0.46	-0.30	
Drainage system outside the house	-0.39	-0.21	
Drainage system inside the house	0.10	0.20	
Number of members with health insurance			
None	-0.26	-0.25	-0.10
One	-0.04	0.06	0.50
Two	0.06	0.17	0.59
Three	0.14	0.27	0.66
More than three	0.32	0.48	0.86
Goods that identify household wealth			
None	-0.47	-0.35	-0.11
One	-0.17	0.05	0.64
Two	0.02	0.25	0.83
Three	0.15	0.40	0.90
Four	0.25	0.52	1.09
Five	0.47	0.75	1.09
Has fixed phone			
Yes	-0.32		
No	0.20		

Notes: Taken from Bernal et al. (2017). The original Spanish version corresponds to SISFOH (2010).

Table II: Variables and weights for IFH construction (Continued)

Variables	Metropolitan Lima	Other urban areas	Rural areas
Roof material			
Other	-0.86	-0.90	
Straw	-0.74	-0.72	
Mat	-0.67	-0.62	
Woven cane	-0.38	-0.23	
Tiles	-0.23	0.03	
Wood or mat	-0.21	0.07	
Concrete	0.17	0.32	
Education of the Household head			
None	-0.51	-0.57	-0.59
Preschool	-0.43	-0.25	-0.08
Primary	-0.28	0.01	0.35
Secondary	-0.06	0.19	0.59
Vocational education (VET)	0.10	0.33	0.68
Undergraduate	0.22	0.55	0.88
Postgraduate	0.40	0.55	0.88
Floor material			
Other	-0.97	-1.12	
Land	-0.60	-0.47	
Concrete	-0.16	-0.01	
Wood	0.08	0.30	
Tiles	0.16	0.40	
Vinyl sheets	0.28	0.51	
Parquet	0.51	0.71	
Overcrowding			
More than six	-0.68		
Between four and six	-0.51		
Between two and four	-0.31		
Between one and two	-0.07		
Less than one	0.24		
Highest level of education in the house			
None			-0.35
Primary			0.11
Secondary			0.41
Vocational education (VET)			0.62
Undergraduate			0.83
Electricity			
No			-0.29
Yes			0.22
Floor made of earth			
Yes			-0.17
No			0.47

Notes: Taken from Bernal et al. (2017). The original Spanish version corresponds to SISFOH (2010).

Appendix B: Predicted values of dimension outcomes

The outcome x_{id} for the education dimension we propose is a predicted value of years of schooling for children between 6 and 14 years old from rural households. This is consistent with the first condition of access to *Juntos*, which requires school enrollment and attendance for this group of children. Instead of working with years of education directly, we survey the empirical literature for Peru to select a pool of determinants of years of schooling, test them by means of a simple linear regression, and calculate the predicted values. To avoid a moral hazard problem, we work with the predicted value instead of the observed variable.[14] The first column of Table III reports the OLS estimates.[15] Finally, the natural threshold z_d for the education dimension is the number of years of education a child should have considering her age (in Peru, her age minus six).[16] We set $\tilde{x}_{id} = 1$ if the household does not have a child between 6 and 14.

As the outcome x_{id} for the health-nutrition dimension, we propose the predicted value of the height-for-age z-score for children aged between 0 and 5 from rural households, which are required by *Juntos* to attend health and growth checks. According to Martorell (1999), the height-for-age z-score captures information as far back in the nutritional history of children as their the intrauterine period. We survey the empirical literature for Peru to select a set of determinants of these z-scores, test them by means of a simple linear regression on an ancillary dataset, and then use the estimated coefficients to compute the predicted z-scores in our LSMS.[17] The second column of Table III reports the OLS estimates we use for this out-of-sample prediction.[18] Finally, the poverty line z_d for the health-nutrition dimension is -2, as suggested by the WHO to identify chronic malnutrition.[19]

The outcome x_{id} for the consumption dimension, in keeping with government practice, is the welfare index IFH, currently used by Peruvian authorities to target *Juntos* beneficiaries. As threshold z_d, we use the average of the official cutoffs for the three geographic clusters where the target population of *Juntos* is located.[20]

[14]In particular, a group of parents may want to drop their children out of school to get the monetary transfer.

[15]The unit of analysis is the rural household with at least one member aged between 6 and 14. In households with more than one such child, the dependent variable is the average of their years of schooling.

[16]If there is more than one child in the age range, the average of the indicators is compared with the average of the deprivation cutoffs.

[17]Our LSMS lacks information on z-scores, so we resort to the 2012 *Encuesta Demográfica y de Salud Familiar*. We take the growth curve provided by the World Health Organization as reference to compute height deviations from age-sex standards.

[18]In households with more than one child under 5, we take the average z-score.

[19]As in the case of education, we use averages if there is more than one child under five. Also, we impose $\tilde{x}_{id} = 1$ if the household does not have any child.

[20]The cutoffs are 36 in cluster 2, 34 in cluster 3 and 38 in cluster 4.

Table III: **Regression on years of education and z-score**

Determinants	**Years of education**[a] **I**	**Z-score**[b] **II**
Parents characteristics		
Father not at home[c]	-0.066	-0.125**
	(-0.054)	(-0.055)
Mother not at home[c]	-0.178	
	(-0.122)	
Low education of mother[d]	-0.202***	-0.311***
	(-0.037)	(-0.039)
Low education of father[d]	-0.179***	
	(-0.036)	
Household's head age		0.005***
		(-0.001)
No health insurance (except SIS)		-0.189*
		(-0.105)
Children characteristics		
Number of male children aged 0-11		-0.068***
		(-0.021)
Number of children aged 0-11		-0.196***
		(-0.043)
Number of children 6-14	-0.065***	
	(-0.016)	
Average age of children aged 6-14	0.878***	
	(-0.007)	
Dwelling characteristics		
Without tap water		-0.518*
		(-0.297)
Without sanitary sewer	-0.136***	-0.233***
	(-0.041)	(-0.056)
No electricity		-0.069*
		(-0.038)
No cellphone or fixed phone line	-0.150***	
	(-0.034)	
Overcrowding	-0.051***	-0.038***
	(-0.01)	(-0.012)
IFH index value	0.034***	
	(-0.005)	
(IFH index value)^2	-0.0003***	
	(0)	
Constant	-5.403***	-0.266
	(-0.151)	(-0.323)
Total Observation	4,688	3,076
R^2	0.818	0.085
Log-Likelihood	-6,145.94	-4,159.58

Notes: *** p<0.01, ** p<0.05, p<0.10. Standard error in parentheses. [a]Enaho (2012): sample of households with at least one child between 6-14 years old. [b]Endes (2012): sample of households with at least one child between 0-5 years old. [c]In the first regression, given that Enaho does not identify family relationship, we assume female household head or female spouse as the mother. Similar procedure is followed in the case of the father. [d]In the first regression, it becomes 0 if there is no female household head, it is the following interaction: (1-female household head without spouse)*(low education of the mother). Similar procedure is followed in the case of the father.