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"Development acupuncture:" mapping the network structure of multidimensional poverty

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ABSTRACT
Despite progress in multidimensional poverty measurement, policy remains fragmented due to limited understanding of how poverty indicators interconnect and co-evolve. We address this by proposing the Poverty Space, a network describing interactions among poverty indicators, and the Poverty Centrality measure, highlighting an indicator's importance in this network. Using data from 67 countries, we find that the Poverty Space is consistent across countries and stable over time. Moreover, more central indicators display higher poverty reduction, likely due to spillovers. We use this to demonstrate how a forward-looking framework can guide interventions, allowing "development acupuncture" to target areas where policy maximizes impact.

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Introduction

Over the last couple of decades, development literature has advanced in understanding poverty as a multidimensional concept. Since Sen's capabilities approach (Sen 1979, 1999), which emphasizes "beings" and "doings" essential for a valued life, researchers have expanded methods to measure multidimensional poverty. The Alkire-Foster counting-based index (Alkire and Foster 2011) has been particularly influential, providing a standardized yet flexible approach for evaluating poverty across various dimensions. Currently, about 40 countries publish national multidimensional poverty indices, and international organizations offer global measures, all of which serve as critical tools for shaping coordinated policy responses.

Despite progress in multidimensional poverty measurement, integrating this perspective into poverty reduction strategies remains challenging. Policy discussions often remain fragmented, with sector-specific responses that overlook the interconnectedness of poverty dimensions. A primary challenge in designing integrated policies is that current measures lack insights into how dimensions are associated across space and time – making it difficult to assess how targeting one dimension could affect others. We can observe the overall outcome of an intervention, but not

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how different dimensions interact to result in that outcome. We know that the various dimensions of poverty do not evolve in isolation. For example, we know that education is linked to health, and 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*. Traditional poverty measures offer a useful snapshot of the joint distribution of deprivations, but they do not capture the underlying structure and dynamics governing these relationships. Indeed, Partha Dasgupta highlighted this gap, noting that “mutual causation,” where variables influence each other over time, complicates our interpretation of static data (Dasgupta 2007).

Quantifying the interconnected structure of multidimensional poverty remains challenging using traditional economic methods. Over the past decade, scholars have begun to use different methods to explore this issue. For example, Suppa, Alkire, and Nogales (2022) apply latent class analysis to examine joint deprivation profiles globally; Ceriani and Gigliarano (2016) employ Bayesian Networks to map poverty dependencies in Europe; Gallardo (2022) uses a similar method for Chile; Duclos, Tiberti, and Araar (2018) explore targeting schemes’ spillover effects on other poverty dimensions in Vietnam and South Africa; and Guerrero and Castañeda (2020) use an agent-based model to analyze structural links between social spending and poverty impacts in Mexico. Motivated by economic complexity methods, we contribute to this literature by leveraging network science to offer a new approach to understanding the interconnected structure of multidimensional poverty.

Economic complexity combines network science with data on economic outcomes to estimate implicit relationships in an economic system (Balland et al. 2022; Hidalgo 2021). Similarly, we apply this approach to poverty dimensions using two methods: 1) proximity metrics, which quantify relationships based on outcome co-occurrences (Guevara et al. 2016; Hidalgo et al. 2007; Kogler, Rigby, and Tucker 2013; Neffke, Henning, and Boschma 2011), and 2) dimensionality reduction, which consolidates these outcomes into a single measure (Hidalgo and Hausmann 2009; Sciarra et al. 2020; Tacchella et al. 2012). Here, we use the former to construct a network representation for the interconnections between various dimensions of poverty called the *Poverty Space*; and the latter to introduce a measure that captures the relative importance the different dimensions within this network called *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 analyze 67 developing countries to map and track changes in the interconnected structure of multidimensional poverty. Our findings show a stable, similar Poverty Space across countries. Core indicators like cooking fuel often have higher Poverty Centrality, whereas indicators like child mortality usually have the lowest centrality scores. We also find that more central indicators tend to experience a larger reduction in deprivation over time. To apply our findings, we integrate the Poverty Space into the Policy Priority Inference (PPI) framework (Guerrero and Castañeda, 2024), enabling targeted interventions that account for cascading effects across poverty indicators. 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 essential for maximizing policy impact. This paper demonstrates how economic complexity methods can identify "key nodes" within the poverty network – dimensions that are highly interconnected and, therefore, most likely to be influenced by a range of policies (Bloch, Jackson, and Tebaldi 2023). Like in acupuncture, targeting specific nodes may trigger effects throughout the system, allowing for more responsive and adaptive development strategies.

Learning from economic complexity: from the Product Space to the poverty Space

Economic complexity has emerged as a novel framework for understanding the structure of economic systems (Balland et al. 2022; Hidalgo 2021). It capitalizes 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 one of the foundational works on economic complexity, Hidalgo et al. (2007) introduced the Product Space – a network capturing the likelihood that a country exports one good if it exports another, thereby reflecting product proximity in the global economy. This proximity metric has been crucial for modeling spillovers and predicting specialization patterns, showing that countries typically diversify into products near those they already produce, leveraging existing economic and infrastructural support. Over the years, proximity metrics like those in the Product Space model have proven highly versatile, extending beyond trade to capture spillovers across diverse activities. For instance, they have been used to model the proximity of scientific fields via co-authorship (Guevara et al. 2016) and innovation domains through patent categories (Kogler, Rigby, and Tucker 2013; Neffke, Henning, and Boschma 2011).

Hidalgo and Hausmann (2009) formalized economic complexity methods through the Product Space, creating centrality measures for product importance in an economy (formally called Economic Complexity Index). These metrics were initially designed to capture the relationship between economic structure and growth, serving as proxies for GDP and long-term economic development (Cristelli et al. 2013; Hausmann et al. 2014; Tacchella et al. 2012). More recently, with the emergence of new policy frameworks, complexity measures have been applied to topics such as inclusive and green growth (Hartmann et al. 2017; Romero and Gramkow 2021; Stojkoski, Koch, and Hidalgo 2023). Today, complexity measures complement aggregate metrics like GDP, guiding structural interventions (Balland et al. 2019; Deegan, Broekel, and Dahl Fitjar 2021; Hassink and Gong 2019; Montresor and Quatraro 2020).

Recently, economic complexity methods have been used to advance data-driven approaches for Sustainable Development Goals (SDGs) and multidimensional inequality. In particular, 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 to address inequality. Similarly, Sciarra et al. (2021) used a network-based approach to rank countries on SDG performance, emphasizing the system's intrinsic complexity.

Building on the diverse applications of economic complexity, we introduce network-based measures for multidimensional poverty and examine their role in forward-looking economic models. This approach addresses the challenge outlined in the 2009 Report of the Commission on the Measurement of Economic Performance and Social Progress, which emphasizes the need for measures that consider interactions among poverty dimensions. Indeed, as Stiglitz, Sen, and Fitoussi (2009, 16) argue, "impacts on indicators across 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."

But, before integrating economic complexity methods into multidimensional poverty analysis, it is essential to clarify the nuances of our approach.

First, while inspired by economic complexity, our approach does not use traditional metrics like the Product Space or Economic Complexity Index. Instead, we adapt the framework to develop metrics tailored for poverty analysis, using network science to map multidimensional poverty's interconnected structure. As shown in subsequent sections, the Poverty Space mirrors the Product Space in its use of proximity metrics, while Poverty Centrality is a unique measure to our approach (based on eigenvector centrality), quantifying each poverty indicator's susceptibility to spillovers (Jackson 2008).

Second, like standard economic complexity methods, our approach does not infer causation (Hidalgo 2023). By analyzing co-occurrences of poverty dimensions within households, we uncover structural relationships among indicators, capturing patterns of interconnections rather than direct causal links. This limitation restricts applicability when cause-effect insights are essential (Ospina-Forero, Castañeda, and Guerrero 2022), as co-occurrences may reflect redundancies rather than true connections (Rajpal and Guerrero 2023). While this limits causal interpretation, our approach remains valuable for informing policy-related questions.

While our approach cannot infer causation, it illuminates structural connections among poverty dimensions. Acting as risk scores, our methods approximate the combined forces driving these relationships and offer strong predictive power for forecasting vulnerabilities and trends in multidimensional poverty. As we will show subsequently, the Poverty Space can be used to anticipate how shifts in one dimension may ripple through others or reveal how broad policies affect specific indicators. This feature is especially useful for policy prediction problems (Athey 2017; Kleinberg et al. 2015) and agent-based policy frameworks (Castañeda, Chávez-Juárez, and Guerrero 2018; Guerrero and Castañeda Ramos 2020; Guerrero, Guariso, and Castañeda 2023). Unlike traditional policy research focused on cause-effect, these methods prioritize predictive modeling to assess potential outcomes, providing an alternative that captures scenario likelihoods stemming from policy decisions. Understanding these structural relationships allows for better measurement of intervention effectiveness and the broader implications within the poverty network. In this way, our methods offer practical tools for forward-looking policy planning, enabling policymakers to mitigate poverty's adverse impacts proactively.

Materials and methods

The multidimensional nature of poverty

We adopt the Alkire-Foster method to define multidimensional poverty (Alkire and Foster 2011), identifying individuals who are deprived in at least k poverty indicators (see Appendix 1). This approach is used to construct a multidimensional poverty index (MPI) for each country c at time t, calculated as the weighted sum of the censored headcount ratio (CHR), $CHR_{ci}(t)$, for each indicator i, i.e. $MPI_{ci}(t) = \omega_i CHR_{ci}(t)$. The CHR reflects the proportion of the population that is both multidimensionally poor and deprived in a specific indicator, with each indicator weighted by ω_i according to its relative importance.

Data

We calculate national level MPIs using data from the Demographic Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS), and following the Global MPI approach developed by Oxford Poverty and Human Development Initiative (OPHI) and the United Nations Development Programme (UNDP). The DHS and MICS datasets provide nationally representative data on poverty indicators for developing countries, covering multiple dimensions of deprivation. These surveys are conducted at different time points across countries, meaning that the available time frame varies. For instance, for North Macedonia, data is available for 2008 and 2019, whereas for Nigeria, the available survey years are 2004 and 2012. More details about the surveys can be found at https://dhsprogram.com/and. https://mics.unicef.org/.

The Global MPI approach uses data from DHS and MICS to assess national poverty across 10 indicators within three dimensions: health, education, and living standards. The indicators are nutrition, child mortality, years of schooling, school attendance, cooking fuel, sanitation, drinking water, electricity, housing, and assets. Households are considered deprived if they fall below set thresholds (see Appendix 2, Table A2.1).

We diverge from the standard Global MPI by assigning equal weights to all indicators, unlike OPHI/UNDP's weighted approach.[1] This choice enables us to investigate relationships without prioritizing any dimension, although it may not necessarily mirror real-world importance. We set a household to be multidimensionally poor if it is deprived in at least one of the 10 indicators, meaning that the CHR matches the headcount ratio for each indicator. We investigate the robustness of our specification using a threshold of 3 (i.e. deprivation in 3+ indicators), finding consistency (see Appendix 3).

While the Global MPI covers over 100 developing countries, not all have multi-year data. To examine poverty dynamics over time, we selected countries with at least two survey years (initial and final year surveys), spaced by a minimum of three years to reduce short-term noise. This results in a dataset of 67 countries from 2003 to 2020 (see Appendix 2, Table A2.2 for details on countries and survey years, and Appendix 2 Figure A2.1 for the distribution of available surveys across years).

The poverty space

The Alkire-Foster method allows us to break down national MPI values into their components and track changes over time, helping us understand how different indicators evolve. This method, however, does not capture the interconnections between deprivations. In practice, policies targeting one deprivation can have indirect effects on others, as improvements in one area may lead to progress elsewhere. These indirect effects, or spillovers, are challenging to measure because they depend on multiple factors, including economic conditions, policy design, and time lags (Alkire et al. 2021; Bellu and Liberati 2005; Bourguignon and Pereira Da Silva 2003; Duclos, Tiberti, and Araar 2018).

To address this limitation, we apply methods from economic complexity and network science to map the structure of poverty and quantify the associations between different deprivations.

Formally, we define a network, the Poverty Space, representing structural relationships between poverty dimensions for each country. In this network, nodes represent poverty indicators, and edges describe the proximity between them based on the conditional probability that a household h experiencing deprivation in indicator i is also deprived in j (Guevara et al. 2016; Hidalgo et al. 2007; Kogler, Rigby, and Tucker 2013; Neffke, Henning, and Boschma 2011), i.e.

$$\Phi_{ij}^{c}(t) = \begin{cases} \frac{\sum_h f_h(t) X_{ih}^{c}(t) X_{jh}^{c}(t)}{\sum_h f_h(t) X_{jh}^{c}(t)}, if i \neq j \\ 0, \ otherwise, \end{cases} \tag{1}$$

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 $f_h(t)$ is the population weight of the household in the sample.

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; Ballon 2023; Suppa, Alkire, and Nogales 2022).

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 describe the 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 can drive spillover effects between indicators. Consider a country where educational deprivation often accompanies housing deprivation, investing in affordable housing near quality schools might also improve education outcomes. Conversely, if deprivation is primarily educational, resources might be better spent on enhancing educational quality.

It is also important to note that the Poverty Space can be dynamic, evolving over time and differing across countries due to factors like economic growth, policy shifts, technological advances, demographic changes, and political or environmental influences.

Poverty centrality

While Equation 1 for calculating pairwise proximities in the Poverty Space is mathematically identical to proximity measures used in economic complexity literature (Hidalgo et al. 2007), the direct application of standard economic complexity metrics like the Economic Complexity Index (ECI) is not appropriate. The ECI methodology relies on mapping capabilities across two distinct sets (locations and activities) in a bipartite structure, which does not align with our unipartite network of poverty indicators.

Instead, we introduce Poverty Centrality (PC), a tailored measure derived from eigenvector centrality, specifically capturing indicator interconnectedness and their susceptibility to indirect spillover effects. PC is simply calculated as the eigenvector in-centrality of each indicator in the Poverty Space:

$$PC_{ci} = \frac{1}{\lambda_1^c} \sum_j \Phi_{ij}^c PC_{cj}, \tag{2}$$

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). A high in-centrality value for an indicator means it is connected to others with similarly high in-centrality, indicating it is a target connection for indicators with high probabilities of co-deprivation.

This measure has two main advantages. First, it provides a holistic view of the interactions among poverty dimensions, identifying which indicators are most central in the poverty network. Second, it highlights indicators that may be especially responsive to changes in other dimensions due to their interconnectedness. Higher Poverty Centrality scores indicate those indicators frequently impacted by shifts in other areas, offering insights for designing more effective poverty reduction strategies by managing indirect intervention effects.

Relating the poverty space to the dynamics of multidimensional poverty

Building on the Poverty Space and Poverty Centrality, we can construct a dynamic view of multidimensional poverty by accounting for potential spillover effects.

To illustrate, consider a direct change in indicator j, $P_{cj}(0) = \delta$ coming as a result of a policy. This leads to spillovers $S_{ci}(0)$ to i immediately with a rate r_{ij}^c, and depends on the fraction of individuals that are deprived in both indicators. That is,

$$\Delta CHR_{ci}(1) \sim S_{ci}(0) = r_{ij}^c \Phi_{ij}^c \delta. \tag{3}$$

The term Φ_{ij}^c comes directly from the Poverty Space and determines the probability that an intervention in j also affects individuals deprived in i.

The spillover effects continue to propagate over time.[2] We can approximate these dynamic changes as

$$\Delta CHR_{ci}(t+1) \sim S_{ci}(t+1) = \sum_j r^c_{ij} \Phi^c_{ij} S_{ci}(t) + O_{ci}(t). \tag{4}$$

Each spillover's strength is determined by the spillover rate r^c_{ij} and conditional probability Φ^c_{ij}. The main term represents individual spillovers, while the higher-order term $O_{ci}(t)$ accounts for overlaps and complexities from simultaneous changes across indicators.

To focus on the primary spillover mechanism via the Poverty Space, we simplify the model by concentrating on the immediate, linear effects in the first term. Due to data limitations, we cannot estimate specific spillover rates r^c_{ij} between indicator pairs, which would require finer temporal data. Thus, we assume a uniform spillover rate r^c across all indicators, yielding the following simplified equation:

$$S_{ci}(t+1) \sim r^c \sum_j \Phi^c_{ij} S_{cj}(t). \tag{5}$$

This is a system of linear difference equations whose solution can be found through the eigenvalues and eigenvectors of $\mathbf{\Phi}_c$. That is

$$\Delta CHR_{ci}(t) \sim S_{ci}(t) = k_1 PC_{ci} \left(r^c \lambda^c_1 \right)^t + L_i(t), \tag{6}$$

where $L_i(t)$ is a linear combination of the other eigenvectors and eigenvalues and k_1 is a constant determined by the initial spillover. Since λ^c_1 is the largest eigenvalue, the overall effect of $L_i(t)$ diminishes quickly compared to the effect of $k_1 PC_{ci} \left(r^c \lambda^c_1 \right)^t$. Hence, the equation shows that indicators with higher Poverty Centrality experience greater changes in the CHR due to spillover effects.

Results

Mapping the interconnected structure of poverty in 67 countries

We begin by we investigating the structural characteristics of the Poverty Space.

First, we examine the relationship between the Poverty Space and the CHR. We do this by pooling data across countries and survey years and normalizing the CHR to sum up to 1 (in order to be comparable to the Poverty Space). We find a very high correlation between these two indicators (Pearson correlation = 0.95), suggesting that the structural properties of the Poverty Space strongly reflect the observed distribution of multidimensional poverty.

Second, in Figure 1(b), we calculate the median poverty centrality for each indicator across all countries, using data from the final survey year. This snapshot of "typical" indicator centrality provides a benchmark for assessing country-specific poverty structures. On average, Cooking Fuel is the most central indicator, followed by Sanitation and Housing, while Child Mortality is the least central. This aligns with studies showing that about 60% of the global poor experience concurrent deprivation in sanitation, housing, and cooking fuel (Suppa, Alkire, and Nogales 2022).

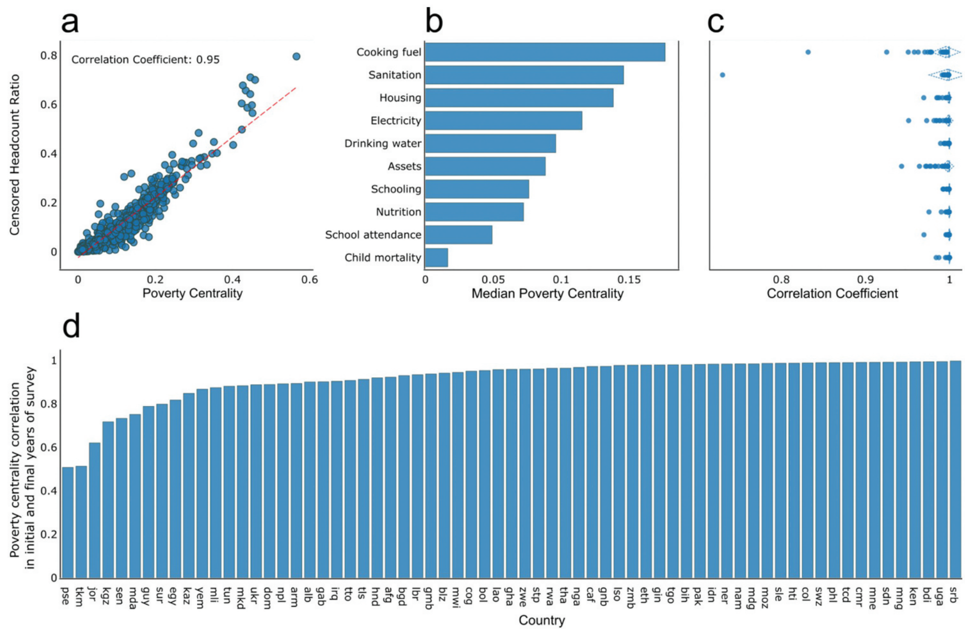


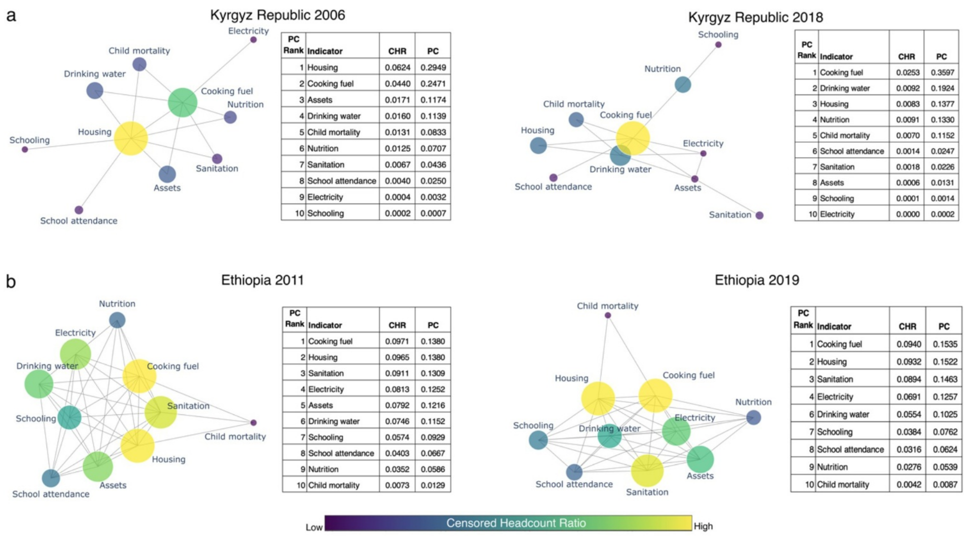
Figure 1. General patterns in the poverty Space. A scatter plot showing the relationship between poverty centrality and the censored headcount ratio across all countries and years. For each survey, the CHR is normalized to sum up to 1. b median centrality of each indicator using data from the final survey year. c Boxplots of correlation in poverty centrality when each indicator is excluded from the poverty Space estimation (final survey year data). d bar chart showing correlations between indicator centrality in initial and final survey years for each country.

A similar pattern emerges across country income groups (Figure A4.1 in Appendix 4), though more variation appears when comparing regions (Figure A4.2), with the Middle East and North Africa showing a distinct structure. This suggests some uniformity in Poverty Spaces globally, with Ethiopia aligning closely to these trends, while the Kyrgyz Republic stands out as an outlier.

From a development perspective, Cooking Fuel's centrality suggests it could benefit indirectly from improvements in related areas, while Child Mortality's peripheral position indicates a need for direct, targeted interventions. This highlights the importance of integrated policies for systemic indicators like Cooking Fuel and focused approaches to reduce Child Mortality effectively.

Third, we assess each country's Poverty Space sensitivity to missing indicators by removing one at a time, recalculating the structural dependence matrix, and comparing the Poverty Centrality of remaining indicators to the original values. Figure 2(c) shows boxplots of the correlation distributions, which are nearly always above 0.9, indicating the robustness of our results to potentially omitted indicators.

Finally, we explore the stability of the Poverty Space over time. Figure 2(d) shows bar charts of correlations between indicator centralities in the initial and final survey years for each country, with most correlations above 0.8, indicating a stable poverty structure within countries.



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 2. Poverty Spaces of the Kyrgyz Republic and Ethiopia. A Kyrgyz Republic in 2006 and 2018. b Ethiopia in 2011 and 2019. Nodes represent poverty indicators, with edges indicating important connections (thresholded to ensure each indicator has at least one connection). Node size reflects poverty centrality (PC), and node color corresponds to the censored headcount ratio (CHR) of the indicator (see equations (1-Equation 2).

This stability of the Poverty Space suggests consistent relationships among poverty dimensions over time and across countries, providing a holistic view of indicator interactions. This understanding helps identify which indicators are most central and, as argued in the next section, may be more likely to experience indirect policy effects. Nevertheless, these similarities should not lead to uniform policy recommendations. Policies must remain context-sensitive, as factors such as institutional capabilities, local socioeconomic conditions, and cultural settings significantly affect their efficacy. Moreover, differing survey periods across countries mean global and local temporal dynamics – such as international development targets or external shocks – should be carefully considered when interpreting the results and formulating policy interventions.

Next, we use the Poverty Space and Poverty Centrality to examine poverty's structural aspects within a country. We focus on the contrasting cases of the Kyrgyz Republic and Ethiopia. Ethiopia represents the typical structural pattern observed in most countries, whereas the Kyrgyz Republic diverges from this pattern and serves as an outlier with its Poverty Space.

Figure 2 presents network visualizations of the Poverty Spaces for the Kyrgyz Republic and Ethiopia, comparing the initial and final survey years. In these visuals, nodes represent poverty indicators, with edges signifying key connections (each network uses a minimum edge weight threshold to ensure all indicators are connected). Node size reflects poverty centrality, while color represents the CHR, from low deprivation (blue) to high (yellow).

In the Kyrgyz Republic (Figure 2(a)), Housing was the most central indicator in 2006 (largest node at the core), while Schooling was the least central (smallest node at the periphery). This suggests that households deprived in any indicator were most likely also deprived in Housing, but rarely in Schooling. Geographic, systemic, and socio-economic factors likely shape this structure, with the Poverty Space aggregating these relationships.

By 2019, Cooking Fuel became the most central indicator, while Housing fell to third, alongside a significant MPI reduction (from 0.176 to 0.063). This shift largely reflects a decline in housing deprivation (from 6% to under 1%), with smaller reductions in Cooking Fuel deprivation (from 4% to 3%), illustrating how poverty structures adapt over time to socio-economic changes and likely policy impacts.

Ethiopia (Figure 2(b)) presents a contrasting case, with a largely stable Poverty Space structure over time. In both 2011 and 2019, Cooking Fuel remained the most central indicator (at the core), while Child Mortality was the least central (at the periphery).

In Appendix 5 we present supplementary analyses supporting the robustness and interpretability of Poverty Centrality as our main measure for identifying structural properties in multidimensional poverty networks. There, we examine the statistical distribution of edge weights across all countries and survey periods, finding moderate network sparsity with median weights around 0.4, and a considerable variability (standard deviation ~ 0.25). We also compare Poverty Centrality with traditional network metrics, showing it correlates positively and strongly ($r = 0.76$) with degree centrality – confirming it primarily identifies indicators with numerous direct connections – but negatively with betweenness centrality ($r = -0.27$), indicating limited overlap with bridging indicators (Beytía 2016; García-Vélez and Nuñez Velázquez 2021). Lastly, through eigen-decomposition, we demonstrate that Poverty Centrality (the first eigenvector) explains approximately 80% of total variance in the Poverty Space, further suggesting its suitability as a dominant explanatory metric.

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

We then examine the dynamic link between poverty structure and incidence by analyzing the association between Poverty Centrality and changes in the censored headcount ratio. By pooling data from all countries, we construct regression models with changes in the censored headcount ratio as the dependent variable and Poverty Centrality as the explanatory variable.[3]

Our regression models are represented as

$$\frac{\Delta CHR_{ci}(t)}{\Delta t} = b_1 PC_{ci}(t) + b_2 x_{ci}(t) + \gamma_c + \delta_i + b_0 + u_{ci}(t). \tag{7}$$

In these regressions, we include controls for country-specific effects (γ_c), capturing phenomena such as economic growth and institutional factors, and for indicator-specific effects (δ_i), accounting for each poverty dimension's unique characteristics and response to policy. Additionally, our models include two explanatory variables ($x_{ci}(t)$): the CHR of each indicator ($CHR_{ci}(t)$) in the initial survey year, providing a baseline for poverty levels, and the sum of CHR for all other indicators ($\sum_{j \neq i} CHR_{cj}(t)$), capturing the broader context of multidimensional poverty within which a specific indicator is embedded. Indicators starting with higher CHR may experience more significant changes due to concentrated efforts in tackling that specific area. By contrast, high levels

Table 1. Change in censored headcount ratio models results.

	Dependent variable				
	Change in censored headcount ratio per year ($\frac{\Delta CHR_{ci}(t)}{\Delta t}$)				
	(1)	(2)	(3)	(4)	(5)
Initial poverty centrality ($PC_{ci}(t)$)		−0.006***	−0.005***	−0.005***	−0.005***
		(0.001)	(0.001)	(0.001)	(0.001)
Initial CHR ($CHR_{ci}(t)$)			−0.008**		−0.009***
			(0.004)		(0.003)
Initial CHRs of all other indicators ($\sum_{j\neq i} CHR_{cj}(t)$)				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

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

of deprivation in other indicators may exert upward pressure on a particular indicator, either through resource constraints or through direct effects of multidimensional poverty.

These variables allow us to isolate the structural impact of poverty on its dynamics across indicators.

Table 1 presents our results. Column (1) shows the results from a baseline model with only dummy variables, explaining about 29% of changes in the CHR (Adjusted R^2 = 0.29). Adding the poverty centrality index in column (2) improves the explanatory power to 37% and suggests that more central indicators tend to have larger decreases in CHRs.

Column (3) includes the initial CHR, and column (4) adds the sum of CHR for other indicators. In column (5), both controls are included. In each of these regression, the negative relationship between poverty centrality and the long-run changes in CHR remains robust. Moreover, indicators with higher initial CHRs show greater decreases over time. The sum of other CHRs also has a negative but insignificant coefficient.

In Appendix 6, we assess the robustness of our findings using three methods. First, for 15 countries with an additional intermediate survey, we estimate the Poverty Space and Poverty Centrality for this midpoint, calculating changes in CHRs from the initial to intermediate and intermediate to final years. This creates an unbalanced panel sample, which we use to re-estimate our model with additional year dummies. Table A6.1. in Appendix 6 shows that Poverty Centrality remains a significant, negative predictor of changes in CHRs over time in even in this homogenous sample.

Second, to address endogeneity, we apply an instrumental variable (IV) approach. Endogeneity may arise from unobserved factors affecting both Poverty Centrality and CHR changes, potentially biasing our estimates. We define an instrument for each indicator as the Poverty Centrality of the same indicator in the country with the most similar Poverty Space. This similarity, measured by the correlation between the Poverty Space edges, provides exogenous variation, as countries with comparable structures likely share similar Poverty Centrality but differ in contextual factors affecting headcount changes. The IV results in Table A6.2. of Appendix 6 suggest that Poverty Centrality remains a significant, negative predictor of long-term CHR changes, thus again underscoring our findings' robustness.

Finally, we also perform a sensitivity analysis to investigate whether Poverty Centrality outperforms alternative network centrality metrics in explaining the future changes in CHR. Specifically, we compare Poverty Centrality with the country-normalized initial CHR and two widely-used network centrality metrics – simple degree centrality and betweenness centrality. The results reported in Tables A6.3. to A6.5 of Appendix 6 indicate that Poverty Centrality consistently demonstrates superior explanatory power compared to these three measures, thus indicating that Poverty Centrality provides distinct and robust insights into the structural determinants of poverty reduction.

From diagnostics to policy

The Poverty Space reveals the interconnected structure of multidimensional poverty but requires additional tools for policy relevance. High centrality in the Poverty Space, for example, does not mean an indicator can be left out of interventions; factors like program effectiveness, feasibility, and budget must also be considered. Therefore, to illustrate the policy potential of the Poverty Space, we integrate it into the Policy Priority Inference (PPI) framework (Guerrero and Castañeda-Ramos, 2024).

PPI is an agent-based, forward-looking model that identifies optimal budget allocations to achieve specific development outcomes by simulating interactions among policy actions. It currently supports Sustainable Development Goals by identifying accelerators and assessing indicators' sensitivity to spending. Using data on conditional relationships between indicators, PPI models spillovers from government actions, with the Poverty Space being a network that could provide crucial insights into poverty-related spillovers.

Incorporating the poverty space into PPI

PPI assumes N policy issues, each measured by an indicator, with poverty indicators represented by the censored headcount ratios. The model simulates indicator dynamics over time using the following equation:

$$CHR_{ci}(t+1) = \begin{cases} CHR_{ci}(t) - \alpha_{ci},\, if\, \varepsilon_{ci}(t) = 1, \\ CHR_{ci}(t) + \alpha'_{ci},\, otherwise. \end{cases} \tag{8}$$

where α_{ci} and α'_{ci} determine CHR improvement or deterioration between time points, and $\varepsilon_{ci}(t)$ is a Bernoulli variable with success probability $e_{ci}(t)$, reflecting effective resource use. The government allocates resources π_i to each policy area, constrained by budget B ($\sum_i \pi_i = B$). Public servants use $P_i \in [0, \pi_i]$ for policy, with $\pi_i - P_i$ indicating inefficiency. This depends on two national 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, indicator improvement also depends on spillovers from other policy areas, represented by an adjacency matrix $\boldsymbol{A}$, where $A_{ij} > 0$ indicates spillovers from j to i. Thus, indicator dynamics result from (1) the government's budget, (2) system inefficiencies, and (3) spillovers from contributions by officials in other areas.

Our goal is to illustrate how spillovers could influence policy effectiveness while holding expenditure and inefficiencies constant. Using the Poverty Space, we incorporate multidimensional poverty dynamics by setting conditional dependencies as:

$$A_{ij} = r^c \Phi^c_{ij}, \tag{9}$$

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

We return to Ethiopia as a case to demonstrate PPI's application in understanding spillover effects in poverty dynamics.

Estimation strategy

PPI provides two methods to analyze multidimensional poverty: 1) through a retrospective and 2) through a prospective analysis. The retrospective analysis examines historical data to understand past dynamics of poverty indicators and policy allocations, allowing us to infer the optimal spillover rate and key model parameters (e.g. α_{ci} and $\alpha^{'}_{ci}$). This analysis identifies how differing spillover rates influence intervention outcomes. The Prospective analysis uses historical insights to project how changes in spillover rates or the Poverty Space could impact poverty dynamics in the future, guiding policymakers on prioritizing poverty indicators for future improvements.

In the retrospective analysis, we use data from 2011 and 2019 on poverty indicators, government expenditure, law and monitoring quality (approximated by World Bank indicators), and the 2011 Poverty Space. We calibrate the model parameters and the optimal spillover by testing rates from 0 to 1 (in 0.05 increments) and select the value that best fits the data.

For the prospective analysis through 2030, we use 2019 data on poverty indicators and the Poverty Space, holding rule of law, monitoring quality, and average expenditure constant. By varying the spillover rate from 0 to 1, we explore how poverty interlinkages may shape multidimensional poverty dynamics. See Appendix 7 for details on data cleaning and calibration.

Findings

Figure 3 illustrates the Poverty Space's impact on PPI simulations.

In Figure 3(a), we show how varying the spillover rate affects Ethiopia's projected MPI for 2030 (black line). The blue dashed line indicates Ethiopia's 2019 MPI (0.567), while the red vertical line marks the optimal spillover rate (0.7) identified in the retrospective analysis. At this rate, Ethiopia's MPI is projected to fall by 0.103 units to 0.464 by 2030. A zero spillover rate would reduce MPI by only 0.036 units, whereas a rate of 1 would reduce it by 0.109 units to 0.458.

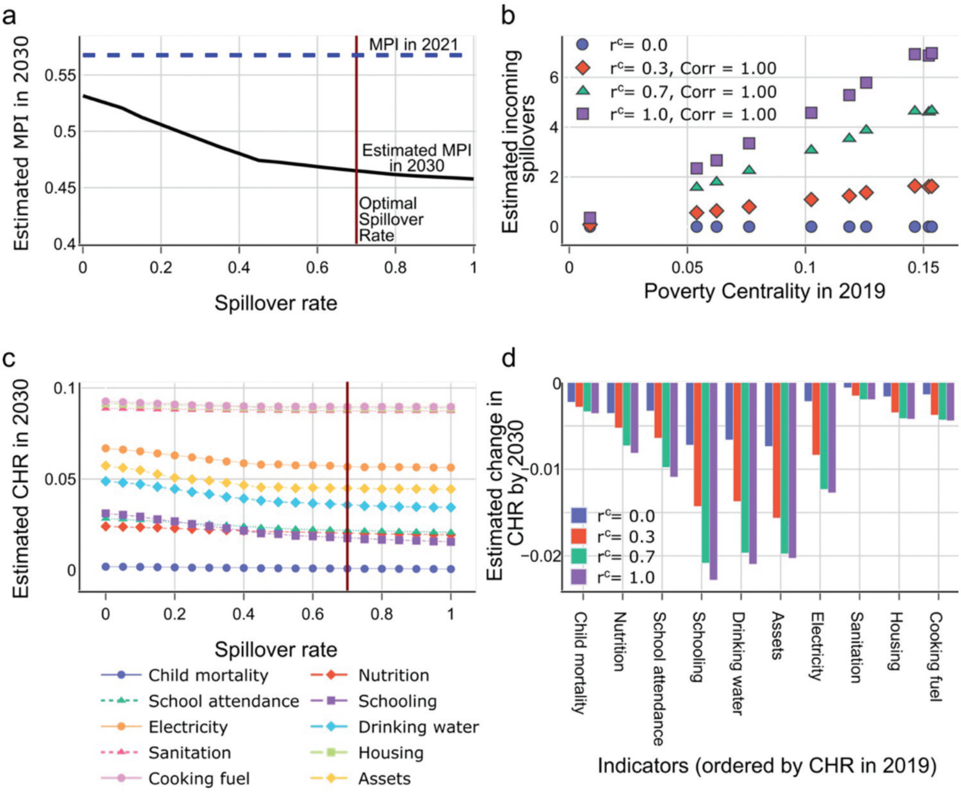


Figure 3. Policy Priority Inference for Ethiopia using the Poverty Space. A Estimated MPI for Ethiopia in 2030 as a function of the spillover rate, with the optimal rate marked by a red line and the 2019 MPI by a blue dashed line. (b) Average incoming spillovers for each indicator (2019–2030) as a function of Poverty Centrality across various spillover rates. (c) Estimated censored headcount ratio for each indicator in 2030 as a function of the spillover rate. (d) bar chart showing changes in censored headcount ratios between 2019 and 2030 for each indicator under various spillover rates, ordered by 2019 CHR values. (a–d) Results are averaged across 100 PPI simulations.

Notably, Ethiopia's MPI is more sensitive to reductions below the optimal spillover rate than to increases beyond it, highlighting the potential importance of accounting for Poverty Space structure in expenditure programs to optimize poverty reduction efforts.

In Figure 3(b), we display the average spillovers received by each poverty indicator (2021–2030) for various r^c values as a function of Poverty Centrality. We find a strong correlation between Poverty Centrality and spillovers across all r^c values, indicating that Poverty Centrality accurately identifies indicators likely to receive spillovers. The actual spillover volume, however, depends on the spillover rate r^c, making Poverty Centrality a relative measure that shows spillover distribution potential while the magnitude varies with r^c.

In Figure 3(c), we show each indicator's CHR as a function of the spillover rate, illustrating how these ratios change with varying r^c. Indicators with the lowest and highest censored headcount ratios appear to be the least affected by changes in r^c, while those with intermediate ratios appear more sensitive, displaying greater fluctuations as r^cvaries.

Figure 3(d) shows a bar chart of changes in the CHR for each indicator under different spillover rates, ordered by 2019 their CHR values. Three indicators with intermediate CHRs in 2019 (Schooling, Drinking Water, and Assets) display the largest CHR changes. At lower spillover rates (0 and 0.3), Assets has the largest CHR decrease, while at higher rates (0.7 and 1.0), Schooling shows the largest decrease. This suggests that higher spillover rates shift resources and policy focus toward amplifying indicators, altering poverty dynamics. Identifying the indicators most responsive to these shifts through the Poverty Space can help policymakers target resources to maximize poverty reduction impact.

Overall, this analysis using Ethiopia's data highlights how integrating the Poverty Space with PPI can enhance understanding of multidimensional poverty dynamics and guide policy interventions. By identifying the optimal spillover rate and assessing changes in the Poverty Space, this approach offers insights into the interconnected factors that might influence poverty reduction. As a final note, it is important to emphasize that, while demonstrated with Ethiopia, this adaptable method can be applied to other countries with relevant data to inform targeted policy strategies.

Discussion

Interdependencies among poverty dimensions can intensify deprivation and create cycles that are hard to break. Understanding these links is crucial for moving beyond isolated policy approaches. Accelerating poverty reduction requires integrated policies that target specific "nodes" to maximize system-wide impact.

In this paper, we applied network science methods, akin to those in economic complexity, to multidimensional poverty, aiming to map interdependencies and identify key nodes. Unlike traditional multidimensional poverty indices that focus on the sum of deprivations, our approach shifts the focus to the structural relationships between indicators. We introduced two measures: the Poverty Space, which represents the networked structure of poverty, providing a holistic view of interconnected dimensions, and Poverty Centrality, which highlights the relative importance of each indicator within this network. We found that more central indicators experience higher poverty reduction over the long run, likely due to spillovers.

Furthermore, applying our findings through the PPI framework demonstrated the practical value of our approach, showing that spillovers in the Poverty Space could lead to policy effectiveness. Overall, these results suggest that network science methods inspired by economic complexity provide a powerful tool for informing multidimensional poverty reduction by identifying key target nodes in the network.

Nevertheless, our study is not without its limitations. First, even though the Poverty Space is largely consistent across nations and time, it may miss dynamic poverty shifts driven by changing socio-economic factors. Our focus on certain poverty dimensions might overlook variables crucial to specific geographic and socio-cultural contexts (Santos 2019). Additionally, global data inconsistencies and biases limit the depth of our representation. While dimensionality reduction helps consolidate data, it may overlook nuanced interactions important for policy. Second, integrating the Poverty Space within the Policy Priority Inference framework has its own limitations, as the Poverty Space does not strictly model causal spillover networks. Accurate modeling would require longitudinal data, often unavailable or inconsistent in developing economies. Instead, the Poverty Space projects a structure to estimate potential spillovers but may not fully capture the exact dynamics in all contexts.

While imperfect, our approach offers a valuable starting point for addressing key policy questions. We provided an initial look at how network science methods can deepen our understanding of multidimensional poverty, and point toward new directions for research. For example, examining context-specific poverty dimensions without cross-country comparability constraints could reveal more granular variations over time and space, advancing insights into poverty's interconnected structure. To accelerate poverty reduction, "acupuncture-like" approaches – targeting complex interdependencies among poverty dimensions – show promise as innovative ways to amplify development impact.

Notes

1. 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. That is, the two health indicators have a weight of 1/6, the two education indicators have a weight of 1/6, and the six living standards indicators have a weight of 1/18.
2. In general, Φ_{ij}^{c} and r_{ij}^{c} are also time dependent.
3. We use the relative changes in the CHR divided by the time length between the first and last year of survey, i.e. $\Delta H_{ci}(t)/\Delta t$ as our dependent variable to account for the fact that the first and last year of survey is not equal among countries, and thus might impact our results.

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Disclosure statement

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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