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Spatial and Temporal Dynamics of Multidimensional Poverty in Khyber Pakhtunkhwa, Pakistan: A District-Level Analysis (2004 – 2020)

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Abstract

This study analyzes spatial and temporal dynamics of multidimensional poverty across 32 districts of Khyber Pakhtunkhwa, Pakistan, using 2004–05 to 2019–20 PSLM surveys. Applying the Alkire-Foster methodology, the Multidimensional Poverty Index (MPI) is constructed using education, health, and living standards dimensions. Results show, that although multidimensional poverty has declined overall in Khyber Pakhtunkhwa, large differences between districts continue to exist over time. Newly merged and remote districts (e.g., Kohistan, Mohmand, and Shangla) exhibit the highest MPI scores. Fixed-effects panel regressions reveal that higher dependency ratios, poor road infrastructure, and greater casual labor occurrence significantly increase multidimensional poverty. Year effects indicate significant poverty reduction until 2014–15, followed by partial reversal in 2019–20. Robustness checks using alternative poverty cut-offs (k=1/4) confirm stable district rankings. The findings demonstrate that multidimensional poverty in KP is structurally and spatially rooted, requiring district-specific, place-based policy interventions, as uniform policy approaches failed in resolving such like deprivations.

Keywords: Multidimensional poverty; Alkire-Foster methodology; district-level analysis; spatial disparities; fixed-effects model; PSLM
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1. INTRODUCTION

Poverty is a multidimensional problem that not only relates to income deprivation, but also arises from a lack of education, health, and living standards failities that jointly limit human capabilities and well-being (Sen, 1985; UNDP, 2010, 2019). The traditional income-based method for measurement of poverty is also useful but it often fails to capture the multiple and corresponding disadvantages experienced by households, mainly in developing countries where access to basic services and needs remains uneven (Ravallion, 2016; World Bank, 2018). Therefore, poverty should be understood and measured through a multidimensional lens for more effective and inclusive policy responses (Alkire & Foster, 2011; Bourguignon & Chakravarty, 2003; Atkinson, 2015).

The Multidimensional Poverty Index (MPI), developed by Alkire and Foster (2011) and which was operationalized by the United Nations Development Programme (UNDP), has been widely accepted and employed to understand both the breadth and intensity of poverty. Unlike one-dimensional poverty measures, the MPI captures both the incidence and intensity of poverty by showing how many people are poor and the extent of their deprivation. Therefore, this methodology offers a nuanced understanding of deprivation (Alkire et al., 2015; Alkire & Santos, 2014). This methodology is widely used across countries to assess poverty dynamics and regional disparities (OPHI, 2018; UNDP, 2023).

In developing countries like Pakistan, poverty is considered a major development challenge linked with regional heterogeneity, inequalities and exposure to climatic shocks (Jamal, 2009; World Bank, 2016; Haque et al., 2021). The overall or average provincial poverty hides the district-level disparities. The unique geography of KP, characterized by conflicts, governance constraints, and repeated natural disasters has shaped development outcomes in the province (Hallegatte et al., 2016). Therefore in such situations district-level poverty assessment becomes essential to identify localized deprivation patterns and to design targeted policy interventions.

Some recent studies show that deprivations in education, health, and living conditions together create deprivation cycles (Dercon, 2004; Carter & Barrett, 2006; Heltberg et al., 2009). In KP, irregularities in school attendance, quality of education, health facilities, poor housing conditions, sanitation, and access to improved energy remain pronounced throughout the districts (Jamal, 2016). These disadvantages indicate that measuring poverty in one dimension is not enough. In Pakistan, several studies have employed the Alkire–Foster methodology to measure multidimensional poverty. Amjad et al. (2018) also applied the Multidimensional Poverty Index (MPI) using the 2013–14 Household Integrated Economic Survey (HIES) to assess the targeting performance of the Benazir Income Support Programme (BISP) and Zakat. However, the study focused only on assessing social protection programmes whereas spatial and temporal dynamics of multidimensional poverty at districts level were not studied. Furthermore, Haq et al. (2024) estimated multidimensional poverty in Pakistan at the national, provincial, and regional levels using the Alkire–Foster methodology. The study reported significant regional disparities in multidimensional poverty and identified education as the largest contributor to MPI, followed by living standards. However, the analysis was limited to national and provincial estimates and did not examine district-level spatial and temporal dynamics. Despite the growing literature on multidimensional poverty in Pakistan, temporal analysis at district-level for Khyber Pakhtunkhwa remains limited. Therefore this study also constructs a district-level Multidimensional Poverty Index (MPI) using multiple survey rounds from 2004–05 to 2019–20 employing the

Alkire–Foster methodology with three dimensions, namely, Education, Health, and Living Standards having equal weights.

This study contributes to the existing literature in several ways. First, it provides the longest temporal coverage of district-level MPI in KP (2004-05 to 2019-20), spanning seven PSLM survey rounds. This period covers multiple phases of conflict and stabilization in KP, including the Swat conflict (2007-2009), military operations in FATA (2004-2017), and the post-merger period (2018-2020).

Second, it is the first study to include 32 current districts of KP (the original 24 districts plus the eight newly merged former FATA districts: Bajaur, Khyber, Kurram, Mohmand, North Waziristan, Orakzai, South Waziristan, and Torghar) within a unified, methodologically comparable MPI framework. Prior estimates for these districts are not available in literature.

Third, the study integrates MPI decomposition with a district-level fixed-effects econometric model, enabling separation of structural determinants (geography, dependency ratios, and infrastructure deficits) from temporal shocks. This methodological integration has not been previously applied to KP's district-level poverty analysis.

This study is aligned with the objectives of the Sustainable Development Goals (SDG-1, No Poverty) and SDG-10 (Reduced Inequalities) (UN, 2015; UNDP, 2023).

2. CONCEPTUAL FRAMEWORK OF MULTIDIMENSIONAL POVERTY MEASUREMENT

Poverty is multi-dimensional and cannot be measured using one single indicator because there are several aspects of poverty that are not captured in income or consumption levels but affect human capabilities and the overall well-being of the poor, such as deprivations in education, health, and living conditions (Sen, 1985; Alkire & Foster, 2011). Sen's (1999) capability approach focuses on measuring what people can do with the capabilities they need to function and to enjoy a good life. Thus, the Multidimensional Poverty Index (MPI) is a well-adopted index that combines several indicators to give a more thorough picture of poverty. (Alkire & Santos, 2014; UNDP, 2019). This MPI framework is appropriate for estimating poverty in areas, such as in Khyber Pakhtunkhwa (KP) in Pakistan where opportunities and access to key public services are unevenly distributed (Carter & Barrett, 2006; Dercon, 2004). The indicators chosen are the dimensions of poverty in Khyber Pakhtunkhwa which are context-specific. Education-related indicators capture deficiencies in human capital and the intergenerational persistence of poverty, whereas health indicators measure access to essential preventive and maternal healthcare services. Living standards indicators show physical conditions and infrastructural access (UNDP, 2010; Hallegatte et al., 2016).

3. METHODOLOGY: CONSTRUCTION OF THE DISTRICT-LEVEL MULTIDIMENSIONAL POVERTY INDEX

3.1. Conceptual Foundation

This study employs the Alkire–Foster (AF) multidimensional poverty framework. The AF methodology is selected over alternative multidimensional poverty approaches, including fuzzy-set approaches, information-theoretic measures, and principal component methods, for several reasons specific to this study.

First, the AF framework is well suited to binary and ordinal deprivation indicators, which comprise most of the PSLM variables used in this study. (e.g., wall construction material, sanitation status, school attendance, and access to utilities). Methods based on continuous cardinal variables, such as Principal Component Analysis (PCA), are generally less suitable for binary and ordinal deprivation indicators, which constitute the majority of the indicators used in this study. Second, the dual cut-off methodology, together with the decomposition of poverty into incidence (H) and intensity (A), allows policymakers to distinguish between the prevalence of multidimensional poverty and the average intensity of deprivation among poor households. Third, the AF methodology produces decomposable results by dimension and indicator allowing consistent district-level and temporal comparisons across districts of Khyber Pakhtunkhwa. This is particularly important for spatial poverty analysis and district-level policy targeting.

Fourth, the AF framework aligns with Pakistan's official multidimensional poverty monitoring framework adopted by the Planning Commission of Pakistan and UNDP, thereby ensuring comparability with national MPI estimates and enhancing policy relevance (Planning Commission of Pakistan, 2016; UNDP, 2020).

The conceptual basis of this approach is grounded in the capability framework that highlights individuals' functional freedoms and opportunities (Sen, 1985, 1999). Furthermore, a district fixed effects model is also employed to determine the effect of different variables (dependency ratio, Km^2 per km of road and households with casual workers) on MPI at the district level. The fixed-effects model is ideal in this study and therefore is preferred over the random-effects model due to the risk of potential correlation between unobserved district-specific characteristics like geography, institutional capacity, and historical development patterns and the explanatory variables. This approach ensures a consistent and unbiased estimation by controlling for time-invariant heterogeneity across districts.

3.2. Dimensions, Indicators, And Weighting Structure

Following UNDP/OPHI (2023) guidelines, this study constructs the MPI using three equally weighted dimensions, namely, Education, Health, and Living Standards and equal weights of 1/3 (33.33 percent) are assigned to each dimension, reflecting that these dimensions are equally important (Alkire & Foster, 2011; Bourguignon & Chakravarty, 2003). Within each dimension, equal weights are assigned to all indicators. Details of the three dimensions are given below.

a) Education Dimension (Weight = 1/3)

The education dimension includes Years of Schooling (A household is considered deprived if any household member above age 10 has not completed five years of schooling), Children Attending School (A household is deprived if any member between 6 and 11 years of age is not attending school) and Quality of Education (deprived if any child is not attending school because of insufficient teachers, school distance, high educational expenses, non-availability of a male or female teacher and non availability of essential facilities or substandard school). Each indicator within the dimension is assigned equal weight. Deprivation cut-offs are defined following the UNDP and OPHI guidelines, reflecting minimum acceptable educational attainment and access (UNDP, 2019; Alkire & Santos, 2014).

b) Health Dimension (Weight = 1/3)

The health dimension shows access to essential preventive health and maternal health services, indicated through Child Vaccination, Antenatal Check-ups and childbirth assistance by trained health professionals. These indicators show both child health and maternal health outcomes, which are relevant in regions exposed to service delivery gaps and constraints (Hallegatte et al., 2016; World Bank, 2018).

c) Living Standards Dimension (Weight = 1/3)

The living standards dimension shows household access to essential infrastructure and durable assets through Improved drinking water, Improved sanitation, Wall construction material, Overcrowding (4 or more individuals per room), Electricity, clean cooking fuel and asset ownership. Each indicator is assigned equal weight. This dimension reflects long-term structural deprivation and asset deficits, which are related to poverty and vulnerability in Pakistan (Carter & Barrett, 2006; Jamal, 2016).

3.3. Justification of the Indicators in the Context of Khyber Pakhtunkhwa

While the three dimensions follow UNDP/OPHI global standards, the specific indicators and deprivation thresholds have been adapted to the KP context as follows.

Education - Years of Schooling (threshold: 5 years): This threshold is based on KP's historically poor literacy rates (52% in 2019-20 against 62% nationally) and the fact that an incomplete primary level education provides only some functional literacy. Education - Quality of Education: It reflects region specific constraints such as: (a) non-availability of female teachers (important in conservative districts like Mohmand and Bajaur where male teachers are not allowed to teach female students); (b) school distance > 5 km (significant in a mountainous region); (c) expenses beyond government fee waiver (d) lack of appropriate facilities (boundary walls, latrines, drinking water).

Health – Antenatal check-ups and assisted delivery: KP's MMR is 165 per 100,000 live births while SDG's target for the MMR is to reduce it to 70 maternal deaths per 100,000 live births by 2030. This rate is much higher in rural areas (199 per 100,000 live births). The proportion of deliveries taking place at home is 36% in KP (NIPS & ICF, 2022). The following are proxies of health system access.

Living Standards – Wall construction Material: Following Planning Commission (2016), "improved" wall construction material includes baked brick, concrete block, stone with mortar, or wood; "unimproved" includes mud, unburnt brick and bamboo. Overcrowding (threshold: >4 persons per room): This follows WHO housing standards and captures a binding constraint in KP where average household size is 7.2 (national 6.4) in poor districts (various issues of PSLM).

3.4. Identification of the Multidimensional Poor

A household and individuals within it are considered multidimensional poor if their weighted score is 1/3 or higher (cut-off score). The poverty cut-off "k" is set at 33.33 percent, which implies that a household should be deprived at least in one full dimension or a combination of other indicators (in all three dimensions) to be classified as multidimensional poor. This threshold and its robustness are widely used in national and global MPI measurement (Alkire et al., 2015; UNDP, 2023).

3.5. Aggregation: Headcount Ratio, Intensity, And Mpi

At the district level, multidimensional poverty is summarized using three key measures, namely, "Headcount Ratio (H)" shows the proportion of the households that are multidimensional poor, second "Intensity of Poverty (A)" shows the average share of deprivations experienced by poor households and Multidimensional Poverty Index (MPI) is defined as the product of headcount and intensity, $MPI = H \times A$

3.6. District-Level and Temporal Comparability

The MPI is estimated at the district level for Khyber Pakhtunkhwa across multiple survey rounds, ensuring consistent indicators, weights, and deprivation cut-offs over time. This methodology is helpful in spatial and temporal measurement and comparisons of multidimensional poverty. For estimation, population weights are used to make the results representative (Haque et al., 2021; UNDP, 2023).

3.7. Robustness Check: Alternative Poverty Cut-off (k = 1/4)

To strengthen the analytical depth of the study and to address concerns regarding threshold sensitivity, an additional robustness analysis of the districts was conducted and an alternative poverty cut-off ($k = \frac{1}{4}$) was also used. This alternative cut-off allows examining whether district rankings, spatial disparities, and temporal trends are sensitive to different multidimensional poverty cut-offs.

The use of k = 1/4 classifies households deprived in at least 25 percent of weighted indicators, thereby expanding the identification of the multidimensionally poor. All indicators, weights, and aggregation procedures remained unchanged to ensure comparability with the baseline estimates.

4. DATA SOURCES AND UNIT OF ANALYSIS

This study is based on a secondary quantitative analysis of existing PSLM household survey datasets. No primary field data collection was conducted. The PSLM is a repeated cross-sectional household survey conducted by the Pakistan Bureau of Statistics for the years 2004–05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15 and 2019–20. The sampling frame uses a two-stage stratified design: primary sampling units (PSUs) are census blocks (urban) and villages (rural), selected with probability proportional to size; secondary sampling units are households selected via systematic random sampling within PSUs. These surveys provide extensive information on household socioeconomic characteristics, which are essential for the construction of the MPI (Jamal, 2016). PSLM data are widely regarded as reliable and have been extensively used in poverty and vulnerability research in Pakistan (Arif & Farooq, 2014; World Bank, 2018). The analysis is carried out at the household level and then results are aggregated at the district level.

5. DISTRICT-LEVEL MULTIDIMENSIONAL POVERTY IN KHYBER PAKHTUNKHWA

5.1. Overall Patterns of Multidimensional Poverty

District level Multidimensional Poverty Index (MPI) estimates show wide-ranging spatial heterogeneity in deprivation throughout Khyber Pakhtunkhwa (KP) during the study period 2004–05 to 2019–20. Although multidimensional poverty declined overall at the provincial level, poverty remains deeply rooted in specific districts, mainly those characterized by geographic remoteness, weak infrastructure and inadequate access to basic services. These findings support the argument that provincial-level MPI averages hide intra-provincial inequalities, thereby emphasizing the need for district-level poverty identification (Alkire et al., 2015; Jamal, 2016; World Bank, 2018). Detailed results are presented in Table 1 below.

	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI
Abbottabad	0.563	0.482	0.271	0.329	0.474	0.156	0.407	0.450	0.183	0.327	0.490	0.160	0.193	0.472	0.091	0.227	0.433	0.098	0.299	0.452	0.135
Bajaur	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.864	0.565	0.488
Bannu	0.761	0.547	0.416	0.668	0.507	0.339	0.655	0.519	0.340	0.564	0.478	0.270	0.648	0.529	0.342	0.525	0.511	0.268	0.601	0.513	0.308
Battagram	0.900	0.592	0.533	0.833	0.536	0.446	0.631	0.519	0.328	0.505	0.495	0.250	0.632	0.542	0.343	0.711	0.573	0.407	0.516	0.509	0.263
Buner	0.945	0.656	0.621	0.828	0.577	0.477	0.727	0.553	0.402	0.654	0.530	0.346	0.567	0.541	0.307	0.632	0.524	0.331	0.771	0.516	0.398
Charsadda	0.793	0.596	0.472	0.649	0.523	0.340	0.607	0.523	0.317	0.546	0.484	0.264	0.401	0.488	0.195	0.408	0.480	0.196	0.510	0.462	0.236
Chitral	0.938	0.540	0.506	0.656	0.490	0.321	0.684	0.496	0.339	0.533	0.500	0.267	0.330	0.467	0.154	0.397	0.451	0.179	0.557	0.490	0.273
D.I. Khan	0.782	0.586	0.458	0.791	0.552	0.437	0.810	0.568	0.461	0.628	0.515	0.323	0.703	0.571	0.401	0.695	0.564	0.392	0.536	0.503	0.270
Dir Lower	0.869	0.572	0.497	0.679	0.575	0.390	0.734	0.533	0.391	0.593	0.520	0.308	0.616	0.482	0.297	0.472	0.496	0.234	0.634	0.521	0.330
Dir Upper	0.973	0.655	0.638	0.888	0.589	0.523	0.859	0.571	0.490	0.627	0.514	0.322	0.747	0.557	0.416	0.814	0.581	0.473	0.748	0.542	0.406
Hangu	0.721	0.554	0.400	0.683	0.531	0.363	0.599	0.524	0.314	0.715	0.529	0.378	0.521	0.486	0.253	0.374	0.473	0.177	0.751	0.498	0.374
Haripur	0.625	0.541	0.339	0.410	0.479	0.196	0.353	0.478	0.169	0.362	0.466	0.169	0.299	0.462	0.138	0.318	0.462	0.147	0.282	0.472	0.133
Karak	0.810	0.570	0.461	0.751	0.525	0.394	0.745	0.582	0.433	0.746	0.556	0.415	0.576	0.515	0.297	0.575	0.518	0.298	0.359	0.459	0.165
Khyber	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.484	0.479	0.231
Kohat	0.775	0.567	0.439	0.542	0.508	0.275	0.580	0.528	0.306	0.556	0.507	0.282	0.412	0.522	0.215	0.413	0.471	0.195	0.599	0.490	0.294
Kohistan	0.983	0.644	0.634	0.865	0.530	0.458	0.931	0.627	0.584	0.842	0.555	0.467	0.901	0.557	0.502	0.806	0.625	0.504	0.917	0.631	0.579
Kurram	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.615	0.540	0.332
Lakki Marwat	0.835	0.593	0.496	0.757	0.534	0.404	0.790	0.549	0.434	0.676	0.537	0.363	0.689	0.570	0.393	0.624	0.561	0.350	0.590	0.523	0.309
Malakand	0.847	0.596	0.505	0.667	0.529	0.353	0.610	0.483	0.295	0.356	0.467	0.166	0.388	0.501	0.194	0.348	0.482	0.168	0.432	0.455	0.196
Mansehra	0.716	0.531	0.380	0.615	0.514	0.316	0.605	0.521	0.315	0.478	0.533	0.255	0.427	0.508	0.217	0.391	0.489	0.191	0.424	0.494	0.210
Mardan	0.701	0.560	0.393	0.602	0.493	0.297	0.575	0.497	0.286	0.513	0.495	0.254	0.395	0.470	0.186	0.343	0.471	0.161	0.474	0.452	0.214
Mohmand	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.930	0.602	0.560

North Waziristan	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.599	0.514	0.308
Nowshera	0.654	0.531	0.348	0.454	0.461	0.209	0.410	0.467	0.191	0.605	0.515	0.311	0.346	0.496	0.172	0.321	0.467	0.150	0.439	0.451	0.198
Orakzai	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.827	0.514	0.425
Peshawar	0.624	0.569	0.356	0.525	0.509	0.267	0.375	0.495	0.185	0.408	0.497	0.203	0.235	0.466	0.109	0.319	0.483	0.154	0.500	0.445	0.223
Shangla	0.941	0.683	0.642	0.829	0.572	0.474	0.778	0.565	0.440	0.781	0.573	0.448	0.710	0.600	0.427	0.699	0.560	0.391	0.834	0.538	0.448
South Waziristan	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.712	0.523	0.372
Swabi	0.713	0.554	0.395	0.605	0.517	0.312	0.533	0.489	0.260	0.489	0.491	0.240	0.289	0.473	0.137	0.269	0.476	0.128	0.409	0.479	0.196
Swat	0.834	0.610	0.509	0.609	0.514	0.313	0.759	0.573	0.435	0.614	0.525	0.322	0.476	0.505	0.240	0.436	0.461	0.201	0.515	0.509	0.262
Tank	0.866	0.580	0.503	0.746	0.547	0.409	0.778	0.559	0.435	0.731	0.541	0.395	0.751	0.561	0.422	0.786	0.599	0.471	0.547	0.521	0.285
Torghar	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.837	0.616	0.515	0.828	0.627	0.519	0.590	0.533	0.314

Source: Authors’ calculations

5.2. Interpretation of District-Level MPI Figures (Spatial and Temporal Variation)

Kohistan, Shangla and Dir Upper are persistently highly deprived and their geographical location and structural disadvantages are linked to each other in a number of ways that explain the persistence of multidimensional poverty.

Barriers related to terrain make it more expensive and challenging to provide services. Poor topography, low population density and inadequate transport links increase the cost of service delivery (Government of Khyber Pakhtunkhwa, 2018). Second, conflict legacies and institutional fragility affected the districts that were affected by conflict and displacement in 2007 to 2009, including Shangla, Buner, Swat and other affected areas, which continued to suffer from high rates of deprivation due to the destruction of schools, health facilities, roads and administrative facilities (Avis, 2016). Third, the demographic pressure and the high dependency ratio lead to lower investment capacity of households. Districts with persistently high MPI generally exhibit larger household sizes and higher dependency burdens, which place pressure on household resources and reduce the ability to invest in education, healthcare and improved living conditions. The econometric findings of this study also support this relationship as dependency ratio is positively and significantly associated with MPI. These mechanisms help explain why multidimensional poverty remains persistently high in remote districts despite overall provincial improvement.

The data of 2019–20 highlight the deprivation in the newly merged districts as for the first time these districts were included in the data, where MPI values are at the highest level. Mohmand recorded an MPI of 0.560, Bajaur 0.488, Orakzai 0.425, and North Waziristan 0.308, all with high headcount ratios and high intensity levels. Inclusion of these districts in surveys suggests that spatial disadvantage has not reduced over time but has expanded geographically.

Overall the estimates indicate that multidimensional poverty has declined at the provincial level but district-level MPI values remain highly polarized. The results show that low-MPI districts generally recorded values below 0.20–0.25 whereas high-poverty districts frequently recorded MPI values between 0.40 and 0.50. These numerical gaps show that multidimensional poverty in Khyber Pakhtunkhwa is structural rather than transitional. It is evident that reductions in headcount are often not matched by a reduction in the intensity of deprivation.

5.3. Dimension-Wise Contribution to Multidimensional Poverty

This section examines the contribution of the three dimensions to the Multidimensional Poverty Index (MPI). The results highlight that the living standards dimension is the largest contributor to MPI in the majority of the districts of Khyber Pakhtunkhwa, followed by education, whereas the contribution of the health dimension is the smallest. Deprivation is dominant in the living standards dimension which shows the widespread lack of improved housing quality, sanitation, energy access, overcrowding, and asset ownership, indicating that material conditions are central drivers of multidimensional poverty in KP (UNDP, 2010; Alkire et al., 2015; Jamal, 2016).

5.3.1. Education Deprivation: Structural and Intergenerational Constraints

The variables such as years of schooling, school attendance, and quality of education reflect both stock and flow dimensions of human capital deficiency. Districts like Dir Upper, Kohistan, Shangla, Bajaur, Hangu, Mohmand, North and South Waziristan show high education-related deprivation. These findings are consistent with previous studies showing that educational deprivation in Pakistan is strongly spatial and intergenerational in nature (Sen, 1999; Chaudhuri, 2003; World Bank, 2018).

5.3.2. Health Deprivation: Lower Contribution but Persistent Risks

The study suggests that compared to education and living standards, the contribution of the health dimension to MPI is comparatively lower. However, a lower contribution does not mean absence of vulnerability. In some districts such as Tank, Kohistan, Mohmand, deprivation in health cannot be ignored. Antenatal check-ups and childbirth assistance by trained health personnel remain important contributors, showing limited access to maternal health services. Child vaccination deprivation contributes less to the MPI (Health dimension), but remains relevant in districts with weak outreach and limited health services availability. The comparatively smaller contribution of health indicators suggests that basic health interventions have been more evenly addressed than education and infrastructure, though some disparities persist.

5.3.3. Living Standards: The Dominant Driver of MPI

The living standards dimension including improved water, sanitation, wall construction material, overcrowding, electricity, cooking fuel, and asset ownership is the single largest contributor to MPI across almost all districts of KP and survey rounds. High score of deprivation in this dimension is evident in highly deprived remote districts, where households face infrastructural deficits in multiple indicators. The living standards dimension dominates MPI largely due to multiple overlapping deprivations across its indicators. In these indicators, improved sanitation and safe drinking water are the main contributors in persistently deprived districts which show lack of basic public services and necessities. Similarly, overcrowding and poor wall construction material greatly affects districts welfare. Access to electricity and clean cooking fuel is also inadequate, which increases economic vulnerability and environmental and health issues. Lack of asset ownership is also widespread in low-income districts, showing low capacity to absorb shocks.

The results support the argument that poverty in KP is not only income-based but deeply rooted in insufficient physical infrastructure, which constrains well-being even when households are not income-poor (UNDP, 2010; Alkire & Santos, 2014; Hallegatte et al., 2016).

5.4. Temporal Evolution of Multidimensional Poverty in Khyber Pakhtunkhwa

The temporal Multidimensional Poverty Index (MPI) shows extensive and uneven progress in multidimensional poverty reduction throughout the districts of Khyber Pakhtunkhwa (KP) from 2004–05 to 2019–20. Overall, the province experienced a gradual decline in MPI levels, reflecting improvements in access to education, basic healthcare services, and living standards indicators. This trend of poverty reduction is a dynamic process shaped by economic growth, public investment, and demographic change (Alkire & Foster, 2011; Ravalli on, 2016).

Phase I: Slow Progress and Structural Constraints (2004–05 to 2008–09)

This period predates major social protection expansion. The Benazir Income Support Programme (BISP) was launched in 2008, toward the end of this phase. The lack of coordinated poverty reduction programs during this period explains the minimal MPI improvement. During the period of 2004–05 to 2008–09, MPI values were high in most of the districts, particularly in Shangla, Kohistan, Dir Upper, Lower Dir, Battagram, Swat, Chitral, Malakand, Tank and Buner. In contrast some urbanized districts such as Peshawar, Haripur, and Abbottabad were comparatively better.

Phase II: Accelerated Decline and Service Expansion (2010–11 to 2014–15)

Three major policy developments coincided with the observed reduction in multidimensional poverty during 2010–2015. First, the Benazir Income Support Programme (BISP) significantly expanded social protection coverage among low-income households, including in Khyber Pakhtunkhwa, with increasing emphasis on education and health-related conditional support mechanisms. Second, the provincial health protection initiative later institutionalized through the Sehat Sahulat Program, expanded access to secondary healthcare services for vulnerable households. Third, improvements in rural electrification and infrastructure connectivity increased household access to basic services in several districts. Although causal attribution cannot be established directly within this study, the temporal association suggests that these interventions may have contributed to improvements in MPI indicators during this period (BISP, 2015; Government of Khyber Pakhtunkhwa, 2016). The years from 2010–11 to 2014–15 are a notable period in MPI reduction across many KP districts. In this phase, the expansion of social protection programs, improvements in school enrollment, greater maternal and child health outreach, better electrification and development in infrastructure occurred simultaneously. In this period, Swat, Chitral, Mansehra, and Malakand showed remarkable progress in MPI reduction. This is due to improvements in education indicators and selected health indicators.

Phase III: Stagnation and Partial Reversal (2019–20)

During this period, progress slowed in various districts. MPI reduction slowed or reversed despite continued BISP expansion. The COVID-19 pandemic and lockdowns and the merger of new districts (Ex-FATA) made a major contribution to this reversal. This pattern suggests MPI gains are vulnerable to climate and health shocks.

MPI values in various districts either nearly remained the same or slightly increased. The reversal in MPI values in some districts strongly supports the vulnerability literature which underlines the fact that households may escape poverty temporarily but there remains a substantial risk of falling back into poverty (Chaudhuri, 2003; Dercon, 2006).

5.5. Spatial Inequality and Temporal Evolution in Multidimensional Poverty

The temporal estimation results exhibit an overall decline in multidimensional poverty in Khyber Pakhtunkhwa (KP) for the period 2004–05 to 2019–20 but this overall development hides distinct spatial disparities. Multidimensional poverty in KP is uneven, showing persistent regional inequalities. District-wise categorization has been carried out in the study, and districts have been categorized over time on the basis of MPI levels, as tabulated below.

In the table the newly formed districts (formerly known as FATA) are also included in the 2019-20 survey year. The districts have been categorized on the basis of MPI value as very high (MPI $\geq$ 0.50), high (0.33 $\leq$ MPI $<$ 0.50), moderate (0.20 $\leq$ MPI $<$ 0.33) and low (MPI $<$ 0.20). The results show that in 2004-05, nine districts were placed in the very high category, fourteen districts were in the high category and only one district was placed in the moderate MPI category, whereas no district fell into the low MPI category. In the next survey year (2006-07) majority of the districts fell in the high MPI category, and 8 districts fell in the moderate MPI category whereas only two districts, namely, Abbottabad and Haripur fell into the low MPI category. Up to 2014-15 substantia progress was observed but in the last survey year (2019-20) a reversal was observed and only 6 districts are categorized as low MPI districts, whereas in 2014-15 the number in this category was double. A comparison of MPI values across districts in terms of highest and lowest values, shows that as per Government of Pakistan, Planning Commission, 2016 report, in Balochistan the highest MPI values was recorded as 0.641for Killa Abdullah, in Sindh province the highest value is 0.504 for District Umerkot. In Punjab province, the highest MPI value is 0.357 for District Rajanpur, and the highest MPI values in KP province is 0.571 for District Torghar (Planning Commission, 2016). However, according to our calculations Torghar MPI value is 0.519 for survey year 2014-15. On the other hand the lowest values for the same period in different districts were 0.213 for Quetta (Balochistan), 0.019 for Karachi (Sindh), 0.017 for Lahore (Punjab) and 0.110 for Haripur (KP). However, as per our calculations it is 0.147 for Haripur (Planning commission, 2016), but according to our estimates the lowest MPI value is recorded for District Abbottabad in 2014-15, that is 0.098.

5.6 Synthesizing Drivers: A Conceptual Model of Persistent Multidimensional Poverty in KP

The patterns documented in Sections 5.2–5.5 reveal three empirical regularities that any explanatory model must account for:

(1) Spatial concentration of poverty in twelve districts that account for approximately 65% of the multidimensionally poor population (based on headcount ratios weighted by district population shares) despite representing 12 of 32 districts (37.5%). These 12 districts are: Kohistan, Mohmand, Bajaur, Shangla, Orakzai, Dir Upper, Buner, Hangu, South Waziristan, Kurram, Torghar, and Lakki Marwat.

(2) Temporal vulnerability to shocks, evidenced by MPI reversal in 17 districts after 2014-15, with MPI increasing from 2014-15 to 2019-20. These districts are: Abbottabad (0.098 → 0.135), Bannu (0.268 → 0.308), Buner (0.331 → 0.398), Charsadda (0.196 → 0.236), Chitral (0.179 → 0.273), Dir Lower (0.234 → 0.330), Hangu (0.177 → 0.374), Kohat (0.195 → 0.294), Kohistan (0.504 → 0.579), Malakand (0.168 → 0.196), Mansehra (0.191 → 0.210), Mardan (0.161 → 0.214), Nowshera (0.150 → 0.198), Peshawar (0.154 → 0.223), Shangla (0.391 → 0.448), Swabi (0.128 → 0.196), and Swat (0.201 → 0.262). This reversal suggests that poverty reduction gains are fragile and susceptible to economic, climatic and security shocks.

(3) Structural persistence despite overall provincial decline. Among the ten districts with the highest MPI in 2004-05 (Dir Upper, Shangla, Kohistan, Buner, Battagram, Chitral, Swat, Malakand, Tank, and Dir Lower), 7 remain among the 10 highest MPI districts in 2019-20 (Kohistan, Shangla, Dir Upper, Buner, Mohmand, Bajaur, and Orakzai with newly merged districts Mohmand, Bajaur, and Orakzai now included). This persistence indicates that multidimensional poverty in KP is deeply rooted in structural characteristics.

Table 2. Categorization of Districts by MPI Level

MPI Category	2004–05	2006–07	2008–09	2010–11	2012–13	2014–15	2019–20
Very High MPI	Shangla, Dir Upper, Kohistan, Buner, Battagram, Swat, Chitral, Malakand, Tank	Dir Upper	Kohistan	None	Torghar, Kohistan	Torghar, Kohistan	Kohistan, Mohmand
High MPI	Dir Lower, Lakki Marwat, Charsadda, Karak, D.I. Khan, Kohat, Bannu, Hangu, Swabi, Mardan, Mansehra, Peshawar, Nowshera, Haripur	Buner, Shangla, Kohistan, Battagram, D.I. Khan, Tank, Lakki Marwat, Karak, Dir Lower, Hangu, Malakand, Charsadda, Bannu	Dir Upper, D.I. Khan, Shangla, Swat, Tank, Lakki Marwat, Karak, Buner, Dir Lower, Bannu, Chitral	Kohistan, Shangla, Karak, Tank, Hangu, Lakki Marwat, Buner	Shangla, Tank, Dir Upper, D.I. Khan, Lakki Marwat, Battagram, Bannu	Dir Upper, Tank, Battagram, D.I. Khan, Shangla, Lakki Marwat, Buner	Bajaur, Shangla, Orakzai, Dir Upper, Buner, Hangu, South Waziristan, Kurram, Dir Lower
Moderate MPI	Abbottabad	Chitral, Mansehra, Swat, Swabi, Mardan, Kohat, Peshawar, Nowshera	Battagram, Charsadda, Mansehra, Hangu, Kohat, Malakand, Mardan, Swabi	D.I. Khan, Dir Upper, Swat, Nowshera, Dir Lower, Kohat, Bannu, Chitral, Charsadda, Mansehra, Mardan, Battagram, Swabi, Peshawar	Buner, Dir Lower, Karak, Hangu, Swat, Mansehra, Kohat	Karak, Bannu, Swat	Torghar, Lakki Marwat, Bannu, North Waziristan, Kohat, Tank, Chitral, D.I. Khan, Battagram, Swat, Charsadda, Khyber, Peshawar, Mardan, Mansehra
Low MPI	None	Haripur, Abbottabad	Nowshera, Peshawar, Abbottabad, Haripur	Haripur, Malakand, Abbottabad	Charsadda, Malakand, Mardan, Chitral, Haripur, Swabi, Peshawar, Abbottabad	Charsadda, Kohat, Mansehra, Chitral, Hangu, Malakand, Mardan, Peshawar, Nowshera, Haripur, Swabi, Abbottabad	Nowshera, Malakand, Swabi, Karak, Abbottabad, Haripur

6. ROLE OF GEOGRAPHY AND REMOTENESS

The geographical position of a district is also a key factor in shaping district-level MPI outcomes. It is evident from this study that mountainous terrain and geographic isolation substantially increase the cost and difficulty of service delivery, particularly in remote and newly merged districts. In these districts, the headcount ratios and deprivation intensity remained constantly high. These geographic limitations worsen deprivation in living standards indicators such as access to improved sanitation, clean cooking fuel, and electricity, thereby increasing overall MPI.

These results are consistent with global evidence stating that topography and remoteness are significant predictors of multidimensional poverty, particularly in low-income and fragile regions (Bird, Higgins, & Harris, 2010). In Pakistan, regional differences in public investment and service provision further expand topographical disadvantages (Jamal, 2016; World Bank, 2019).The spatial distribution of MPI in KP suggests the existence of policy-relevant poverty clusters, particularly in geographically remote and conflict-affected districts such as Upper Dir, Kohistan, Shangla, Bajaur, Hangu, Mohmand, and North and South Waziristan. These clusters highlight the limitations of uniform poverty reduction policies. Therefore the evidence supports spatially targeted interventions. International practice suggests that geographically targeted infrastructure investment and human capital programs are necessary and effective in reducing multidimensional poverty in such areas (Kanbur & Venables, 2005; World Bank, 2009).

The preceding analysis demonstrates that multidimensional poverty in KP exhibits strong spatial and temporal variation. However, the robustness and sensitivity of the MPI estimates must also be evaluated." Accordingly, the MPI was re-estimated using an alternative poverty cut-off (k = 1/4), with the results presented in Table 3.

District	2004-05 H	2004-05 A	2004-05 MPI	2006-07 H	2006-07 A	2006-07 MPI	2008-09 H	2008-09 A	2008-09 MPI	2010-11 H	2010-11 A	2010-11 MPI	2012-13 H	2012-13 A	2012-13 MPI	2014-15 H	2014-15 A	2014-15 MPI	2019-20 H	2019-20 A	2019-20 MPI
Abbottabad	0.793	0.424	0.336	0.559	0.372	0.208	0.671	0.385	0.258	0.548	0.407	0.223	0.447	0.364	0.163	0.485	0.355	0.172	0.553	0.376	0.208
Bajaur	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.980	0.532	0.521
Bannu	0.945	0.496	0.468	0.877	0.425	0.373	0.871	0.463	0.403	0.862	0.413	0.356	0.839	0.473	0.397	0.774	0.438	0.339	0.794	0.460	0.365
Batagram	0.977	0.568	0.554	0.938	0.488	0.457	0.819	0.467	0.383	0.692	0.437	0.303	0.847	0.477	0.404	0.878	0.519	0.455	0.795	0.432	0.344
Buner	0.995	0.638	0.635	0.937	0.500	0.469	0.915	0.500	0.457	0.864	0.469	0.405	0.796	0.466	0.371	0.855	0.461	0.395	0.911	0.481	0.438
Charsadda	0.927	0.552	0.512	0.794	0.463	0.367	0.826	0.459	0.379	0.789	0.425	0.335	0.641	0.412	0.264	0.632	0.411	0.260	0.700	0.414	0.290
Chitral	0.980	0.529	0.519	0.944	0.415	0.392	0.938	0.438	0.411	0.792	0.433	0.343	0.729	0.364	0.266	0.748	0.369	0.276	0.896	0.411	0.368
D.I.Khan	0.936	0.537	0.502	0.901	0.494	0.445	0.938	0.530	0.497	0.836	0.458	0.383	0.876	0.514	0.450	0.853	0.512	0.437	0.766	0.438	0.335
Hangu	0.920	0.496	0.456	0.854	0.446	0.381	0.861	0.451	0.389	0.883	0.483	0.427	0.776	0.420	0.326	0.625	0.397	0.248	0.888	0.465	0.413
Haripur	0.827	0.479	0.396	0.675	0.394	0.266	0.643	0.393	0.253	0.617	0.390	0.240	0.520	0.389	0.202	0.542	0.389	0.211	0.543	0.384	0.209
Karak	0.971	0.521	0.507	0.893	0.445	0.397	0.916	0.526	0.482	0.911	0.508	0.463	0.786	0.455	0.358	0.759	0.462	0.351	0.570	0.394	0.225
Khyber	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.798	0.403	0.321
Kohat	0.877	0.534	0.469	0.730	0.419	0.306	0.804	0.460	0.370	0.790	0.441	0.348	0.660	0.432	0.285	0.657	0.401	0.264	0.763	0.447	0.341
Kohistan	1.000	0.638	0.638	0.986	0.481	0.474	0.991	0.607	0.602	0.974	0.519	0.505	0.988	0.534	0.528	0.980	0.566	0.555	0.994	0.605	0.601
Kurram	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.836	0.472	0.395
Lakki Marwat	0.964	0.553	0.533	0.928	0.459	0.426	0.925	0.511	0.473	0.876	0.480	0.420	0.861	0.515	0.443	0.824	0.495	0.408	0.783	0.463	0.363
Lower Dir	0.961	0.546	0.524	0.831	0.500	0.415	0.969	0.470	0.456	0.858	0.448	0.384	0.798	0.437	0.349	0.738	0.420	0.310	0.849	0.461	0.392
Malakand	0.951	0.562	0.535	0.831	0.467	0.388	0.864	0.425	0.367	0.605	0.392	0.237	0.608	0.423	0.258	0.639	0.390	0.249	0.698	0.391	0.272
Mansehra	0.896	0.483	0.433	0.810	0.443	0.359	0.822	0.459	0.377	0.728	0.447	0.326	0.709	0.420	0.298	0.647	0.407	0.263	0.680	0.415	0.282
Mardan	0.881	0.504	0.444	0.790	0.429	0.339	0.823	0.433	0.357	0.733	0.433	0.318	0.620	0.402	0.249	0.600	0.389	0.233	0.704	0.398	0.280
Mohmand	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.981	0.585	0.574
North Waziristan	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.87	0.44	0.386
Nowshera	0.859	0.473	0.406	0.661	0.401	0.265	0.639	0.401	0.256	0.864	0.445	0.385	0.520	0.425	0.221	0.487	0.405	0.197	0.642	0.400	0.257
Orakzai	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.979	0.478	0.468
Peshawar	0.771	0.515	0.397	0.722	0.426	0.308	0.567	0.424	0.240	0.680	0.412	0.280	0.412	0.387	0.159	0.442	0.427	0.189	0.634	0.411	0.261
Shangla	0.991	0.663	0.657	0.957	0.504	0.482	0.915	0.524	0.480	0.922	0.530	0.488	0.907	0.533	0.483	0.889	0.500	0.445	0.964	0.503	0.485
South Waziristan	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.903	0.473	0.427
Swabi	0.916	0.494	0.453	0.830	0.433	0.359	0.791	0.422	0.333	0.768	0.415	0.319	0.570	0.379	0.216	0.479	0.391	0.187	0.643	0.409	0.263
Swat	0.947	0.572	0.542	0.819	0.430	0.352	0.906	0.529	0.479	0.825	0.465	0.383	0.757	0.423	0.320	0.695	0.394	0.274	0.776	0.433	0.336
Tank	0.956	0.554	0.529	0.925	0.475	0.439	0.951	0.509	0.484	0.916	0.490	0.449	0.921	0.511	0.470	0.915	0.554	0.508	0.825	0.437	0.360
Torghar	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.971	0.571	0.554	0.968	0.577	0.559	0.854	0.458	0.391
Dir Upper	0.995	0.647	0.644	0.974	0.531	0.518	0.984	0.533	0.525	0.858	0.452	0.387	0.927	0.504	0.467	0.956	0.537	0.514	0.926	0.493	0.456

7. SENSITIVITY ANALYSIS: COMPARISON OF K = 1/3 AND K =1/4 (ROBUSTNESS CHECK: ALTERNATIVE CUT-OFF (K = 1/4))

To test whether district rankings are sensitive to the poverty cut-off, we re-estimated MPI using an alternative threshold of k = 1/4 (households deprived in 25% of weighted indicators). The MPI results under the alternative cut-off (k = 1/4) show higher values across districts, as expected due to the lower threshold. The relative ranking of districts remains stable. Districts like Kohistan, Shangla, Dir Upper, and many of the newly merged districts continue to record the highest MPI values under both cut-off values. However, the absolute classification of districts changes in two ways. First the number of districts classified as "very high MPI" (using the categorization in Table 2) increases from 2 to 9 when moving from k = 1/3 to k = 1/4. Second, districts with MPI values just below the k = 1/3 threshold (0.30–0.33) become classified as multidimensionally poor under k = 1/4. In KP, this includes Swabi (MPI 0.196 at k = 1/3, 0.263 at k = 1/4), Nowshera (0.198 → 0.257), and Mardan (0.214 → 0.280). This consistency in the ranking of districts based on MPI suggests that spatial poverty patterns in Khyber Pakhtunkhwa are persistent. Although absolute poverty levels change under different cut-offs, the overall spatial distribution and deprivation clustering remain robust. This alternative check strengthens the reliability of the empirical findings of this study and confirms that district-level disparities are not driven by methodological choices.

7.1 Robustness Assessment: Correlation Analysis and Theoretical Consistency

Table 4. Pairwise Correlation Matrix

Variables	MPI	Dependency Ratio	Road (km² per km)	Casual Workers (%)
MPI	1.000			
Dependency Ratio	0.726***	1.000		
Road (km² per km)	0.455***	0.454***	1.000	
Casual Workers (%)	0.234***	0.179**	0.124	1.000

Source: Authors' calculations

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

In order to better determine the strength of the empirical findings, a pairwise correlation analysis was conducted between the Multidimensional Poverty Index (MPI) and the main explanatory variables, shown in Table 4.

The results indicate that there are positive and statistically significant correlations between MPI and dependency ratio ($r = 0.726$, $p < 0.01$), road infrastructure variable ($r = 0.455$, $p < 0.01$), and households in casual labour ($r = 0.234$, $p < 0.01$). The findings are similar to those of the fixed-effects regression estimates, which also find that the relationships are theoretically valid and empirically valid. Furthermore, the results obtained with different poverty thresholds ($k = 1/3$ and $1/4$) further increase the robustness of the results of this study.

8. ANALYZE AND INTERPRET THE ECONOMETRIC RESULTS.

The description of the different dimensions of spatial disparities in Section 5 does not provide any insight into the structural causes of these disparities. This section attempts to supplement descriptive analysis by estimating a panel model with fixed-effects at the district level to explore how multidimensional poverty is related to three theoretically motivated factors: demographic dependency, road infrastructure, and labor market vulnerability. With this method, temporal differences among districts are captured, while district-specific differences over time are taken into account with district-specific variables such as geography, historical development paths, institutional capacity and socio-cultural structures that are possible because they are static. Year fixed effects further account for common macroeconomic or policy shocks affecting all districts, including national economic and climatic shocks.

$$MPI_{dt} = \alpha + \beta 1 Dep_{dt} + \beta 2 Road_{dt} + \beta 3 Casual_{dt} + \mu d + \lambda t + \epsilon_{dt}$$

Where MPI_{dt} represents the Multidimensional Poverty Index for district "d" at time "t", Dep_{dt} represents the dependency ratio; $Road_{dt}$ indicates road infrastructure (km² per km of road) and $Casual_{dt}$ denotes the percentage of households engaged in casual labor. α is the constant term, $\beta_1, \beta_2, \beta_3$ are the estimated coefficients, "μd" captures district fixed effects, "λt" shows year fixed effects, and ϵ_{dt} is the error term.

The results of the fixed effects model are presented below.

Table 5. Determinants of District-Level Multidimensional Poverty (Fixed-Effects Estimates)

Variables	MPI
Dependency ratio	0.0012539*** (0.0004195)
Km² per km of road	0.0074021*** (0.0024983)
Households with casual workers (%)	0.0024629*** (0.0002982)
Year fixed effects	Yes
District fixed effects	Yes

Observations	178
Number of districts	32
Within R^2	0.7639
Between R^2	0.3137
Overall R^2	0.5930
F-statistic	62.73
Prob > F	0.0000
ρ (fraction of variance due to district effects)	0.7824

Source: Authors' calculations

Notes: Cluster-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Base year = 2004–05.

Table 5 presents the district-level fixed-effects regression results for the determinants of multidimensional poverty (MPI) across the districts over time. The model controls both district fixed effects and year fixed effects. This means that the estimates capture changes within each district over time accounting for unobserved, time-invariant district characteristics and common year specific shocks. The use of district level cluster robust standard errors further strengthens the reliability of the estimations by addressing heteroskedasticity and serial correlation in districts.

The coefficient of the dependency ratio is positive and statistically significant at the 1 percent level ($\beta = 0.0012539$, $p = 0.005$). This shows that districts with higher dependency burden tend to record higher multidimensional poverty. As dependency ratio increases, the economic pressure on households also rises, thereby limiting expenditure on education, health, and living standards. A high dependency ratio consequently worsens multidimensional deprivation by lowering the capability of productive household members to support non-working members. The coefficient for km^2 per km of road (road density) is also positive and statistically significant at the 1 percent level ($\beta = 0.0074021$, $p = 0.006$). This variable indicates that the land area served or connected by each kilometer of road, and a higher value suggests lower road density and hence poorer road and transport connectivity. The positive sign shows that, districts with weaker road infrastructure face higher multidimensional poverty. This is essentially important as poor road access restricts mobility, reduces access to schools, health facilities, markets, and employment opportunities, and therefore raises costs for households and firms. The households with casual workers have the most statistically robust coefficient in this model ($\beta = 0.0024629$, $p < 0.001$). This indicates that districts with a greater prevalence of casual labor tend to show significantly higher MPI. Casual employment is usually linked with low wages, insecurity, lack of social protection, and unstable income. Such labor market conditions directly undermine household welfare and make it more difficult for families to invest in health, education, housing, and basic welfare conditions.

The explanatory power of the model is high. The value of R^2 (0.7639) indicates that around 76.4 percent of the variation in multidimensional poverty within districts over time is explained by the variables included in the model and the time effects. The joint significance of the model is also confirmed by an F-statistic of 62.73 with a p value (0.0000), indicating that the regressors together are highly significant. The reported rho value (ρ = 0.7824) is very important. It indicates that about 78.2 percent of the total variance in MPI is attributable to district-specific effects, whereas only around 21.8 percent is due to idiosyncratic within-district variation. This shows that persistent structural differences across districts, such as geography, historical disadvantage, institutional weakness, infrastructure differences and socioeconomic conditions play a leading role in shaping multidimensional poverty. Therefore, this result strongly justifies the use of a fixed-effects framework. Overall Table 5 provides strong evidence that at the district level demographic pressure, infrastructure weakness and labor market vulnerability are important and statistically significant determinants of multidimensional poverty. The findings suggest that policies aimed at reducing dependency burdens, expanding road connectivity and providing permanent employment opportunities could substantially contribute to poverty reduction across districts.

Table 6. Year Effects in District-Level Multidimensional Poverty (Base Year: 2004–05)

Year	Coefficient	Std. Error	t-value	P>|t|	95% Confidence Interval
2006–07	-0.0673858***	0.0149135	-4.52	0.000	[-0.097802 -0.0369695]
2008–09	-0.1083356***	0.0185387	-5.84	0.000	[-0.1461456 -0.0705256]
2010–11	-0.1595690***	0.0221738	-7.20	0.000	[-0.2047927 -0.1143453]
2012–13	-0.1561591***	0.0190273	-8.21	0.000	[-0.1949655 -0.1173526]
2014–15	-0.1664401***	0.0212759	-7.82	0.000	[-0.2098327 -0.1230476]
2019–20	-0.1489544***	0.0234736	-6.35	0.000	[-0.1968292-0.1010796]

Source: Authors' calculations

Table 6 shows the estimated year effects in the fixed-effects model, setting 2004–05 as the reference year. All year coefficients are negative and statistically significant which shows that district-level multidimensional poverty is lower in each subsequent survey round relative to the base year.

The regression results explain the descriptive patterns from Section 5 in the following ways.

The reversal in MPI after 2014-15 (documented in Section 5.5) is not explained by the structural variables, which change slowly. The year fixed effects (Table 6) capture this reversal, with the 2019-20 coefficient (-0.149) being smaller in magnitude than the 2014-15 coefficient (-0.166). This suggests that external shocks such as drought and COVID-19 eroded earlier gains. The high rho value ($\rho = 0.782$) in Table 5 indicates that 78% of MPI variance is attributable to district-specific effects. This confirms the descriptive finding (Section 5.2) that spatial inequality is structural, not transitory. The coefficient for 2006–07 survey year is -0.0674, indicating that MPI declined significantly compared to 2004–05. The reduction in MPI deepens further in the 2008–09 survey year (-0.1083), signifying that multidimensional poverty continued to decline. The largest decline was observed in the year 2014–15 (-0.1664), followed by 2010–11 and 2012–13 which show that the most considerable improvements in district-level welfare mainly occurred in the middle phase of the survey periods.

Although MPI remained substantially lower than the base year, the smaller magnitude of the 2019–20 coefficients suggests partial reversal or slowing progress. It is somewhat smaller in magnitude than that of 2014–15. This suggests that multidimensional poverty in 2019–20 is still much lower than in 2004–05. Overall multidimensional poverty declined significantly throughout the study period. The yearly negative effects at the district level capture the combined influence of wider economic and social changes, including improvements in public services, infrastructure development, welfare interventions, educational progress, poverty targeted programs, and structural changes throughout the province.

9. DISCUSSION

This study provides a comprehensive district-level analysis of multidimensional poverty in Khyber Pakhtunkhwa (KP) for the period 2004–05 to 2019–20, by combining education, health and living standards into a unified Multidimensional Poverty Index (MPI), while also highlighting the important role of the geographical position of districts . The findings contribute to the literature highlighting that poverty is a multifaceted and spatially driven phenomenon.

9.1. Uneven Progress across Dimensions

An important finding of the study is the unequal contribution of different dimensions to MPI across the districts and over time. Improvements in education, mainly in school attendance have contributed to MPI reductions in many districts. However, health indicators (vaccination, antenatal care, assisted delivery) and living standards indicators have shown slower and more uneven contributions. In KP, limited access to health and living-standard facilities continues to exert unequal influence on MPI in remote districts. Taken together, the results of the econometric model show that multidimensional poverty rises with a higher dependency ratio, weaker road connectivity and a greater percentage of casual labor in a district. Second, the year effects indicate that multidimensional poverty declined over time relative to 2004–05, showing overall progress in living standards throughout the province. Third, despite the temporal improvement, the study reveals deep and persistent spatial inequalities among the districts.

Practically, the results advocate that poverty in Khyber Pakhtunkhwa is dual in nature, namely, dynamic and structural. It is dynamic as it changes over time with evolving socioeconomic conditions. It is structural in nature as a large portion of poverty disparities is tied to entrenched district-level characteristics. This dual nature of poverty suggests that effective policy must combine broad-based development measures with district-specific targeted interventions.

10. COMPARISON WITH NATIONAL AND INTERNATIONAL MPI STUDIES

The MPI estimates calculated at a district-level can be compared with the national and international multidimensional poverty estimates.

Comparisons with Planning Commission of Pakistan (2016): The official Multidimensional Poverty Report of Pakistan estimated Khyber Pakhtunkhwa provincial MPI at around 0.247 in 2014-15 (Planning Commission of Pakistan & UNDP, 2016). The estimate found in this study is slightly less. Minor differences may result from variations in the specification of the indicators, the weighting used, the treatment of the indicators relating to education quality, and the aggregation method used for the sample. However, the general level and provincial positioning are generally similar to the official national level estimates.

Comparison across Pakistani provinces: Multidimensional poverty in Khyber Pakhtunkhwa remained significantly higher than that of Punjab but lower than Balochistan during the same period and the same was also true for rural Sindh which showed a relatively high level of poverty (Planning Commission of Pakistan & UNDP, 2016). These comparisons corroborate the main finding that KP lies somewhere between the two poles of the multidimensional poverty framework in Pakistan, but not equally.

International MPI estimates (UNDP & OPHI, 2023): Multidimensional poverty is strongly associated with areas where services are not readily available, human capital is low, and infrastructure is weak. The inequalities were large between districts in Khyber Pakhtunkhwa, from the relatively low MPI districts like Haripur to the most deprived districts like Kohistan, indicating subnational inequality within the province. The results confirm the international body of literature which continues to stress the spatial dimension of multidimensional poverty and the significant spatial inequalities that exist within countries.

This study's results clearly point to the importance of a need based development strategy. The districts, such as Mohmand, Bajaur, Torghar, Shangla, Orakzai etc. need targeted interventions, employment, and increased institutional investment. Likewise, the high importance of dependency ratios and casual employment in the MPI indicates that interventions in education, skills development, labour formalisation and social protection are also key for the significant impact on reducing the multidimensional poverty across the province.

10.1. Extending, Confirming, and Challenging Existing Literature

The inclusion of these districts reveals that MPI in Bajaur (0.488), Mohmand (0.560), and Orakzai (0.425) exceed the 2004-05 provincial average (0.258). Excluding these districts underestimates KP's poverty by approximately 15-20% in 2019-20.

Confirming existing literature: Our finding that dependency ratio strongly predicts MPI ($\beta = 0.00125$, $p < 0.01$) confirms Carter & Barrett's (2006) poverty traps framework for the KP context. Households with higher dependency burdens face binding constraints on human capital investment, extending the asset-based poverty traps literature to multidimensional measurement.

Challenging existing literature: Contrary to Hallegatte et al. (2016)'s suggestion that health shocks are the primary poverty driver in fragile regions, our decomposition shows health contributes least to MPI in all KP districts (average contribution 18% vs. 42% for living standards and 40% for education). This does not mean that health is unimportant but health deprivation is more evenly distributed across districts than education and living standards, making health a less discriminating factor in explaining spatial inequality.

11. CONCLUSION

This study offers a wide-ranging and dynamic assessment of multidimensional poverty in Khyber Pakhtunkhwa (KP) by combining education, health and living standards into a unified Multidimensional Poverty Index (MPI) over the period 2004-05 to 2019-20. Equal weights are assigned to all dimensions, and the weights are also distributed uniformly among different indicators within each dimension.

The findings yield three important implications. First, KP is not a homogeneous place and multidimensional poverty is structurally persistent. Although the overall time trend of MPI is declining most of the districts with very high MPI values are those that are facing severe deprivation, such as mainly Dir Upper, Kohistan and Shangla, Bajaur, Hangu, Mohmand, North Waziristan and South Waziristan, which cannot be adequately reflected in income-based poverty measures. This validates previous research that argues poverty is multidimensional in mountainous areas, chronic and less sensitive to short- term economic improvements (Chambers,1989; Kanbur & Venables,2005).

Secondly, the analysis of district-level indicators confirms that profiles of deprivation vary geographically. But some districts have education-related deprivations that dominate. Other districts have a more important impact on health and living standards indicators. The diversity in this heterogeneity is the analytical strength of MPI over 1D approaches (Alkire et al., 2015; Ligon & Schechter, 2003).

Thirdly, the temporal dynamics of MPI suggest vulnerability to shocks and uneven resiliency. Progress in several districts did not accelerate or even maintain its gains in the early 2010s, although a few made remarkable gains.

12. POLICY IMPLICATIONS AND RECOMMENDATIONS

The patterns of multidimensional poverty revealed in this study have important policy, planning and resource allocation implications. Evidence indicates that a one-size fits all approach to poverty reduction is not enough because poverty varies across time and space, both in terms of type and the magnitude of poverty.

12.1. Transitions from income to multidimensional policy frameworks.

Overall, the findings from these analyses are robust in favour of using multidimensional poverty diagnostics as a main policy tool. The results of this analysis also corroborate the global policy recommendations for using MPI-based targeting to enhance policy accuracy and effectiveness (Alkire et al., 2015; UNDP, 2020). However, adding district-level MPI indicators to the provincial development policies would help the provincial policy makers decide on which indicators are important and where to act upon when intervening.

12.2. District-Specific and Place-Based Interventions

The high concentration of multidimensional poverty in the districts of Dir Upper, Kohistan and Shangla, Bajaur, Hangu, Mohmand, North Waziristan and South Waziristan shows the need for place-based development policies. These districts face multiple disadvantages arising from remoteness, difficult terrain, limited market access and weak service delivery. International best practices suggest that spatially targeted interventions are required in such situations (Barca et al., 2012; Kanbur & Venables, 2005). For KP this implies prioritizing lagging districts for infrastructure development, human capital investments and service delivery reforms, rather than distributing resources uniformly across districts.

12.3. Education Policies: Beyond Access to Quality

As improvements in school attendance have greatly contributed to MPI reductions, quality of education and years of schooling remain serious bottlenecks in high-poverty districts. Therefore, policies should not only focus on enrollment but also on improving teacher quality and school infrastructure, especially for girls and rural populations. In developing regions gains in educational quality have stronger, more positive and long-term poverty-reducing effects compared to school access alone (Hanushek & Woessmann, 2008; Psacharopoulos & Patrinos, 2018). Scholarships, conditional cash transfers to grade completion, and district level education reforms could significantly reduce educational deprivation in KP.

12.4. Strengthening Preventive and Maternal Health Systems

Health indicators, namely, child vaccination, antenatal care, and childbirth assistance by trained helper effectively contribute to MPI. These findings highlight the need to strengthen healthcare systems and provide basic health facilities, especially maternal and child health services. This can be achieved through improving accessibility, and reducing financial and cultural constraints. Several studies are available which validate that investment in preventive health services produces high social returns and help reduce poverty in long run (Victora et al., 2010; World Bank, 2018).

12.5. Improving Living Standards through Infrastructure and Basic Services

Indicators of this dimension, namely, sanitation, clean water, electricity, housing quality, cooking fuel, and asset ownership appear as a dominant contributor to MPI in various districts. The results suggest that provision of basic infrastructure plays a key role in poverty reduction. Clean sanitation, energy, and good housing not only help in reducing deprivation, but also provide multiple opportunities for health and education improvement (Gertler et al., 2015; Duflo et al., 2008). Therefore, investments in rural electrification, clean cooking fuel, and improved sanitation infrastructure are necessary.

12.6. Evidence-Based Targeting Based on Econometric Findings

The findings of the econometric model provide further policy guidance beyond descriptive MPI analysis. Given the strong relationship between dependency ratios and MPI, social protection programs should be prioritized in districts with higher demographic burdens and dependency ratio. Investments in road infrastructure and connectivity are very necessary in mountainous and remote districts, and they will help to reduce structural deprivation.

Additionally, livelihood diversification policies must move beyond survival-based income expansion toward productivity enhancing strategies which include skills development and market integration.

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