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Article

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Sharpening the Welfare-Consistency of the Mainstream Multidimensional Poverty Identification Method, with Illustration on Nigerian Data

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Abstract

In theory, accounting for nonmonetary dimensions can help sharpen the identification of the poor. In practice, data constraints on nonmonetary dimensions prevent researchers from using the welfare-consistent identification methods traditionally used in monetary poverty measurement. The pragmatic identification methods used when measuring multidimensional poverty are criticized for their lack of welfare-consistency (Ravallion 2011). This paper considers one solution that holds the potential to improve the welfare-consistency of these pragmatic identification methods and illustrates how this solution can be implemented in practice in the context of Nigeria in 2019. The empirical illustration suggests that this solution may substantially affect the identification of the multidimensionally poor. The results also find substantially different poverty comparisons between multidimensional poverty and monetary poverty even though monetary poverty (1) is high in Nigeria in 2019, (2) is very heterogeneously distributed across Nigerian states, and (3) is integrated as one component of the multidimensional poverty measure.

JEL classification: I32

Keywords: Multidimensional Poverty, Poverty Identification, Welfare Consistency

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1 Motivation

Identifying who is poor and who is not poor is important in practice. It is necessary to help target policy efforts on individuals with the lowest well-being. Crucially, identifying the poor is the first step in the construction of any poverty measure (Sen 1976). The second step, which attributes a poverty score to all poor individuals, directly builds on the identification step. Poverty identification methods are thus a central component of poverty measures, which are commonly used to monitor progress.

There is now a consensus that well-being is multidimensional (Stiglitz, Sen, and Fitoussi 2009). Therefore, properly identifying individuals with the lowest well-being requires accounting not only for monetary dimensions, but also for nonmonetary ones. Poverty measurement practices, long dominated by monetary poverty, are increasingly considering multidimensional poverty.

One key difficulty is that data constraints prevent researchers from using the same identification methods for multidimensional poverty as the methods traditionally used for monetary poverty. Monetary poverty uses prices to aggregate across the different "dimensions" (i.e., across the different goods and services consumed) in a way that is broadly consistent with preference (Ravallion 2015). A preference-based identification method is compelling because an individual identified as poor under some bundle should not be identified as nonpoor under another bundle that she deems worse than the first bundle. Therefore, several authors have suggested using preference-based methods when identifying the multidimensionally poor (Maasoumi and Lugo 2008; Decancq, Fleurbaey, and Maniquet 2019). Unfortunately, these methods can hardly be used in practice because of two major data constraints. First, no well-defined prices are readily available for nonmonetary dimensions. Also, preference-elicitation techniques based on alternative data, such as subjective well-being or stated preferences, do not seem mature enough to be used in practice (Decancq and Nys 2021; Benjamin et al. 2023). As a result, practitioners do not have the necessary information on preferences for applying these methods. A second difficulty is that the data on nonmonetary outcomes are often ordinal or even categorical, while the data on monetary outcomes capture quantities and are thus cardinal.

To circumvent these two data constraints, several authors, such as Alkire and Foster (2011) and Pattanaik and Xu (2018), propose "pragmatic" methods to identify the multidimensionally poor. These "pragmatic" methods can be readily applied given the available data. However, neither their parametric mathematical formula nor the values for their parameters are selected with the objective to approximate a preference-based identification of the poor.[1] That is, these pragmatic methods set aside welfare-consistency in the sense that they do not explicitly aim at identifying the multidimensionally poor from some threshold indifference curve. The pragmatic method proposed by Alkire and Foster (henceforth AF) is the most used in applications. Its mathematical formula is based on a weighted sum of binary deprivation statuses. In practice, its parameters are typically selected in an ad hoc fashion, as in the case of the global Multidimensional Poverty Index (MPI) or of the World Bank's Multidimensional Poverty Measure (MPM).[2]

Ravallion (2011) criticizes the AF identification method as well as its implementations on the ground they are not "welfare-consistent," that is, not preference-based. He worries that the trade-offs made across different dimensions could deviate too much from the marginal rates of substitution of the relevant preference.[3] Ravallion proposes another identification method whose mathematical formula admits marginal rates of substitutions as parameters, and he suggests estimating their values from data on preferences. Thus, Ravallion's criticism focuses on the first data-constraint, namely the absence of well-defined prices.

1 A few research studies aim at selecting the values of these parameters without relying on a variant of the "equal-weights" approach, e.g., Al-Ajlani et al. (2020) or Bennett (2021).

2 Sometimes, weights are selected through consultative processes. This constitutes a welcome improvement, but the relationship between weights obtained in this way and preferences remains unclear.

3 See also Ravallion (2012) for an argument against well-being aggregations that make implausible trade-offs across dimensions.

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However, his paper does not focus on the second data constraint, namely that many nonmonetary achievements are ordinal and captured through categorical variables. Yet, identification methods based on categorical variables cannot capture plausible marginal rates of substitution across ordinal achievements. Indeed, categorical variables imply poverty identification contours that have either zero or infinite marginal rates of substitution (cfr discussion of fig. 3 at the end of section 2).

Decerf (2023) further studies the criticism raised by Ravallion. He develops a preference-based theory of multidimensional poverty identification that acknowledges that the relevant preference is only partially known. His theoretical results rank the mathematical formulas of alternative pragmatic identification methods as a function of their "welfare-consistency," namely their ability to approximate a plausible threshold indifference curve. When data are cardinal, the identification method proposed by Ravallion does not unambiguously dominate the AF method. In contrast, the method proposed by Pattanaik and Xu (2018) dominates both the AF method and the Ravallion method. However, the methods of Ravallion and Pattanaik and Xu cannot be used with ordinal and categorical data. Decerf proposes a refinement of the AF identification method that dominates the AF method in terms of welfare-consistency and can also be used with ordinal and categorical data. The basic idea is to account for the depth of deprivation in a given variable by moving from *binary* deprivation statuses (deprived vs. nondeprived) to *trinary* deprivation statuses, where deprived individuals can be either moderately or extremely deprived. Unfortunately, Decerf (2023) has no empirical section. Thus, Decerf does not illustrate how this refined AF identification method could be implemented in practice in the presence of cardinal and categorical variables and does not study whether such refined AF method would make an empirical difference with the classical AF method. This paper aims at filling these two gaps.

Before proceeding, it is important to acknowledge two key points made by Ravallion that remain unaddressed in this paper. First, preferences are not elicited. As a result, the present study's aggregation of different dimensions is ad hoc in the sense that it reflects the authors' views rather than those of poor individuals. The refined AF methodology allows identifying the poor in a way that better approximates a plausible indifference curve, but there is no guarantee that this paper's proposal approximates the *relevant* indifference curve, which remains unknown (see section 2). Second, and related to the first point, there is no guarantee that this study's identification of individuals with the lowest well-being is better than that made by a purely monetary poverty measure. Indeed, it remains theoretically possible that this paper's ad hoc aggregation yields such an imperfect approximation of the relevant indifference curve that its aggregation has zero added-value or a negative one. Ravallion expressed his skepticism about aggregating across dimensions without preference data, partly because of the risk of doing more harm than good. Yet, once data on the relevant preference becomes available, the flexibility allowed by the refined AF method will allow better exploiting this data than the AF method.

This paper proposes one way of implementing the refined AF identification method and studies its empirical relevance in the context of Nigeria in 2019, one of the poorest countries in the world with a large population. The illustration on Nigerian data probes the answer to two empirical questions:[4]

> Question 1: what is the magnitude of the impact that the implementation of the refined AF method has on the set of poor individuals?
> Question 2: how different is monetary poverty identification from the refined AF identification?

Importantly, the analysis probes the answer to question 2 with a definition of multidimensional poverty that integrates monetary poverty as one of its dimensions.[5] Moreover, the study does so in the Nigerian context where monetary poverty is high—40.5 percent of Nigerians are below their national poverty

4 The paper's empirical ambitions are limited to these two questions. It does not claim that its poverty indicators are better suited for Nigeria than Nigeria's official poverty indicators.

5 Other studies contrasting monetary from nonmonetary poverty measures in the context of developing countries, like Salecker, Ahmadov, and Karimli (2020) need not integrate monetary poverty inside their multidimensional indicator.

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line—and very heterogeneously distributed across the Nigerian states—their poverty rates range from 10 percent to 90 percent (Lain, Schoch, and Vishwanath 2024). This context is thus conservative in the sense that these two features should reduce the relative impact that nonmonetary dimensions can have on poverty identification and on poverty comparisons.

For question 1, the results suggest that the AF refinement can have a substantial impact. This paper's results suggest that ignoring this information on depth—by bundling together extreme and moderate forms of deprivation—may decrease the fraction of individuals identified as multidimensionally poor by as much as one quarter.

For question 2, the results suggest that accounting for nonmonetary dimensions substantially affects the set of poor individuals and could thus have important policy implications. The study classifies multidimensionally poor individuals into two categories that are *not* mutually exclusive: "monetary" poor individuals—who are below Nigeria's national poverty line, which is virtually equal to the "extreme" International Poverty Line (IPL) of the World Bank[6] in 2019—and "other-dimensions" poor individuals—whose nonmonetary deprivations are sufficient to classify them as multidimensionally poor. As expected, other-dimensions poverty is positively correlated with monetary poverty. However, the correlation is far from perfect. As a result, more than one-third of other-dimensions poor individuals are not monetary poor. Ignoring nonmonetary dimensions leads to "omitting" these individuals when identifying low well-being and thus affects poverty comparisons. Importantly, the analysis shows that the proportion of omitted poor individuals tends to be larger for states that have relatively *small* monetary poverty rates. The results suggest that the impact of accounting for nonmonetary dimensions on poverty comparisons is increasing over time at the global level given the progress made since 1990 against extreme monetary poverty (World Bank 2022a).

Third, using the head-count ratio as poverty index,[7] the study quantifies in two ways the impact that nonmonetary dimensions have on poverty comparisons across Nigerian states. It finds that 9 percent of pairwise comparisons of states are reversed when switching from a classic monetary poverty measure to the study's preferred version of the multidimensional poverty measure. This shows that pairwise comparisons from these two measures are positively correlated, but this correlation is far from perfect. The study's second method assumes that a hypothetical social-protection budget is allocated across states proportionally to the poverty recorded in the different states. This second method quantifies the fraction of the budget that must be re-allocated across states when switching from one poverty measure to another. This second method is less sensitive to measurement errors than the one based on rank reversals. The study finds that 6 percent of the budget must be re-allocated across states when switching from a classic monetary poverty measure to the study's preferred version of the multidimensional poverty measure. When interpreting these figures, recall that the study's multidimensional poverty measure integrates monetary poverty as one of its dimensions and that Nigeria has a high monetary poverty rate that is very heterogeneously distributed across Nigerians states.

This article's main contribution to the vast literature on multidimensional poverty measurement lies in proposing one implementation of the refined AF identification method and probing its empirical implications. To be sure, this refined AF identification method differs in important ways from alternative proposals and similar-looking research papers. In a nutshell, no other paper uses three deprivation statuses per variable to improve welfare-consistency when identifying the multidimensionally poor. First, and closest to this paper, several alternative identification methods have mathematical formulas that re-

Studies that do integrate it, like Battiston et al. (2013) or Evans, Nogales, and Robson (2023), base their multidimensional indicator on the classical Alkire-Foster method.

6 See Jolliffe et al. (2024) for a definition of the IPL in 2017 PPPs and Decerf (2025) for the conceptual foundations and limitations of the IPL.

7 It remains an open question whether this paper's findings would still hold when using a depth-sensitive poverty index.

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quire cardinal data (Ravallion 2011; Pattanaik and Xu 2018), while the refinement this paper considers can also be used on ordinal and categorical data. Second, some authors study the constraints placed on the identification method by properties imposed on the poverty measure (Bosmans, Lauwers, and Ooghe 2018; Datt 2019). These papers thus put more emphasis on the fairness properties of the poverty measure than on the "welfare-consistency" of its associated identification method.[8] In contrast, the perspective of the present paper puts more emphasis the welfare-consistency of the identification method.[9] Third, a large literature *takes as given* the AF identification method and its mathematical formula but studies alternative values for its parameters. For instance, Alkire and Seth (2016) identify "destitutes" using more austere dimension-specific cut-offs or a more austere poverty identification threshold. Dhongde et al. (2016) study how to set AF weights when some dimensions are deemed more important ("basic") than other dimensions. Yalonetzky (2014) studies the conditions under which the poverty comparisons of AF measures are robust to all plausible values of its parameters. Duclos, Sahn, and Younger (2006) also study the robustness of multidimensional poverty comparisons, with the particularity that their criterion does not assume a particular mathematical formula for the identification method. These authors study robustness and thus leave aside the question of how to identify the poor. Fourth, some papers assume that the mathematical formula of the identification method is exogenously given and then study the properties of the multidimensional poverty index (Alkire and Foster 2011). Several of these papers assume the union approach is used for identification (Tsui 2002; Bourguignon and Chakravarty 2003). Fifth, Seth and Yalonetzky (2021) study the measurement of poverty based on a unique categorical dimension. When a unique dimension is considered, there are no welfare-consistency issues when identifying the poor because there is no need to aggregate across dimensions. Hence, none of these papers considers a poverty-identification method based on several dimensions-specific cut-offs.

The remainder is organized as follows. Section 2 presents the refined AF identification method and exposes the conceptual reasons why this refinement has the potential to improve welfare-consistency. Section 3 presents two versions of this paper's identification method ("baseline" and "preferred" designs). Section 4 presents the study's results on the extent of poverty in Nigeria and how it can be decomposed into the contribution of alternative dimensions. Section 5 quantifies the impact that nonmonetary dimensions have on poverty comparisons. Section 6 concludes.

2. Refined Identification of the Poor

This section exposes a conceptual limitation of the Alkire-Foster methodology and presents one pragmatic refinement that improves on this limitation.

Preference-Based Definition of the (Multidimensionally) Poor

A preference-based definition of the (multidimensionally) poor starts from a preference-based definition of well-being. Consider a utility function U that represents the relevant preference over achievement vectors $x = (x_1, \ldots, x_m)$, which captures individual achievements in the m dimensions affecting well- being. An individual with achievement vector x is defined to be (multidimensionally) poor if her utility is smaller than some utility threshold U^*, that is, $(x) < U^*$. Observe this definition is purely ordinal: it only relies on the ranking over achievement vectors represented by function U. This definition can thus accommodate

8 Datt (2019) shows that only the union approach is consistent with the properties he considers. Clearly, the union approach does not perform optimally in terms of welfare consistency as it cannot properly identify cumulators (see section 2).

9 One reason to prioritize the welfare-consistency of the identification method is that the head-count ratio is frequently used in public communications. Another reason is that a coarse identification method decreases the relevance of good properties. Indeed, the fact that a poverty measure treats fairly the individuals it identifies as poor is of limited interest if those individuals were drawn at random.

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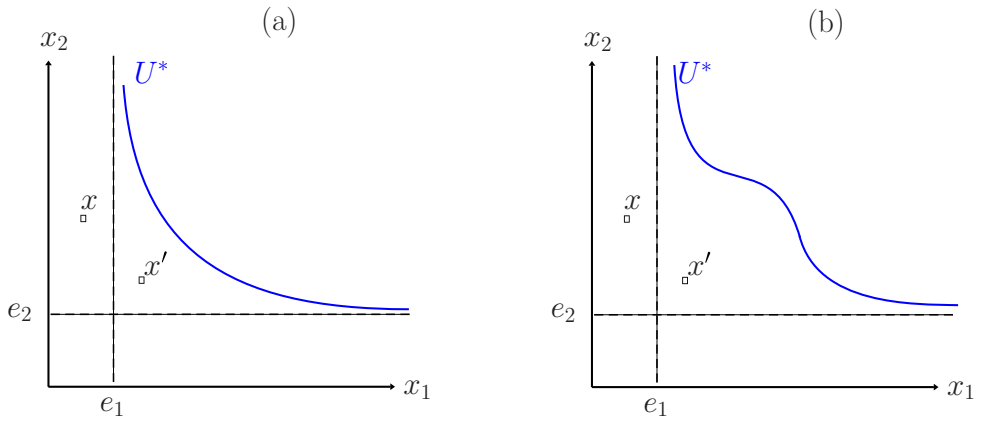
Figure 1. Two Types of Poor Individuals under a Preference-Based Definition of the Poor



Source: Authors' drawing.
Note: Indifference curve U^* is in blue, an individual is an extremor if she consumes x and a cumulator if she consumes x'. *Indifference curve U^* is convex when the two dimensions are cardinal (a) but not necessarily when one dimension is ordinal (b).

different frameworks used to conceptualize multidimensional poverty, like functionings and capabilities or minimal rights.

As graphically illustrated for the case m = 2 in fig. 1, individuals are poor when their achievements vector falls below indifference curve U^*. As argued in Decerf (2023), the shape of this indifference curve should obey two restrictions that reflect upper and lower bounds for the substitutability across dimensions. First, indifference curve U^* admits a positive asymptote in each of the core dimensions of well-being. This restriction reflects the view that if an individual achievement is below an extreme threshold $e_j > 0$ in a core dimension of well-being, she must be poor regardless of her achievements in the other dimensions (Sen 1999, Nussbaum 2009; Alkire et al. 2015). Second, indifference curve U^* has strictly positive marginal rates of substitution. This restriction reflects the views that individuals with utility level U^* are always willing to slightly decrease their achievement in one dimension provided their achievements in other dimensions are sufficiently increased (Ravallion 2011). It is likely that any definition of the multidimensionally poor that violates any of these two restrictions is both unrealistic from a positive perspective and not compelling from a normative perspective.

An immediate consequence of such preference-based definition of the poor is that there are two types of poor individuals. First, an "extremor" is poor because at least one of her achievements is extremely low, that is, $x_j \leq e_j$ for some core dimension j. This is a sufficient condition to be poor, but not a necessary condition as implied by the second type. Second, a "cumulator" is poor because she cumulates moderately low achievements in several dimensions, even though none of her achievements is extremely low. In fig. 1, an individual with achievement vector x is an extremor, and an individual with achievement vector x' is a cumulator.

Two remarks are worth making. First, the graphical illustrations of the definition of a poor individual that are used below are all based on a strictly convex indifference curve U^*, as in panel (a) of fig. 1. Strict convexity is a natural assumption when dimensions are captured by cardinal variables. However, the two restrictions do not imply such strict convexity. When some dimension is captured by an ordinal variable, indifference curve U^* could have the shape illustrated in panel (b) of fig. 1. Importantly, the choice of using a strictly convex indifference curve U^* in the illustrations is without loss of generality for the study's purposes. Second, it is a priori not possible to rank these two types of poor as a function of well-being. Indeed, some cumulators are worse off than some extremors (and vice versa). Hence, the

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terminology "extremor" reflects an extreme outcome in one dimension, not necessarily an extremely low level of well-being.

Identifying the Poor When Indifference Curve U^* Is Only Partially Observed

The previous section discussed a conceptualization of the poor. This section moves to the practice of identifying the poor given the information at hand and the nature of the dimensions considered.

One key information constraint in practice is that indifference curve U^* is imperfectly known. The practitioner observes the achievement vector x. An identification method is used to determine whether the individual consuming x is poor or not. This method is typically an inequality with a mathematical formula that depends on x on one side and a poverty threshold on the other side. For instance, in the special case of monetary poverty, the mathematical formula is the market value of the quantities of goods and services consumed (x), and the threshold is a poverty line.

The identification method is "imperfect" when indifference curve U^* is imperfectly known (Decerf 2023). That means that the practitioner is bound to make identification errors, that is, identify as poor an individual who is not poor (inclusion error) or identify as nonpoor an individual who is poor (exclusion errors). To see this, observe that any identification method can be illustrated graphically through its associated "poverty contour," which is the frontier of the subset of achievement vectors for which individuals are identified as poor. Because indifference curve U^* is imperfectly known to the practitioner, the shape of the poverty contour is bound to differ from the shape of indifference curve U^*. This is not necessarily a problem for monetary poverty, because the availability of price data allows adjusting the shape of the poverty contour to the achievement vector considered.[10] However, price data are not available for nonmonetary dimension. As a result, a unique poverty contour is used to evaluate all achievement vectors and identification errors are inevitable.

Decerf (2023) develops a theory that compares imperfect identification methods. Making such comparisons is useful as it allows designing better identification methods. In a nutshell, this theory implies that an identification method is better (than another one) when the shape of its associated poverty contour better approximates the shape of indifference curve U^*. This point further develops Ravallion's criticism of multidimensional poverty measures. Ravallion, who comes from a monetary-poverty perspective, notes the absence of price data for nonmonetary dimensions and wonders whether the poverty contour correctly captures the marginal rate of substitution between dimensions, at one point of the indifference curve U^*. Although an important aspect, this is not the complete story when considering nonmonetary dimensions. Indeed, when using a unique poverty contour, this contour should correctly approximate the whole indifference curve U^*.

The partial knowledge of indifference curve U^* does not prevent researchers from comparing imperfect identification methods (Decerf 2023). Indeed, the extremor versus cumulator classification of poor individuals, which is implied by the two restrictions on indifference curve U^*, helps making such comparisons. To illustrate this point, this article shows that the identification of the poor can be unambiguously improved when going beyond monetary poverty. Two dimensions of well-being are considered in fig. 2.a: consumption and health. Consumption is measured by the monetary value of the commodities consumed, while health is measured by some indicator of health status. In practice, the monetary approach identifies the poor by selecting a "poverty line," which is a cut-off in the consumption dimension illustrated in fig. 2 by the monetary value z_1. Individuals are thus identified as poor by the monetary approach when $x_1 < z_1$. The "identification contour" associated to this purely monetary approach is the vertical line drawn in red in fig. 2.a. This approach makes both exclusion errors and inclusion errors. For instance, an individual

10 For monetary poverty, price data allow adjusting the shape of the poverty contour relevant to evaluate achievement vector x. Indeed, the poverty contour (=the budget line) depends on the price vector prevailing at the achievement vector x, which corresponds to the marginal rate of substitution of preference U^* at x. As a result, even though the shapes of the indifference curve U^* and the poverty contour differ, the practitioner can identify the poor without making errors.

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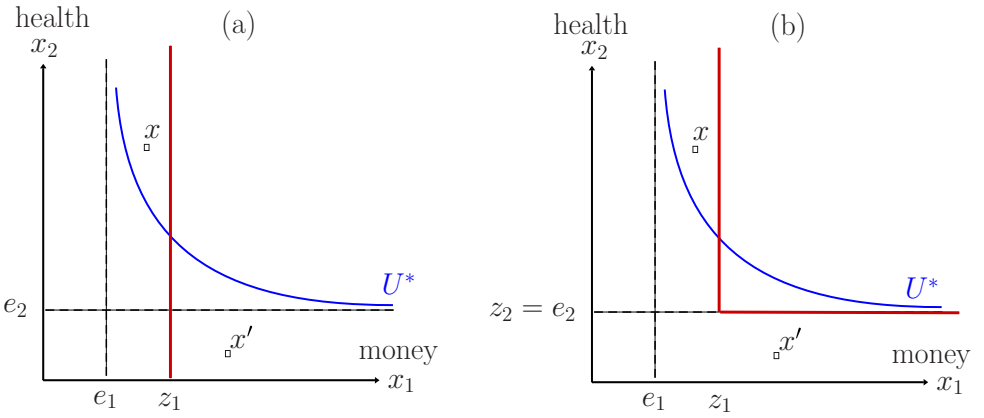
Figure 2. A Monetary Poverty Measure Makes Identification Errors (a). A Multidimensional Identification Based on the Union Approach Makes Fewer Identification Errors (b)



Source: Authors' drawing.
Note: Indifference curve U^* is in blue and identification contours are in red.

with achievement vector x is identified as monetary deprived even though she is not (multidimensionally) poor. In turn, another individual with achievement vector x' is not identified as monetary deprived even though she is (multidimensionally) poor.

Of course, the fact that the monetary approach makes identification errors is not a sufficient reason to discard it because any identification method makes identification errors when nonmonetary dimensions matter for well-being. However, aggregating across dimensions allows unambiguously reducing the amount of identification errors. This is illustrated in fig. 2.b. Consider the (extreme) health deprivation cut-off $z_2 = e_2$. The union approach based on cut-offs z_1 and z_2, whose identification contour is drawn in red, identifies the (multidimensionally) poor strictly better than the monetary approach. Indeed, it strictly reduces the number of exclusion errors (x' is now correctly identified as poor), and it does not make more inclusion errors. The identification contour of the union approach is an unambiguously better approximation of indifference curve U^* than the identification contour of the monetary approach. Observe the practitioner does not need to know the whole indifference curve U^*. Knowing (a lower bound for) the extreme health deprivation cut-off e_2 is sufficient to unambiguously improve on the monetary approach.

A Refinement of the Alkire-Foster Identification Method

The most popular method for the identification of the (multidimensionally) is proposed by Alkire and Foster (2011) and best exposed in Alkire et al. (2015). In a nutshell, this method starts from binary deprivation statuses in m dimensions. An individual is deprived in dimension j when her achievement x_j is smaller than the deprivation cut-off z_j, that is, $s_j = 1$ when $x_j < z_j$, otherwise $s_j = 0$. The AF methodology identifies an individual as poor when the weighted sum of her deprivation statuses is too large, that is,

$$\sum_{j=1}^{m} w_j s_j \geq k \tag{1}$$

where w_j is the weight given to dimension j and k is the poverty identification threshold. This clever method avoids an important practical issue faced by both the intersection approach and the union approach. These

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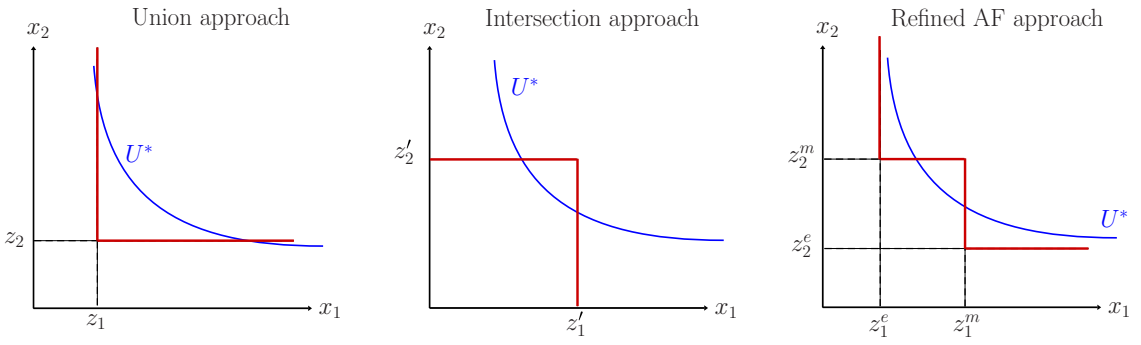
Figure 3. The Refined AF Approach (c) Can Identify the Poor Better than the Union Approach (a) or the Intersection Approach (b).



Source: Authors' drawing.
Note: Indifference curve U^* is in blue and identification contours are in red.

two approaches tend to irrelevance when the number m of dimensions increases, unless the deprivation cut-offs are changed to increasingly implausible values.[11]

One limitation of the AF methodology is to rely on binary deprivation statuses, which follows from the use of a unique cut-off in each dimension. This feature does not provide much flexibility to simultaneously identify both cumulators and extremors. This limitation is illustrated in fig. 3, which considers two dimensions only. Under two dimensions, the AF methodology essentially boils down to either the union approach or the intersection approach, depending on the values given to the weights. The union approach is well-suited to identify extremors but does not perform well at identifying cumulators. As suggested in the left panel, the reason is that the union approach requires rather small cut-offs z_j to limit the inclusion errors that larger cut-offs would entail. In contrast, the intersection approach is well-suited to identify cumulators, but does not perform well at identifying extremors. As suggested in the middle panel, the reason is that the intersection approach requires rather large cut-offs z_j' to limit the exclusion errors that smaller cut-offs would entail.

The article emphasizes that the limitation discussed above does not originate in the values selected for the parameters of the AF method. Indeed, there are no values for the cut-offs z_j and the weights w_j that would simultaneously identify both cumulators and extremors. Rather, this limitation originates in the "mathematical formula" of the AF identification method, that is, in the fact it relies on binary deprivation statuses, and thus cannot account for the "depth" of deprivation in a given dimension.

Decerf (2023) proposes a simple refinement of the AF methodology that helps improve on this limitation. The idea is to slightly twist its "mathematical formula" by considering three deprivation statuses, which requires using two cut-offs in each dimension j: one extreme cut-off z_j^e and one moderate cut-off z_j^m. Then, an individual can have three mutually exclusive deprivation statuses in each dimension j: extremely deprived when $x_j < z_j^e$, moderately deprived when $z_j^e \leq x_j < z_j^m$ and nondeprived otherwise. Extremors can be properly identified by using the union approach on individuals who have at least one extreme deprivation. Cumulators can be properly identified by using the intersection approaches on individuals who have several moderate deprivations. As illustrated in the right panel of fig. 3, the shape of the identification contour associated to this refinement better approximates indifference curve U^* than the identification contours of the union and intersection approaches. This paper provides the first illustration of how this refinement could be implemented in practice.

11 When the number m of dimensions increases, if dimension-specific cutoffs are unchanged, then the fraction of individuals identified as poor by the union approach tends to 1 while the fraction of individuals identified as poor by the intersection approach tends to 0 (Dotter and Klasen, 2017).

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Clearly, one could think of other similar refinements. For instance, using three dimension-specific cut-offs would permit an even better approximation of indifference curve U^*. However, using three such cut-offs would increase even further the number of parameters that the practitioner must select. In practice, a trade-off must be made between the simplicity and the conceptual validity of the identification method. This study's proposal on how to implement the above refinement aims at limiting the increase in the number of parameters that the practitioner must select. In the remainder, the article focuses on identification and uses the head-count ratio for comparison purposes. This poverty index violates well-known properties. As discussed in the conclusion, it is perfectly possible to combine this article's identification method with other poverty indices that satisfy classical properties.

Before presenting this study's multidimensional poverty indicator, a remark on marginal rates of substitution is in order. As observed in the Introduction, many nonmonetary achievements are ordinal and captured through categorical variables. For instance, an individual's educational outcome can be captured by a variable tracking whether she has no schooling, some schooling but no diploma, or a diploma. Assume for the sake of the argument that these three outcomes respectively correspond to extreme, moderate, and absence of education deprivation. Further assume that the health dimension is similarly captured by a categorical variable whose three outcomes respectively correspond to the same three health deprivation statuses. Consider now the identification contour associated with the refined AF identification method, illustrated in red in the right panel of fig. 3. At any bundle on this identification contour, the marginal rate of substitution, that is, the slope of this identification contour, is either 0 or infinite. This marginal rate of substitution cannot be equal to that of indifference curve U^*. The same remark holds for the union or intersection identification contours associated with the AF identification method. This shows that, for the purpose of poverty identification, the weights in eq. (1) do not capture marginal rates of substitution. Rather, together with the poverty identification threshold, they define the shape of the identification contour. In the two-dimensional case, they capture whether this shape corresponds to the union or to the intersection approach.[12]

3. Designing a Refined MPM With Nigerian Data

This section proposes one way of implementing the refined identification method described in the first subsection of section 2, in the context of Nigeria in 2019. The article discusses how the necessary choices can be made consistently with the theory exposed in section 2. Importantly, the proposed indicator is exploratory and is intended as a mere illustration. Beyond providing a proof of concept, the study's empirical ambitions are limited to proposing a plausible indicator to probe the answer to the two questions raised in the introduction.

Deprivation Mapping

The study proposes two designs, that is, two versions, for the multidimensional poverty indicator: a "baseline" design and a "preferred" design. The "baseline" design provides conservative answers to the two questions because it accounts for fewer nonmonetary dimensions. The text presents all results for the "baseline" design, which is easier to discuss. Yet, the study views the "preferred" design as more plausible and thus also presents the main results for the "preferred" design.

The unit of analysis is the individual. The main difficulty is that the relevant information is often available only at the household level. This is typically the case for monetary outcomes, which are only observed at household level. In contrast, health outcomes are sometimes available at the individual level. This is fortunate because health outcomes are expected to be very unequal across household members, if only be-

12 See panels a, c, e in fig. S1 in the online supplementary material of Decerf (2023) for identification contours associated to the AF identification method in the three dimensions case.

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cause of lifecycle effects.[13] Tracking outcomes using different units of analysis for different dimensions is not necessarily a problem, but it requires making strong assumptions to translate the observed household-level outcomes into individual-level outcomes. For instance, equal sharing of monetary resources is often assumed for the monetary dimension.

The study considers monetary deprivation (consumption in Nigeria) alongside multiple nonmonetary dimensions. While the relative importance of dimensions may vary by context, certain aspects remain universally critical—particularly consumption and health. Building on these fundamentals, the study deliberately includes security and housing in the framework, with education added in the preferred specification. World Bank (2018) demonstrated that security deprivation reveals unique vulnerability patterns that income-based measures cannot detect. Their exploratory analysis incorporating security indicators uncovered that crime incidence often correlates weakly or inversely with monetary poverty. This critical finding shows security threats affect populations across income levels, potentially even more severely among nonpoor households. Conventional poverty measures would completely miss these vulnerable groups who, despite adequate consumption, live under constant threat of violence. By integrating security alongside traditional dimensions, the article's framework captures these distinct aspects of well-being that are equally essential for poverty reduction in the Nigerian context.

Each dimension is covered by a series of dimension-specific variables. The main step for the implementation of the refined AF methodology presented in section 2 is to define what the analysis calls the "deprivations mapping." For each individual and each dimension, the deprivation mapping defines the circumstances under which the individual is extremely, moderately, or not deprived in the dimension. The deprivation mapping defines the link between the individual outcomes captured by the dimension-specific variables and the individual's deprivation statuses in that dimension. Using mathematical terminology, this link is a "mapping" from outcomes variables to deprivation statuses. Before discussing some conceptual principles guiding the definition of the deprivation mapping (see second subsection of section 3), the remainder of this subsection presents what this mapping looks like in the illustration.

Table 1 defines the study's deprivation mappings for the baseline and preferred designs. Consider first the baseline design. It begins with the monetary dimension. In Nigeria, the monetary aggregate is defined as the market value of consumption. In 2019, the national poverty line was \$1.93 per person per day in 2011 PPPs (see World Bank 2022b, p. 19). The national monetary line was thus almost equal to the World Bank's extreme poverty line, which is \$1.9 per person per day (2011 PPPs). The deprivation mapping for the baseline design assumes that an individual is extremely monetary deprived if her consumption is below the national poverty line, otherwise she is not monetary deprived. Given that an extreme deprivation automatically confers (multidimensional) poverty status, this assumption is equivalent to the one used by the WB's MPM, which automatically classify as (multidimensionally) poor individuals who are below the extreme monetary line.

This article succinctly describes the nonmonetary deprivations used in the baseline design. In the health dimension, individuals are extremely deprived in three cases: they suffer from a heavy disability, they are an underweight woman between 15 and 49 years old (age-window and gender for which data are available), or they are a stunted child.[14] In turn, individuals who are not extremely health deprived are moderately health deprived in two cases: they suffer from a mild disability, or they suffer from severe overweight (obesity). In the security dimension, an individual is extremely security deprived if over the last two years her household has been victim of an insecurity event with "physical" consequences or if she lives in a district where at least a quarter of the households have been victim of an insecurity event

13 Studies looking at intrahousehold distribution of monetary resources also find substantial inequalities (Lise and Seitz 2011; Lechene et al. 2021).

14 Data constraints imply that information on underweight men is not available. Therefore, the poverty measure, which the study constructs for illustrative purposes, cannot be used to compare poverty across men and women. For parallel reasons, it cannot be used to compare poverty across children and adults.

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Table 1. Deprivation Mapping: from Dimension-Specific Variables to Deprivation Statuses

Dimensions	Deprivation status	Variables
Monetary	Extreme	The household annual consumption per capita is below national poverty line evaluated to 137,430 Naira annual per capita (PA NGA).
	Moderate (only Preferred)	*The household annual consumption per capita is above national poverty line but below state societal poverty line: 1 + 0.5 x where x is the median state consumption in $ per day per capita.*
Health	Extreme	The individual suffers from at least one disability causing him a lot of difficulties in daily life or/and suffers from an extreme bad nutritional status, meaning a stunting condition for children (HAZ[1] < −2) or being undernourished (BMI[2] < 18.5) for adults.
	Moderate	The individual suffers from at least one disability causing him only some difficulties in daily life and/or suffers from a moderate nutritional status, meaning being obese (30 < BMI) for adults.
Housing	Extreme	The individual belongs to a household deprived regarding all following household-level variables: (1) Household lacks access to limited-standard drinking water[3]; (2) Household lacks access to limited-standard sanitation[4]; (3) Household has no access to electricity; (4) Household has inadequate housing.[5]
	Moderate	The individual belongs to a household deprived regarding three of the following household-level variables: (1) Household lacks access to limited-standard drinking water; (2) Household lacks access to limited-standard sanitation; (3) Household has no access to electricity; (4) Household has inadequate housing.
Security	Extreme	The individual belongs to a household, subjected during the last 12 months to an extreme insecurity event[6] or belongs to a local government area (LGA) with at least one quarter of neighborhood households subjected to crime/violence with extreme consequences during the last 12 months.
	Moderate	The individual belongs to a household, subjected during the last 12 months to a moderate insecurity event[7] or belongs to a local government area (LGA) with at least one quarter of neighborhood households subjected to crime/violence with moderate consequences during the last 12 months.
Education (only Preferred)	*Extreme*	*The individual is a school-age child up to the age of grade 8, not enrolled in school.*
	Moderate	*The individual belongs to a household in which no adult (age of grade 9 or above) has completed primary education, and no adult can read nor write.*

[1]Height for Age Z score.
[2]Body Mass Index
[3]Limited-standard drinking water refers to drinking water that comes from an improved source, defined as those that are likely to be protected from outside contamination, and from fecal matter in particular. It includes for example, piped, borehole, protected dug well, rainwater, or delivered water (PSPR 2018, WHO)
[4]Limited-standard sanitation refers to improved sanitation facilities, defined as those that hygienically separate human waste from human contact, including flush/pour flush to piped sewer system, septic tank, or a composting latrine (PSPR 2018, WHO)
[5]Inadequate housing refers to houses characterized by at least one of the following three conditions: the floor is of natural materials, the roof or the walls are of rudimentary materials (UNDP)
[6]Extreme insecurity events include events where any member of the household has been murdered, injured, or disabled, subjected to sexual violence, captured, or abducted, or made a refugee
[7]Moderate insecurity events include events where any member has been physically attacked, forced to work, restricted from going to school or hospitals, robbed, or where household's dwelling has been damaged, or household land has been occupied or taken by force.
Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: This table presents, for each baseline and preferred scenario, the combination of basic variables that allow to define, for each poverty dimension—monetary, education, health, housing, security-, a state of nondeprivation, moderate deprivation, and extreme deprivation.

with "physical" consequences. In turn, an individual who is not extremely security deprived is moderately security deprived if her household has been victim of an insecurity event with "material" consequences or if she lives in a district where at least a quarter of the households have been victim of an insecurity event with "material" consequences. In the housing dimension, the study considers whether an individual lives in a household that has access to electricity, limited-standard drinking water, limited-standard sanitation, and whose dwelling is made of appropriate materials. An individual is extremely housing deprived if her

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household is deprived in the four housing variables and moderately housing deprived if her household is deprived in three housing variables.

The deprivation mapping for the preferred design is the same as that of the baseline design, except that the former additionally considers a moderate monetary deprivation status and the education dimension. An individual is moderately monetary deprived if her consumption is above the national poverty line but below the WB's societal poverty line in her state.[15] An individual is extremely education deprived if she is a child not enrolled in school. An individual is moderately education deprived if she lives in a household where no adult has completed primary education, and no adult can read or write.

Principles Guiding the Necessary Choices for the Study's Identification Method

This section finalizes the baseline and preferred designs of the multidimensional poverty measure. One piece is missing: the exact aggregation of an individual's deprivation statuses into her (multidimensional) poverty status. The section also comments on some conceptual principles guiding the design and the differences with the classical AF methodology.

Aggregation of Deprivations

The study's refined AF method requires both a deprivation mapping and a method to aggregate deprivation statuses into (multidimensional) poverty status. The latter method follows the theory presented in section 2. That is, two types of individuals are (multidimensional) poor. First, any individual who suffers from at least one extreme deprivation is identified as poor (extremor). Second, any individual who is not an extremor but cumulates enough moderate deprivations is identified as poor (cumulator). This illustration assumes that **two** moderate deprivations are sufficient to be considered poor. All the necessary choices have been made to compute the fraction of (multidimensionally) poor, which is denoted by H.

Six important remarks are in order.

First, the key difference between the refined AF method and the classical AF method lies in the way the former treats some dimension-specific variables. Instead of using a unique cut-off per variable, leading to a binary deprivation status, the refined method uses two cut-offs, which thus allows capturing the depth of deprivation in the considered variable. Take for instance the consumption variable. The classical AF method would consider a household to be monetary deprived when her consumption is below a unique poverty line. The refined method allows considering two different poverty lines, namely the official line and the societal poverty line (preferred design). As a result, households fall into three mutually exclusive categories: extremely consumption deprived, moderately consumption deprived (between the two poverty lines), and not deprived in the consumption variable. The BMI values are similarly partitioned into three mutually exclusive categories, respectively leading to extreme, moderate or absence of deprivation. Two cut-offs are also used for the disability variable, although these cut-offs are implicit because this variable is categorical rather than cardinal. The classical AF method would typically consider that an individual either suffers from disability or does not. The study's refined AF method allows distinguishing two types of disabilities, one moderate and one extreme, depending on whether the disability causes "some" or "a lot of" difficulties in daily life. Suffering from one extreme disability is sufficient to be multidimensionally poor. In contrast an individual suffering from a moderate disability is multidimensionally poor only if she also suffers from other deprivations. Observe that the same remark holds for the security variable.

Second, the design of the deprivation mapping should be selected while accounting for the way in which deprivations statuses are aggregated. For extreme deprivation status, the selection of dimension-specific

15 The WB societal poverty line is a (weakly) relative monetary line whose monetary threshold increases with median income but is never smaller than the extreme poverty line (Jolliffe and Prydz 2021). Considering individuals whose income is between the extreme and societal poverty lines as moderately monetary deprived is consistent with the view that being absolutely income poor is worse than being only relatively income poor (Decerf 2017; Decerf and Ferrando 2022).

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variables conferring extreme deprivation should be plausibly consistent across dimensions. Assume as a starting point that an individual whose consumption is below the extreme poverty line ($1.9 per day in 2011PPPs) is considered extremely monetary deprived and thus (multidimensionally) poor. The components of the mapping related to extreme deprivation in other dimensions must be broadly consistent with this starting point. Take the health dimension for example. Loosely speaking, it should be plausible that, ceteris paribus, suffering from a heavy disability leads to a similarly low well-being level as having consumption below the extreme poverty line. Graphically, the extreme deprivation cut-offs selected in different dimensions should "approximate" the same indifference curve U^* (recall the right panel of fig. 3 in section 2). Then, the components of the mapping related to moderate deprivations must be consistent with both this starting point and the (arbitrary) assumption that two moderate deprivations are sufficient to be considered poor. Indeed, it should be plausible that suffering only from one moderate deprivation in one dimension leads to a higher level of well-being than suffering from one extreme deprivation. Loosely speaking, it should be plausible that, ceteris paribus, suffering only from a mild disability leads to a higher well-being level as having consumption below the extreme poverty line. Graphically, the moderate deprivation cut-off selected in one dimension should not approximate the same indifference curve U^* approximated by the extreme deprivation cut-off in another dimension (recall the right panel of fig. 3 in section 2). Then, it should also be plausible that suffering from **two** moderate deprivations leads to a similarly low well-being level as having consumption below the extreme poverty line. For instance, it should be plausible that suffering from a mild disability and belonging to a household that has been victim of crime with only material consequences leads to a similarly low well- being level as having consumption below the extreme poverty line. These are the considerations that should guide the design of the deprivation mapping. Empirical methods, like surveys using vignettes or subjective well-being questions, could in principle be used to assess whether these relationships plausibly hold.

Third, beyond the selection of the number of moderate deprivations leading to poverty (in this case: two), this study's identification of the (multidimensionally) poor does not require selecting explicit values for weights (across dimension-specific variables). Of course, the refined AF method does assume trade-offs across such variables, like the classical AF method. However, not having to select explicit values for weights may sometimes help improve identification by increasing the information used. At least this will be the case if practitioners feel compelled to use equal weights. Practitioners are likely to feel compelled to use equal weights because deviating from the "equal weights" dominant practice requires a good justification. Practitioners may lack the legitimacy or the scientific underpinning necessary to select a particular value for these weights. Thus, when using equal weights is the only easily defensible solution, the practitioner loses options that could help better identify individuals with low well-being. For instance, the practitioner may discard well-being–relevant information by bringing together categories that would otherwise be ordered. For instance, she would not discriminate between heavy and mild forms of disabilities (or between crimes with "physical" or merely "material" consequences), but rather bundle them together and label them as health deprivation. Alternatively, in any given dimension, the practitioner may only consider dimension-specific variables leading to a similar level of well-being, excluding potentially useful variables. As discussed in the conclusion, if this paper's identification method is combined with a poverty index that satisfies classical properties, then researchers would need to select explicit values for the index's weights.

Fourth, comparing results across two nested designs, like this study's baseline and preferred design, does not require any adjustment. In contrast, to meaningfully perform such comparisons, the classical AF methodology would have to change the values selected for its weights and identification threshold (see eq. 1). The study's preferred design differs from its baseline design because the former considers an additional dimension and an additional moderate consumption-deprivation status. The theory exposed in section 2 explains in which sense the results can be meaningfully compared across the two designs. Fundamentally, the preferred design can be assumed to make a more detailed job at identifying the (multidimensionally) poor than the baseline design because the latter omits well-being–relevant information. This is at least

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true if the extension of the deprivation mapping defining the study's preferred design is consistent with the deprivation mapping defining its baseline design. Given that the former is a mere extension of the latter, consistency only requires that the same principles described in the second remark (see above) also guide the design of the extension.[16]

Fifth, from a conceptual perspective, having information at the individual level allows accounting for extreme forms of deprivations that are not equally shared within the household. Think for instance of heavy disabilities. Arguably, individuals afflicted by such disabilities have a level of well-being that is too low and should thus be considered as (multidimensionally) poor. However, other individuals living in their household need not be considered poor if they are not themselves sufficiently deprived in other dimensions. When using the household as unit of analysis, accounting for such heavy disability leads to many identification errors.[17] Hence, a framework combining three deprivation statuses with the individual as unit of analysis holds the potential to reduce identification errors. To be sure, moving the unit of analysis at the individual level also raises challenges. Among those, some deprivations only affect certain subgroups of the population. For instance, women have specific health needs related to pregnancy, children have specific education needs, and so on. Accounting for group-specific needs favors inclusion, but it comes at the cost of comparability. Indeed, it becomes harder to compare the poverty across two subgroups when some variables only capture outcomes for one subgroup.

Sixth, data constraints prevent researchers from adequately covering several dimensions or properly accounting for joint distribution. The issue arises in this study's design for the nutrition variables considered as part of the health dimension. This study does not have data on bad nutrition outcomes except between 15 and 49 years old and below 5 years old. For the large fraction of the population outside of these two age windows, the article conservatively assumes that their nutrition status is normal. Moreover, because nutrition outcomes come from a separate survey, this study had to impute the nutrition outcomes from DHS to NLSS (see 1)for details on the imputation model). This imputation is not expected to have a large impact on results given the small fraction of the population for which the study has bad nutrition status (see Table A1.1 in appendix 1). However, one should bear in mind that the study's results suffer from this limitation.

4. Poor Individuals in Nigeria in 2019

This section presents the data sources, the context and the basic results describing the set of poor individuals in Nigeria in 2019. This set is defined by the identification method. The analysis focuses on the respective contributions of alternative dimensions and the impact of some assumptions underlying the study's design. Section 5 presents the results that quantify the extent to which poverty comparisons are altered when accounting for nonmonetary dimensions.

Data Sources and the Nigerian Context

This paper compares poverty across the 36 states of Nigeria in 2019. As explained below, this is a conservative context to probe the answer to question 1: what is the magnitude of the impact that the implementation of the refined AF method has on the set of poor individuals?

16 For instance, the definition of moderate monetary deprivation should lead to approximately the same well- being level as having a mild disability.

17 When using the household as unit of analysis, considering all household members as poor whenever one member has a heavy disability would imply many inclusion errors. An alternative would be to consider a household as moderately deprived when one of its members has an extreme form of deprivation. This alternative is clearly less attractive because it could also lead to different types of identification errors. For instance, the heavily disabled individual would incorrectly be considered nonpoor if her disability is the only form of deprivation afflicting her household. Or all other members of her household would incorrectly be considered poor if the household has only one other moderate form of deprivation.

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Data Sources

The analysis relies on two main data sources: the 2018–19 Nigeria Living Standards Survey (NLSS) and the 2018 Nigeria Demographic and Health Survey (DHS). The NLSS 2018–19 is a large-scale household survey, focusing on measuring living conditions of the population, collected by the National Bureau of Statistics of Nigeria (NBS) between September of 2018 and October of 2019. The NLSS questionnaire includes wide-ranging modules, covering demographic indicators, education, health, labor, expenditures on food and nonfood goods, nonfarm enterprises, household assets and durables, access to safety nets, housing conditions, economic shocks, exposure to crime and farm production indicators. The final sample, consisting of 22,110 households, was designed to deliver robust estimates of living standards, with a focus on household expenditures and poverty headcount ratios. The margin of error averages 2 percent at the national level and remains below 10 percent at the state level. Consequently, the sample is representative at the state, zonal, and national levels. However, due to the unstable security situation in Borno at the time of the survey, the sample for Borno is considered nonrepresentative and not comparable to other states.

To facilitate comparisons across space and time, and to enable comparisons with the poverty line, the consumption aggregate is spatially and temporally deflated and converted to per capita terms.[18]

The additional data source, the 2018 NDHS, is a survey implemented by the National Population Commission (NPC), whose data collection took place from 14 August to 29 December 2018. It provides estimates of basic demographic and health indicators, especially, nutrition data relying on records of anthropometry measurements of children under 5 and women between 15 and 49.

Monetary Poverty Is High and Heterogeneously Distributed Across Nigerian States

Nigeria provides a conservative context for the study's purpose. Answering question 1 requires contrasting poverty comparisons obtained from the monetary dimension alone with poverty comparisons obtained from a multidimensional poverty measure aggregating the monetary and the nonmonetary dimensions.[19] As shown below, Nigeria has a high monetary poverty rate, and this rate is very heterogeneous across the 36 Nigerian states. Accounting for nonmonetary dimensions is less likely to reverse poverty comparisons in a context where the monetary dimension already provides a stark contrast across states.

Monetary poverty was high in Nigeria in 2019. That year, some 40.5 percent of Nigerians had their monetary aggregate below the national poverty line. Monetary poverty was also distributed unequally across Nigeria in 2019. That year, five states had less than 10 percent monetary poverty while two states had more than 85 percent. The map shown in fig. 4 illustrates this heterogeneity across geographical units called "zones," which are groups of several states. The map shows the heterogeneity in poverty rates across the six zones of Nigeria. Each of the three zones in the south has less monetary poverty than each of the three zones in the north. Monetary poverty in the southwest zone is about 10 percent while monetary poverty in the northeast zone is about 70 percent.

18 The prices that Nigerian households faced in 2018/19 may have differed depending on where they lived and the time at which data were collected; year-on-year CPI inflation in Nigeria in October 2019—just after the survey finished—stood at 11.6 percent. To account for this, an internationally recognized approach is used to construct a price deflator; this is then applied to the nominal values of household consumption to create "deflated values," which can be compared across time and space. Additionally, since some households are larger than others, household-level deflated consumption is converted to per capita terms by dividing by household size (World Bank 2022b).

19 A definition of multidimensional poverty that accounts for both the monetary and nonmonetary dimensions is consistent with the conceptualization of the poor as being the individuals who have low well-being. This is at least the case if well-being depends on both, a view that is mainstream in the welfare economics literature.

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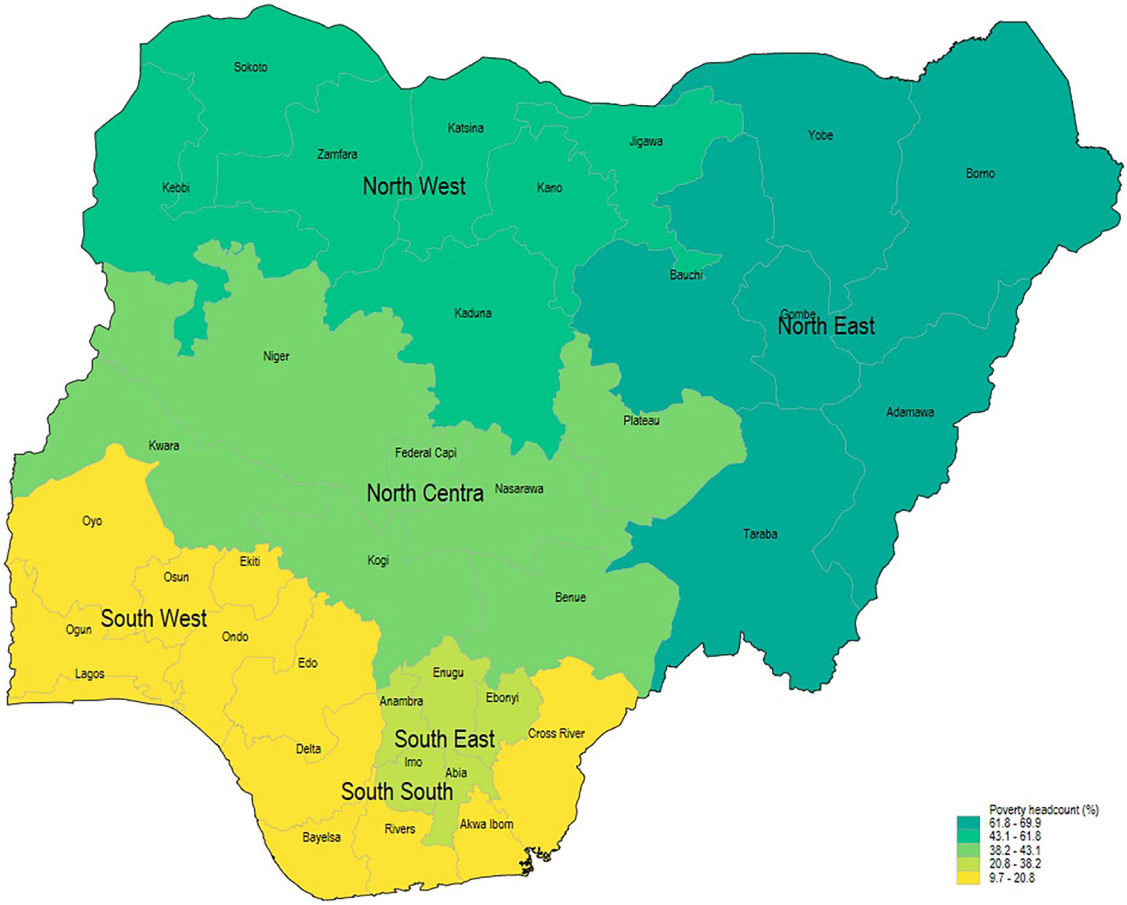
Figure 4. Prevalence of Monetary Poverty in Nigeria, per Zone



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019.
Note: The figure presents, for each zone, the share of individuals below the national poverty line. A cross-check was performed during the analysis using World Bank (2022b), and the findings are consistent with theirs at both the national and state levels.

Sets of Poor Individuals

This subsection focuses on the fraction of multidimensionally poor individuals H. The objective is to get a sense of the source of their (multidimensional) poverty status both in terms of type of deprivation (extreme or moderate) and in terms of type of dimensions, monetary or nonmonetary.

Incidence and Geographic Distribution of Deprivations

The analysis begins with results associated with the deprivation mapping for the baseline design. These basic results provide insights that will shed light on the respective impacts that alternative dimensions have in later results.

Figure 5 provides a first glance at the prevalence of different type of deprivations at the national level. The baseline design considers four dimensions. For each of these dimensions the histogram shows the fraction of individuals in each of the three deprivation statuses: extreme, moderate, or not deprived. The figure immediately reveals that the monetary dimension is by far the most consequential dimension given the study's design. Not only does the monetary dimension have the largest incidence of deprived individuals (40.5 percent), but by assumption all of them are extremely deprived. All the nonmonetary

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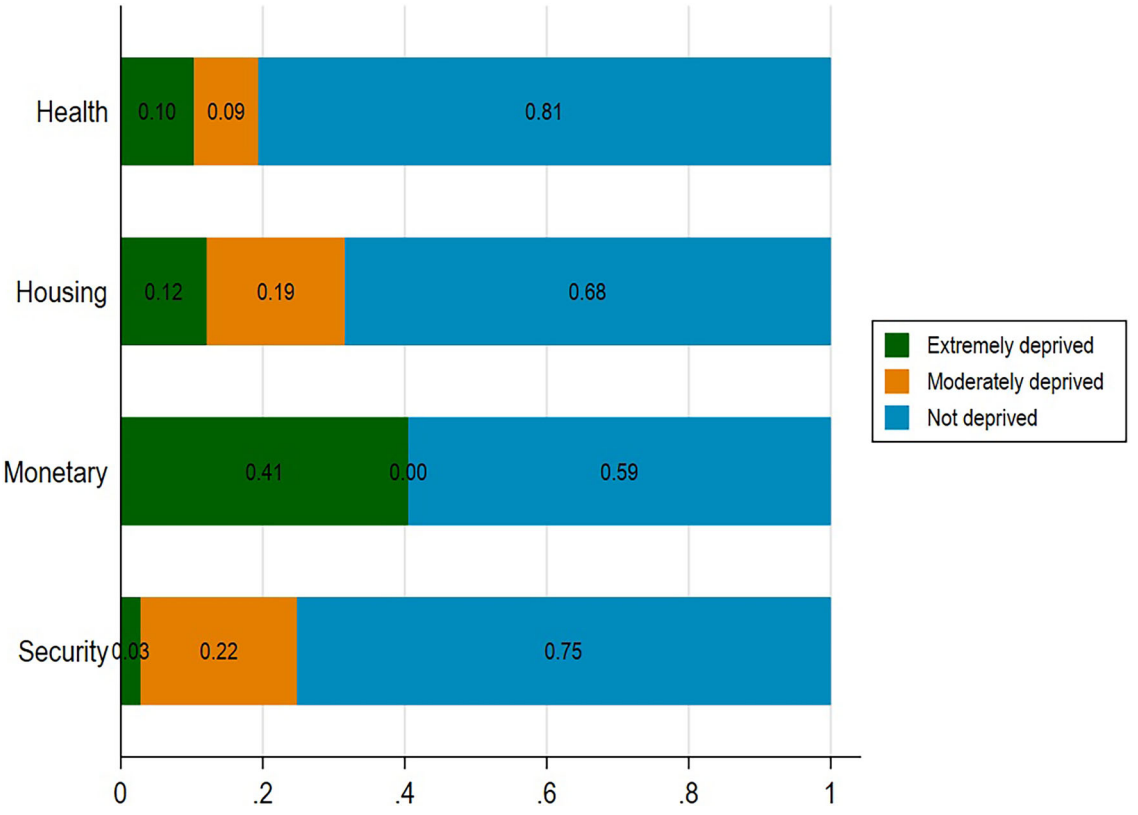
Figure 5. Prevalence of Extreme and Moderate Deprivations per Dimension for Nigeria, Baseline Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The figure presents, for each dimension considered in the baseline scenario—monetary, health, housing, security—the share of individuals according to their state of deprivation: nondeprivation, moderate deprivation, extreme deprivation.

dimensions have a smaller incidence of deprivation, and much smaller incidence of extreme deprivation. Among the nonmonetary dimensions, housing is the most consequential. Observe that security has a larger deprivation incidence than health but a much smaller extreme deprivation incidence than health. Figure A1.1 in appendix 1 provides the corresponding histogram for the study's preferred design.

To provide a sense of the respective importance of dimension-specific variables, Table A1.1 in appendix 1 provides the incidence in the population for each of these dimension-specific variables. For instance, 10 percent of the population faces severe health deprivation. This percentage includes 2.9 percent with significant disabilities, 2.3 percent who are underweight women aged 15 to 49, and 5.5 percent who are stunted children. Also, a sense of the correlation between deprivation statuses in the three nonmonetary dimension is given in the Venn diagram in fig. A1.3 in appendix 1. For instance, this diagram shows that 1.7 percent of the population is deprived in the three nonmonetary dimensions.

Figure 6 provides an idea of the distribution across zones of these deprivations. As illustrated in fig. 4, monetary deprivation is very heterogeneously distributed across zones, with regions in the south having low and regions in the north having high monetary deprivation. The same holds for the housing dimension. Importantly, the geographic distribution of housing deprivation is roughly the same as that of monetary deprivation. In contrast, the incidence of health deprivation is approximately equally distributed across zones. Interestingly, the geographic distribution of extreme health deprivation is positively correlated with that of monetary deprivation while that of moderate health deprivation is negatively correlated with that

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Figure 6. Prevalence of Extreme and Moderate Deprivations per Dimension per Zone, Baseline Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The figure presents, for each dimension considered in the baseline scenario—monetary, health, housing, security— the prevalence in percent of moderate deprivation, extreme deprivation within each of the six Nigeria's zones classified in ascending order of monetary deprivation.

of monetary deprivation.[20] Finally, the security deprivation is geographically distributed in a way that seems uncorrelated to monetary deprivation. The correlation between the distribution across states of alternative deprivations is further illustrated in the maps provided in fig. A1.2 in appendix 1.

20 One reason that could explain the negative geographic correlation between monetary deprivation and moderate health deprivation is that the latter mostly reflects mild disabilities, which may afflict older individuals (who are typically more numerous in richer regions).

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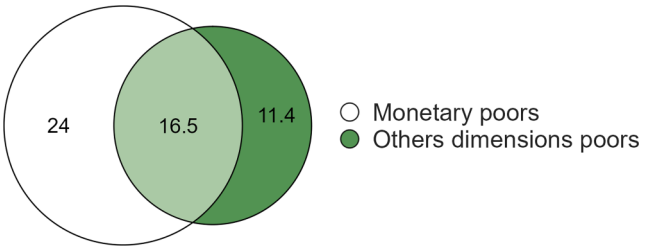
Figure 7. Classification of Multidimensionally Poor Individuals in Nigeria, Baseline Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: Using a Venn diagram, the figure shows the decomposition of multidimensional poverty, defined within the baseline scenario, into "Only monetary poverty" (transparent area), "Other dimensions-additional poor" or "Omitted poor" for individuals multidimensionally poor without being monetary poor (dark green) and "Other dimensions—twice poor)" or "Consistently poor" for individuals cumulating monetary and other dimensions (light green).

Fraction and Types of Multidimensionally Poor Individuals

The theory outlined in section 2 defines two types of (multidimensionally) poor: extremors and cumulators. By assumption, all individuals who are monetary deprived are extremors. However, some extremors are not monetary deprived, like, for instance, individuals whose sole extreme deprivation is in a nonmonetary dimension.

To answer question 1, it is interesting to consider a second classification of (multidimensionally) poor individuals. The study calls **monetary poor** the (multidimensionally) poor individuals who have an extreme monetary deprivation. The study calls **other-dimensions poor** the individuals whose nonmonetary deprivations are sufficient to classify them as multidimensionally poor. Hence, an individual who is other-dimensions poor either has an extreme nonmonetary deprivation or cumulates several moderate deprivations.[21] Because multidimensionally poor individuals can be both monetary poor and other-dimensions poor, the study further distinguishes other-dimensions poor individuals into two categories. First, the **consistently poor** are both monetary poor and other-dimensions poor.[22] Then, the **omitted poor** are other-dimensions poor but they are not monetary poor. As the latter taxonomy suggests, the national consumption poverty measure, which only accounts for the monetary dimension, makes exclusion errors on the individuals that are called omitted poor. Finally, the analysis calls **only monetary poor** the monetary poor who are not other-dimensions poor.

Both classifications of (multidimensionally) poor individuals are policy-relevant in different ways. First, distinguishing extremors from cumulators is relevant because the policies to fight these two kinds of poverties are different. For instance, no extremor can escape (multidimensionally) poverty when government policies only reduce moderate deprivations. Second, distinguishing monetary poor from other-dimensions poor is not only useful for the study's purpose in contrasting its multidimensional poverty measures with a monetary poverty measure. As shown by Bolch, Lopez-Calva, and Ortiz-Juarez (2022), cross-section data on nonmonetary dimensions of deprivation help distinguish between transient and chronic monetary poor individuals. Their results suggest that the consistently poor are more likely to be chronic monetary poor than the only monetary poor. Again, the best policies to tackle chronic and transient monetary poverty are different.

The Venn diagram in fig. 7 illustrates the prevalence of these four types of (multidimensionally) poor in Nigeria. The diagram reveals that the fraction of (multidimensionally) poor individuals in Nigeria in 2019 is 51.9 percent. The fraction of monetary poor is (again) 40.5 percent, and the fraction of other-

21 For the preferred design, the study also classifies as other-dimensions poor any individual who cumulates several moderate deprivations, even when one of these moderate deprivations is monetary.

22 The "consistently poor" terminology is borrowed from Whelan et al. (2003) and Bolch, Lopez-Calva, and Ortiz-Juarez (2022).

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dimensions poor is 27.9 percent. The fraction of other-dimensions poor is by definition the sum of the fractions of consistently poor and omitted poor, respectively 16.5 percent and 11.4 percent.

Two facts are worth emphasizing here. First, being monetary poor is positively correlated to being other- dimensions poor. An intuitive quantitative sense of this correlation is provided by the coefficient of overlap between monetary and other-dimensions poverty, which is defined as

$$coefficient\ of\ overlap = \frac{fraction\ of\ monetary\ poor\ indiv.\ who\ are\ other-dimensions\ poor}{fraction\ of\ not\ monetary\ poor\ indiv.\ who\ are\ other-dimensions\ poor}$$

and whose value is 2.1 in the Nigerian population. Loosely speaking, a monetary poor individual is 2.1 times as likely to be other-dimensions poor than an individual who is not monetary poor. Second, ignoring nonmonetary dimensions of well-being leads to a significant omission in terms of properly capturing low well-being. Indeed, 11.4 percent of the Nigerian population is not monetary poor but still has a well-being level that this study's identification method deems too low. Conversely, ignoring the monetary dimension leads to an even greater omission in terms of properly capturing low well-being. Indeed, 24 percent of the Nigerian population is only monetary poor, that is, not other-dimensions poor but monetary poor.

The Venn diagrams in fig. 8 further study the 11.4 percent of omitted poor, who are thus other-dimensions poor but not monetary poor. These diagrams shed light on the nonmonetary dimensions and types of deprivations that make these individuals (multidimensionally) poor. Among the 11.4 percent who are omitted poor, 8.2 percent are extremors and 3.2 percent are cumulators. The left panel focuses on the 8.2 percent of omitted poor individuals who are extremors, which implies that the sum of all percentages in that panel is equal to 8.2 percent. The three bubbles each capture extreme deprivation status for one of the three nonmonetary dimensions considered in the baseline design. The diagram reveals that 0.7 percent of the population ($0.7 = 0.5 + 0.1 + 0.1 + 0$) are omitted poor who suffer from at least two extreme forms of nonmonetary deprivations. The right panel focuses on the 3.2 percent of omitted poor individuals who are cumulators, which implies that the sum of all percentages in the intersections of the right panel is equal to 3.2 percent ($3.2 = 0.1 + 1.5 + 0.4 + 1.2$). The three bubbles each capture moderate deprivation status in one of the three nonmonetary dimensions considered in the baseline design. These diagrams reveal that health and housing are the most consequential extreme forms of deprivation for omitted extremors while security is the most consequential moderate form of deprivation for omitted cumulators (security adds $2.8 = 1.5 + 1.2 + 0.1$ omitted poor cumulators).

Table 2 provides a sense of the geographic distribution of different types of (multidimensional) poverty. Each of the three zones in the north has a larger fraction of (multidimensionally) poor individuals than each of the three zones in the south. This pattern is no surprise given that monetary poverty has the same geographical distribution and monetary poverty has a larger incidence than other-dimensions poverty in Nigeria. A more interesting insight of Table 2 is that other-dimensions poverty is less heterogeneously distributed across space than monetary poverty. Indeed, the fraction of other-dimensions poverty varies between 16.2 percent and 45.6 percent while the fraction of monetary poor individuals varies between 9.7 percent and 69.9 percent. This is confirmed by comparing the respective coefficients of variations for these two forms of poverty. One implication of this different heterogeneity across space is that ignoring nonmonetary dimensions has a proportionally larger impact when evaluating the *incidence* of poverty in the southern zones than in the northern zones. For instance, the two zones with the largest fraction of omitted poor are in the south. This finding may be surprising given that (1) zones in the south have a smaller fraction of other-dimensions poor than zones in the north and (2) other-dimensions poverty has a similar correlation with monetary poverty in the north as in the south, as suggested by the coefficient of overlap. A key reason for this larger impact in southern regions is that other-dimensions poverty is less heterogeneously distributed across space than monetary poverty. Another fact worth highlighting in Table 2 is that consistent poverty is the type of poverty most heterogeneously distributed across space. Consistently poor individuals are highly concentrated in northern zones. Clearly, this follows from the fact

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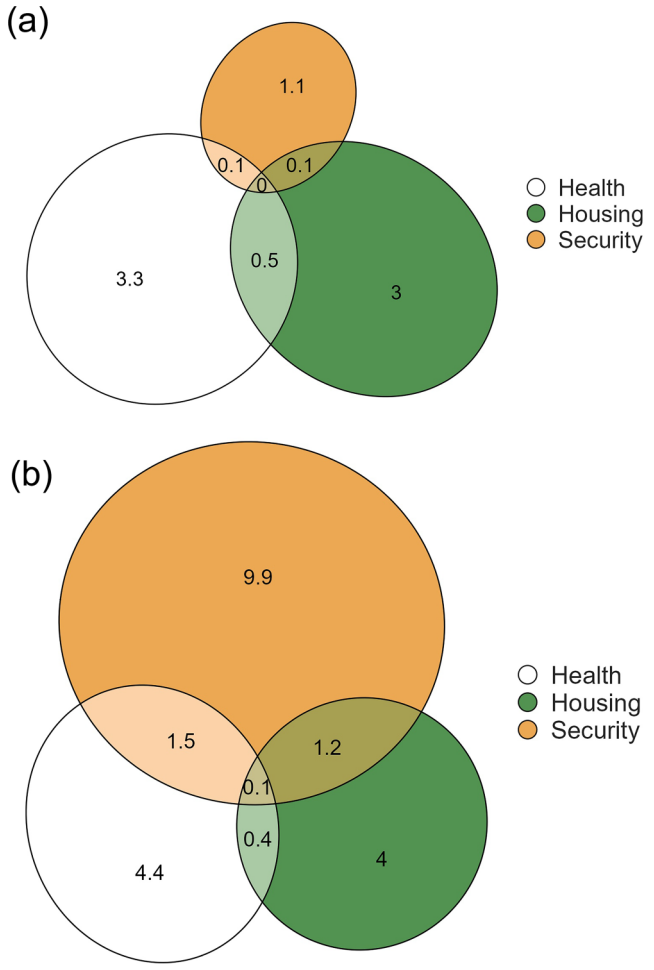
Figure 8. Overlap of the Nonmonetary Deprivations Suffered by Omitted Poor, Baseline Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The left panel shows the fraction of the Nigerian population that is simultaneously (1) not monetary poor and (2) suffers from an extreme nonmonetary deprivation. The right panel shows the fraction of the Nigerian population that is simultaneously (1) not monetary poor, (2) does not suffer from an extreme nonmonetary deprivation and (3) suffers from a moderate nonmonetary deprivation.

Table 2. Prevalence of Different Types of Multidimensionally Poor Individuals, per Zone, Baseline Scenario

Zones	National	South West	South South	South East	North Central	North West	North East	Coefficient of variation across states
Multidimensionally poor	51.9%	23.3%	36.1%	45.1%	54.2%	71.7%	80.5%	0.44
Monetary poor	40.5%	9.7%	20.8%	38.2%	43.1%	61.8%	69.9%	0.61
Other- dimensions poor	27.9%	16.2%	20.9%	15.4%	30.0%	37.0%	45.6%	0.47
Omitted poor	11.4%	13.5%	15.3%	6.9%	11.1%	10.0%	10.6%	0.52
Consistently poor	16.5%	2.6%	5.6%	8.4%	18.9%	27.0%	34.9%	0.79
Coefficient of overlap	2.1	1.8	1.4	2.0	2.2	1.7	1.4	0.30

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table shows different poverty rates: multidimensional poverty, monetary poverty, and nonmonetary poverty at the national level and within Nigeria's six zones. The table also shows the level of overlap between monetary poverty and other dimensions poverty, materialized by the overlap coefficient. The variability of each of the above measures is compared using the coefficient of variation across stated presented in the last column.

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Table 3. Impact of Each Nonmonetary Dimensions on Other-Dimensions Poverty Rates

National poverty headcounts			
Other-dimensions poor (%)		**Omitted poor (%)**	**Consistently poor (%)**
		Baseline Scenario	
All dimensions kept	27.9	11.4	16.5
Health	18.1	6.5	11.6
Housing	14.9	6.9	8.0
Security	21.4	7.6	13.8
		Preferred Scenario	
All dimensions kept	34.9	15.7	19.1
Education	30.5	14.0	16.5
Health	27.0	11.2	15.8
Housing	22.8	11.4	11.4
Security	27.7	10.9	16.8

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table shows, other-dimensions poverty rates when all nonmonetary dimensions are taken into account and when one of them is removed, for the baseline and the preferred scenario. The overall other-dimensions poverty rate is decomposed into omitted poverty and consistent poverty.

that northern zones have both higher monetary poverty rates and higher other-dimensions poverty rates. This potentially suggests that chronic monetary poverty might be largely concentrated in the northern zones (Bolch, Lopez-Calva, and Ortiz-Juarez 2022).

Impact of Assumptions on the Fraction of Poor

This paper further studies the sources of (multidimensional) poverty by using another method. It slightly changes the assumptions of its design to study the impact of these assumptions.

First, it looks at the respective impact of the three nonmonetary dimensions of the baseline design (health, housing and security). More precisely, the paper contrasts the fraction of other-dimensions poor and omitted poor when removing one of these three dimensions from its design. Table 3 provides the results. The results reveal that the importance of one dimension not only depends on the fraction of deprived individuals but also on the correlation between that dimension and monetary poverty. Indeed, for this paper's baseline design, housing has the largest incidence of deprivation and removing this deprivation has the largest impact on the fraction of other-dimensions poor. However, housing is much more correlated with monetary poverty than health. As a result, health has the largest impact on the fraction of omitted poor. Table 3 also shows the result of the same analysis for the preferred design. For this study's preferred design, security, the dimension least correlated with monetary poverty has the largest impact on the fraction of omitted poor.

Second, this paper looks at the impact of considering both extreme and moderate deprivation statuses for non-monetary dimensions, as suggested by the theory presented in section 2. To do this, counterfactual poverty rates are computed by converting any extreme deprivation into a moderate deprivation. More precisely, the analysis computes the fraction of other-dimensions poor when counterfactually assuming that individuals who are extremely deprived in a nonmonetary dimension are in fact moderately deprived in that nonmonetary dimension. For these counterfactual estimates, individuals can be other-dimensions poor only if they cumulate deprivations in at least two nonmonetary dimensions. The results are presented in Table 4 and reveal that these fractions are decreased by slightly more than one-third in the baseline design and by about a quarter in the preferred design (table A1). The smaller decrease for the preferred design reflects the fact that the preferred design features four nonmonetary dimensions, instead of just

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Table 4. Impact of Two Deprivations Statuses (Extreme and Moderate) on Poverty Rates, Baseline Scenario

National poverty headcounts			
Other-dimensions poor (%)		**Omitted poor (%)**	**Consistently poor (%)**
Extreme deprivation considered	27.9	11.4	16.5
All nonmonetary deprivations are assumed moderate	16.2	6.7	9.5

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table presents other-dimensions poverty rates in Nigeria (1) under the baseline scenario, i.e., when the two-thresholds cut-offs (extreme and moderate deprivation) are applied for each nonmonetary dimension and (2) under a modification of the baseline deprivation mapping such that only a one-threshold cut-off is applied for each nonmonetary deprivation (that is, only the moderate deprivation status is considered: any extreme nonmonetary deprivation is converted into a moderate deprivation). The overall other-dimensions poverty is decomposed into omitted poor and consistently poor to account for individuals who are both monetary and other-dimensions poor.

three for the baseline design.[23] Overall, this significant reduction suggests that the extreme deprivation status, which allows accounting for the depth of deprivation, plays an important role in this paper's methodology to identify the (multidimensionally) poor.

5. Impact on Poverty Comparisons

This section uses two different methods to assess the impact of nonmonetary dimensions on poverty comparisons. Now, poverty comparisons require a poverty measure, which is the combination of an identification method and a poverty index. In the remainder of the paper, it is assumed that the poverty index is the head-count ratio. As is well known from Sen (1976), the head-count ratio violates many desirable properties. Yet, for present purposes, using the head-count ratio is conservative, because the different poverty comparisons that are found can be entirely attributed to the respective identification methods. If instead another index is used, say the poverty gap ratio for monetary poverty and the adjusted head-count ratio (M0) for multidimensional poverty, part of the difference in poverty comparisons could be attributed to the fact that these two indices are different.

First, the paper quantifies the frequency with which nonmonetary dimensions reverse the poverty ranking between two states. One limitation of this approach is that poverty rankings can be reversed for very small differences in the poverty measures, which might not be statistically significant. The second method does not suffer from this limitation and thus provides a robustness check on the first method. For the second method, the study quantifies the fraction of the budget for a hypothetical social policy that should be transferred across states when allocating this budget according to multidimensional poverty rather than monetary poverty.

Quantifying Re-Rankings

Table 5 reports the fraction of all pairwise state comparisons that are reversed for different pairs of poverty measures. For instance, the fraction of states whose comparison is reversed when ranking them by monetary poverty rather than by multidimensional poverty (preferred design) is 9 percent. This shows that the ranking of states by these two indicators is highly correlated. By comparison, when comparing two uncorrelated measures, the analysis expects the percentage of these "re-rankings" to be 50 percent. To provide some perspective, the paper also compares the fraction of re-rankings when moving from mean consumption to monetary poverty, which is 5 percent in Nigeria. The table considers the following

23 The more numerous are the nonmonetary dimensions, the more numerous are the opportunities for individuals to cumulate deprivations in at least two nonmonetary dimensions. At one extreme, with only one nonmonetary dimension, the fraction of other-dimensions poor individuals would fall to zero when removing the extreme deprivation status (at least in the paper's baseline design for which no individual is moderately monetary deprived).

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Table 5. Percentage of States Pairwise Comparisons Reversed between pairs of Poverty Measures

	Baseline			Preferred		
	All states	States with $H_M < 50$	States with $H_M \geq 50$	All states	States with $H_M < 50$	States with $H_M \geq 50$
Average consumption -VS- H_M	5%	10%	8%	5%	10%	8%
Average consumption -VS- H	9%	22%	12%	11%	28%	13%
H_M -VS- H	7%	16%	13%	9%	22%	13%
H_{OD} -VS- H_M	19%	25%	40%	20%	23%	40%
H_{OD} -VS- H	16%	16%	24%	11%	13%	13%

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table shows the percentage of pairs of states whose comparison is reversed between two different poverty measures: average consumption, monetary poverty rate (H_M), multidimensional poverty rate (H), and other-dimensions poverty rate (H_{OD}). Results are presented for each scenario, baseline and preferred. For each scenario, restrictions are applied in order to consider only states with a monetary poverty rate below 50 percent, on the one hand, and those with a monetary poverty rate above 50 percent, on the other. The aim of these restrictions is to reduce the disparity between compared states.

list of indicators: mean consumption, monetary poverty (H_M), multidimensional poverty (H) and other-dimensions poverty (H_{OD}).

Table 5 reveals the following findings. First, the rankings of all these poverty measures are highly correlated in Nigeria. This is not very surprising as this is typically the case for any two meaningful poverty measures. Yet, one key reason why the rankings of Nigerian states are highly correlated is that they have highly heterogeneous well-being levels (according to all three measures). Recall for instance that monetary poverty ranges between 10 percent and 90 percent in those states. Clearly, it is unlikely to find that two indicators of well-being disagree when comparing two states with respectively 20 and 80 percent monetary poverty. This is especially true if both indicators account for monetary poverty, for instance, this is the case for H_M and H. To give a sense of the correlation between rankings among less dissimilar states, the study also computes the fraction of re-rankings between states that have less than 50 percent poverty and the fraction of re-rankings between states that have more than 50 percent poverty. For instance, the fraction of re-rankings between monetary poverty and multidimensional poverty (preferred design) are 22 percent and 13 percent, respectively in the former and latter subset of states.

Second, it might be surprising that the analysis finds this level of re-rankings between monetary poverty and multidimensional poverty in spite of the fact that (1) multidimensional poverty accounts for monetary poverty and (2) monetary poverty is high and heterogeneously distributed. The reason is that other-dimension poverty is very far from perfectly correlated with monetary poverty. The fraction of re-rankings between monetary poverty and other-dimensions poverty (preferred design) is an astonishing 20 percent. If one focuses on states with more than 50 percent of monetary poverty, the fraction of re-rankings rises to 40 percent.

Finally, it is worth noting that the study finds fewer re-rankings across all states between monetary and multidimensional poverty than between other-dimensions and multidimensional poverty. The reason is that, although multidimensional poverty accounts for both monetary and other-dimension poverty, the former is more prevalent and more heterogeneously distributed. As a result, multidimensional poverty comparisons are more driven by monetary poverty.

Quantifying Budget Transfers Across States

Quantifying re-rankings is a binary method to probe changes in poverty comparisons. Indeed, a ranking between two states is either reversed or not. The limitation of this method is that, when the ranking is not reversed, the changes in the relative poverty levels of the two states being compared are not accounted for. The method used in this subsection accounts for such changes.

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Table 6. Fraction of (Hypothetical) Budget Reallocated across States between Pairs of Poverty Measures

	Baseline (%)	Preferred (%)
Average consumption -VS- H_M	5.7	5.7
Average consumption -VS-H	8.1	9.1
H_M -VS- H	4.7	6.0
H_{OD} -VS- H_M	12.3	12.0
H_{OD} -VS- H	14.4	13.6

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table considers a hypothetical policy that allocates a budget across Nigerian states proportionally to (minus) the state's total well-being (see appendix 3 for details). The table presents the fraction of the budget that must be re-allocated across states when changing from one well-being measure to another: monetary poverty rate (H_M), multidimensional poverty rate (H) and other-dimensions poverty rate (H_{OD}).

The next method is based on a hypothetical social policy. Assume that the Nigerian government has a budget for social protection policies. Further assume that this budget is distributed across states proportionally to needs as captured by a poverty measure. This budget is assumed to be distributed proportionally to the number of poor individuals in each state. Consider the following simplified example with two states, where state A has 0 monetary poor and 1 multidimensionally poor individual while state B has 1 monetary poor and 3 multidimensionally poor individuals. Under monetary poverty, state B receives 100 percent of the budget, while under multidimensional poverty state B receives 75 percent of the budget and state A 25 percent. The fraction of the total budget that must be transferred is thus 25 percent, from state B to state A.

Table 6 shows the fraction of the total budget that must be transferred when comparing two of the following list of indicators: average consumption, monetary poverty (H_M), multidimensional poverty (H) and other-dimensions poverty (H_{OD}).[24] The fraction transferred corresponds to 6 percent of the budget when moving from monetary poverty to multidimensional poverty (preferred design). This transfer has the same magnitude as the transfer when moving from average consumption to monetary poverty (5.7 percent). Again, the table suggests that moving from monetary poverty to multidimensional poverty impacts these transfers more than moving from other-dimensions poverty to multidimensional poverty.

To be sure, the results of this section for the baseline design are not entirely driven by the inclusion of the security dimension, which is the nonmonetary dimension that is least correlated with the monetary dimension. When replacing in the baseline design the security dimension by the education dimension, Table 5 reveals that the percentage of all states pairwise comparisons reversed between H_M and H is 5 percent (instead of 7 percent) and for Table 6 that the fraction of the hypothetical budget to be reallocated between H_M and H is 4.1 percent (instead of 4.7 percent).

The results of this section thus suggest that accounting for nonmonetary dimensions has non-negligible implications, even in a country with high monetary poverty and when using this study's poverty measure that also accounts for monetary poverty.

6. Concluding Comments

The mainstream AF method for identifying the multidimensionally poor is not welfare consistent (Ravallion 2011). This is unsurprising given that data constraints on nonmonetary outcomes make welfare consistency unachievable in practice. However, the mainstream AF method is not flexible enough to

24 When contrasting poverty with average consumption, this study uses a straightforward adaptation of this method that accounts for the fact that poverty *decreases* with well-being while average consumption *increases* with well-being, which is described in detail in appendix 3.

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implement a definition of the poor that satisfies two minimal restrictions: (1) an individual is poor as soon as her outcome in one important variable is extremely low and (2) an individual is poor if she cumulates moderately low achievements in several variables. Implementing such definitions requires an identification method that distinguishes extremely low achievements from moderately low achievements in a given variable. Decerf (2023) suggests using two cut-offs for the same variable, which define three mutually exclusive deprivation statuses: extreme deprivation, moderate deprivation, and absence of deprivation. This paper proposes one way of implementing this suggestion in practice. The results for Nigeria in 2019 suggest that the method can substantially change the set of individuals identified as poor.

Equipped with this refined identification method, this study examines the significance of accounting for nonmonetary outcomes when measuring poverty. It finds that doing so has a particularly important impact in contexts where monetary poverty is smaller.[25] The intuition is that, in this study's data, nonmonetary outcomes are less heterogeneously distributed than monetary outcomes. As a result, the set of omitted poor individuals, that is, those who are multidimensionally poor but not monetary poor, is proportionally larger in contexts with fewer monetary poor individuals. Given the historic reduction of global extreme monetary poverty over the past decade, this result suggests that accounting for nonmonetary outcomes might become increasingly relevant.

In the future, the exact design of the deprivation mapping, which links dimension-specific variables to deprivation statuses, and the aggregation of deprivations statuses into multidimensional poverty status would benefit from more empirical work. Again, these aspects can be investigated through preferences-elicitation techniques, following the conceptual guidelines discussed in section 3. The study emphasizes that, unlike what is sometimes assumed, such an investigation should not restrict itself to estimating the average marginal rates of substitution across dimension-specific variables at some reference achievement bundle on indifference curve U^*. Rather, as discussed in section 2, the goal is to estimate the whole indifference curve U^*. The aggregation of dimension-specific variables into multidimensional poverty status should be such that the identification contour approximates reasonably well indifference curve U^* (Jones 2022; Decerf 2023).

This paper focuses on improving the identification of the poor. For this reason, when constructing a poverty measure, the study has assumed that the poverty index is the head-count ratio. However, this index has well-known shortcomings. Notably, it ignores the intensity of poverty. For this reason, the global MPI and the World Bank MPM both rely on a different poverty index (denoted M0), which accounts for both the incidence and the intensity of poverty. As shown by Alkire and Foster (2011), index M0 satisfies several properties. Among those, M0 is improved when a poor household escapes some form of deprivation (dimensional monotonicity) and M0 can be decomposed into the respective contributions of all dimensions (dimensional breakdown). The head-count ratio violates both of these properties.

Importantly, this does not mean that a poverty measure that identifies the poor using the refined AF method cannot satisfy these properties. Indeed, instead of the head-count ratio, one could simply pick another index that satisfies these properties. This is the case of index M0.[26] Replacing the head-count ratio by index M0 directly yields a poverty measure that satisfies both dimensional monotonicity and dimensional breakdown even if this poverty measure identifies the poor with the refined AF method described in this paper (without using any weights). However, as noted in the Introduction, such poverty measure might violate some other fairness property. This article does not view such a violation as a sufficient reason for discarding this approach because it has concluded that the welfare-consistency of the identification method is at least as important as such fairness properties. Admittedly, defining a poverty measure based on the refined AF method and index M0 will require selecting values for M0's weights.

25 See for instance the fraction of re-rankings between H_M -VS- H reported in Table 5, which is larger for states where H_M is smaller than 50 percent than for states where H_M is larger than 50 percent.

26 By definition, M0 = HA, where H is the head-count ratio, A is the average intensity of deprivation among poor individuals and the intensity of poverty is the sum of weights for each deprivation.

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Under the refined AF method, two weights must be selected for variables like consumption for which three deprivation statuses are considered. The weight for values of consumption leading to extreme deprivation must be at least as large as the weight for values of consumption leading to moderate deprivation.

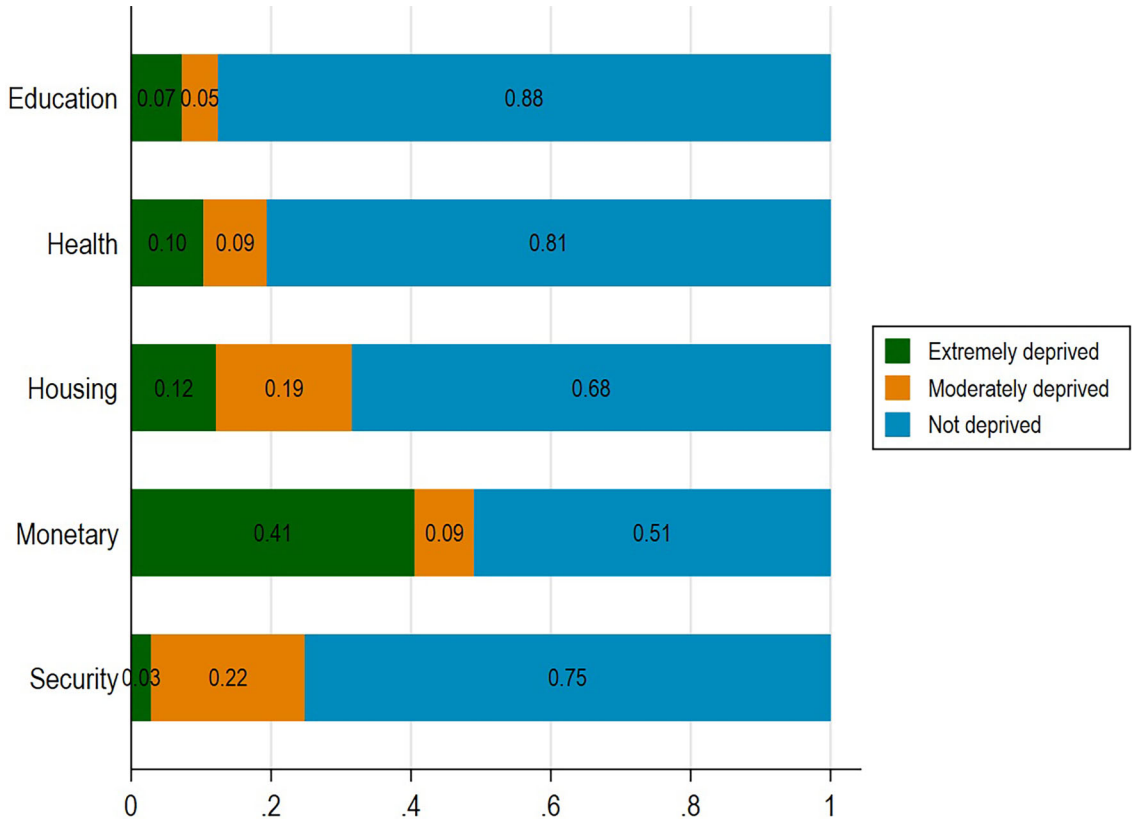
Finally, more research is needed to produce reliable methods to elicit the relevant preference over nonmonetary achievements. In particular, these methods should elicit preferences not only over continuous variables, but also over categorical variables. This would help identify which dimensions are most relevant and how much they should be weighed. The ad hoc aggregation criticism raised by Ravallion still needs to be properly addressed.

Data Availability Statement

The data used is available upon request on WBG and DHS websites, as well as in the replication package for the working paper version: https://drive.google.com/drive/folders/11dRGL3_KGuZAFBnlXk4esxi52gG4NbtK.

Appendix 1. Additional Figures and Tables

Figure A1.1. Prevalence of Extreme and Moderate Deprivations per Dimension for Nigeria, Preferred Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The figure presents, for each dimension considered in the baseline scenario—monetary, health, housing, security—the share of individuals according to their state of deprivation: nondeprivation, moderate deprivation, extreme deprivation.

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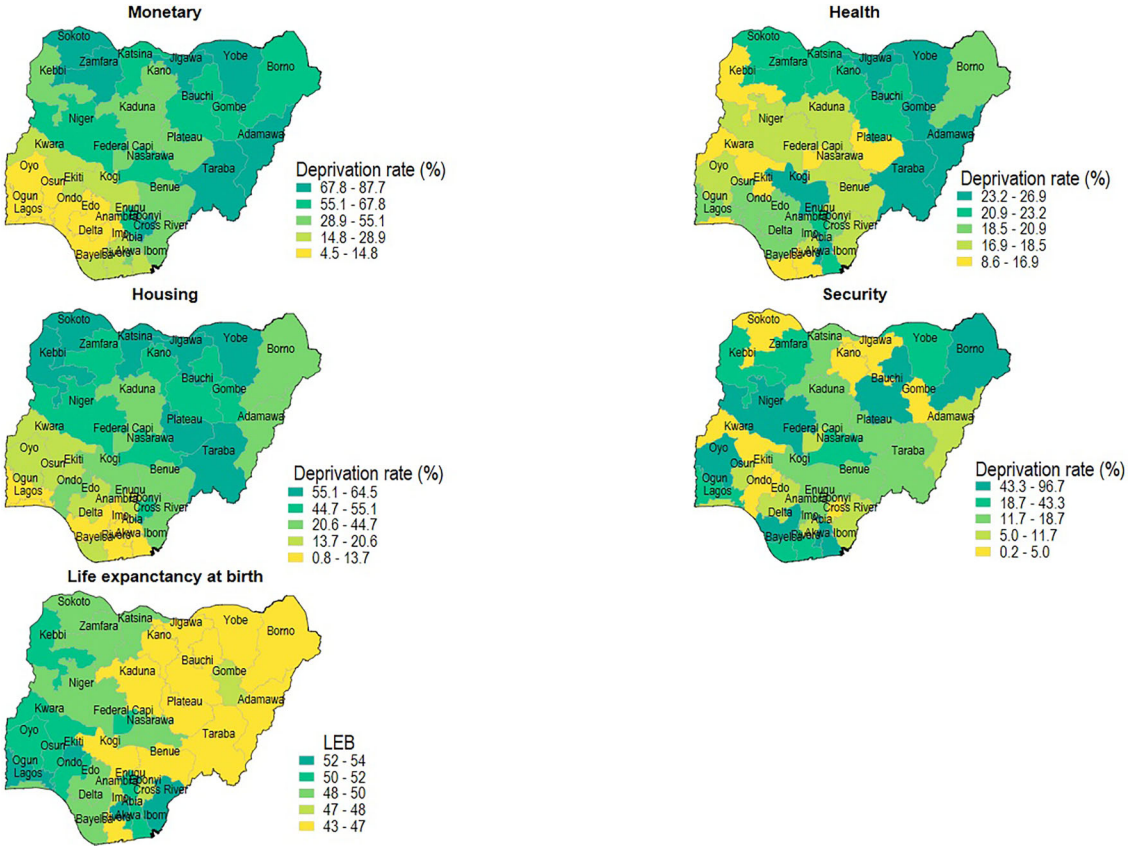
Figure A1.2. Geographic Distribution of Deprivation (Extreme + Moderate) per State, Baseline Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The figure presents, for each dimension considered in the baseline scenario—monetary, health, housing, security—the geographic distribution, within the 37 Nigerian states, of the deprivation (extreme and moderate) rate in percent. Life expectancy at birth within each state is also presented.

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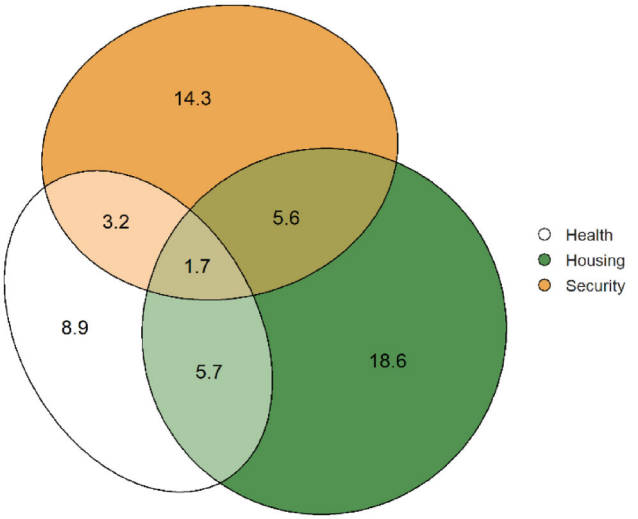
Figure A1.3. Overlap of Nonmonetary Deprivation (Extreme and Moderate) in Nigeria, Baseline Scenario



Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: Using a Venn diagram, the figure shows the share of deprived (extreme and moderate) individuals per each nonmonetary dimension (health, housing, and security) and the interactions with deprivations in other nonmonetary dimensions.

Table A1.1. Prevalence for Each of the Dimensions-Specific Variables in Nigeria

Dimensions	Variables	% of target individuals	% of overall individuals
Monetary	Household annual consumption per capita is below national poverty line	40.5	40.5
	Household annual consumption per capita is above national poverty line but below state societal poverty line	8.5	8.5
Health	Individual suffers from at least one severe disability	2.9	2.9
	Individual suffers from at least one mild disability	6.0	6.0
	Children suffer from stunting	31.7	5.5
	Undernourished women 15–49	9.7	2.3
	Undernourished men 15–49	0.0	0.0
	Obese women 15–49	10.8	2.5
	Obese men 15–49	5.4	1.1
Education	School-age child up to the age of grade 8 not enrolled in school	16.9	7.2
	Adults: age of grade 9 or above has not completed primary education	21.7	12.4
	Adults: age of grade 9 or above cannot read or write	28.4	16.2
Housing	Household lacks access to basic-standard drinking water	56.3	56.3
	Household lacks access to basic-standard sanitation	64.1	64.1
	Household has no access to electricity	39.7	39.7
	Household has inadequate housing	42.2	42.2
Security	Individual belongs to a household, subjected during the last 12 months to an extreme insecurity event	2.2	2.2
	Individual belongs to a household, subjected during the last 12 months to a moderate insecurity event	13,5	13,5

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table shows the prevalence of the basic variables used to define the moderate and extreme deprivation thresholds for each poverty dimension. Results are expressed as a percentage of the Nigerian population.

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Table A1.2. Impact of Two Deprivations Statuses (Extreme and Moderate) on Poverty Rates, Preferred Scenario

		National poverty headcounts	
Others-dimensions poor (%)		Omitted poor (%)	Consistently poor (%)
Extreme deprivation considered	34.9	15.7	19.1
All nonmonetary deprivations are moderate	25.0	11.8	13.2

Source: Authors' estimates based on data from Nigeria Living Standard Survey 2019 and Nigeria Demographic and Health Survey 2018.
Note: The table presents other-dimensions poverty rates in Nigeria (1) under the baseline scenario, i.e., when the two-thresholds cut-offs (extreme and moderate deprivation) are applied for each nonmonetary dimension and (2) under a modification of the baseline deprivation mapping such that only a one-threshold cut-off is applied for each nonmonetary deprivation (i.e., is, only the moderate deprivation status is considered: any extreme nonmonetary deprivation is converted into a moderate deprivation). The overall other-dimensions poverty is decomposed into omitted poor and consistently poor to account for individuals who are both monetary and other-dimensions poor.

Appendix 2. Imputation Model for Nutritious Outcomes

Given the lack of available information on individual health in the Household Living Conditions Survey (NLSS), the main source of data used in this study, a related survey, Nigeria's Demographic Health Survey (DHS) 2018, was used to infer information on the nutritional status of individuals. The general approach used was to build a model from DHS data, from which the nutritional status of individuals interviewed in the NLSS were inferred, in order to reproduce the representative distribution of the nutritional status in DHS. The construction of this model is succinctly describe in this appendix.

Nutritional statuses

The nutritional status of individuals was first defined considering the age and sex of the individuals. Three main categories were thus retained: children, defined as all individuals between 0 and 5 years of age inclusive, and adult men and women, that is, those between 15 and 49 years of age.

The nutritional status of children was measured on the basis of the height-for-age z score—number of standard deviations of the actual height of a child from the median height of the children of his/her age as determined from the standard sample—from which three standard classes were identified:

$$\begin{aligned} -2 < HAZ &\quad \text{Normal (Well nourished)} \\ -3 < HAZ < -2 &\quad \text{Moderately Stunted (Moderately Malnourished)} \\ HAZ < -3 &\quad \text{Severely Stunted (Severely Malnourished)} \end{aligned}$$

Stunting is a condition that results from chronic or recurrent undernutrition, usually associated with poverty, poor maternal health and nutrition, frequent illness, and/or inappropriate feeding and care in early life. Stunting prevents children from reaching their physical and cognitive potential.

As for the nutritional status of adults, it has been defined on the basis of the body mass index (BMI), which is calculated according to height and body mass, and which makes it possible to estimate the corpulence of a person. Three categories have been formed from the variable:

$$\begin{aligned} BMI < 18.5 &\quad \text{Undernourished} \\ BMI >= 18.5 \& BMI < 30 &\quad \text{Normal (Wellnourished)} \\ BMI > 30 &\quad \text{Obese} \end{aligned}$$

Modeling Approach

The nutritional status has been modeled from DHS data using a multinomial logit regression for each type of individual (children and adults). In order to capture the heterogeneity that may be present between zones—standard of living, local agricultural cultures, accessibility of markets, etc.—a model for each of the six zones of Nigeria was compiled. The following variables were identified as factors influencing the nutritional status of individuals:

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The asset index, which is supposed to represent the household's standard of living and includes characteristics of the dwelling, and the movable and immovable assets owned by the household:

- Socio-demographic characteristics of the household's head, such as age, gender,
- Education level, marital status
- Socio-demographic characteristics of the individual when applicable
- Location (urban/rural) and household size

Inference Approach

Nutritional status has been imputed in NLSS data using, on the one hand inferred probabilities from the model built in DHS data and, on the other hand, estimated thresholds such that NLSS data could reproduce DHS individuals' nutritional status per zone.

In particular, thresholds have been chosen such that shares of adult women categories (undernourished, normal, obese) and shares of children (normal, moderately stunted, extremely stunted) are similar to shares in DHS data per zone. However, due to lack of information in DHS data on other demographic categories of population (children between 6 and 14, adult men between 15, and 49 and elders over 50), some assumptions have been made on shares of undernourished/obese among those people, in a conservative approach, on the basis of available third-source information:

- Half as many obese men as obese women in the 15–49 age group, in each of the zones of Nigeria, a conservative assumption in light of Chukwuonye et al. (2013).
- No undernourished men in the 15–49 age group (conservative approach)
- All individuals in the 6–14 and over-50 age groups are in a normal nutritional condition (conservative approach)

Choice of Classification Thresholds

The process of classifying individuals into one or the other of the categories, once a binary logit probability model has been estimated, generally consists of assigning an individual to a group if its probability of belonging is greater than a certain level, and further examining the distribution table between observed values and the predicted values. The choice of the classification threshold is therefore decisive, since the quality of the predictions obtained depends on it.

Several methods are generally accepted for the choice of the binary categorization threshold, some of them relying on the choice of a 50 percent threshold assuming equi-probability between the events, or the choice of a more or less demanding threshold depending on the impact of first or second species errors. In the framework of this analysis, the method applied is based on the a priori information available on the observed values in the DHS data and on additional assumptions presented in the preceding paragraph.

However, since this analysis was conducted in the context of a multinomial regression model (three categories), the classification of individuals required the choice of not one, but two thresholds. To do so, a sequential approach was adopted. In a first step, a binary classification, on the basis of discriminating one category from the two others, was performed using the estimated initial probabilities. In a second step, a second binary classification in the class regrouping two categories was performed, this time, based on the conditional probabilities.

Appendix 3: Quantifying Hypothetical Budget Transfers Across States

Appendix 3 details the method the study used to compute the fraction of the total budget that must be transferred when moving from one poverty measure to another. Three poverty measures are considered, namely the fraction of monetary poor individuals (H_M), the fraction of multidimensionally poor individuals (H), and average consumption. The difficulty is that, as noted in the text, poverty decreases with

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well-being while average consumption increases with well-being. A natural solution is to replace the fraction of poor by the fraction of nonpoor, for instance, to compare average consumption to $(1 - H)$. Then, the social protection transfers can be interpreted as tax contributions that are collected proportionally to well-being, the larger well-being, the larger the tax.

The transfer when switching from monetary poverty to multidimensional poverty is computed as

$$Transfer\ (H_M vs\ H) = \frac{1}{2}\sum_{s=1}^{Nb\ states}\left|\frac{Pop_s*(1-H_{Ms})}{\sum_{s'} Pop_{s'}*(1-H_{Ms'})} - \frac{Pop_s*(1-H_s)}{\sum_{s'} Pop_{s'}*(1-H_{s'})}\right|$$

where *Pops* denotes the population in state s.

The transfer when switching from multidimensional poverty to average consumption is computed as

$$Transfer\ (average\ cons.\ vs\ H) = \frac{1}{2}\sum_{s=1}^{Nb\ states}\left|\frac{Pop_s*(1-H_s)}{\sum_{s'} Pop_{s'}*(1-H_{s'})} - \frac{Pop_s*c_s}{\sum_{s'} Pop_{s'}*c_{s'}}\right|$$

Where c_s denotes average consumption in state s.

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