Development acupuncture: The network structure of multidimensional poverty and its implications[*]

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August 14, 2024

Abstract

While development literature has come a long way in conceptualizing and measuring poverty multidimensionally, policy interventions to address it remain trapped in fragmented sector-specific approaches. One of the main challenges in implementing integrated policy responses to multidimensional poverty reduction is understanding how the different dimensions are interlinked and how they jointly evolve over time. For example, disentangling how a person's health, education, and standards of living all interact in a dynamic sense. Motivated by economic complexity methods and applications, we use network science to propose two new measures to understand the interconnected structure of multidimensional poverty: the Poverty Space (a network that visualizes the interactions among different indicators of poverty) and Poverty Centrality (a measure of the relative importance of each indicator within this network). Applying these measures to 67 developing countries using data from the OPHI/UNDP Global Multidimensional Poverty Index, we find that the structure of multidimensional poverty networks is similar across countries and stable over time. We also find that indicators that are more central in the Poverty Space witness a more significant reduction in the censored headcount ratio over time, compared to peripheral indicators. We then use these results to demonstrate how the Poverty Space can be applied in policy: using the forward-looking Policy Priority Inference framework to help guide policy choices. Overall, our research points to the relevance of using network science methods to help identify key "nodes" in the structure of multidimensional poverty where applied pressure (targeted interventions) could lead to a greater effect on the system as a whole.

Keywords: Multidimensional poverty, network science, economic complexity, proximity metrics, dimensionality reduction

JEL codes: I31, I32, C63

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[*] We are grateful to Omar Guerrero, Gonzalo Castañeda, and Phillip Koch for their comments on this paper. The datasets and codes necessary to replicate the empirical analysis in this paper are available online. The findings, interpretations, and conclusions in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank, the Executive Directors of the World Bank or the governments they represent; nor do they necessarily represent the views of the United Nations, including UNDP, or the UN Member States.

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1. Introduction

Development literature has come a long way in understanding poverty as a multidimensional concept. Since Amartya's Sen's formalization of the capabilities approach (Sen, 1979, 1999), which argued for a broader view of poverty based on the underlying set of "beings" and "doings" required for individuals to pursue a life that they have reason to value, researchers have developed and refined approaches for measuring multidimensional poverty (Basu and Lopez-Calva, 2011; Alkire, Roche and Seth, 2013). There has been an extensive body of work proposing dimensions and indicators, deprivation thresholds, and aggregation methods. In particular, the use of the Alkire-Foster method to create a counting-based index has propelled key advances in measurement and contributed to the development of indices around the world (Alkire and Foster 2011). Today, around 40 countries have published national multidimensional poverty measures (in addition to the global measures published by international organizations), offering a powerful tool to guide coordinated policy action.

However, the transition from measuring poverty multidimensionally to designing poverty reduction interventions that take this multidimensionality into consideration is still incomplete. Policy discussions continue to be trapped in fragmented sector-specific responses. One of the main challenges in implementing an integrated policy approach to multidimensional poverty reduction is that current measures do not offer information on how the different dimensions are associated to each other over time—and thus how policies targeting one dimension could have impacts across the other dimensions. We can observe the overall outcome of an intervention, but not how different dimensions interact to result in that outcome. We know that the various dimensions of poverty do not evolve in isolation. For example, know that education is linked to health, and that health depends on nutrition and housing characteristics. In this sense, when we observe different indicators in a traditional multidimensional poverty measure, what we are actually observing is a vector of *state* variables that are co-determined over time as a *dynamic system*. Current measures offer a useful snapshot of the joint distribution of deprivation in each of these state variables at a point in time, but they do not reveal information about the structure of the dynamic process that governs the interactions between them. Partha Dasgupta observed this distinction when writing on the challenges of understanding poverty traps using only static descriptions of variables—arguing that the "presence of mutual causation (namely, several variables influencing one another over time) has implications for interpreting data" (Dasgupta, 2007).

Unveiling and quantifying this interconnected structure of multidimensional poverty presents a challenge for traditional economic techniques. Over the past decade, scholars have begun to use different methods to explore this issue. For example, Suppa, Alkire, and Nogales (2022) use latent class analysis to summarize information on different profiles of joint deprivations across the developing world; Ceriani and Gigliarano (2016) use Bayesian Networks to visualize the structure of dependence among different dimensions of poverty in Europe; Gallardo (2022) implements a similar approach for studying the structure of poverty in Chile; Duclos, Tiberti, and Araar (2018) use targeting dominance techniques to explore potential spillover effects of targeting schemes on other dimensions of poverty in Vietnam and South Africa; and Guerrero and Castañeda (2024) use an agent-based model to look at the structural interrelations between social expenditure and impacts across multiple dimensions of poverty in Mexico. The analysis of the interactions goes from a concern about the "weight structure" among the different dimensions to attempts to disentangle the interrelations among variables. Motivated by economic complexity approaches, this paper leverages network science methods to contribute to this growing body of literature by offering a new approach to understanding the interconnected structure of multidimensional poverty.

The field of economic complexity combines network science methods with information about the distribution of economic outcomes in a given space to estimate measures for the implicit relations present in an economic system (Hidalgo, 2021; Balland *et al.*, 2022). Here, we introduce a similar approach to measuring the relationships between poverty dimensions. Specifically, we leverage two methods from economic complexity: 1) metrics of proximity and 2) dimensionality reduction techniques. Metrics of proximity quantify the structural relationships between outcomes based on their co-occurrences within the population (Hidalgo *et al.*, 2007; Neffke, Henning and Boschma, 2011; Kogler, Rigby and Tucker, 2013; Guevara *et al.*, 2016), while dimensionality reduction techniques summarize the spatial distribution of an economic outcome into a single number (Hidalgo and Hausmann, 2009; Tacchella *et al.*, 2012; Sciarra *et al.*, 2020). In this study, we use the former to construct a network representation that illustrates the interconnections between various dimensions of poverty (which we call by analogy the *Poverty Space)* and the latter to introduce a measure that captures the relative importance the different dimensions within this network (which we define as *Poverty*

Centrality). We then use granular data to explore the co-occurrences of poverty indicators at the household level and build network maps for each country.

Using data from the Global Multidimensional Poverty Index (MPI), we apply these metrics in 67 developing countries to map the interconnected structure of multidimensional poverty and explore changes in its structure over time. Our findings reveal a remarkable similarity in the structure of the Poverty Spaces across countries and their stability over time. Specific indicators like cooking technology at home (cooking fuel, which is associated to living conditions at home) consistently emerge as nodes located at the core of this network, while indicators like child mortality tend to be located in the periphery. To bring a more dynamic perspective and capture pathways for spillover effects, we also explore the association between how central a poverty indicator is and the change in the incidence of people deprived in that indicator over time. We find that more central indicators in the Poverty Space also tend to experience a more significant reduction in their censored headcount ratio over time. Finally, to apply our findings in a policy context, we integrate the Poverty Space network into the Policy Priority Inference (PPI) framework (Guerrero and Castañeda Ramos, 2020). This integration enables us to explore how the structure of poverty could be associated with the potential effectiveness of targeted interventions. PPI serves as a forward-looking, agent-based model that leverages networks of structural relationships to prioritize policy initiatives, originally aimed at achieving sustainable development goals (Guerrero and Castañeda, 2024). By using the information offered by the Poverty Space on the structural relationships among poverty indicators, PPI can be implemented to prioritize different policy interventions, recognizing the potential cascading effects across various indicators of poverty.

Understanding the interconnected structure of multidimensional poverty is critical for maximizing the impact of policies to reduce it. By shedding light on the web of connections within the structure of multidimensional poverty, this paper shows how economic complexity methods can help us to better pinpoint the "key nodes" within that network. These key nodes represent the most interconnected dimensions within the poverty network and become pivotal areas of focus for interventions (Bloch, Jackson and Tebaldi, 2023). Just like in an acupuncture intervention, development strategies that target specific nodes could have a greater effect on the system as a whole.

The remainder of the paper is structured as follows. Section 2 reviews the literature to build a case for applying economic complexity approaches in the context of multidimensional poverty. Section 3 provides an overview of the methods used for developing the Poverty Space, the Poverty Centrality measure, and for conducting the dynamic analysis. Section 4 summarizes the data underpinning our analysis. Section 5 discusses the results, where we begin by illustrating the utility of the Poverty Space as a tangible metric for mapping the structure of poverty. This is followed by an empirical exploration of the association between poverty's structural nuances and its dynamics over time. We end this section by demonstrating the integration of the Poverty Space within the PPI framework. Section 6 concludes.

2. Learning from Economic Complexity: From the Product Space to the Poverty Space

The field of economic complexity has emerged as a novel framework for understanding the intricacies of economic systems (Hidalgo, 2021; Balland *et al.*, 2022). Similar to the case of multidimensional poverty, the inception of economic complexity was driven by the need to grasp the nuanced structures of economies. Economic complexity approaches capitalize on network science techniques to analyze data on the spatial distribution of industries, products, and exports and quantify the structural relationships of economic outputs.

In this vein, Hidalgo *et al.* (2007) introduced the Product Space, a network that serves as a prime example of a proximity metric. It captures the conditional probability that a country will export a good if it exports another good, reflecting the proximity between products in the global economy. This approach has proven instrumental in modeling spillovers and predicting future specialization patterns. In particular, studies have shown that countries tend to diversify their export portfolios by moving toward products that are close in the Product Space to those that they already produce, thus benefiting from established economic environments and supportive infrastructure.

Over the years, however, the real strength of using proximity metrics to construct networks, like the Product Space model, has demonstrated their versatility and adaptability. Namely, the proximity metrics of the Product Space transcend the boundary of trade, extending their analytical power to model spillovers across a wide array of activities. For example, this could encompass the proximity of scientific disciplines based on co-authorship (Guevara *et al.*, 2016), innovation domains based on patent categories (Neffke, Henning and Boschma, 2011; Kogler, Rigby and Tucker, 2013), or other sets of interconnected activities.

Hidalgo and Hausmann (2009) used the Product Space to formally introduce the concept of economic complexity and created network-based centrality measures for the implicit importance of products in an economy (called, respectively, the Economic Complexity Index and the Product Complexity Index). These measures, which condense high-dimensional data into a single index, have provided invaluable insights into countries' potential for inclusive green growth (Tacchella *et al.*, 2012; Cristelli *et al.*, 2013; Hausmann *et al.*, 2014; Hartmann *et al.*, 2017; Romero and Gramkow, 2021; Stojkoski, Koch and Hidalgo, 2023). Today, these metrics are used to complement aggregate indexes such as GDP and guide structural interventions (Balland *et al.*, 2019; Hassink and Gong, 2019; Montresor and Quatraro, 2020; Deegan, Broekel and Fitjar, 2021).

More recently, economic complexity approaches have been applied for the development of data-driven methods to understand progress towards the Sustainable Development Goals (SDGs) and in addressing multidimensional inequality. For instance, El-Maghrabi *et al.* (2018) applied these methods to prioritize SDG targets for countries, while Lapatinas and Katsaiti (2023) developed the EU Multidimensional Equality Complexity Index, using a network science perspective to tackle inequality. Additionally, Sciarra *et al.* (2021) employed a network-based methodology to rank countries' performance on the SDGs, thereby highlighting the intrinsic complexity within the system.

Motivated by the diverse application of economic complexity methods, this paper introduces network-based measures for multidimensional poverty and explores their application in forward-looking models of economies. This responds to the important challenge noted in the 2009 Report of the Commission on the Measurement of Economic Performance and Social Progress on the need to have measures that are capable of considering the complicated interactions between different dimensions of poverty. As Stiglitz et al. (2009; p 16) highlight, "when designing policies in specific fields, impacts on indicators pertaining to different quality-of-life dimensions should be considered jointly, to *address the interactions between dimensions* and the needs of people who are disadvantaged in several domains" (emphasis added).

Before we present the integration of economic complexity methods within multidimensional poverty analysis, it is essential to understand the nuances of our approach.

First, while our approach is motivated by the economic complexity literature, the metrics used are not identical to those traditionally used in the field, such as the Product Space or the Economic Complexity Index. Instead, we adapt the conceptual framework of economic complexity to develop new metrics suited to the analysis of poverty. We primarily employ network science techniques to map and analyze the interconnected structure of multidimensional poverty. As we will show in the subsequent sections, the Poverty Space is identical to the Product Space in its use of proximity metrics (though through different outcomes), whereas Poverty Centrality is a measure unique to our approach, based on eigenvector centrality (Jackson, 2008), to quantify the susceptibility of each poverty indicator to spillovers.

Second, just like standard economic complexity approaches, a key limitation of our method lies in its lack of causal inference: the inferred network relationships do not imply causation (Hidalgo, 2022). By using information on the co-occurrence of the different dimensions of poverty within a household, they offer insights into structural relationships among poverty indicators (and to what extent they are context-specific or can be generalized), reflecting the patterns of interconnections rather than direct causal links. This characteristic can limit their applicability in scenarios where understanding the cause-effect relationships between poverty indicators is critical (Ospina-Forero, Castañeda and Guerrero, 2022). Moreover, even if co-occurrence patterns suggest a strong relationship, this may not necessarily imply complementarity across indicators—as this may be the result of redundancies rather than true connections (Rajpal and Guerrero, 2023). This limitation, however, does not weaken the value of our approach for shedding light on policy-related questions, but it does require careful interpretation of the results.

While our approach cannot infer causation or complementarity per se, it does shed important light on the structural connections between various dimensions. Namely, our methods (and economic complexity methods in general) act as risk scores, approximating the combined forces that drive the relations between different dimensions of poverty, irrespective of the sources of these relationships. They also could offer strong predictive power, enabling the forecasting of potential vulnerabilities or future trends in multidimensional poverty. By decoding the web of connections between dimensions of poverty, these methods can anticipate how changes in one dimension could potentially ripple across others, or how general policies affect specific indicators. This feature is particularly beneficial in the realm of policy prediction problems (Kleinberg *et al.*, 2015; Athey, 2017) and recent agent-based policy priority frameworks (Castañeda, Chávez-Juárez and Guerrero, 2018; Guerrero and Castañeda Ramos, 2020; Guerrero, Guariso and Castañeda, 2023). Rather than primarily focusing on the cause-effect relationship as in traditional policy research, these problems require a robust predictive model to understand potential outcomes. Here, economic complexity methods offer a useful alternative as they reveal the likelihood of various scenarios stemming from policy decisions and thus could be helpful in evaluating the effectiveness of poverty reduction strategies. By understanding how the structural relationships of one indicator relate with deprivations in other indicators, we can better measure the overall effectiveness of an intervention and understand its wider implications in the poverty network as a whole. In this light, our methods could offer valuable insights for forward-looking policy planning and interventions aimed at alleviating multidimensional poverty. This predictive power could not only enrich our understanding of poverty, but it could also provide a practical tool for policymakers to preemptively mitigate the adverse impacts of poverty.

3. Methods

3.1. The Multidimensional Nature of Poverty

We adopt the Alkire-Foster method to define multidimensional poverty (Alkire and Foster, 2011). It recognizes the multifaceted nature of poverty and considers a range of deprivation types that individuals may experience concurrently, such as lack of access to education or employment, poor health conditions, and substandard living conditions. By analyzing these deprivation profiles, this method enables us to identify individuals who are multidimensionally poor, that is, those who are deprived in at least k poverty indicators). These insights are then leveraged to construct a multidimensional poverty index (MPI).

Mathematically, the MPI, denoted as $M_c(t)$ for a country c in time t is computed as the sum of the censored headcount ratio $H_{ci}(t)$ of an indicator i. The censored headcount ratio represents the proportion of the population that is both multidimensionally poor and also deprived in that specific indicator. Therefore,

$$M_c(t) = \sum_i \omega_i H_{ci}(t), \tag{1}$$

where ω_i signifies the relative weight of an indicator in contributing to overall poverty. The weights reflect the relative importance of each dimension in the context of overall poverty. This flexibility allows us to account for different societal or policy emphases on specific deprivation types.

The additive structure of the Alkire-Foster method allows us to break down the MPI and associate its temporal variations to specific poverty indicators. More crucially, it allows us to investigate the dynamic relations between different poverty indicators – to see how changes in one poverty indicator may influence changes in others, and how these interactions could, in turn, impact overall multidimensional poverty.

Namely, we can describe the change in the censored headcount ratio $\Delta H_{ci}(t)$ between two points in time conceptualized as a function $\Delta H_{ci}(t) \sim f(P_{ci}(t), S_{ci}(t))$ of direct policy interventions $P_{ci}(t)$ impacting indicator i directly, and spillover effects $S_{ci}(t)$ originating from factors initially targeting other indicators. The idea here is that this function is not deterministic but stochastic, and both $P_{ci}(t)$ and $S_{ci}(t)$ increase the likelihood of a decrease in the censored headcount ratio.

The direct effects of a factor, which are the immediate impacts on a poverty indicator, can be evaluated by collecting baseline and post-intervention data, then applying statistical methods to estimate the impact of the factor (Bourguignon and Da Silva, 2003; Bellu and Liberati, 2005; Alkire *et al.*, 2021). However, isolating and quantifying the spillover effects — the indirect impacts on a poverty indicator resulting from changes in other indicators — can be a complex process. The challenges stem from multiple sources, including the numerous influencing factors, the delay and variability of these effects, data limitations, intricate interactions between poverty indicators, and the differing impacts across various individuals and contexts (Duclos, Tiberti and Araar, 2018).

3.2. The Poverty Space

The direction and intensity of spillovers are determined by both the structure of poverty and the underlying dynamics that drive the effects of various interventions. Economic Complexity methods can help us introduce network science to quantify the structure of poverty and understand its relationship with the dynamics of multidimensional poverty.

Our methods leverage information about the spatial joint distribution of poverty within an economy to define a network representation of the structural relationships between poverty dimensions which we refer to as the Poverty Space. This network is specific for each country. In it, the nodes are indicators of different dimensions of poverty. The edges connecting the indicators describe the proximity between them through the conditional probability that a household h experiences deprivation in indicator i provided it is already experiencing deprivation in j (Hidalgo *et al.*, 2007; Neffke, Henning and Boschma, 2011; Kogler, Rigby and Tucker, 2013; Guevara *et al.*, 2016). That is,

$$\Phi_{ij}^{c}(t) = \begin{cases} \frac{\sum_h w_h(t) X_{ih}^{c}(t) X_{jh}^{c}(t)}{\sum_h w_h(t) X_{jh}^{c}(t)}, \; if\ i \neq j \\ 0\ , \text{ otherwise,} \end{cases} \tag{2}$$

where $X_{ih}^{c}(t)$ is a binary variable indicating the presence of deprivation in indicator i in household h at time t (i.e., $X_{ih}^{c}(t) = 1$ indicates deprivation), and $w_h(t)$ is the population weight of the household.

This network of conditional relationships effectively translates the interconnections between dimensions of poverty into a mathematically tractable framework. Interestingly, the pairwise proximity index used here for quantifying the structural relationships has already been used in the multidimensional poverty literature to understand the associations across poverty indicators (Alkire and Ballon, 2012; Suppa, Alkire and Nogales, 2022; Ballon, 2023).

We recall that the structural relationships we are modeling are not causal links, but rather they describe the spatial co-occurrence of different poverty indicators among the population (Ospina-Forero, Castañeda and Guerrero, 2022). The rationale behind this approach is that the spatial co-occurrence of different indicators of poverty can illuminate the intertwined forces driving the relationships between indicators, independent of their root causes. For instance, a household could be deprived in both education and housing due to a multitude of factors, ranging from economic constraints to health issues and geographic location. The entries of the Poverty Space reveal the likelihood of encountering a household that is deprived in education, given that it is already deprived in housing. This is regardless of the specific drivers behind this relationship.

These relationships could drive the spillover effects between indicators. Consider a hypothetical country where there is a high probability of households suffering from educational deprivation, given they are already deprived in housing. In such a case, targeted interventions in housing may indirectly affect education. By investing in affordable housing near quality schools, an improvement in school attendance and performance could follow. Conversely, if the deprivation is primarily in education and not in housing, resources could potentially be more efficiently directed towards enhancing educational quality.

We must also note that the Poverty Space is not defined as a static network. It could evolve over time and differs across countries due to numerous dynamic factors such as economic growth, policy changes, technological advancements, demographic and social changes, environmental factors, health conditions, globalization effects, and even political instability or conflicts.

3.3. Poverty Centrality

We adopt the eigenvector in-centrality approach to reduce the dimensionality of the Poverty Space and quantify the significance of each indicator within this network. When an indicator has a high in-centrality value, it signifies that this indicator is a target of other indicators that themselves have high in-centrality. That is to say, an indicator with high eigenvector in-centrality is not just connected to many other indicators, but specifically to those that are observed to have higher probabilities for being deprived given they are deprived in another indicator.

We call this centrality measure as Poverty centrality $\tilde{S}_{ci}$ of indicator i in country c, and formally define it as

$$\tilde{S}_{ci} = \frac{1}{\lambda_1^c} \sum_j \Phi_{ij}^c \, \tilde{S}_{cj}, \tag{3}$$

where λ_1^c is the largest eigenvalue of $\mathbf{\Phi}_c$.

The solution to this equation is the right eigenvector of $\mathbf{\Phi}_c$ associated with its largest eigenvalue (normalized to sum up to 1).

The advantage of adopting this measure is twofold. Firstly, it provides a holistic, high-level perspective of the interplay among poverty dimensions, highlighting which indicators are more central in the network of poverty. Secondly, it facilitates the identification of indicators that might be particularly responsive to changes in other dimensions, due to their interconnectedness. These indicators, represented by higher Poverty Centrality scores, could be the ones that are most often at the receiving end of the effects of changes in other dimensions. Understanding this can help in anticipating and managing the indirect effects of interventions targeting other poverty dimensions, thereby offering valuable insights for designing more effective poverty reduction strategies.

3.4. Dynamics

We then build on the Poverty Space and Poverty Centrality to reveal a dynamic picture of multidimensional poverty through an exploration of spillover effects.

To understand this relationship, assume that we isolate a single change in j, $P_{cj}(0) = \delta$. For simplicity, we will assume that the change $P_{cj}(0)$ affects i immediately with a rate r_{ij}^c. This leads to a likelihood for the change in the headcount ratio of i:

$$\Delta H_{ci}(1) \sim S_{ci}(0) = r_{ij}^c \Phi_{ij}^c \delta. \tag{4}$$

The intuition behind this approach is that the Poverty Space Φ_{ij}^c determines the probability that an intervention in j is also likely to reach individuals who are poor in i, and thus indirectly affect indicator i as well with a rate r_{ij}^c.

The spillover effects continue to propagate over time.[5] Under this approach, we can represent these dynamic changes in a linear form as

$$\Delta H_{ci}(t+1) \sim \mathrm{S}_{ci}(t+1) = \sum_j r_{ij}^c \Phi_{ij}^c \mathrm{S}_{ci}(t) + O_{ci}(t). \tag{5}$$

This equation represents the changes in the headcount ratio for indicator i at time $t+1$ as a function of the spillovers from all other indicators at time t, with the strength of each spillover effect characterized by the interaction of the spillover rate (r_{ij}^c) and the conditional probability (Φ_{ij}^c). The

[5] In general, Φ_{ij}^c and r_{ij}^c are also time dependent.

additive first term on the right-hand side of the equation captures the individual spillover effects, yet it does not account for potential overlaps, interactions and complexities that might arise from simultaneous changes in multiple indicators. The higher order term, $O_{ci}(t)$, provides an additional control for these complexities.

However, to maintain clarity and focus on the primary spillover mechanism through the Poverty Space, we will simplify the model and concentrate primarily on the immediate and linear effects captured in the first term of the equation. Unfortunately, due to the constraints of our data, we cannot effectively estimate the spillover rates (r_{ij}^{c}) between specific pairs of indicators. This estimation would require temporally fine-grained data regarding the changes, which is not readily available in our dataset. Consequently, we will assume a uniform spillover rate (r^{c}) across all indicators. This simplification results in the following reformulated equation:

$$\mathrm{S}_{ci}(t+1) \sim r^{c} \sum_{j} \Phi_{ij}^{c} \mathrm{S}_{cj}(t). \tag{6}$$

This is a simple linear system of difference equations whose solution can be written in terms of the eigenvalues and eigenvectors of $\boldsymbol{\Phi}_{\mathrm{c}}$. That is

$$\Delta H_{ci}(t) \sim \mathrm{S}_{ci}(t) = k_1 \tilde{S}_{ci} (r^{c} \lambda_1^{c})^{t} + L_i(t), \tag{7}$$

where $L_i(t)$ is a linear combination of the other eigenvectors and eigenvalues (since λ_1^{c} is the largest eigenvalue, the overall effect of this term diminishes quickly in comparison to the effect of $k_1 \tilde{S}_{ci} (r^{c} \lambda_1^{c})^{t}$ and $k_1 < 0$ is a constant determined by the initial condition (initial spillover).

From the above equation we can clearly notice the relationship between Poverty Centrality and the overall change in the headcount ratio – indicators with higher centrality are more affected by spillover effects.

4. Data

To empirically apply these methods, we utilize data and definitions from the Global Multidimensional Poverty Index (MPI) developed by the Oxford Poverty and Human Development Initiative (OPHI) with the United Nations Development Programme (UNDP). The Global MPI is a robust measure that evaluates multidimensional poverty, using 10 different poverty indicators across three dimensions (health, education, and living standards). The 10 indicators include nutrition, child mortality, years of schooling, school attendance, cooking fuel, sanitation, drinking water, electricity, housing, and assets. A household is considered deprived in an indicator if it falls below a defined threshold (see Table A1.1 in Appendix 1 for the deprivation criteria used for each indicator). The underlying survey data for the indicators draws primarily from the Demographic Health Survey (DHS) program and the Multiple Indicator Cluster Surveys (MICS). The Global MPI was chosen for its comprehensive coverage and consistency in measuring poverty indicators.

However, this paper makes an important deviation from the standard Global MPI measure. While the OPHI/UNDP MPI assigns different weights to each of the ten indicators,[6] this paper weighs all of the indicators equally. The reason for this departure lies in the nature of our research question. By assigning equal weight to each indicator, we ensure that no single dimension is prioritized over another, allowing us to investigate the complex relationships in an agnostic manner. It is important to note that this weighting scheme may not necessarily reflect the relative importance of different dimensions of poverty in real-world scenarios, but it is a methodological choice that allows us to delve deeper into the structural relationships among these dimensions. Throughout the analysis, we assume that a household is multidimensionally poor if it is deprived in at least one of the 10 indicators used by the MPI. This means that any household that is deprived is automatically considered multidimensionally poor. To test the robustness of the results, we also replicate the analysis under different thresholds for multidimensional poverty. In Appendix 2 we show the results using a threshold of 3 (a household is considered multidimensionally poor if it is deprived in 3 or more indicators). We find that the results are consistent across thresholds. Note that for case described in the main body of the text (a threshold of 1), the censored headcount ratio (the proportion of the population that is both multidimensionally poor and also deprived in that specific indicator) is the same as the headcount ratio for that indicator.

[6] The Global MPI's three dimensions (health, education and living standards) are weighted to contribute equally to the index. Thus, the underlying ten indicators are each weighted accordingly to ensure 1/3 contribution at the dimension level. This means that each of the two health indicators has a weight of 1/6, each of the two education indicators has a weight of 1/6, and each of the six living standards indicators has a weight of 1/18. Note that the selection of dimensions and indicators for the Global MPI was prepared following a process of consultation and comparison against the available data. For individual country MPIs, the selection of dimensions and weighting structure may reflect context specific values.

While the Global MPI has data for over 100 developing countries, not all countries have data for more than one year. As our analysis seeks to also investigate dynamics over time, we required at least two data points for each country—with the aim of an extended time lag in between years (as poverty dynamics can be slow to change). For this reason, we restrict the dataset to those economies that have surveys available for more than one year *and* have a minimum gap of three years between the first and last survey. This strategy helps us to minimize noise in the changes in multidimensional poverty resulting from short-term measurements. As a result of these selection criteria, our dataset includes information for 67 countries for the period between 2003 and 2020 (Table A1.2 in Appendix 1 lists the covered countries and their survey years).

5. Results

5.1. Mapping the interconnected structure of poverty in 67 countries

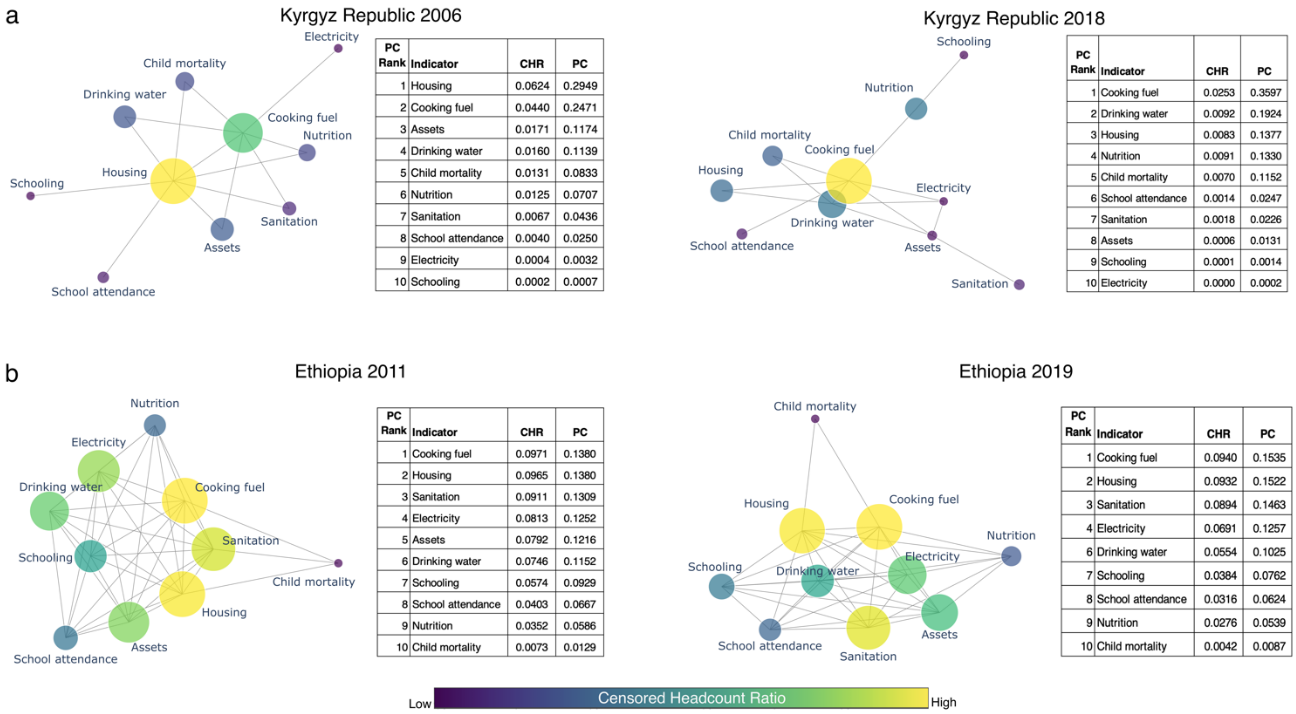
We begin by showing how the Poverty Space and Poverty Centrality can help us understand the structural aspects of poverty within an economy. For illustration purposes, we focus on the countries of the Kyrgyz Republic and Ethiopia which present contrasting cases in terms of the structure and stability of their Poverty Spaces.

Figure 1 displays network visualizations of the Poverty Spaces for the Kyrgyz Republic and Ethiopia, comparing the initial and final years of the survey. In these graphics, nodes signify poverty indicators, and the edges between them indicate important connections (for the visualization, for each network we use a threshold value calculated as the minimum edge weight for which every poverty indicator has at least one connection). The node size corresponds to its poverty centrality (the larger the node, the more central the indicator), while its color matches the censored headcount ratio of the indicator (ranging from a low share of people deprived in the indicator in blue to a high share deprived in yellow).

Focusing on the Kyrgyz Republic (Figure 1 a), we see that Housing was the most central indicator in 2006 (located in the core and denoted by the largest node), while Schooling was the least central (located in the periphery and denoted by the smallest node). This suggests that a household in 2006, if deprived in any other indicator, was most likely to also lack adequate Housing. Conversely, if a household was deprived in any indicator, it was the least probable to also be deprived in Schooling. Various factors such as geographic location, access to quality services, systemic inequality, and socio-economic policies could contribute to this specific poverty structure. The Poverty Space compiles these factors into a network visualization, revealing the underlying relationships between poverty indicators.

Moreover, the Poverty Space allows us to track the evolution of poverty structures over time. By 2019, Cooking fuel moved up the ranks to become the most central indicator in the Kyrgyz Republic, while Housing fell to number three. During this time, the MPI also fell drastically (from 0.176 to 0.063, using our definition for poverty). This decline was driven mostly by reductions in the share of people deprived in Housing (from 6% to less than 1%), whereas reductions in the share of people deprived in indicators like Cooking Fuel were lower (from around 4% to 3%). This suggests that the dynamic relationships among poverty indicators adapt in response to socio-economic changes and potential policy interventions.

Ethiopia (Figure 1 b) provides a contrasting case. Here, the Poverty Space structure remained largely consistent over time. In both 2011 and 2019, Cooking Fuel was the most central indicator (located in the core), while Child Mortality was the least central (located in the periphery).



Kyrgyz Republic 2006

PC Rank	Indicator	CHR	PC
1	Housing	0.0624	0.2949
2	Cooking fuel	0.0440	0.2471
3	Assets	0.0171	0.1174
4	Drinking water	0.0160	0.1139
5	Child mortality	0.0131	0.0833
6	Nutrition	0.0125	0.0707
7	Sanitation	0.0067	0.0436
8	School attendance	0.0040	0.0250
9	Electricity	0.0004	0.0032
10	Schooling	0.0002	0.0007

Kyrgyz Republic 2018

PC Rank	Indicator	CHR	PC
1	Cooking fuel	0.0253	0.3597
2	Drinking water	0.0092	0.1924
3	Housing	0.0083	0.1377
4	Nutrition	0.0091	0.1330
5	Child mortality	0.0070	0.1152
6	School attendance	0.0014	0.0247
7	Sanitation	0.0018	0.0226
8	Assets	0.0006	0.0131
9	Schooling	0.0001	0.0014
10	Electricity	0.0000	0.0002

Ethiopia 2011

PC Rank	Indicator	CHR	PC
1	Cooking fuel	0.0971	0.1380
2	Housing	0.0965	0.1380
3	Sanitation	0.0911	0.1309
4	Electricity	0.0813	0.1252
5	Assets	0.0792	0.1216
6	Drinking water	0.0746	0.1152
7	Schooling	0.0574	0.0929
8	School attendance	0.0403	0.0667
9	Nutrition	0.0352	0.0586
10	Child mortality	0.0073	0.0129

Ethiopia 2019

PC Rank	Indicator	CHR	PC
1	Cooking fuel	0.0940	0.1535
2	Housing	0.0932	0.1522
3	Sanitation	0.0894	0.1463
4	Electricity	0.0691	0.1257
6	Drinking water	0.0554	0.1025
7	Schooling	0.0384	0.0762
8	School attendance	0.0316	0.0624
9	Nutrition	0.0276	0.0539
10	Child mortality	0.0042	0.0087

Figure 1. The Poverty Spaces of the Kyrgyz Republic and Ethiopia. a The Poverty Space of the Kyrgyz Republic in 2006 and 2018. **b** The Poverty Space of Ethiopia in 2011 and 2019. **a-b** Nodes are poverty indicators, whereas the edges between two poverty indicators highlight that these indicators have an important connection. For each network we use a threshold value calculated as the minimum edge weight for which every poverty indicator has at least one connection. Moreover, in these networks, the size of the nodes is proportional to its poverty centrality (PC), whereas the color of a node proportional to the censored headcount ratio of the indicator (CHR).

We investigate the structural characteristics of the Poverty Space in multiple ways.

First, we investigate the relationship between the Poverty Space and the censored headcount ratio. Interestingly, in both Ethiopia and the Kyrgyz Republic and for both time periods, we find that more central indicators are also those that have higher censored headcount ratios. Indeed, when we pool data from every country and every period, we find a correlation between poverty centrality and the headcount ratio (Figure 2 a). Though, this correlation is only moderate, suggesting that the Poverty Space and the headcount ratio do not offer the same information about the structure of multidimensional poverty.

Second, in Figure 2 b, we determined the median poverty centrality score for each indicator across all countries, using only data from the final survey year. This measurement provides a snapshot of an indicator's "typical" importance across countries, offering a benchmark to assess the uniqueness of a country's poverty structure. On average, Cooking Fuel emerges as the most central indicator (located in the core), followed by Sanitation and Housing, with Child Mortality being the least central (located in the periphery). This is consistent with other recent studies suggesting that around 60% of the global poor experience simultaneous deprivation in sanitation, housing and cooking fuel (Suppa, Alkire and Nogales, 2022).

A similar pattern is also observed when we compare the structure of poverty across different country income groups (Figure A3.1 in Appendix 3). Interestingly, the structure shows higher variation when we compare as regional groups (Figure A3.2 in Appendix 3), with the Middle East and North Africa region standing out as having the most different structure compared to other regions. Overall, this suggests some uniformity in the structure of Poverty Spaces across different nations. Going back to our country illustrations, we see that Ethiopia's poverty structure aligns more closely with global trends, while the Kyrgyz Republic stands out as an outlier.

From a development perspective, the centrality of Cooking Fuel indicates its susceptibility to being influenced by other poverty indicators, meaning that improvements in related areas could potentially also have an important impact on access to clean cooking fuel. In contrast, the peripheral position of Child Mortality, characterized by low spillover rates, suggests it requires more direct and targeted policy interventions. This highlights the need for integrated approaches that address the systemic factors influencing indicators like Cooking Fuel, while also implementing direct policies to effectively reduce Child Mortality.

Third, we also evaluated the sensitivity of the Poverty Space in each country to missing poverty indicators. This involved removing one poverty indicator at a time, recalculating the structural dependence matrix, and comparing the Poverty Centrality of the rest of the indicators in the recalculated matrix to their original values. Figure 2 c displays boxplots representing the distribution of the correlation between the poverty centrality measures when one indicator is removed. Our analysis reveals that this correlation is almost always above 0.9. This lack of significant differences suggests the robustness of our results.

Finally, we investigated the stability of the Poverty Space across time. Figure 2 d shows a bar chart giving the correlations between the centrality of an indicator in the initial and final survey year for each country. We find that, in general, the correlation is almost always above 0.8 (with few outliers), indicating that the structure of poverty within countries remains relatively stable over time. This high level of stability suggests that the key relationships among poverty dimensions are consistent across time.

This high level of stability suggests that the key relationships among poverty dimensions are consistent across time and space. By bringing together the poverty centrality scores across all different indicators for each country, we can gain a comprehensive understanding of how these indicators interact with each other. This holistic view helps to identify which indicators are most central and, as we will see in the following section, potentially more likely to be indirectly affected by policies.

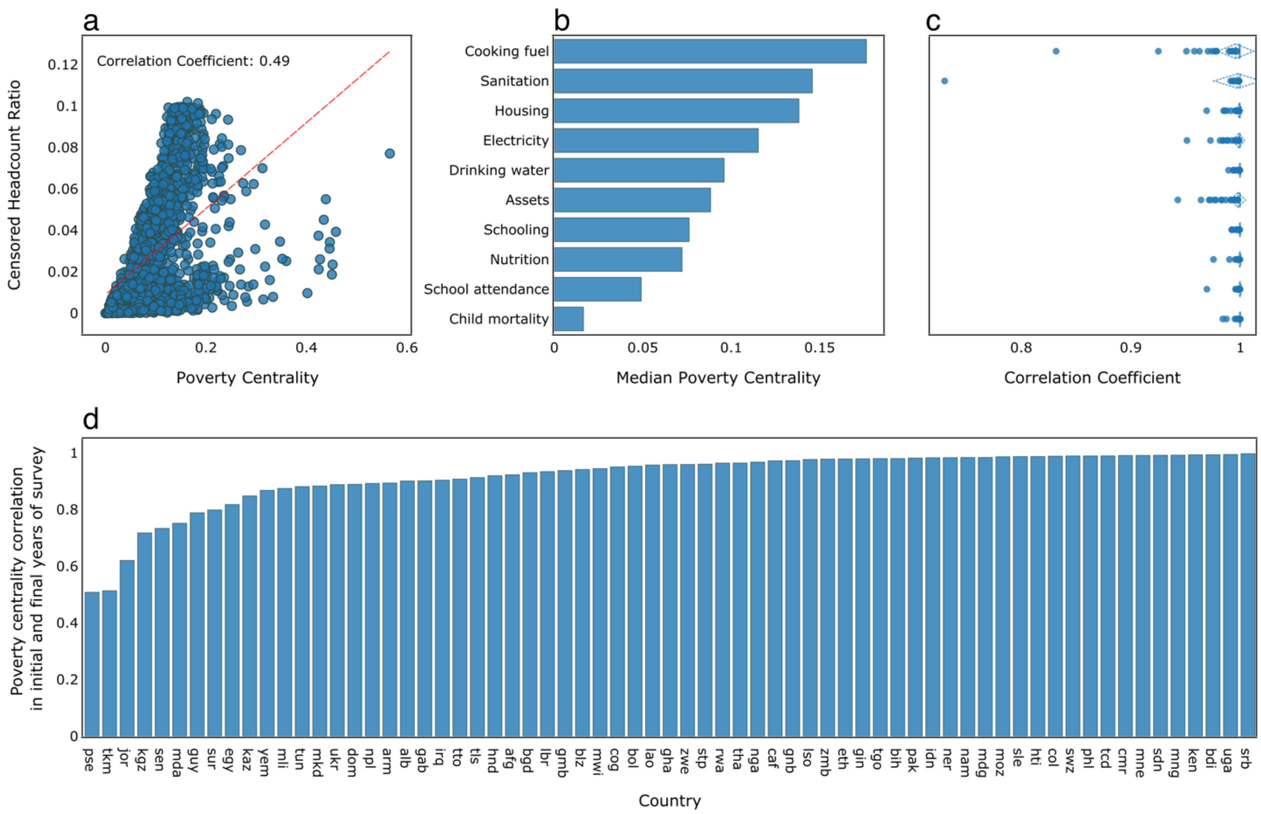


Figure 2. General patterns of the Poverty Space among countries. a Scatter plot for the relationship between poverty centrality for all indicators and the censored headcount ratio with pooled data across all countries and years. **b** Median centrality of each indicator across countries by using data only for the final survey year. **c** Boxplots for the correlation in poverty centrality when the respective indicator is excluded from the estimation of the Poverty Space using data only for the final survey year. **d** Bar chart for each country giving the correlations between the centrality of an indicator in the initial and final survey year.

5.2. Exploring the dynamic association between the structure and the incidence of poverty over time

We then turn to unpacking the dynamic association of the structure and incidence of poverty, through the mediating role of spillover effects. To do this, we look at the empirical association between the Poverty Centrality measure and the changes in the censored headcount ratio of a poverty indicator by pooling data from all participating countries and constructing regression models in which the dependent variable is the change in the censored headcount ratio from the first to the last year of surveys for each poverty indicator and country. In these regressions our Poverty Centrality measure is used as an explanatory variable.[7]

Our regression models are represented as

$$\frac{\Delta H_{ci}(t)}{\Delta t} = b_1 \tilde{S}_{ci}(t) + b_2 x_{ci}(t) + \gamma_c + \delta_i + b_0 + u_{ci}(t). \tag{8}$$

In the presented regression models, we include additional control variables to account for country, and indicator-specific effects ($u_{ci}(t)$ is the error term). These variables are represented by γ_c, and δ_i respectively. γ_c controls for country-specific effects that are relevant between the initial and final year of survey, such as economic growth and even cultural, historical, or institutional factors. Moreover, δ_i is used to control for intrinsic characteristics of each dimension of poverty, such as the different pace of change of each indicator or its sensitivity to policy interventions.

In addition to the factors mentioned earlier, our models also incorporate two other explanatory variables represented by $x_{ci}(t)$. One of these is the headcount ratio of the specific indicator for each country $H_{ci}(t)$ in the first year of survey. This variable is essential as it provides a baseline measure of the poverty levels in a specific dimension. It is crucial to control for this initial level as the reduction in poverty may be significantly influenced by the starting point; indicators starting with higher levels of

[7] We define the relative changes as the changes in the headcount ratio divided by the time length between the first and last year of survey, i.e., $\Delta H_{ci}(t)/\Delta t$. We introduce this normalization because the tie length between the first and last year of survey is not equal among countries, and thus might impact our results.

poverty in a specific dimension may experience more significant changes due to concerted efforts in tackling that specific area.

The second additional explanatory variable is the sum of the headcount ratios of all other indicators in the initial survey year, excluding the indicator under consideration, $\sum_{j \neq i} H_{cj}(t)$. This variable captures the broader context of multidimensional poverty within which a specific indicator is embedded. This could be important because the potential spillover effects from other indicator of poverty can influence the trajectory of poverty reduction in the indicator of interest. High levels of deprivation in other indicators may exert upward pressure on a particular indicator, either through resource constraints or through direct effects of multidimensional poverty. Conversely, in situations where overall multidimensional poverty is relatively low, improvements in a specific indicator may be more readily achieved due to a lower intensity of spillover effects.

By including these variables in our model, we consider the primary factors affecting changes in poverty levels across different indicators, allowing us to isolate the unique contribution of the structure of poverty on multidimensional poverty dynamics.

Table 1 illustrates the results from our regression models.

In column (1) of Table 1, we present a baseline regression model that includes only the dummy variables, which accounts for approximately 29% of the observed changes in the censored headcount ratio (Adjusted $R^2 = 0.29$). When we add our poverty centrality index (column (2)), we get a significant improvement in the model's explanatory power (Adjusted $R^2 = 0.37$). More importantly, we find that more central indicators usually have larger decreases in the headcount ratio, as suggested by our analysis in the previous section.

In column (3), we include the initial censored headcount ratio of the indicator $H_{ci}(t)$ as an additional variable, while column (4) adds the sum of the headcount ratios of all other indicators, excluding the one under consideration. Lastly, in column (5), we include both control variables in our regression model. Our results demonstrate that the negative and significant relationship between poverty centrality and long-run changes in headcount ratios persists even after adjusting for these controls. Additionally, we find that indicators with higher initial censored headcount ratios display larger decreases over time.

The sum of the headcount ratios of also has a negative coefficient in the final model, though it is not significant.

Table 1. Change in censored headcount ratio models results.

	Dependent variable:				
	Change in censored headcount ratio per year $(\frac{\Delta H_{ci}(t)}{\Delta t})$				
	(1)	(2)	(3)	(4)	(5)
Initial poverty centrality ($\tilde{S}_{ci}(t)$)		-0.006^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
		(0.001)	(0.001)	(0.001)	(0.001)
Initial censored headcount ratio ($H_{ci}(t)$)			-0.008^{**}		-0.009^{***}
			(0.004)		(0.003)
Initial headcount ratios of all other indicators ($\sum_{j \neq i} H_{cj}(t)$)				0.008^{**}	-0.001
				(0.004)	(0.001)
Constant	-0.002^{***}	-0.002^{**}	-0.001^{*}	-0.006^{**}	0.001^{**}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)
Observations	652	652	652	652	652
R^2	0.370	0.441	0.447	0.447	0.447
Adjusted R^2	0.288	0.367	0.373	0.373	0.373
Country dummy (α_c)	Yes	Yes	Yes	Yes	Yes
Indicator dummy (β_i)	Yes	Yes	Yes	Yes	Yes

Note: Robust Standard errors in parentheses.*p<0.1, **p<0.05, ***p<0.01.

To ascertain the robustness of our findings, we use two different approaches.

First, we utilize data for 15 countries that have an additional survey conducted between the initial and final years of the survey period. For these nations, we estimate the Poverty Space (and the corresponding Poverty Centrality) for all three survey years and compute the change in headcount ratio between the first and second, as well as the second and third survey years. This enables us to construct a new unbalanced panel sample which is then used to re-estimate our model. To maintain the restrictiveness of the model we also include year dummies in this analysis. The results, presented in Table 2, affirm that Poverty Centrality remains a significant and negative predictor of changes in headcount ratios over time even within this more homogeneous sample.

Table 2. Change in censored headcount ratio models results with restricted and unbalanced panel data.

	Dependent variable:				
	Change in censored headcount ratio per year ($\frac{\Delta H_{ci}(t)}{\Delta t}$)				
	(1)	(2)	(3)	(4)	(5)
Initial poverty centrality ($\tilde{S}_{ci}(t)$)		-0.010***	-0.009***	-0.009***	-0.009***
		(0.002)	(0.003)	(0.003)	(0.003)
Initial censored headcount ratio ($H_{ci}(t)$)			-0.003		-0.001
			(0.003)		(0.016)
Initial headcount ratios of all other indicators ($\sum_{j\neq i} H_{cj}(t)$)				0.003	0.002
				(0.005)	(0.014)
Constant	-0.002***	-0.001*	0.001*	-0.002	0.002
	(0.000)	(0.001)	(0.000)	(0.003)	(0.008)
Observations	296	296	296	296	296
R^2	0.198	0.318	0.318	0.318	0.318
Adjusted R^2	0.097	0.229	0.226	0.227	0.224
Country dummy (α_c)	Yes	Yes	Yes	Yes	Yes
Indicator dummy (β_i)	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes

Note: Robust Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Second, to address potential endogeneity concerns, we implement an instrumental variable (IV) approach. Endogeneity might arise because of unobserved factors influencing both Poverty Centrality and the changes in the censored headcount ratio, leading to biased coefficient estimates.

The IV approach helps us tackle this issue by using an additional variable as an instrument. This variable should be related with Poverty Centrality, but uncorrelated with the error term of our model. Here, for each indicator in a country we define the instrumental variable as the respective Poverty Centrality measure of the same indicator in the country with the most similar Poverty Space in the initial time period (estimated through the coefficient of correlation between the edges of the Poverty Space). The logic behind this instrument is that countries with similar Poverty Spaces should also exhibit similar Poverty Centrality, but the exact circumstances (such as policy environment, demographic dynamics, etc.) leading to changes in the censored headcount ratio will not necessarily be the same, providing us with a source of exogenous variation.

Our IV regression results, displayed in Table 3, consistently indicate that Poverty Centrality is a significant and negative predictor of the long-run changes in the headcount ratio. Moreover, the F-statistics for the significance of the instrument is always above 400, suggesting the validity of our instrument (see Appendix 3 for first stage results).

Thus, through both of our robustness checks, our findings remain consistent, reinforcing the importance of considering the Poverty Space in analyses of multidimensional poverty dynamics.

Table 3. Change in headcount ratio models results using IV approach.

	Dependent variable:				
	Change in censored headcount ratio per year ($\frac{\Delta H_{ci}(t)}{\Delta t}$)				
	(1)	(2)	(3)	(4)	(5)
Initial poverty centrality ($\tilde{S}_{ci}(t)$)		-0.006***	-0.005***	-0.005**	-0.005***
		(0.001)	(0.002)	(0.002)	(0.002)
Initial censored headcount ratio ($H_{ci}(t)$)			-0.008*		-0.009**
			(0.005)		(0.004)
Initial headcount ratios of all other indicators ($\sum_{j\neq i} H_{cj}(t)$)				0.008*	-0.001
				(0.005)	(0.001)
Constant	-0.002***	-0.002**	-0.001*	-0.006**	0.001*
	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)
Observations	637	637	637	637	637
R^2	0.371	0.407	0.429	0.429	0.429
Adjusted R^2	0.287	0.326	0.350	0.350	0.350
Instrument F-statistic		569.26	411.90	411.90	411.90
Country dummy (α_c)	Yes	Yes	Yes	Yes	Yes
Indicator dummy (β_i)	Yes	Yes	Yes	Yes	Yes

Notes: In this case the number of data points increases because for some countries the most similar country has data on fewer than 10 indicators. See Table A7 for first-stage results. Robust Standard errors in parentheses.*p<0.1, **p<0.05, ***p<0.01.

5.3. From diagnostics to policy

The Poverty Space offers important diagnostic information on the interconnected structure of multidimensional poverty. However, in order to link it to policy discussions, it needs to be complemented by additional tools. For example, if a node has a high level of centrality in the Poverty Space, this does not automatically mean that we could leave that indicator out of policy interventions and let spillovers resolve its dynamics —this could depend on various factors such as effectiveness of programs, ease of implementation, or budgetary constraints. Here, we illustrate the potential policy relevance of the Poverty Space by integrating it into the Policy Priority Inference (PPI) framework (Guerrero and Castañeda-Ramos, 2024). The goal of this application is to showcase how combining our descriptive network-based methods with structural frameworks for sustainable development policy can provide a refined instrument for decision-making and help to understand how spillovers from policy actions could relate with multidimensional poverty dynamics.

PPI is a forward-looking, agent-based model that serves as a tool to infer optimal policy priority pathways (i.e., how much the government should allocate in different areas at a certain point in time, given their budget) to achieve the desired levels of specific development outcomes. By "forward-looking", we mean that it anticipates future trends and developments based on current and past data. "Agent-based" implies that it models the interactions of individual entities (or "agents") to simulate the collective behavior of a system. Within this framework, policy actions take the form of budgetary allocations specifically designed to improve development indicators. PPI makes it possible to simulate budgetary allocations and identify government programs that operate as accelerators of development, or to establish which indicators have a limited sensitivity to expenditure Its current application is oriented toward the Sustainable Development Goals (Guerrero and Castañeda, 2024).

The essence of PPI's functionality lies in its reliance on data that captures the network of conditional relationships between development indicators. This network enables modeling of the spillovers that could result from government actions. To this end, the Poverty Space—as a network that provides insights into spillovers in the context of interventions to address multidimensional poverty—serves as a crucial complementary input to the model.

Incorporating the Poverty Space into PPI: Formally, PPI assumes there are N policy issues, each with an indicator measuring its level of development. In our case, these are different poverty indicators measured by their censored headcount ratio. The model simulates the dynamics of these indicators over time up to a specified final time point using the following equation:

$$H_{ci}(t+1) = \begin{cases} H_{ci}(t) - \alpha_{ci}, \text{if } \varepsilon_{ci}(t) = 1, \\ H_{ci}(t) + \alpha'_{ci}, \text{ otherwise.} \end{cases} \quad (9),$$

where α_{ci} and α'_{ci} are parameters determining the extent to which the censored headcount ratio improves (α_{ci}, meaning that the CHR decreases) or deteriorates (α'_{ci}, meaning that the CHR increases) between two time points. The success outcome $\varepsilon_{ci}(t)$ is a Bernoulli random variable with a probability of success $e_{ci}(t)$. This success depends on the effective utilization of government-allocated resources in public policy. Specifically, at each time point, the government allocates an amount of resources (π_i) to each policy issue (i), constrained by a total budget: ($\sum_i \pi_i = B$). Then, a public servant responsible for the issue uses ($P_i \in [0, \pi_i]$) effectively in policy, with ($\pi_i - P_i$) representing the amount diverted for personal gain, known as inefficiency. The amount that is used by the public servant, and hence the degree of inefficiency, depends on two national-level parameters: (1) the quality of law (lower quality allows officials to contribute less to the policy issue and retain more resources), and (2) the quality of monitoring (higher quality monitoring increases the likelihood of punishment for misappropriation).

In addition to the public servant's contribution, the improvement of an indicator also depends on public policies of other officials through spillover effects. These interdependencies are modeled as a network represented by an adjacency matrix ($\boldsymbol{A}$), where ($A_{ij} > 0$) if there are spillovers from (j) to (i), and ($A_{ij} = 0$) otherwise. Consequently, the dynamics of an indicator result from (1) the government's budget, (2) the system's inefficiencies, and (3) the spillovers from contributions of public servants responsible for other issues.

Our goal is to showcase how spillovers affect the effectiveness of government policies while keeping government expenditure and systematic inefficiencies constant. The Poverty Space network allows us to integrate the dynamics of multidimensional poverty into this model. Specifically, we follow equation (6) and assume the conditional dependencies are given as:

$$A_{ij} = r^c \, \Phi_{ij}^c, \tag{10}$$

where the spillover rate r^c remains a free parameter in this model.

In this section, we return to the Ethiopia case as an example to demonstrate how PPI can be used to infer the potential effect of spillovers within a country's poverty dynamics.

Estimation Strategy: PPI offers two distinct methods for analyzing multidimensional poverty. First, the "retrospective" analysis seeks to understand past dynamics by leveraging historical data from an initial survey year, revealing how poverty indicators and policy priorities (budget allocations for an indicator) have evolved over a certain observation period to reach observed values in a final year. This analysis can infer an optimal spillover rate (the spillover rate that best fits the data) and other model parameters (e.g., α_{ci} and α'_{ci}). Understanding these parameters is essential as spillover rates can vary widely or modestly between dimensions and countries, influencing policy intervention outcomes. Second, the "prospective" analysis uses historical insights to understand how changes in the spillover rate or the Poverty Space could affect multidimensional poverty dynamics over a future period. This approach guides policymakers on which poverty indicators to prioritize and when, helping to inform effective intervention strategies for future improvements.

In the retrospective analysis, we use national data on poverty indicators from the first survey year (2011) and the last survey year (2019), government expenditure data (per capita in constant USD) from 2011 to 2019, data on the quality of law and monitoring from the World Bank's World Governance Indicators for 2011 (the quality of law is approximated with the rule of law variable, whereas the quality of monitoring with the control of corruption), and the estimated Poverty Space for 2011. We estimate the model parameters and find the optimal spillover rate by calibrating the model with spillover rates ranging from 0 to 1 (in increments of 0.05) and calculating the goodness of fit. The rate providing the best fit on average is our optimal spillover rate. See Appendix 4 for more details on the data cleaning and calibration procedures for our PPI analysis.

We then conduct a prospective analysis until 2030 using data from the final survey year (2019) and Poverty Space data for the same year. We assume that the rule of law and quality of monitoring remain at the 2019 level and that government expenditure remains at its average value from 2011 to 2019. In this analysis, we again vary the spillover rate from 0 to 1 to perturb the Poverty Space structure and assess how poverty interlinkages could impact multidimensional poverty dynamics.

Findings: Figure 3 details the impact of the Poverty Space on the inferred PPI simulations.

First, in Figure 3 a we visualize how varying the spillover rate impacts PPI's estimated MPI for Ethiopia in 2030 (black line). The blue horizontal dashed line represents Ethiopia's MPI in 2019 (0.567, the beginning of the prospective simulation), while the red vertical line marks the optimal spillover rate identified in the retrospective analysis. Our analysis finds this value to be 0.7, indicating that spillovers could heavily influence Ethiopia's multidimensional poverty dynamics. If the spillover rate remains at this level, we project Ethiopia's MPI to decrease by 0.103 units by 2030 (to 0.464). Conversely, if the spillover rate drops to 0, the MPI would fall by only 0.036 units (to 0.531). An increase in the spillover rate to 1 (implying that the spillover network matches the Poverty Space) would result in a 0.109 unit decline in MPI (to 0.458). Interestingly, our results indicate that Ethiopia's multidimensional poverty dynamics are more sensitive to reductions in the spillover rates below the optimal value than to further decreases in the spillover rate beyond this point. Specifically, the MPI increases more noticeably when the spillover rate is decreased below the optimal level compared to the decrease in the MPI observed when the spillover rate is further reduced. These findings suggest that the effectiveness of the expenditure programs towards reduction poverty could be strongly affected by spillovers between indicators, and that expenditure programs are in general more effective when the structure of poverty is included in the analysis.

Next, in Figure 3 b, we show the average spillovers (between 2021 and 2030) received by each poverty indicator during the prospective analysis for various values of r^c as a function of Poverty Centrality. We observe a nearly perfect correlation between these two variables for each choice of r^c. This indicates that Poverty Centrality effectively reflects the spillovers in PPI simulations. Importantly, it suggests that while Poverty Centrality can identify which indicators are most likely to receive spillovers, the actual volume of spillovers is dependent on the rate r^c. Thus, Poverty Centrality serves as a relative metric, providing insights into the potential distribution of spillovers among indicators, but the magnitude of these spillovers varies with the spillover rate.

Moving on to Figure 3 c, we illustrate the censored headcount ratio of each indicator as a function of the spillover rate. This analysis allows us to see how each poverty indicator's censored headcount ratio changes as the spillover rate varies. Indicators with the lowest and highest values for the censored headcount ratio show the least susceptibility to changes in the spillover rate, indicating that their censored headcount ratio remains relatively stable even as r^c varies. In contrast, indicators with intermediate levels of the censored headcount ratio appear the most susceptible, showing greater fluctuations with changes in r^c.

Figure 3 d provides a more detailed view by plotting a bar chart for the changes in the censored headcount ratio for each indicator under different spillover rates (the indicators are ordered according to their CHR value in 2019 from lowest to highest). Indeed, three indicators with intermediate levels of CHR in 2019 (Schooling, Drinking Water, and Assets) display the largest change in CHR due to changes in the spillover rate. For lower spillover rates (in this case 0 and 0.3), Assets appears as the indicator with the largest decrease in CHR, whereas for higher spillover rates (in our case 0.7 and 1.0), Schooling becomes the indicator with the largest decrease in CHR. This result could be due to shifts in policy priorities driven by spillover effects. When higher spillover rates are present, resources and attention may be redistributed towards amplifying indicators, thereby changing the dynamics of multidimensional poverty within the country. This underscores the importance of spillover effects in the development of policy interventions aimed at reducing multidimensional poverty. By identifying which indicators are most responsive to these shifts, policymakers can better target their efforts to maximize the impact of resource allocation and intervention strategies, ensuring that critical areas receive the necessary support to reduce poverty effectively.

Altogether, this analysis, based on Ethiopia's data, demonstrates the potential of integrating the Poverty Space with PPI for understanding the dynamics of multidimensional poverty and informing policy interventions. By identifying the optimal spillover rate and analyzing how changes in the Poverty Space could affect the dynamics the censored headcount ratio, this analysis could provide a nuanced understanding of how interconnected factors might influence poverty reduction. It is important to note that our approach, while demonstrated with Ethiopia, is adaptable and can be applied to other countries with relevant Poverty Space data to tailor effective policy strategies.

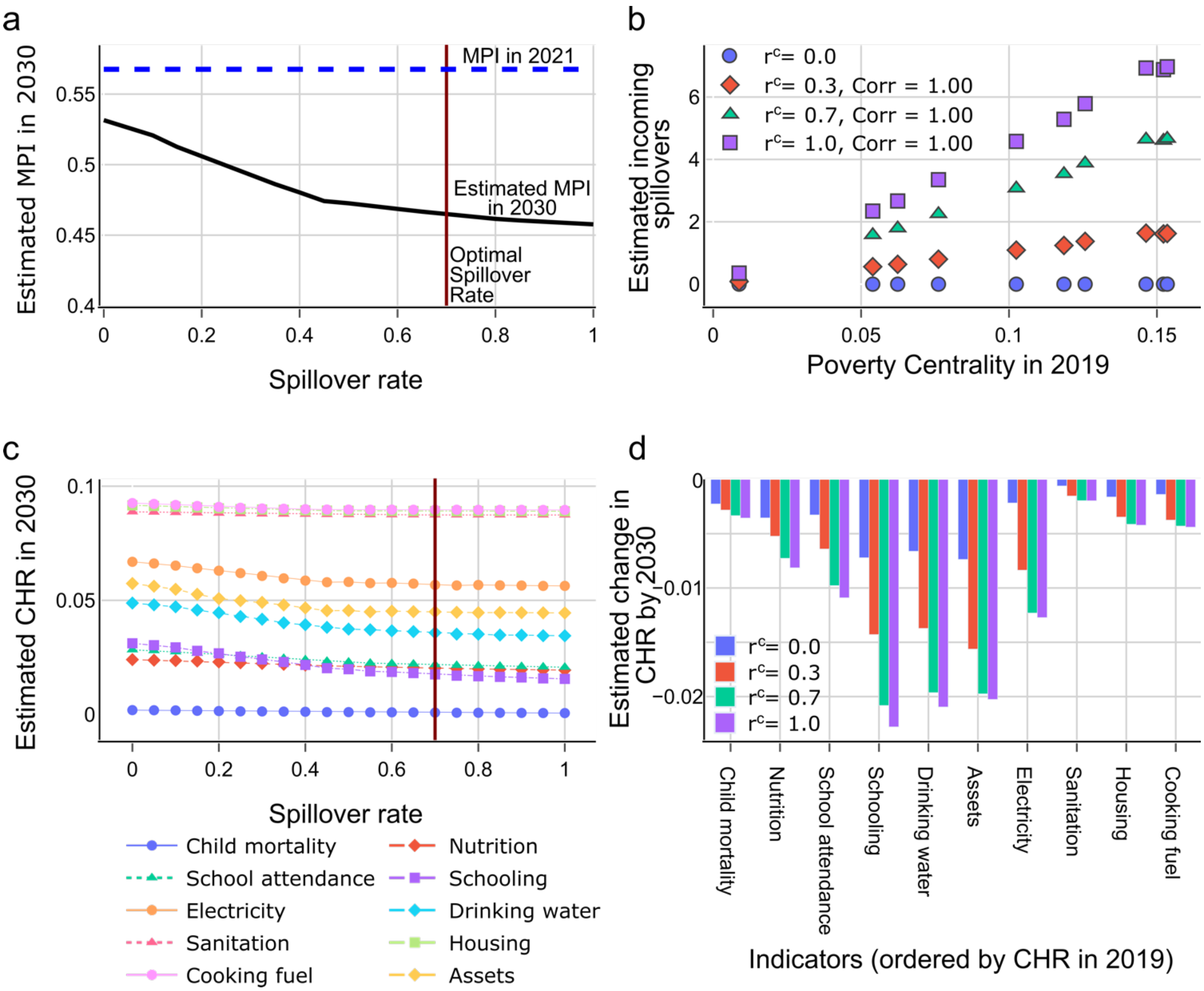


Figure 3. Policy Priority Inference for Ethiopia using the Poverty Space. a Estimated Multidimensional Poverty Index for Ethiopia in 2030 as a function of the spillover rate that perturbs the poverty Space. The red vertical line is the optimal spillover rate discovered in the retrospective analysis, whereas the blue dashed horizontal line is the MPI in 2019 **b** The estimated average incoming spillovers (across all time from 2019 to 2030) for each indicator as a function of Poverty Centrality for various spillover rates **c** Estimated censored headcount ratio for each indicator in 2030 as a function of the spillover rate **d** Bar chart for the estimated changes in the censored headcount ratio between 2030 and 2019 for each indicator and for various spillover rates. The indicators are ordered according to their CHR value in in 2019. **a-d** The results are averaged across 100 PPI simulations.

6. Development Acupuncture: Addressing Poverty Multidimensionally

The interdependencies between different dimensions of poverty can intensify the experience of poverty and create cycles of deprivation that are challenging to break. Understanding those interdependencies is critical for being able to move beyond policy approaches that target dimensions separately.

Accelerating poverty reduction efforts will require integrated policy approaches that consider the complex interconnected structure of multidimensional poverty—seeking to apply pressure to specific "nodes" that can help to maximize impacts across the system.

In this paper, we introduced network science methods (similar to the ones used in economic complexity) into the realm of multidimensional poverty to help better understand those interdependencies and map those nodes. We introduced two new measures to this effect. The Poverty Space offered a novel representation of the networked structure poverty in an economy. In doing so, it provided a holistic vantage point to dissect the interconnectedness of these dimensions, revealing patterns and structures that were previously obscured. Complementarily, the Poverty Centrality measure highlighted the relative importance of individual poverty indicators within this complex network.

But, how to turn this diagnostic into policy? The application of our findings through the Policy Priority Inference (PPI) framework offered a practical demonstration of the value of our methodology for guiding policy choices in the context of dynamic interaction effects. We found that the spillovers through the Poverty Space could impact the effectiveness of government policies and that this impact could be economically important. Taken together, these findings suggest that network science methods motivated from economic complexity approaches can offer a powerful new tool to inform policymaking for multidimensional poverty reduction by helping to identify relevant target nodes in the network.

Nevertheless, we must acknowledge that this study has several limitations. First, the inherently persistent nature of the Poverty Space, remarkably consistent across nations and time, may not capture the constant changes and nuances of poverty influenced by changing socio-economic factors. The spectrum of poverty dimensions that we highlighted here may have unintentionally missed certain pivotal variables, especially those inherently critical to distinct geographic and socio-cultural contexts (Santos, 2019). Furthermore, the potential inconsistencies and inherent biases in global data pools also constrain our understanding and representation of poverty. To this end, our dimensionality reduction methods, while a potent tool for data consolidation, are not immune to potential oversights and risk sidelining nuanced interactions that could have important policy implications. Second, the incorporation of the Poverty Space within the Policy Priority Inference framework is also not without its limitations. A critical observation here is that the Poverty Space, in its current iteration, does not fully emulate spillover networks in the strictest “causal” sense. Proper modeling of these networks demands longitudinal data, which is rarely available in developing economies and often inconsistent across regions. The Poverty Space navigates around this limitation by projecting a structure that can help to predict potential spillovers, but with the understanding that it might not precisely mirror the actual dynamics of these interplays in all settings.

While imperfect, this approach offers a new way to begin answering critical policy questions. This paper offered a first look at how these methods can enrich our understanding of multidimensional poverty, and points toward fresh avenues for deeper exploration. In particular, looking at dimensions that are relevant in specific contexts or regions (without the limitations of cross-country comparability) may allow more granularity in terms of variation over time and across space is a key area where future research could help to advance our understanding of the interconnected and dynamic structure of multidimensional poverty. If the world is going to get back on track in its efforts to eradicate poverty, efforts to accelerate progress will be necessary. Acupuncture-like approaches, based on the complex interactions among poverty dimensions, considering the underlying structural interdependencies between deprivations, appear promising as one innovative means for amplifying development impact.

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Appendix 1. List of poverty indicators and countries included in the analysis

Table A1.1. List and Definitions of Poverty Indicators.

Indicator	**Deprivation definition**
Nutrition	Any person under 70 years of age for whom there is nutritional information is undernourished.
Child mortality	A child under 18 has died in the household in the five-year period preceding the survey.
Years of schooling	No eligible household member has completed six years of schooling.
School attendance	Any school-aged child is not attending school up to the age at which he/she would complete class 8.
Cooking fuel	A household cooks using solid fuel, such as dung, agricultural crop, shrubs, wood, charcoal, or coal.
Sanitation	The household has unimproved or no sanitation facility or it is improved but shared with other households.
Drinking water	The household's source of drinking water is not safe or safe drinking water is a 30-minute or longer walk from home, roundtrip.
Electricity	The household has no electricity.
Housing	The household has inadequate housing materials in any of the three components: floor, roof, or walls.
Assets	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck.

Table A1.2. List of Countries Included in the Analysis and Available Surveys.

Country	Available surveys	Country	Available surveys	Country	Available surveys
Afghanistan	2011 (MICS), 2016 (DHS)	Haiti	2012 (DHS), 2017 (DHS)	Pakistan	2013 (DHS), 2018 (DHS)
Albania	2009 (DHS), 2018 (DHS)	Honduras	2006 (DHS), 2012 (DHS), 2019 (MICS)	Palestine	2010 (MICS), 2014 (MICS), 2020 (MICS)
Armenia	2010 (DHS), 2016 (DHS)	Indonesia	2012 (DHS), 2017 (DHS)	Philippines	2013 (DHS), 2017 (DHS)
Bangladesh	2014 (DHS), 2019 (MICS)	Iraq	2011 (MICS), 2018 (MICS)	Rwanda	2010 (DHS), 2015 (DHS), 2020 (DHS)
Belize	2011 (MICS), 2016 (MICS)	Jordan	2012 (DHS), 2018 (DHS)	Sao Tome and Principe	2009 (DHS), 2019 (MICS)
Bolivia	2003 (DHS), 2008 (DHS)	Kazakhstan	2011 (MICS), 2015 (MICS)	Senegal	2005 (DHS), 2017 (DHS), 2019 (DHS)
Bosnia and Herzegovina	2006 (MICS), 2012 (MICS)	Kenya	2009 (DHS), 2014 (DHS)	Serbia	2010 (MICS), 2014 (MICS), 2019 (MICS)
Burundi	2010 (DHS), 2017 (DHS)	Kyrgyz Republic	2006 (MICS), 2014 (MICS), 2018 (MICS)	Sierra Leone	2013 (DHS), 2019 (DHS)
Cameroon	2011 (DHS), 2018 (DHS)	Laos	2012 (MICS), 2017 (MICS)	Sudan	2010 (MICS), 2014 (MICS)
Central African Republic	2010 (MICS), 2019 (MICS)	Lesotho	2009 (DHS), 2014 (DHS)	Suriname	2006 (MICS), 2010 (MICS), 2018 (MICS)
Chad	2010 (MICS), 2015 (DHS)	Liberia	2007 (DHS), 2013 (DHS), 2020 (DHS)	Thailand	2012 (MICS), 2019 (MICS)
Colombia	2010 (DHS), 2016 (DHS)	Madagascar	2009 (DHS), 2018 (MICS)	Timor-Leste	2010 (DHS), 2016 (DHS)
Dominican Republic	2007 (DHS), 2019 (MICS)	Malawi	2010 (DHS), 2016 (DHS), 2020 (MICS)	Togo	2010 (MICS), 2014 (DHS), 2017 (MICS)
DR Congo	2005 (DHS), 2015 (MICS)	Mali	2006 (DHS), 2018 (DHS)	Trinidad and Tobago	2006 (MICS), 2011 (MICS)
Egypt	2008 (DHS), 2014 (DHS)	Moldova	2005 (DHS), 2012 (MICS)	Tunisia	2012 (MICS), 2018 (MICS)
Eswatini	2010 (MICS), 2014 (MICS)	Mongolia	2010 (MICS), 2013 (MICS)	Turkmenistan	2006 (MICS), 2019 (MICS)
Ethiopia	2011 (DHS), 2016 (DHS), 2019 (DHS)	Montenegro	2013 (MICS), 2018 (MICS)	Uganda	2011 (DHS), 2016 (DHS)
Gabon	2000 (DHS), 2012 (DHS)	Mozambique	2003 (DHS), 2011 (DHS)	Ukraine	2007 (DHS), 2012 (MICS)
Gambia	2013 (DHS), 2020 (DHS)	Namibia	2007 (DHS), 2013 (DHS)	Yemen	2006 (MICS), 2013 (DHS)
Ghana	2011 (MICS), 2018 (MICS)	Nepal	2011 (DHS), 2016 (DHS), 2019 (MICS)	Zambia	2007 (DHS), 2014 (DHS), 2018 (DHS)
Guinea	2012 (DHS), 2018 (DHS)	Niger	2006 (DHS), 2012 (DHS)	Zimbabwe	2011 (DHS), 2015 (DHS), 2019 (MICS)
Guinea Bissau	2014 (MICS), 2019 (MICS)	Nigeria	2013 (DHS), 2018 (DHS)		
Guyana	2009 (DHS), 2014 (MICS), 2020 (MICS)	North Macedonia	2011 (MICS), 2019 (MICS)		

Notes: DHS means that the survey was sourced from the Demographic and Health Surveys Program (https://dhsprogram.com/), whereas MICS means that the survey was sourced from the Multiple Indicator Cluster Surveys by UNICEF (https://mics.unicef.org/).

Appendix 2. Additional results with alternate threshold for multidimensional poverty (poor in at least 3 indicators)

Figure A2.1. Reproduces Figure 2 from the main manuscript, describing the general patterns of the Poverty Space among countries using an alternate threshold for defining multidimensional poverty. Instead of a threshold of 1, this figure reproduces the results using a threshold of 3 (a household is defined as multidimensionally poor if it is deprived in at least 3 indicators).

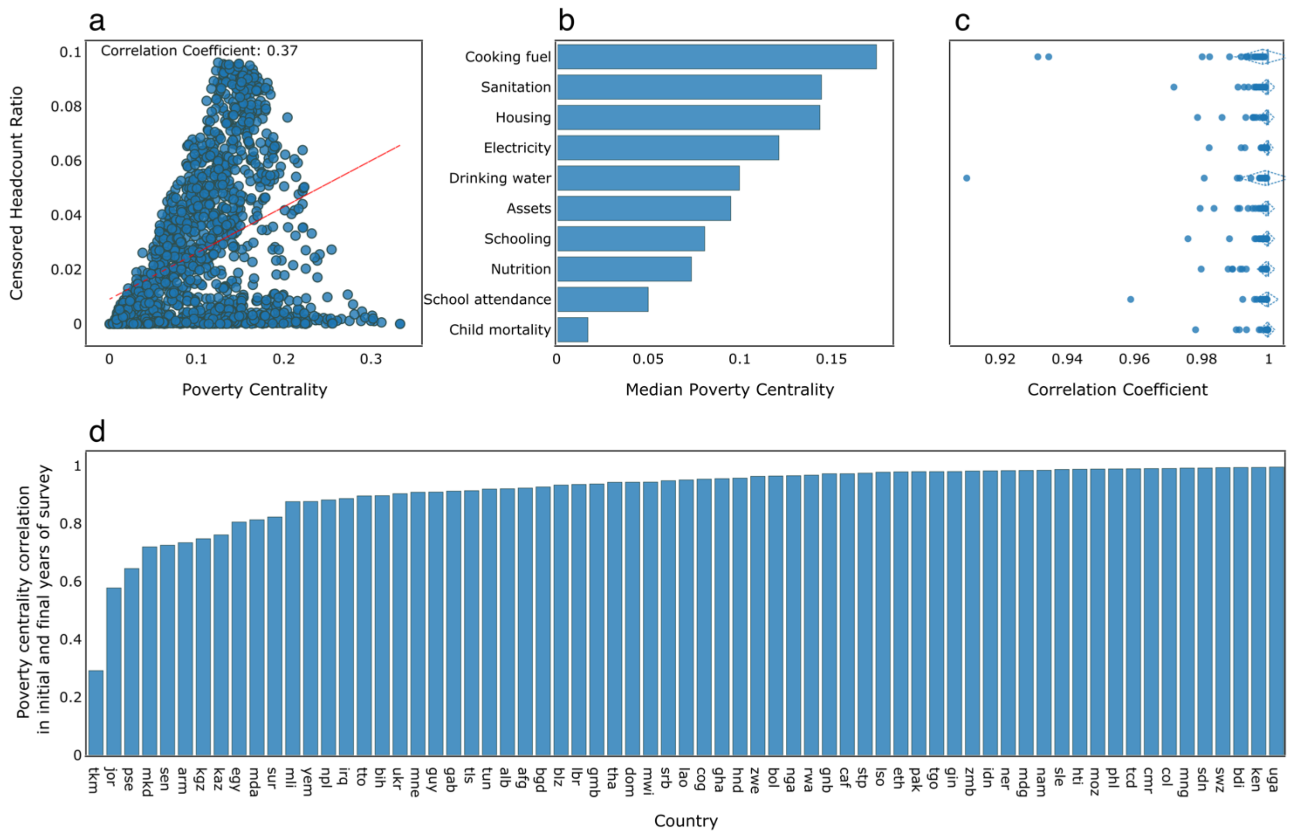

Figure A2.2 General patterns of the Poverty Space among countries using a threshold for being multidimensionally poor in at least 3 indicators. a Scatter plot for the relationship between poverty centrality for all indicators and the censored headcount ratio with pooled data across all countries and years. **b** Median centrality of each indicator across countries by using data only for the final survey year. **c** Boxplots for the correlation in poverty centrality when the respective indicator is excluded from the estimation of the Poverty Space using data only for the final survey year. **d** Bar chart for each country giving the correlations between the centrality of an indicator in the initial and final survey year.

Appendix 3. Statistics for median centrality of each indicator across countries by income group and by region

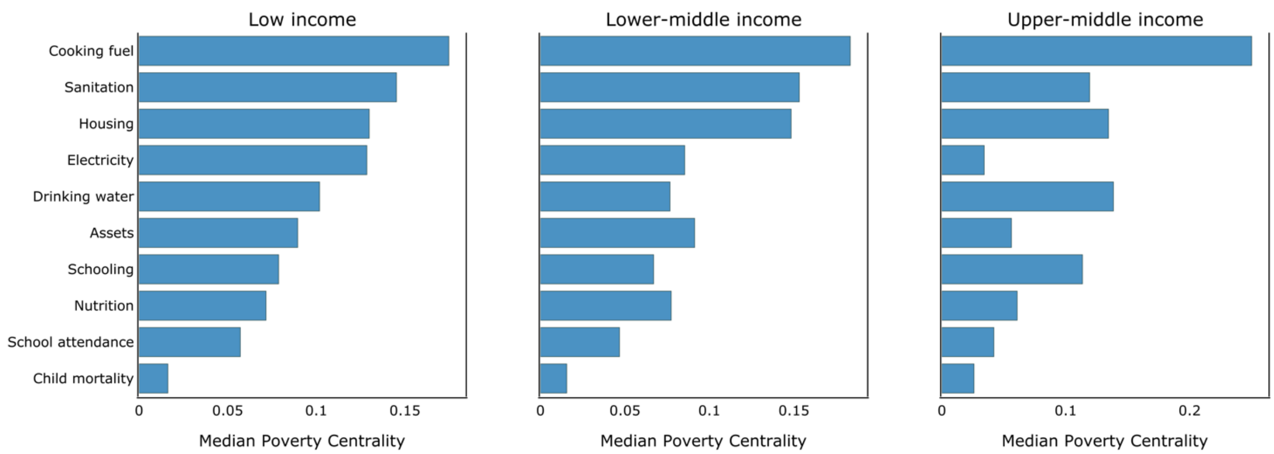

Figure A3.1 Median centrality of each indicator across country income groups by using data only for the final survey year.

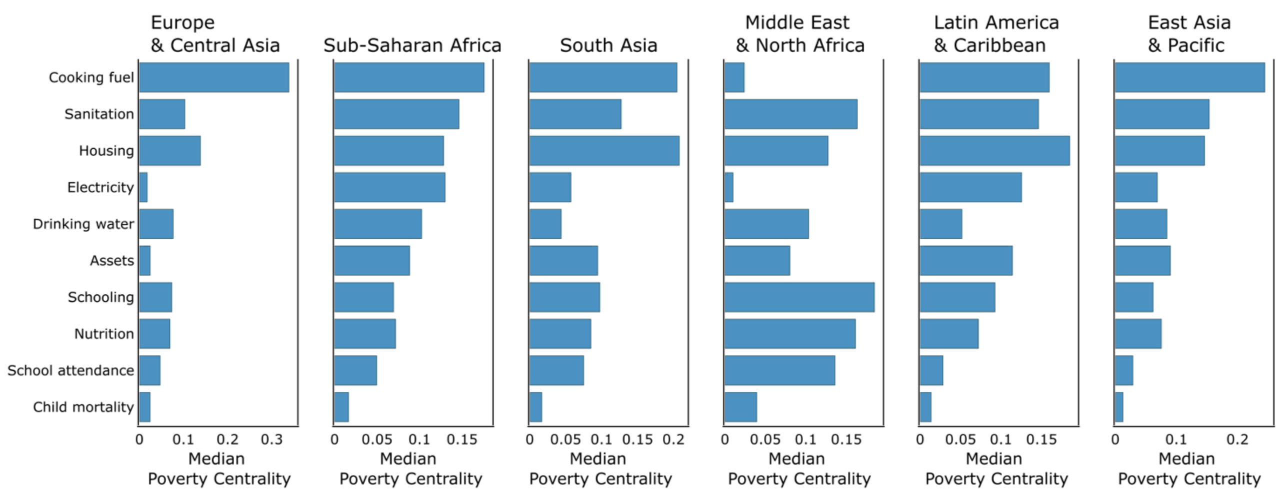

Figure A3.2 Median centrality of each indicator across region groups by using data only for the final survey year.

Appendix 4. Additional information on the Policy Priority Inference Model Setup

Besides the data on the network structure, PPI also requires data on 1) government expenditure over time (during the retrospective analysis), 2) data on the quality of law and monitoring, and 3) data on the initial estimates for the growth probabilities $e_{ci}(t)$ which in the initialization are assumed to be fixed values within the data (they do not change over the calibration period).

Government expenditure data: For the retrospective analysis, we approximate the government expenditure $B(t)$ using annual data from the World Bank's development indicators on general government final expenditure as a percentage of GDP. We transform this data to be in per capita constant 2021 USD (in PPP) simply by multiplying with World Bank's GDP per capita estimates. PPI also requires the government expenditure data to be de-trended we do this by estimating a linear trend regression model

$$B(t) = a_0 + a_1 t + u(t),$$

and removing the trend component from the model. That is, for each year we calculate an estimate $\hat{B}(t)$ for the government expenditure and use it as an input in PPI as $\hat{B}(t) = a_0 + u(t)$. Also, PPI typically runs its calibration process with time increments that are much smaller than a year (in order to converge PPI requires more than 50 simulation time steps). Here we assume that there are 6 simulation steps in a year (meaning that we calibrate PPI with a total of 54 steps). Due to this, the yearly data needs to be transformed such that the total budget of the country within the six steps that correspond to a one year matches the government expenditure. We do this by simply assuming that the government distributes its budget equally within each simulation step in a year ($\hat{B}(t)/6$).

In the prospective analysis we assume that the yearly value of the government budget is the same always and it is equal to the average of the estimated values for the government expenditure between 2011 and 2019.

Quality of law and monitoring: We approximate the quality of law and monitoring using data from World Bank's World Governance Indicators. The data on the quality of law comes from the rule of law variable and the quality of monitoring from the control of corruption variable. In the retrospective analysis we set their value to the ones observed in 2011, whereas in the prospective analysis we set their values to ones observed in 2019. Because, in general, both the rule of law and the control of corruption can have a negative value, in each year we transform them using a max-min technique (by using the ensemble of all countries with available data).

Growth probabilities data: For the retrospective analysis and parameter estimation we also need to provide PPI with an initial estimate for the growth probabilities. In our dataset, we have 3 data on the poverty indicators of Ethiopia for 3 survey periods (2011, 2016, and 2019). This is a relatively short time-series which might make it difficult to estimate the initial value for the growth probabilities. While we have this in mind, we also acknowledge that most of the countries in our dataset have always shown improvement in the indicator's value. Since the changes in the indicator values are relatively homogeneous, this allows us to take the easiest approach for calculating the growth probabilities. That is, we estimate the growth probabilities by calculating how many times an indicator improved from one period to another, and divide that amount by the number times that the indicator changed. To reduce potential noise, we set the values for each indicator that did not exhibit improvement to 0.1, and for the indicators that always showed improvement to 0.9.