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Measuring Children's Multidimensional Poverty under Constraints: An Empirical Exploration in Punjab, Pakistan

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Abstract

There is widespread concern that household measures of poverty, even if disaggregated by age cohorts, are not able to depict child conditions, and should be supplemented by individual child measures. There are normative reasons to prefer the most precise measure possible and practicable methods to do so. In parallel, because of the cost of data collection, and the implicit requirement that policy actors confidently master multiple indices, there is an empirical question of how results vary between these measures – e.g. for assessing which districts are the poorest. Using 2017–18 data for the Province of Punjab in Pakistan, this paper compares a household multidimensional poverty index (Proxy MPI_P) that proxies the official MPI of Pakistan, with two others: 1) the child disaggregation of that same Proxy MPI_P, and 2) an individual-level Child MPI, which is constructed at the level of the individual child and adds a fourth dimension of childhood conditions, with age-appropriate indicators such as nutrition, schooling, child labour, and child marriage. The analysis compares multidimensional poverty levels and indicator composition for all three measures across the districts of Punjab. Results show that although naturally the indicator information in the individual child measure is far richer, in this dataset, district-wise rankings are highly robust across the three multidimensional poverty measurement approaches. Further empirical assessments from different datasets and using different specifications are required to assess the generality of this finding.

Keywords: Poverty measurement, multidimensional poverty measurement, child poverty.

JEL classification: I32, J13, O1.

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1. Introduction

It is often recognised that children experience poverty differently from adults, and that children can be deprived in distinct ways at various points of their childhood and adolescence (Biggeri, Ballet, and Comim 2011; Boyden et al. 2019).

A large literature has implemented child multidimensional poverty measures (see footnote 3). These papers commonly advocate the use of individual child measures (often age-specific), rather than household measures because children experience multidimensional poverty differently. That justification is incontrovertible, but there are two additional constraints: data and policy. Extensive individual child data are lacking in some regularly implemented household surveys – such as Pakistan's PSLM. Can these MPIs illuminate any aspects of children's lives? Also, as Alkire et al (2024) elaborate, there is an additional time cost to the additional policy attention implied to competently engage disjoint measures. Hence the governments of Mexico and Chile have included child indicators and/or dimensions in their national MPIs, and used their child-disaggregated all-population, national multidimensional poverty indices (MPIs) to shape policy (CONEVAL 2020; Ministerio de Desarollo Social y Familia 2020). The reason: they assess that the child-disaggregation provides sufficient guidance for the policies it informs. Some governments have released two measures – a national MPI and a disjoint (differently structured) child MPI (Alkire et al. 2016; MIDES, MEC, and INEC 2019, OPHI and NESDEC 2019). And, to decrease the policy time cost and increase impact, some have released an individual child MPI that directly links to the national MPI (Sri Lanka 2023, Nigeria 2022). Dirksen and Alkire 2021 introduce each of these approaches and provide a critical analysis of the pros and cons of each. However as yet the discussion lacks vital empirical analysis: do linked individual child measures give distinct assessments as to where the levels of poverty are the highest?

This paper empirically implements and compares three measures for Punjab that can be made from a particular dataset somewhat align with the national MPI structure. We find that the district level analyses from the Proxy MPI (MPIP), do not provide significantly different information from the level of district poverty by the Child MPI.[1] So while the individual child MPI has more indicators hence more precision and policy information in terms of indicator composition of poverty, the district rankings of the less child-specific (but more frequently available) national MPI

[1] In related work (Alkire, Ul Haq, Alim 2019), we have also undertaken a gendered and intrahousehold individual child analysis of children's deprivations in variables such as school attendance. Such methods could also be applied to individual deprivations within the MPIs discussed here.

closely approximate those of the Child MPI. Naturally, this finding is dataset specific and needs to be examined with other datasets and measurement specifications, both across time and contexts, to ascertain its generality.

Why Punjab? As the most populous of Pakistan's regions – with a population share of 52.9%, or 110 million, according to the 2017 Census of Pakistan – (Pakistan Bureau of Statistics n.d.), Punjab is home to a large share of Pakistan's population, and furthermore contains considerable intra-provincial differences. Fully 42.9% of Punjab's population are children below the age of 18, making the province's child population larger than that of any other region in Pakistan, and, indeed, with the exception of Sindh province, larger than any overall population in other provinces or regions of Pakistan. Widespread multidimensional poverty among these children merit serious attention and analyses.

National MPI results for Punjab province showed that, in 2014/15, almost one in three (31.4%) people in Punjab were multidimensionally poor – a larger proportion than suggested by monetary metrics. On average, each poor person was deprived in about half (48.4%) of the weighted national MPI indicators. In the decade between 2004/5 and 2014/15, Punjab reduced its MPI value by 40.2% - the largest relative reduction of MPI across all provinces and regions of Pakistan. Findings also revealed that by 2014/15, deprivations in educational attainment (years of schooling) and access to health facilities were the largest contributors to multidimensional poverty levels in Punjab (Planning Commission of Pakistan, UNDP Pakistan, and OPHI 2016).

The remainder of this article proceeds as follows. Section 2 reviews the literature on child poverty, with in-depth analyses of the active literature in Punjab which has informed the motivation, direction, and analysis of this study. Section 3 presents the data used for the computations and introduces the Alkire Foster (AF) method, the structure of the original National MPI and the Proxy MPI_P, their age disaggregation, and the structure of the Child MPI. Section 4 presents the main results. Section 4.1 presents results of the proxy MPI_P for Punjab province in 2017/18. Section 4.2 provides the child-disaggregated results of the MPI_P by age, urban-rural area, division, and district. Section 4.3 presents Punjab's individual Child MPI, i.e. the MPI_P augmented by child labour and nutrition and children's cognitive development. Section 4.4 offers a comparative analysis of 1) the extent to which the household and child-disaggregated MPI_P proxy the individual Child MPI; 2) the congruence of relative patterns between the three measures, assessed by district rankings, correlations, and pairwise comparisons considering standard errors; and 3) of the congruence between the MPI_P and the levels of children's nutritional deprivation for each province. Section 5 concludes.

2. Multidimensional Poverty and Child Poverty in Punjab

Research questions relevant to this topic have been activity considered in the literature. For example, Roelen (2017), Chzhen and Ferrone (2017) and Kim (2018) found considerable divergence in level, overlap, and trend between monetary and multidimensional poverty child poverty, using longitudinal and/or cross-sectional data, but did not compare household vs child MPIs.[2]

Many authors rue the data constraints facing multidimensional child indices. For example, Hannum et al. (2017) observe that data sources often omit key variables required to assess multidimensional poverty, whereas Guio et al. (2017) observe that data on children in the EU surveys are only available at household not individual child level.

A large set of papers construct individual child multidimensional poverty indices (at times creating multiple age-specific MPIs), and analyse the levels, trends, composition, and disparities across gender, age, region or area.3 Authors most commonly utilize a logit analysis (examples include Byegon, Kabubuo-Mariara and Wambugu; Kamal Amjad Yaqoob et al; Ibara Ossouna 2021, and Dutta 2020); others use multi-level analysis (Haq and Abbas), spatial autocorrelation (Wang Hai Cai Shi 2022), Machine learning (Usman and Kopezewski), Shapley decomposition (Mujaddad and Anwar) or OLS regressions (Agyire-Tettey et al), to uncover determinants and associates of multidimensional child poverty and its reduction. While in-depth comparisons do exist for household versus gendered measures (Vijaya, Lahoti and Swaminathan 2014, Bessell 2015, Klasen and Lehoti 2020), comparable comparisons of household and individual child measures are far less evident. This paper starts to address that gap.

The next section examines the literature in Punjab Pakistan, identifying the province-specific need and value-added of the present study, and literature gaps it contributes to closing (Section 2.1). Next, it considers the available evidence on multidimensional poverty within Punjab across population subgroups and intra-provincial regions (Section 2.2). Then it reviews evidence on existing child multidimensional poverty indices, also taking into consideration a more extensive set of studies that provide age-disaggregated or child-specific results from overall multidimensional

2 Hjelm et al (2017) claim, incorrectly, that 'the MPI is not a child-specific measure' when in fact the MPI methodology is general and has been extensively used with individuals as well as households as the unit of identification.

3 Selected examples from this extensive literature include Noble et al 2006, Roelen, Gassmann, and de Neubourg 2009, 2010, 2011; Amarante, Arim, and Vigorito 2010; Alkire and Roche 2012; Callander, de Neubourg et al. 2012; Schofield, and Shrestha 2012; Roche 2013; Trani and Cannings 2013; Trani, Biggeri, and Mauro 2013; Chzhen et al. 2015; Chzhen and Ferrone 2017; Roelen 2017, 2018; Ballón et al 2018; Mishra, Ray, and Risse 2018; Hoolda 2019; Alkire, Ul Haq and Alim 2019, Klasen and Lehoti 2020; Shen and Alkire 2022; Srbinoski Petreski Petreski 2022.

poverty measures (Section 2.3). Finally, it reviews studies on individual child deprivations that identify priority indicators relevant for the measurement of children's multidimensional poverty in Punjab (Section 2.4).

2.1 Multidimensional Poverty in Punjab in National Comparison

When comparing the four provinces of Pakistan – Balochistan, Khyber Pakhtunkhwa, Punjab, and Sindh –studies on multidimensional poverty often found the level of poverty to be lowest in Punjab (Khan et al. 2011; Naveed and Ali 2012; Planning Commission of Pakistan, UNDP Pakistan, and OPHI 2016; OPHI 2023).[4] Indeed, no Punjabi district ranks among the poorest quintile in the multidimensional poverty measures for Pakistan implemented by Naveed and Ali (2012) and Naveed, Ghaus and Wood (2016), for instance, and only two rank among the 46 poorest, whereas 14 out of 23 least poor districts were located in Punjab.

Various reasons have been used to explain these relatively low poverty levels in Punjab, including, *inter alia,* the quality and availability of social service provision (Naseem 2012; Naveed, Ghaus and Wood 2016) and safety nets (Azeem 2016) in Punjab vis-à-vis other regions of Pakistan, sometimes with reference to the empirical relationship of local governance to welfare state typologies (Naveed, Ghaus and Wood 2016) or policy changes after the 18th Amendment to the Pakistani constitution, which introduced new welfare standards and granted more policy autonomy to the provinces (Jamal 2014b, Naveed and Ali 2012); the agglomeration of industries and other economic drivers and – closely related to the aforementioned – comparatively favourable infrastructural conditions in Punjab; but also the frequency and endurance of conflicts and environmental events in other parts of the country (Naveed, Ghaus, and Wood 2016).

However, with a population of about 110 million in 2017 (Pakistan Bureau of Statistics, 2017) Punjab is also, and by far, home to the largest share of Pakistan's population (52.9%), including a large share of the poor population – a fact that is frequently overlooked when poverty headcount ratios are not put into context of overall population figures (Azeem 2016; Naveed, Ghaus, and Wood 2016; Planning Commission of Pakistan, UNDP Pakistan, and OPHI 2016; Government of the Punjab 2018; OPHI 2023). Indeed, Naveed, Ghaus, and Wood (2016) found that less than

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[4] When the four provinces are taken into consideration together with the other three, considerably less populous, administrative divisions of Pakistan, including the two (autonomous) regions Azad Jammu and Kashmir, Gilgit-Baltistan, and Islamabad Capital Territory (ICT) as well as the federally administered tribal areas (FATA), these studies usually rank poverty incidence in Punjab second lowest, after ICT. One exception is Pakistan's National MPI, according to which the incidence and intensity of multidimensional poverty was lowest in Azad Jammu and Kashmir. Seeand. Planning Commission of Pakistan, UNDP Pakistan, and OPHI (2016).

a third of Punjab's districts have been found to be home to about 30% of Pakistan's multidimensionally poor and a quarter of its severely multidimensionally poor.[5]

2.2 Multidimensional Poverty in Punjab

Similarly to findings at national level, the literature on multidimensional poverty in Punjab has observed significant and persistent intra-provincial differences. The MPI and headcount ratios were generally higher in rural areas, lower in the Northern districts than in central Punjab, and highest in the south. Discrepancies are clearly visible (Jamal 2009; Naveed and ul-Islam 2010; Awan, Waqas, and Aslam 2011; Ashraf and Usman 2012; Naveed and Ali 2012; Khan et al. 2014a,b; Khan et al. 2015; Khan et al. 2016; Naveed, Ghaus, and Wood 2016; Planning Commission of Pakistan, UNDP Pakistan, and OPHI 2016; OPHI 2023; and Saleem, Shabbir, and Khan 2019). These regional patterns have been shown to be associated, *inter alia*, with higher degrees of urbanisation and industrialisation in northern districts, and with their relatively high level of integration into national and international labour markets (Cheema, Khalid, and Patnam 2008; Naveed, Ghaus, and Wood 2016).

Disaggregated results of the Pakistan National MPI results for Punjab confirmed findings from the literature, revealing overall positive trends, but persistent urban-rural inequalities. In 2014/5, 43.7% of the rural Punjabi population were multidimensionally poor, compared to 6.3% among those living in urban areas. Results also showed that, across the 36 districts of Punjab, the incidence of multidimensional poverty was highest in the south-western districts of Muzaffargarh, Rajanpur, and D.G. Khan (64.8%, 64.4%, and 63.7%, respectively), but fell to 4.3% in Lahore (Planning Commission of Pakistan, UNDP Pakistan, and OPHI 2016).

2.3 Child Multidimensional Poverty in Punjab

Previous studies on multidimensional poverty from the global through the regional and national down to the subnational level repeatedly pointed to disproportionately high deprivations among children.[6] According to the 2024 global MPI, for example, 27.9 percent of children live in poverty compared to 13.5 percent of adults, and half of the world's poor were children (OPHI and UNDP 2024).

5 In addition to the studies reviewed below, see Muschett (2019), and Licona, Aparicio and Villagómez (2019).
6 In addition to the studies reviewed below, see also Muschett (2019) and Licona, Aparicio, and Villagómez (2019).

Taking up the longstanding finding that about half of the world's multidimensionally poor children live in South Asia, Alkire, Ul Haq and Alim (2019) presented age-disaggregated results of the 2018 global MPI for seven countries in the region.[7] Using 2017–18 data from the Pakistan Demographic and Health Surveys (DHS), they found that almost two in five (39.1%) children aged 0–4 were undernourished. Results also suggested that more than one in four (26.3%) school-aged children in Pakistan were not attending school – more than 15 percentage points above regional average – with girls more frequently out of school than boys, and the majority of out of school children (89.2%) were multidimensionally poor. Intra-household inequalities among children in multidimensionally poor households were widespread, with more than one in five (22.4%) living in households were at least one school-aged child was not attending school whilst at least one was, and more than one in three (33.7%) of children under five living in households where at least one child was malnourished and at least one was not. These frequencies of intra-household inequalities are more than ten percentage points above the South Asian average.[8]

Similarly, age-disaggregation of Pakistan's National MPI (2014/15) for seven age cohorts (0–4; 5–9; 10–14; 15–17; 18–24; 25–59; 60+) in Punjab province suggests, whilst noting positive trends in poverty reduction across all age groups, that children in general, and the three youngest age-cohorts in particular, bear the greatest burden. With a multidimensional poverty incidence of 38.2% (0–4), 42.6% (5–9), and 33.7% (10–14) vis-à-vis a Punjab average of 31.5% – and average multidimensional poverty intensity at 49.3% (0–4), 50.3% (5–9), and 49.3% (10–14), compared to a province-wide average of 48.6%, the youngest are both most frequently and most severely multidimensionally poor.

In addition to these general results, motivating a more thorough examination of child multidimensional poverty in Punjab, there are two direct precedents to the study of child multidimensional poverty in Punjab. Sher et al. (2012), applied the Alkire-Foster method at the household level for a district-level analysis of child multidimensional poverty in Punjab, using 2007-08 MICS data. Considering the indicators *drinking water, sanitation, vitamin A, immunisation, health access, school enrolment, and overcrowding,* they found household-level multidimensional poverty to be highest in Rajanpur district (0.326) and lowest in Lahore (0.152). However, the choice of

7 The global MPI is an internationally comparable measure of acute multidimensional poverty for more than 100 developing countries, annually published as part of the Human Development Report by UNDP and OPHI. See '[The global Multidimensional Poverty Index]' page at OPHI website for more information.

8 See also Alim and Alkire (2019). The techniques of gendered and intrahousehold analyses used in that study could be applied to the National MPI school attendance indicator – nutrition data are not available from the PSLM.

indicators, weights, and cut-offs has not been explicitly justified against the context and purpose under discussion here.

One study also explicitly addressed multidimensional child poverty in Punjab at the individual level, applying a Multidimensional Overlapping Deprivation Analysis (MODA) for the measurement of child-specific depth and breadth of deprivations.[9] However, this study considered child multidimensional poverty for one Punjabi Tehsil (subdistrict) exclusively. The measure was based on a small-scale survey, and yielded results that are distinct from the overall literature on child deprivations across Punjab (Shabir and Rahim 2017).

The other precedent is Alkire Vaz and Oldiges (2025), which articulates the so-called' drawer approach' to measuring multidimensional child poverty and is a direct methodological precedent to the measurement and analysis approach we follow. This study, which was circulated long before its publication, augmented the National MPI of Nepal with a child-specific dimension having age-specific indicators across the lifecycle of children. The weights and poverty cutoff were adjusted to retain the results of the National MPI identification function, but identify additional children as individually poor (see also Section 3.2).[10] The data were analysed at the individual child level, and provided more nuanced measurement and analysis.

Household-level Multidimensional Poverty Measures with Child Components

Although the literature on multidimensional child poverty in Punjab is still limited, there is a growing body of literature on household-level multidimensional poverty measures at the national, provincial, and district level that include child indicators. Of the 3 billion people living in countries with official national MPIs, all include child indicators except for 3 countries. Along with the literature on individual deprivations that children in Punjab are frequently affected by, such measures offer valuable information on particularly prevalent child deprivations.

Most of these multidimensional poverty measures employed the Alkire Foster (AF) dual cut-off method using the household as unit of identification and included various and different child and non-child components. MPIs that include Punjab include, *inter alia*, Chaudhry et al. (2015), Planning Commission of Pakistan, UNDP Pakistan, and OPHI (2016), and OPHI (2023). MPIs including district-level assessments or comparisons and featuring or exclusively focusing on Punjab or its subregions, are, Naveed and ul-Islam (2010), Awan, Waqas, and Aslam (2011), Khan

[9] MODA is an adaptation of Alkire and Foster (2011) and engages the 1989 Convention on the Rights of the Child and Gordon et al. (2003). See de Neubourg et al. (2012). See also Vaz, Oldiges, and Alkire (2019b) and Evans (2019).

[10] See also Vaz, Oldiges, and Alkire (2019a).

et al. (2011), Ashraf and Usman (2012), Naveed and Ali (2012), Niazi and Khan (2012) (Punjab only), Ali et al. (2014) (Punjab only), Khan et al. (2014a,b), Afzal, Rafique and Hameed (2015), Khan et al. (2015), Saboor et al. (2015), Zahra and Zafa (2015) (urban slums in Lahore only), Azeem (2016), Khan et al. (2016), Naveed, Ghaus, and Wood (2016), and Azeem, Mugera, and Schilizzi (2018) (Punjab only).[11]

Results from these studies depend on the data and respective measurement method employed – i.e. which dimensions and indicators, weights, and deprivation and multidimensional poverty cut-offs are chosen. They are thus not straightforwardly comparable across this large spectrum of MPIs. However, studies that reported results by indicator generally confirmed inter- and intra-provincial geographical patterns observed elsewhere for child and household poverty in Punjab, found child-deprivations to be major contributors to overall multidimensional poverty levels, and revealed clear gendered discrepancies in child deprivation, thus pointing to a number of priority areas (Awan, Waqas, and Aslam 2011; Ashraf and Usman 2012; Naveed and Ali 2012; Afzal, Rafique and Hameed 2015; Khan et al. 2015; Saboor et al. 2015; Azeem 2016; Khan et al. 2016; and Naveed, Ghaus, and Wood 2016). Results also accord with key insights from, and problems identified in, the literature on individual child deprivations, largely based on MICS and DHS micro-data. These are more thoroughly reviewed in the next section.

2.4 Dimensions and Indicators of Child Poverty in Punjab

This section provides a review of the literature related to the dimensions and indicators that are covered in the Proxy and Child MPIs in Punjab.

Education

Education and, more specifically, school attendance was the most clearly visible child-specific contributor to household MPIs across Punjab. According to Naveed, Ghaus, and Wood's (2016) measure, for example, child enrolment has consistently been single biggest contributor to household MPIs.[12] In 2017, 23 million school-age children did not attend school – placing Pakistan second on the global ranking of out-of-school children; 10.5 million of these children lived in Punjab (NEMIS 2018). Studies thereby found out-of-school status to be visibly gendered, with a strictly larger proportion of girls than boys being out of school (Jamal 2014a and UNICEF and Government of Pakistan 2017). Furthermore, Naveed and Ali (2012) noted stark inter-district

11 Note that this list is non-exhaustive.

12 See also Niazi and Khan (2012) and Azeem, Mugera, and Schilizzi (2018).

discrepancies in the contribution of school attendance to multidimensional poverty levels within Punjab. According to their methodology, in the MPI-poorest district of Rajanpur, for instance, child enrolment contributed as much as 15%, whereas it contributed less than 6% to overall MPI in least poor Jhelum. On top of school attendance, early child education educational quality and gender parity have been identified as key priorities (Unicef and Government of Pakistan 2017; NIPS and ICF 2018; and NEMIS 2018; Bureau of Statistics Punjab 2018). Not more than 37% of children in Punjab attended pre-primary education in 2014 (Unicef and Government of Pakistan 2017). In terms of educational quality, children in the south performed better than children in central and northern Punjab (Unicef and Government of Pakistan 2017).

Health

In addition, child-specific *health*-related deprivations, including child mortality, and lack of ante- and postnatal care have been highlighted as priorities. With a rate of 66 infant deaths per 1000 live births, Punjab has one of the highest infant mortality rates in Pakistan (Unicef and Government of Pakistan 2017 and Government of the Punjab 2018). According to the measure proposed by Azeem, Mugera, and Schilizzi (2018), child mortality contributed 17% to overall multidimensional poverty levels in Punjab in 2011/12. For child immunisation, the literature noted major improvements, with 99% children receiving some, and 80% of children in Punjab receiving all basic vaccinations (NIPS and ICF 2018), though Butt et al. (2020) note that improvements have not in all areas translated into the desirable health outcomes and that Polio has not yet been eradicated.

In addition, whilst pre- and postnatal care are not directly child-specific, they have been shown to be reliable proxies for child well-being. NIPS and ICF (2018) pointed out how immediate postnatal care is crucial for child neonatal mortality, since a high proportion of child deaths occur within 48 hours after birth.

As per Pakistan's National MPI methodology, immunisation is a minor contributor to overall MPI levels in Punjab (2%), along with antenatal care (1.7%) and assisted delivery (1.3%), whereas deprivations in access to health facilities, for the entire household, made the second largest contribution to MPI (21.5%) (Planning Commission of Pakistan, UNDP Pakistan, and OPHI 2016).[13]

[13] MICS Punjab does not include the indicator of access to health facilities.

Nutrition, Water and Sanitation

Multiple studies have drawn attention to high levels of child stunting, wasting and underweight in Punjab (Government of Pakistan 2011; Mushtaq et al. 2011; Afzal 2013; Arif et al. 2014; Jamal 2014a; Unicef and Government of Pakistan 2017; NIPS and ICF 2018; Kumar et al. 2019). According to the 2018 Pakistan National Nutrition Survey, 36.4% of children under five in Punjab were stunted, 25.3% were underweight, and 15.3% were wasted (Government of Pakistan and Unicef 2019; see also World Bank 2018). Unicef Pakistan and Government of Pakistan (2017) reported that not more than 17% of children were exclusively breast-fed within the first six months.

Previous studies also revealed strong associations between improved sanitation and child health throughout Pakistan, profiling the special importance of WASH (Water, Sanitation, and Hygiene), along with appropriate feeding practices and health care provision, to fight malnutrition and its effects (Unicef 2017; Bureau of Statistics Punjab 2018; World Bank 2018).[14]

Child Labour and Child Protection

Additional priorities that have been identified concerning *childhood conditions* in Punjab include *child labour* and *child protection.* In 2017–18, 13.4% of children aged 5–17 in Punjab – 16.6% boys and 10.1% girls, and 17.5% of children in rural areas vis-à-vis 6.5 in urban areas –are in child labour (Bureau of Statistics Punjab 2018). Ali, Khan, and Kazmi (2011) profiled that 40% of children aged 5–17 years in the Punjabi district of Sahiwal are in child labour and particularly vulnerable to exploitation, abuse, and ill-health.

Child marriage and teenage pregnancy and parenthood have been identified as further key areas of child vulnerability. According to the most recent 2017–18 DHS data, 6% of Punjabi children had begun childbearing in their teenage years (NIPS and ICF 2018). Higher rates of teenage motherhood have thereby also been positively correlated with higher child mortality in Punjab, with neonatal mortality rates being almost twice as high for mothers less than twenty years of age than for mothers aged 20–29 (Sathar, Sadiq, and Ashfaq 2015). MICS 2017–18 key findings also profiled that 80.8% of children aged 1–14 in Punjab had experienced aggression, violence or physical punishment as form of discipline and more than 45.6% had experienced it in severe form (Bureau of Statistics Punjab 2018).

14 See also Ali (2019), Asif et al. (2019), and Grossman, Khalil, and Ray (2019).

Building on this literature, the present study aims is to pinpoint precisely how empirical analysis varies between district level values of the national MPI, the child-disaggregated national MPI and individual child MPI while addressing the following research questions:

- When estimated using MICS Punjab and these MPI definitions, do the National MPI_P, the Child-disaggregated National MPI_P, and the Child MPI converge?
- How well does the Proxy MPI_P that lacks child nutrition reflect the district level poverty which would emerge if child nutritional data were available at the district level?

3. Data and Methodology

3.1 Data

The data used to compute the proxy MPI for Punjab and the Punjab Child MPI is the 2017–18 Punjab Multiple Indicator Cluster Survey (MICS) 2017–18 (MICS 2019). Uniquely, Pakistan does not produce a National MICS; rather each province produces and uploads their Provincial MICS data onto the MICS data space. Punjab's MICS provides internationally comparable information about the situation of children and women and aims at producing data that is usable, *inter alia,* for policy, national development plans, and to track progress against the Sustainable Development Goals (SDGs). The 2017–18 MICS Punjab was designed to provide information at the province level, for urban and rural areas, and down to the district level.

Punjab's MICS 2017–18 surveyed 51,660 households, including 79,510 women (aged 15–49 years), 39,445 men (aged 15–49), 37,052 children aged 5–17, and 42,408 children under 5 years or age in the interviewed households. The overall response rates were 93.1 per cent (women), 68.1 per cent (men), 95.8 per cent (children 5–17), and 93.8 per cent (children 0–4), respectively, for the individual interviews (Bureau of Statistics Punjab 2018).

Since the MICS sample design allows for analyses of children, the Child MPI restricts analyses to a subsample of the data, namely information pertaining to children (age 0–17) only. [15] The analysis then introduces two additional Child MPI indicators: a) Child nutrition and labour and b) Cognitive development. Because child labour was collected for only a subset of children, the data used for this analysis follows that subsample, hence corresponds to 52.5% of the children's

15 The children population accounts for 42.9% of the sampled observations (this is, sampled household members). According to Punjab's MICS survey report 2017–18, "The sample for the MICS Punjab, 2017–18 was designed to provide estimates for a large number of indicators on the situation of children and women at the Punjab level, for urban and rural areas, and for all 36 districts of Punjab" (P. 3).

(weighted) sampled observations, mainly due to missing information in the child labour sub-indicator defined for children aged 5–18.

3.2 National MPI and Proxy MPI for Punjab: Measurement Design

Table 1 shows the structure of the proxy MPI for Punjab (MPI_P) and the Child MPI, meaning its dimensions, indicators, and weights. The Proxy MPI sought to reconstruct the National MPI from 2017-19 MICS Punjab data. Unfortunately, the MICS survey did not cover all national MPI indicators. Hence the MPI_P drops two indicators of the National MPI (school quality and access to health facilities) and changes four indicator definitions. Nearly all these changes reduce the precision of the National MPI for children. It is hoped that the next MICS survey will include all the National MPI questions. To adjust for missing indicators, others were re-weighted, so that in the MPI_P, school attendance has a weight of 1/6, rather than 1/8, and the three indicators in health dimension are weight 1/9 instead of 1/18 each.

Four indicator definitions were modified, three because the MICS collected information on a narrower age range. Immunisation was re-specified to apply to children below the age of 3 instead of 5 years. Similarly, in MICS questionnaires ante-natal care and assisted delivery apply only to women who given birth within the last two years instead of three years. Lastly, the sub-indicator of land of the MPI_P using MICS only captures deprivation related to the ownership of irrigated land, whilst the National MPI used information regarding the possession of differing amounts of both irrigated and non-irrigated land. Table 1 specifies the indicators used in the Proxy MPI_P.

In contrast to the MPI_P and the National MPI, which identify the poverty status of each person at the household level, the unit of identification of the Child MPI in Punjab is the individual child (0 to 17). Structurally, the first three dimensions of the Child MPI – as presented in Table 1: education health, and livings standard – are **exactly** the same as in the MPI_P. Their weights have been proportionally re-adjusted to sum to 75%, so that an additional equally-weighted dimension of **childhood conditions** can be included in the Child MPI. This fourth dimension consists of two equally weighted indicators capturing age-specific sub-indicators that cover the cycle of childhood. The indicator 'Child nutrition and labour' considers, the nutritional status of children under 5 years of age in terms anthropometric conditions of stunting or underweight. For children between 5 and 17 years of age it considers age-specific indicators of child labour. The second indicator, 'cognitive development', has indicators for six different age cohorts: exclusive breastfeeding in the first 6 months of age; birth registration and neglect among children 6–23 months old; safety and stimulation among children 24–35 months of age measured by safety and stimulation ; preschool, safety and stimulation among children 36–59 months of age; school attendance among children

5–14 years old; and Not in Education, Employment, or Training (NEET), child marriage, or parenthood among 15–17 year olds). The indicators were selected based on what was available for each cohort in the MICS survey and aligned with child priorities.

The Child MPI's multidimensional poverty cut-off *k* is set at 25%. This creates an identification function that matches that of the national MPI structurally. As in the National MPI, any person deprived in at least one of the dimensions or equivalent of weighted indicators (33.33%) is identified as multidimensionally poor. Hence every child who was identified as poor by the National MPI is also identified as poor in this measure – but additional individual child indicators are now also included. This structure allows for a straightforward comparison of the poverty identification in MPI_P and Child MPI, and permits a pioneering analysis, done later in this study, of the value-added of including additional deprivations of other children into a multidimensional poverty measure for Punjab province.

Table 1. Structure of the Proxy MPIP and Child MPI - Dimensions, Indicators, Deprivation Cut-offs, and Weights

Dimension	Indicator	Deprivation Cut-off: A child is deprived if…	Weight (%) Proxy MPI	Weight (%) Child MPI
Education	Years of schooling	at least one man and one woman in the household above 10 years of age has not completed 5 years of schooling.	1/6=16.7%	1/8=12.5%
	Child school attendance	any school-aged child in the household is not attending school (between 6 and 11 years of age).	1/6=16.7%	1/8=12.5%
Health	Immunization	any child under the age of 5 (for MICS, 3 years) is not fully immunised according to the vaccinations calendar (households with no children under 5/3 are considered non-deprived).	1/9= 11.1%	1/12= 8.33%
	Ante-natal care	any woman in the household who has given birth in the last 3 (for MICS, 2) years did not receive ante-natal check-ups (households with no eligible woman are considered non-deprived).	1/9= 11.1%	1/12= 8.33%
	Assisted delivery	any woman in the household has given birth in the last 3 (MICS 2) years attended by untrained personnel (family member, friend, traditional birth attendant) or in an inappropriate facility (home, other) (households with no eligible woman are considered non-deprived).	1/9= 11.1%	1/12= 8.33%
Living Standards	Water	the household has no access to an improved source of water according to MDG standards, considering distance (less than a 30-minute return trip): tap water, hand pump, motor pump, protected well, mineral water.	1/21= 4.8%	1/28= 3.57%
	Sanitation	the household has no access to adequate sanitation according to MDG standards: flush system (sewerage, septic tank and drain).	1/21= 4.8%	1/28= 3.57%
	Walls	the household has unimproved walls (mud, uncooked/mud bricks, wood bamboo, other).	1/42= 2.4%	1/56= 1.79%
	Overcrowding	the household is overcrowded (4 or more people per room).	1/42= 2.4%	1/56= 1.79%
	Electricity	the household has no access to electricity.	1/21= 4.8%	1/28= 3.57%
	Cooking fuel	the household uses solid cooking fuels for cooking (wood, dung cakes, crop residue, coal/charcoal, other).	1/21= 4.8%	1/28= 3.57%
	Assets	Deprived if the household does not have more than two small assets (radio, TV, iron, fan, sewing machine, video cassette player, chair, telephone, watch, air cooler, bicycle) OR no large asset (refrigerator, air conditioner, tractor, computer, motorcycle), AND has no car.	1/21= 4.8%	1/28= 3.57%
	Land and Livestock	Deprived if the household is deprived in land AND deprived in livestock, i.e.: a) Deprived in land: the household has less than 2.25 acres of non-irrigated land AND less than 1.125 acres of irrigated land,	1/21= 4.8%	1/28= 3.57%

		b) Deprived in livestock: the household has less than 2 cattle, fewer than 3 sheep/goats, fewer than 5 chickens AND no animal for transportation (urban households are considered non-deprived)		
Child Conditions	Child Nutrition and Labour	*Nutritional Status*: a child below 5 years of age is underweight or stunted *Child labour (5-17)* a child is involved in child labour under the following conditions: (a) children 5–11 years old who, during the reference week, did at least one hour of economic activity and/or more than 21 hours of unpaid household services, (b) children 12–14 years old who, during the reference week, did at least 14 hours of economic activity and/or more than 21 hours of unpaid household services, (c) children 15–17 years old who, during the reference week, did at least 43 hours of economic activity.		1/8=12.5%
	Cognitive Development	*Exclusive Breastfeeding* A child below 6 months of age is deprived if that child is not exclusively breastfed. *Birth Registration, Neglect*: A child between 6 to 23 months of age is deprived if his/her birth was not registered OR if he/she was left alone or under the supervision of another child more than one hour at least once during the last week. *Safety and Stimulation:* A child aged 24-35 months is deprived if he/she was left alone or under the supervision of another child more than one hour at least once during the last week no one read/sung etc to child OR someone is involved with the child in no more than 3 of the following activities: reading books, telling stories, sing songs, taking outside, playing, and drawing things for or with the child. *Preschool, Safety and Stimulation*: A child between 36 to 59 months of age is deprived if someone is involved with the child in no more than 3 of the following activities: reading books, telling stories, sing songs, taking outside, playing, and drawing things for or with the chid OR the child can't recognise and don't know the symbol of all numbers from 1 to 10. *School Attendance including Preschool*: A child between 5 to 14 years of age is deprived if the child is not attending school *NEET plus marriage/child School Attendance*: A child between 15 to 17 years of age is deprived if not in education OR employment OR is married /with child.		1/8=12.5%

Deprivation profiles across these indicators are constructed for each person, and the weights of the deprivations each person experiences are added up to create their deprivation score. this dual-cutoff approach uses two kinds of cut-offs to decide whether a person is deprived and whether she is poor: (a) an indicator-specific deprivation standard or cut-off, where a person is considered deprived in each indicator if their achievement falls below the cut-off (as defined in column 3 of Table 1), and (b) a cross-dimensional multidimensional poverty cut-off, which specifies the minimum deprivation score or share of deprivations required to qualify a person or a household as MPI-poor. Following the National MPI, the poverty cut-off for the Proxy MPI_P was set at 33%, meaning a person who is deprived in at least one full dimension or the weighted sum of indicators equal or higher than 33% in order to be counted as multidimensionally poor. The Child-disaggregated MPI_p follows this same structure Its cutoff is 25% because it has four dimensions rather than three, so the identification is parallel.

The proxy MPI_P and the Child MPI are all estimated using the dual-cutoff counting method (Alkire and Foster 2011; Alkire *et al.* 2015). A poverty profile is constructed for each person or child (henceforth described as person). To estimate any MPI, information on the poor is aggregated into the adjusted headcount ratio or MPI. MPIs combine two aspects of poverty:

$$MPI = M_0 = H\,x\,A.$$

1) **Incidence (H)**: the percentage of people who are poor, because their weighted deprivation score is the same as or higher than the poverty cutoff.

2) **Intensity (A)**: the average percentage of dimensions in which poor people are deprived, or the average deprivation score of poor persons.

MPIs can be equivalently computed as the weighted sum of censored headcount ratios – which show the percentage of people who were identified as poor and are deprived in an indicator. Because of this structure, MPIs satisfy the axiom of dimensional breakdown – after identification they can be broken down by indicators to show the composition of poverty. This feature of indicator detail brings added policy relevance to the analysis. Combined with another measurement desideratum satisfied be the Alkire-Foster method – the axiom of subgroup decomposability – it allows the exploration of headline results and indicator composition of an MPI across population subgroups, making visible who the poorest are and where they live as well as which deprivations constitute poverty across different population subgroups, thus allowing cross-sectoral policies to prioritise key deprivations.

4. Results

This section introduces the results of Punjab's 2017/18 MPI Proxy (MPI_P), the Child Disaggregation of the National MPI, and the Child MPI (Table 2). The following undertakes a comparative analysis of all three measures as well as additional analyses of nutritional indicators.[16]

4.1 National MPI Proxy 2017/18

The Proxy MPI_P reveals that, in 2017/18, almost one in four (23.6%) people in Punjab were multidimensionally poor and, on average, deprived in a little less than half (46.6%) of the weighted MPI_P indicators. Districts in the southern parts of the province were disproportionately affected

16 In related work (Alkire, Ul Haq, Alim 2019), we have also undertaken a gendered and intrahousehold individual child analysis of children's deprivations in variables such as school attendance. Such methods could also be applied to individual deprivations within the MPIs discussed here.

Table 2. MPI_P Results for Punjab Province and Subgroups, 2017/18

					d_educ	d_satt	d_immu	d_ante	d_trde	d_wtr	d_sani	d_wall	d_ovcr	d_elct	d_ckfl	d_asst	d_land	
	Sub-group	**MPI**	**H (%)**	**A (%)**	**YoS**	**SAt**	**Immu**	**ANC**	**AD**	**Elc**	**San**	**Wtr**	**Wls**	**CkF**	**As**	**OC**	**L *and* L**	**Pop. share (%)**
Punjab		0.110	23.6%	46.6%	22.2%	9.0%	8.4%	3.4%	7.1%	2.2%	14.1%	8.7%	18.2%	3.1%	20.9%	12.9%	11.1%	
Area	Urban	0.037	8.4%	43.6%	7.8%	4.0%	3.6%	1.6%	3.2%	0.7%	2.8%	1.1%	6.8%	0.5%	4.4%	4.2%	0.0%	36.3
	Rural	0.152	32.3%	47.0%	30.4%	11.9%	11.1%	4.4%	9.4%	3.0%	20.6%	13.0%	24.7%	4.7%	30.3%	17.8%	17.4%	63.7
Division	Bahawalpur	0.192	39.1%	49.2%	37.6%	18.0%	13.0%	8.2%	10.9%	4.1%	24.6%	16.2%	30.3%	6.6%	37.6%	21.6%	16.9%	10
	DG Khan	0.256	50.7%	50.5%	47.9%	21.0%	19.7%	5.8%	20.3%	4.3%	35.2%	30.8%	40.4%	12.6%	49.7%	29.4%	23.1%	9.4
	Faisalabad	0.092	20.2%	45.3%	19.3%	6.4%	7.2%	2.2%	5.6%	1.8%	13.5%	5.9%	14.8%	2.9%	17.8%	12.2%	9.2%	12.6
	Gujranwala	0.046	10.5%	43.6%	9.0%	3.5%	4.4%	2.2%	3.7%	0.5%	4.4%	1.4%	8.2%	0.3%	6.9%	5.2%	6.2%	14.8
	Lahore	0.063	14.2%	44.2%	13.4%	5.2%	6.0%	2.5%	4.5%	1.4%	5.4%	2.2%	11.5%	0.6%	9.5%	7.1%	5.9%	17.1
	Multan	0.126	28.0%	45.1%	26.8%	10.6%	8.1%	2.5%	7.1%	2.0%	16.9%	8.4%	20.9%	3.2%	26.0%	14.8%	15.1%	11.6
	Rawalpindi	0.047	10.8%	43.4%	9.6%	3.6%	4.2%	1.9%	3.2%	2.6%	4.5%	3.2%	7.4%	0.3%	7.3%	5.1%	5.4%	9.3
	Sahiwal	0.122	27.3%	44.7%	26.0%	9.5%	7.9%	3.1%	6.7%	1.7%	16.3%	6.3%	21.6%	2.6%	25.6%	15.7%	15.3%	6.9
	Sargodha	0.125	27.7%	45.2%	25.8%	9.9%	9.8%	3.6%	6.8%	2.7%	19.1%	13.5%	20.8%	2.6%	26.1%	13.9%	10.0%	8.2
District	Attock	0.079	17.8%	44.5%	16.0%	5.5%	7.5%	4.0%	6.3%	4.6%	6.3%	5.6%	12.1%	0.5%	12.9%	8.6%	8.3%	1.8
	Bahawalnagar	0.151	33.2%	45.6%	31.0%	10.6%	12.2%	5.2%	8.5%	5.1%	21.4%	9.2%	26.6%	4.5%	32.4%	17.1%	12.6%	2.7
	Bahawalpur	0.202	41.1%	49.0%	39.8%	17.7%	12.7%	8.4%	11.6%	4.9%	27.0%	17.4%	29.0%	7.4%	39.5%	23.7%	20.3%	3.1
	Bhakkar	0.172	37.5%	45.9%	34.6%	14.4%	15.5%	3.8%	10.5%	0.0%	25.1%	22.5%	28.0%	3.0%	36.9%	19.2%	10.4%	1.8
	Chakwal	0.047	10.7%	44.4%	10.1%	2.3%	4.4%	1.6%	2.5%	1.9%	6.5%	4.5%	7.6%	1.0%	9.2%	6.6%	5.1%	1.4
	Chiniot	0.125	28.3%	44.2%	27.3%	8.5%	7.0%	2.3%	5.5%	0.2%	24.1%	11.7%	19.4%	5.1%	26.6%	18.5%	12.6%	1.2
	DG Khan	0.293	54.7%	53.5%	50.5%	24.4%	27.5%	7.6%	26.9%	10.6%	38.4%	37.2%	43.1%	15.9%	53.4%	29.1%	20.1%	2.3
	Faisalabad	0.072	16.0%	45.0%	15.2%	5.2%	6.2%	1.6%	4.6%	2.6%	9.4%	3.3%	12.0%	1.3%	12.7%	9.5%	8.0%	6.8
	Gujranwala	0.044	10.2%	43.2%	8.3%	3.8%	5.1%	3.0%	4.2%	0.2%	2.0%	1.2%	7.6%	0.0%	4.1%	5.1%	5.3%	4.7
	Gujrat	0.026	5.9%	43.5%	5.5%	1.8%	2.0%	0.7%	1.5%	0.5%	3.5%	0.4%	4.6%	0.0%	4.8%	3.5%	3.7%	2.6

	Hafizabad	0.081	17.8%	45.1%	15.8%	6.0%	7.0%	5.0%	5.5%	1.0%	9.9%	4.5%	15.3%	1.1%	13.2%	9.2%	7.9%	1.1
	Jhang	0.145	31.6%	46.0%	30.0%	9.0%	11.5%	4.0%	9.1%	0.8%	23.7%	11.3%	22.3%	7.5%	30.4%	19.9%	12.2%	2.6
	Jhelum	0.033	8.4%	39.3%	7.6%	2.1%	2.1%	0.2%	1.2%	2.3%	5.1%	2.0%	6.1%	0.3%	6.6%	4.0%	5.3%	1.2
	Kasur	0.133	29.2%	45.6%	27.1%	8.0%	12.6%	5.5%	9.7%	2.8%	14.6%	5.1%	23.8%	1.3%	25.9%	15.4%	18.0%	3.2
	Khanewal	0.121	26.2%	46.1%	24.5%	8.2%	10.9%	3.8%	7.8%	0.9%	15.5%	5.6%	20.4%	3.7%	24.4%	15.4%	14.0%	2.9
	Khushab	0.171	36.4%	47.0%	34.4%	12.3%	13.4%	4.6%	8.4%	9.5%	27.0%	25.6%	26.1%	6.5%	35.3%	20.0%	10.0%	1.3
	Lahore	0.034	7.7%	44.1%	7.3%	3.9%	4.2%	1.6%	2.8%	0.8%	1.8%	0.8%	6.3%	0.3%	2.6%	3.3%	0.0%	9.6
	Layyah	0.142	31.2%	45.5%	29.8%	8.6%	9.5%	3.4%	9.9%	0.1%	19.6%	15.0%	23.4%	6.6%	30.9%	18.6%	15.1%	1.7
	Lodhran	0.193	41.4%	46.6%	39.9%	18.6%	10.8%	3.9%	9.0%	4.5%	28.1%	17.1%	29.7%	4.0%	40.7%	21.6%	22.9%	1.5
	MandiBahauddin	0.085	18.8%	45.1%	17.0%	5.7%	6.8%	3.3%	5.9%	1.2%	12.1%	3.3%	15.2%	0.8%	16.5%	9.3%	11.9%	1.5
	Mianwali	0.126	27.9%	44.9%	26.1%	11.2%	9.2%	2.6%	7.7%	3.6%	17.0%	13.2%	21.7%	1.6%	27.6%	12.7%	7.6%	1.5
	Multan	0.109	24.8%	43.9%	23.7%	10.0%	5.0%	1.4%	6.4%	1.9%	15.3%	8.5%	17.9%	2.1%	22.0%	12.3%	13.9%	4.5
	Muzaffargarh	0.240	50.5%	47.5%	48.4%	19.4%	14.7%	4.0%	16.9%	0.4%	35.3%	25.4%	40.8%	8.6%	49.0%	29.4%	27.1%	3.8
	Nankana Sahib	0.081	19.2%	42.2%	18.6%	5.5%	3.9%	1.7%	3.6%	2.2%	12.3%	5.6%	15.6%	0.6%	16.8%	11.2%	10.5%	1.3
	Narowal	0.041	10.1%	40.6%	8.4%	2.4%	4.2%	0.5%	3.6%	0.0%	4.8%	0.9%	7.5%	0.3%	9.2%	4.4%	5.7%	1.6
	Okara	0.124	28.0%	44.4%	26.3%	8.9%	8.2%	3.7%	7.8%	2.3%	16.5%	5.4%	22.7%	1.4%	25.1%	15.5%	17.0%	3
	Pakpattan	0.143	32.1%	44.7%	30.5%	9.6%	9.5%	4.6%	7.8%	1.8%	18.8%	9.3%	24.6%	4.6%	31.6%	20.4%	16.0%	1.7
	Rajanpur	0.360	65.8%	54.7%	62.0%	32.5%	30.9%	9.9%	29.2%	8.7%	46.4%	50.1%	52.9%	22.9%	65.2%	40.8%	26.1%	1.7
	Rawalpindi	0.038	8.8%	43.1%	7.5%	3.6%	3.3%	1.7%	2.7%	2.1%	3.1%	2.3%	6.0%	0.0%	4.9%	3.6%	4.5%	5
	RY Khan	0.213	41.5%	51.3%	40.2%	23.2%	13.9%	10.0%	11.9%	2.7%	24.9%	20.0%	33.8%	7.4%	39.7%	23.2%	17.1%	4.1
	Sahiwal	0.103	22.8%	45.2%	22.1%	10.2%	6.2%	1.3%	4.3%	0.9%	14.2%	5.4%	17.9%	2.6%	22.0%	12.4%	12.6%	2.2
	Sargodha	0.086	19.9%	43.5%	18.3%	6.3%	5.9%	3.4%	4.1%	1.2%	14.3%	5.0%	15.1%	1.5%	16.9%	9.6%	10.8%	3.6
	Sheikhupura	0.072	17.0%	42.5%	15.8%	6.4%	5.7%	2.5%	4.6%	1.4%	4.5%	2.2%	13.3%	0.6%	11.1%	8.9%	9.9%	3.1
	Sialkot	0.038	8.6%	43.8%	7.3%	3.2%	3.5%	1.6%	3.3%	0.8%	3.1%	0.9%	6.8%	0.3%	5.2%	4.1%	6.3%	3.4
	TT Singh	0.068	14.9%	45.9%	14.4%	5.7%	5.1%	1.9%	4.4%	1.1%	7.7%	4.2%	12.1%	1.3%	13.0%	7.8%	7.4%	2
	Vehari	0.122	27.5%	44.5%	27.0%	9.7%	8.7%	2.1%	6.2%	1.8%	14.7%	6.4%	21.2%	4.1%	25.8%	14.6%	14.0%	2.7

Source: Authors' calculations based on MICS 2017–18.

by multidimensional poverty, with MPI values ranging from 0.026 in Gujrat and 0.033 in Jhelum, to 0.293 in DG Khan and 0.360 in Rajanpur. Disaggregated results furthermore show that multidimensional poverty incidence is 32.3% in rural areas, which is far higher than in urban parts of the province, where 8.4% are multidimensionally poor.

4.2 The Child-disaggregated MPI$_P$

The MPI$_P$ is built at the household level and thus might be expected not to profile child poverty very much. But age disaggregation shows that multidimensional poverty afflicts just under one in five adults but sadly nearly one in three children are poor (29.5%). Furthermore, on average poor children bear a higher deprivation or intensity of poverty than adults – 47.8% as opposed to 45.3% for adults under 65 years of age. Note that children comprise 42.9% of the population, and adults 18–64, 52.5% of the population with the older group having 4.6% of the population. Table 3 further shows additional age-disaggregation of the MPI$_P$ and its associated information platform, examining the composition of children's overall disadvantage. Results indicate that children are indeed disproportionately deprived in *all* MPI$_P$ indicators. Figure 1 shows the censored headcount ratios of each indicator disaggregated by the age group. Children's deprivations are significantly higher in every indicator.[17] Children were particularly more likely to share their household with uneducated adults, and to live in overcrowded spaces.

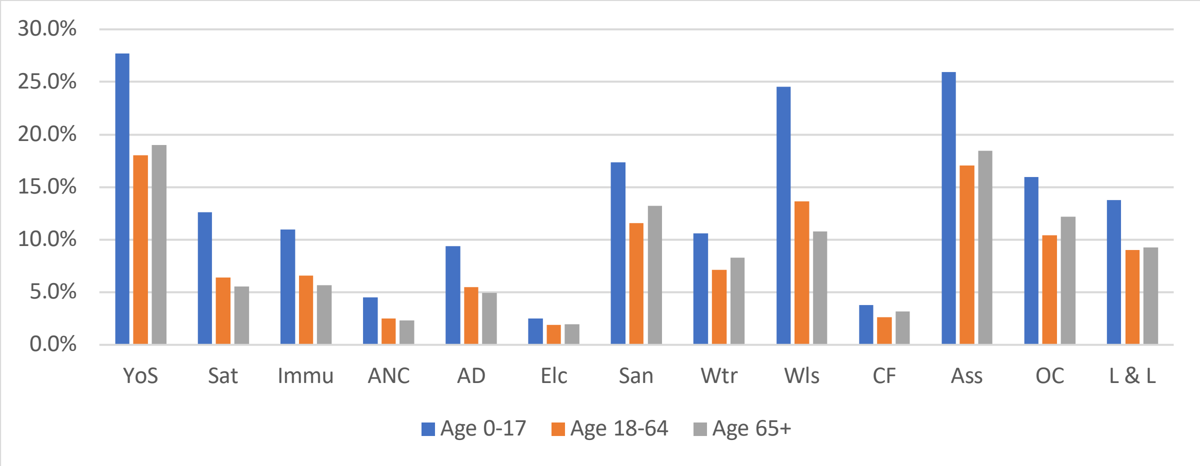
Table 3. MPI$_P$ Results for Punjab, 2017/18, by Age Group

Age group	Population share	MPI	H	A
Age 0–17	42.9	0.141	29.5%	47.8%
Age 18–64	52.5	0.087	19.2%	45.3%
Age 65+	4.6	0.088	20.0%	43.8%

Source: Authors' calculations based on data from MICS 2017–18

17 Using 95% significance here and subsequently unless otherwise specified

Figure 1: Censored Headcount Ratios by Age



Source: Authors' calculations based on data from MICS 2017–18.

4.3 Child MPI Results

According to an individual level Child MPI which considers two additional, age-appropriate indicators for each child, the incidence of multidimensional poverty for children age 0–17 in 2017/18 is 47.1% – well above the 29.5% of the child-disaggregated Proxy MPI. So, 17.6% of children aged 0–17 were not poor by the child-disaggregated MPI but are poor by the child MPI. The average intensity of poverty (A) is 42.8%. By gender, the child MPI and incidence are not significantly different for boys and girls. The largest contributors to poverty are deprivations of schooling and cognitive development. These results highlight the importance of parenting and schooling which together may influence a child's school performance and school life expectancy.

Tables 4–6 present the results of the Child MPI for Punjab in 2017/18 using a poverty cut-off equal to 25%.

Table 4. Incidence, Intensity and Child MPI, 2017/18

Children	Index	Value	Confidence Interval (95%)	
Poverty Cut-off (k)	Child MPI	0.202	0.198	0.206
k value = 25%	Headcount ratio (H, %)	47.1%	46.4%	47.8%
	Intensity (A, %)	42.8%	42.5%	43.1%

Source: Authors' calculations based on data from MICS 2017–18.

Table 5. Incidence, Intensity and Child MPI, 2017/18

Boys	Index	Value	Confidence Interval (95%)	
Poverty Cut-off (k)	Child MPI	0.200	0.196	0.204
k value = 25%	Headcount ratio (H, %)	47.2%	46.4%	48.0%
	Intensity (A, %)	42.4%	42.1%	42.7%

Source: Authors' calculations based on data from MICS 2017–18.

Table 6. Incidence, Intensity and Child MPI, 2017/18

Girls	Index	Value	Confidence Interval (95%)	
Poverty Cut-off (k)	Child MPI	0.203	0.199	0.208
k value = 25%	Headcount ratio (H, %)	47.0%	46.2%	47.8%
	Intensity (A, %)	43.3%	42.9%	43.6%

Source: Authors' calculations based on data from MICS 2017–18.

Table 7 presents information for the Child MPI at the District level. According to results, 19 out of the 36 districts in Punjab have a Child MPI larger than the average of the region. These districts are home to half of the Punjab population (49%), have an incidence larger than 50%, and an intensity larger than 40%. Within this set of constituencies, the district of Rajanpur has the largest Child MPI. In this district, situated in the southern border of Punjab, 83.6% of the children are multidimensionally poor and experience an intensity equal to 55.3%.

Table 7. Child MPI by District, 2017/18

		Child MPI			Incidence (H, %)			Intensity (A, %)		
District	Population Share (%)	Value	Confidence Interval (95%)		Value	Confidence Interval (95%)		Value	Confidence Interval (95%)	
Gujrat	2.5%	0.081	0.070	0.093	22.6%	20.1%	25.4%	35.6%	34.1%	37.2%
Jhelum	1.1%	0.089	0.077	0.103	25.2%	22.0%	28.8%	35.3%	33.9%	36.6%
Lahore	8.8%	0.093	0.082	0.106	24.6%	22.0%	27.5%	37.7%	36.5%	39.0%
Rawalpindi	4.6%	0.097	0.084	0.112	26.5%	23.5%	29.7%	36.7%	35.2%	38.3%
Sialkot	3.4%	0.109	0.099	0.121	29.2%	26.7%	31.7%	37.4%	35.9%	39.0%
Narowal	1.6%	0.110	0.094	0.129	31.2%	26.9%	35.7%	35.4%	34.1%	36.7%
Gujranwala	4.8%	0.114	0.102	0.127	30.7%	27.8%	33.6%	37.2%	36.2%	38.2%
Chakwal	1.3%	0.116	0.099	0.135	29.8%	26.2%	33.6%	38.9%	37.0%	40.8%
Attock	1.6%	0.155	0.136	0.177	39.7%	35.8%	43.8%	39.1%	37.4%	40.9%
Faisalabad	6.9%	0.156	0.142	0.171	38.9%	35.8%	42.0%	40.1%	38.9%	41.2%
Mandi Bahauddin	1.5%	0.159	0.144	0.176	39.4%	35.9%	43.0%	40.4%	39.1%	41.8%
Sheikhupura	3.1%	0.160	0.142	0.179	41.4%	37.3%	45.5%	38.6%	37.4%	39.8%
Tt Singh	2.0%	0.164	0.141	0.191	40.1%	35.1%	45.2%	41.0%	39.2%	42.9%
Nankana Sahib	1.3%	0.168	0.139	0.202	42.8%	36.1%	49.8%	39.3%	37.6%	41.1%
Hafizabad	1.1%	0.171	0.148	0.198	42.3%	37.5%	47.4%	40.5%	38.3%	42.8%
Sargodha	3.4%	0.174	0.159	0.190	44.6%	41.2%	48.1%	39.0%	37.9%	40.2%
Sahiwal	2.3%	0.183	0.159	0.210	43.9%	39.0%	48.9%	41.8%	40.1%	43.4%
Multan	4.6%	0.211	0.195	0.228	51.3%	48.1%	54.5%	41.1%	40.2%	42.1%
Mianwali	1.4%	0.216	0.192	0.242	52.9%	48.1%	57.6%	40.8%	39.4%	42.3%
Okara	3.1%	0.222	0.199	0.246	54.3%	49.6%	58.9%	40.8%	39.6%	42.1%
Vehari	2.8%	0.223	0.201	0.247	53.8%	49.2%	58.3%	41.4%	40.2%	42.7%
Chiniot	1.3%	0.231	0.209	0.254	55.8%	51.2%	60.3%	41.3%	39.9%	42.8%
Khanewal	2.8%	0.235	0.213	0.259	55.0%	50.7%	59.2%	42.8%	41.2%	44.3%
Kasur	3.1%	0.239	0.220	0.259	55.8%	52.1%	59.3%	42.8%	41.5%	44.0%
Layyah	1.8%	0.240	0.210	0.274	57.4%	51.3%	63.3%	41.9%	40.2%	43.6%
Pakpattan	1.7%	0.245	0.217	0.275	58.3%	52.5%	63.9%	42.0%	40.3%	43.8%
Jhang	2.8%	0.254	0.231	0.277	58.8%	54.4%	63.0%	43.1%	41.8%	44.4%
Khushab	1.1%	0.255	0.226	0.286	57.1%	51.5%	62.6%	44.6%	42.7%	46.5%
Bahawalnagar	2.8%	0.263	0.239	0.289	61.3%	56.5%	65.8%	43.0%	41.8%	44.2%
Bhakkar	1.7%	0.280	0.256	0.304	63.6%	59.5%	67.4%	44.0%	42.5%	45.5%
Bahawalpur	3.2%	0.301	0.275	0.328	63.3%	58.9%	67.4%	47.5%	46.0%	49.1%

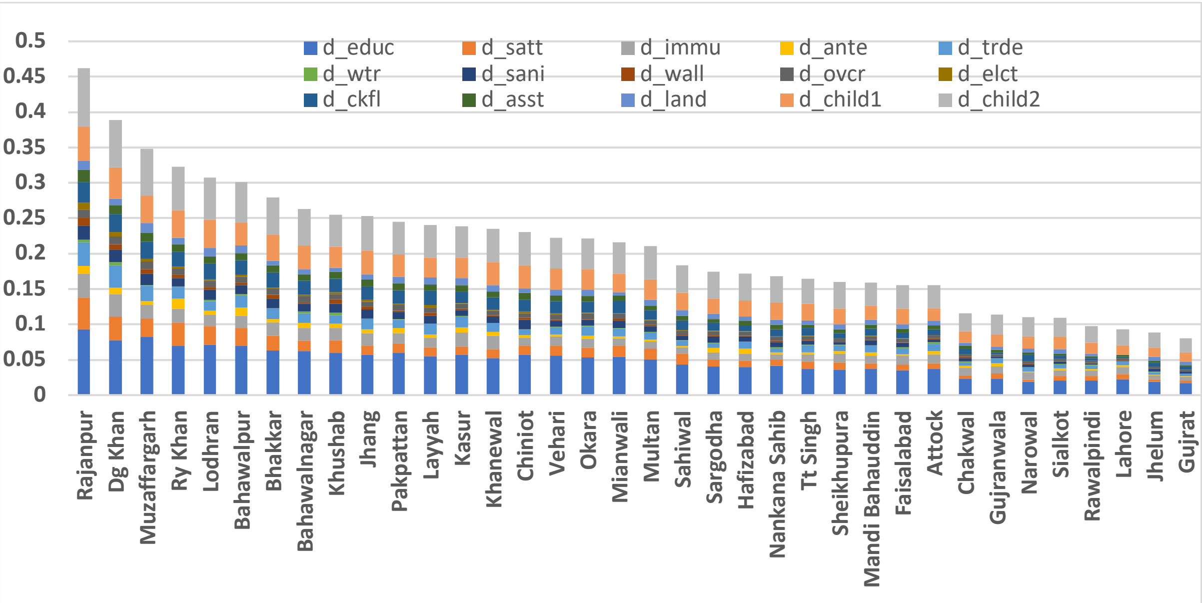
Lodhran	1.5%	0.307	0.280	0.336	68.2%	63.4%	72.7%	45.0%	43.4%	46.6%
Ry Khan	4.4%	0.323	0.296	0.352	64.8%	60.4%	69.0%	49.8%	48.2%	51.5%
Muzaffargarh	4.3%	0.348	0.327	0.371	74.9%	71.3%	78.1%	46.5%	45.3%	47.8%
Dg Khan	2.5%	0.389	0.357	0.423	75.4%	70.8%	79.5%	51.6%	49.5%	53.7%
Rajanpur	2.0%	0.462	0.423	0.501	83.6%	79.3%	87.1%	55.3%	52.3%	58.2%
Punjab	**100**	0.202	0.198	0.206	47.1%	46.4%	47.8%	42.8%	42.5%	43.1%

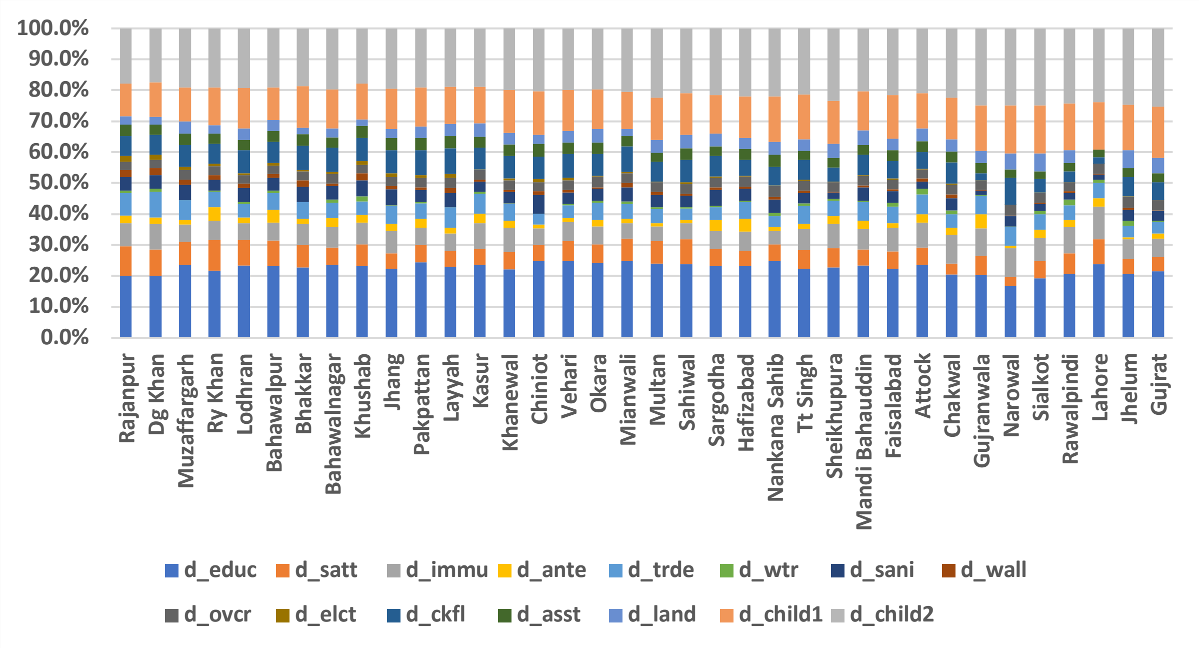
Source: Authors' calculations based on data from MICS 2017–18.

In Figure 2, the weighted percentage contribution of each indicator is depicted to show the composition of the Child MPI nationally and by district.

Note that there is a (deliberate) double counting of a kind in school attendance: the National MPI considers a household deprived if *any* child is not attending school. The Child MPI again considers a child deprived if *that individual child* is not attending school. In the latter case, both indicators will register a deprivation, hence augmenting the weight on that single indicator (for school-aged children who are out of school) to 25%. The logic for this is that school attendance is of vital importance, and also that a child who is attending school but shares their household with a child who is not is, in some ways, also deprived and their own school career may be at risk.

Figure 2a and 2b: Absolute and Percentage Contribution of Each Indicator to Child MPI by district, 2017/18





Source: Authors' calculations based on data from MICS 2017–18.

In Figure 2a, the height of the bars is the value of MPI, and the districts are ranked from the poorest (Rajanpur) to least poor (Gujrat). The striped components reflect the weighted contribution of each indicator. The size of the stripes can be directly compared: a larger stripe indicates that a higher percentage of the population are poor and deprived in that indicator. For example, compare Khushab and Jhang, we see that their level of MPI is about the same. But the deprivations in years of schooling and child school attendance are higher in Khushab, whereas in Jhang, Child Nutrition andand Labour and Cognitive Development are bigger challenge.

Figure 2b shows the percentage contributions of each indicator to the MPI, so one can easily look across even the least poor districts to examine how their composition varies. We can see at a glance that the two child indicators at the top of the bars contribute visibly across every district, and that the share does not vary a great deal among the poorest districts. The relative contribution of the child indicators increases in the least poor districts, especially Lahore, indicating that even in very low poverty contexts, profiling child deprivations adds new information.

4.4 Comparative Analysis

This empirical implementation delivered three supplementary poverty measurements: 1) the proxy MPI_P for Punjab, 2) the MPI_P disaggregated by children (aged 0–17). And 3) the Child MPI. This section explores district-level variations. In particular, we conduct a pairwise comparison to examine to what extent these measures show convergent results in terms of the incidence (H), intensity (A) and the MPI. The first section produces basic rank-correlations to analyze to what extent the results of the different measures overlap at district-level. Then, it studies the nutritional indicator and Child MPI disaggregated by age-groups. Next, it conducts an additional analysis on nutrition and MPI, and finally, comparatively analyses the school attendance indicator with information on learning outcomes at the district level.

4.4.1 Child Indicators

Table 8 shows the redundancy and association tests using the MICS 2017–18 among all the Proxy and Child MPI indicators, using uncensored headcount ratios for children aged 0–17 only.[18] The information refers to redundancy coefficient (R). The coefficient R is obtained by dividing the proportion of people with simultaneous deprivation in any two indicators, by the minimum of the two indicators' uncensored headcount ratios.[19] Across all indicators some high association is rather mechanical – for example electricity and walls have very low incidence, and cooking fuel very high, so the high redundancy is to be expected. There is a surprisingly high redundancy between years of schooling (which in Pakistan, is gendered) and child school attendance. It is much higher than the association for example between the related global MPI indicators (which are not gendered) and invites further scrutiny. As for the child indicators, cognitive development has the highest redundancy with school attendance (0.73) which is unsurprising as, for children out of school, the measures coincide. Rather less predictably, the largest coefficient for child nutrition and labour corresponds to overcrowding (0.65). Interestingly the next largest association for child nutrition and labour is precisely found with cognitive development (0.64) – so the two new child indicators overlap to some extent.

18 The Uncensored Headcount Ratio refers to the share of the relevant population that are deprived in any indicator across the population. For tables of Uncensored Headcount ratios of the Proxy and Child MPI Please see Appendix Tables A7–A9 and B7–B9.

19 The coefficient R takes values of 0% when no one is identified as deprived in both indicators being considered, and 100% when every individual who is deprived in the indicator with the lowest incidence of deprivation, is also deprived on the other indicator.

Table 8. Redundancy tests

	Years of schooling	School attendance	Immunization	Antenatal care	Assisted delivery	Water	Sanitation	Walls	Overcrowding	Electricity	Cooking fuel	Assets	Land and livestock	Child nutrition and labour	Cognitive development
Years of schooling	.														
School attendance	0.804	.													
Immunization	0.499	0.324	.												
Antenatal care	0.713	0.268	0.478	.											
Assisted delivery	0.687	0.277	0.433	0.641	.										
Water	0.39	0.109	0.258	0.072	0.14	.									
Sanitation	0.753	0.514	0.304	0.457	0.412	0.27	.								
Walls	0.808	0.36	0.328	0.294	0.279	0.158	0.677	.							
Overcrowding	0.704	0.786	0.629	0.773	0.743	0.542	0.745	0.738	.						
Electricity	0.946	0.427	0.402	0.205	0.375	0.11	0.841	0.678	0.797	.					
Cooking fuel	0.758	0.797	0.578	0.774	0.758	0.502	0.836	0.947	0.638	0.993	.				
Assets	0.791	0.466	0.272	0.424	0.368	0.217	0.559	0.508	0.769	0.846	0.791	.			
Land and livestock	0.545	0.361	0.308	0.356	0.373	0.314	0.424	0.388	0.64	0.391	0.685	0.48	.		
Child nutrition and labour	0.614	0.361	0.314	0.382	0.358	0.23	0.392	0.367	0.652	0.422	0.692	0.338	0.358	.	
Cognitive development	0.561	0.722	0.535	0.607	0.58	0.407	0.548	0.597	0.632	0.682	0.647	0.542	0.462	0.642	.
Uncensored Headcount ratio	45.1%	11.7%	24.9%	6.4%	15.4%	7.8%	27.6%	14.4%	55.9%	4.0%	55.6%	23.7%	32.9%	23.8%	42.9%

Source: Authors' calculations based on data from MICS 2017–18 – see Table B7 in the Appendix

Table 9 shows the correlation between the uncensored headcount ratios for each district of each indicator of the Child MPI (recall, these refer only to the population of children aged 0–17) with the respective district MPI values from Child MPI, MPIP and the MPIP disaggregated by children. These correlations are high (above 0.97) for the new child indicators included in the Child MPI with any of these three MPI measurements. So, it is interesting even the two measures that do not include those indicators (bold) proxy them.

Table 9. Correlation between uncensored headcount ratios and the MPI values of the Proxy MPIP, the Child-disaggregated MPIP and the Child MPI by district.

Uncensored headcount ratios	Proxy MPIP	Child-disaggregated MPIP	Child MPI
Years of schooling	0.937	0.943	0.960
School attendance	0.963	0.959	0.937
Immunization	0.681	0.648	0.629
Antenatal care	0.697	0.709	0.661

Assisted delivery	0.906	0.904	0.899
Electricity	0.059	0.059	0.042
Sanitation	0.871	0.869	0.889
Water	0.897	0.894	0.859
Walls	0.887	0.894	0.922
Cooking fuel	0.917	0.903	0.884
Assets	0.746	0.765	0.786
Overcrowding	0.938	0.935	0.956
Land and livestock	-0.078	-0.082	-0.029
Child Nutrition and Labour	**0.949**	**0.947**	**0.958**
Cognitive development	**0.990**	**0.992**	**0.966**

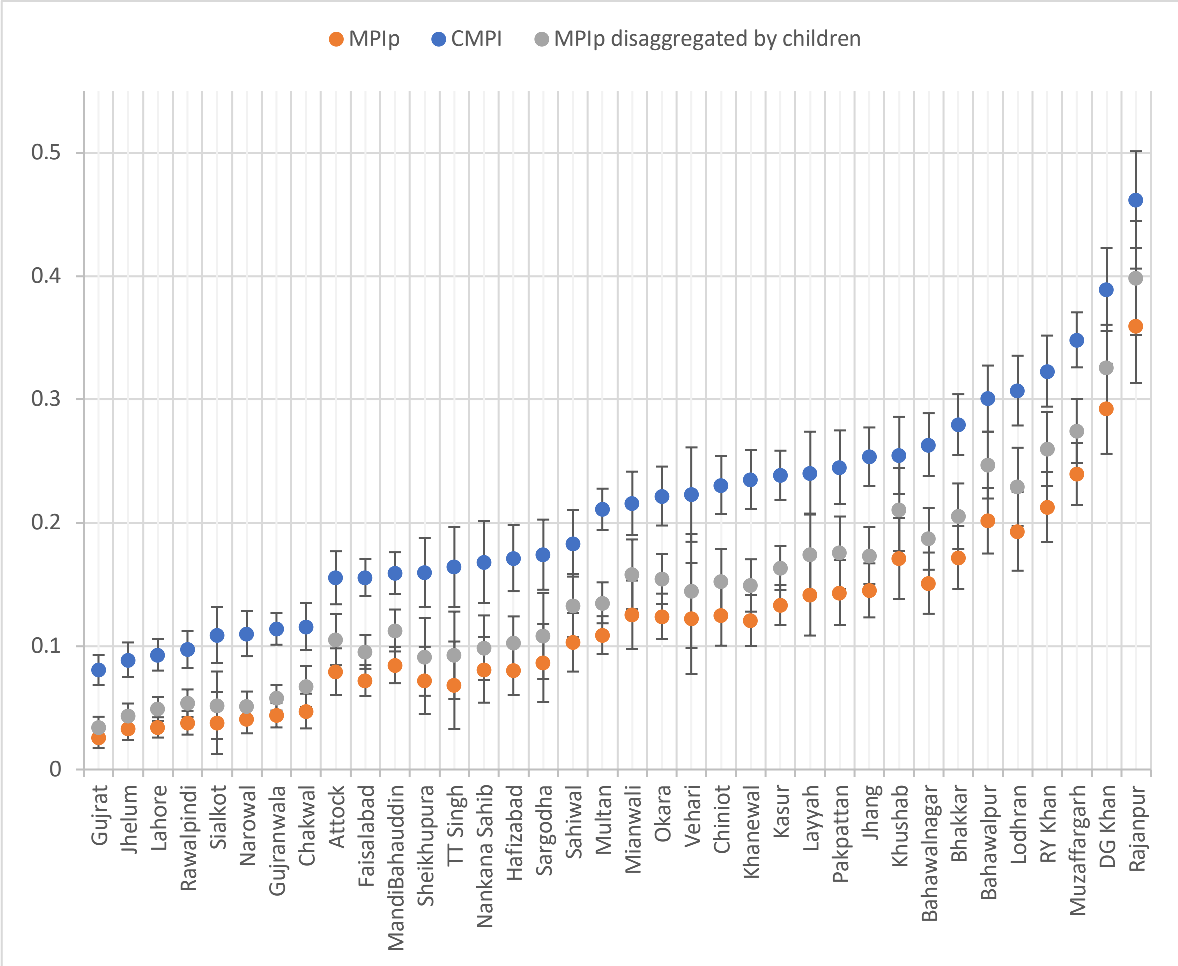
Source: Authors' calculations based on data from MICS 2017–18.

4.4.2 District Rankings[20]

Figure 3 shows the value of the MPI_P the Child-disaggregated MPI_P and the Child MPI and their corresponding 95% confidence intervals. The Child MPI usually displays the highest level amongst these measurements and is statistically different from the Proxy MPI_P. However, the Child-Disaggregated MPI and Child MPI_P overlap only for six districts including the two poorest districts – D G Khan and Rajanpur. Still, overall levels vary: the paired t-tests for equality of means confirms that the district mean of the Child MPI is significantly different from that of MPI_P and that from the MPI_P disaggregated by children. Yet at the district level the Child MPI does not radically alter the relative ranking of districts: it broadly coincides with the patterns of the Child-disaggregated MPI, and especially so in the poorer districts.

20 In this section we refer here to the MPI as M0 to distinguish it from the three measures used in this analysis for Child MPI and the proxy MPI_p.

Figure 3. MPIp, Child-disaggregated MPIp and Child MPI with 95% confidence intervals, 2017/18



Source: Authors' calculations based on data from MICS 2017–18.

Table 10 shows the ranking distributions by district using the incidence (H), the intensity (A) and MPI. Recall that rank analyses are crude because they rely only on the point estimate and do not consider confidence intervals so may be over precise. Yet in the case of MPI, 13 of the 36 districts had the exact same ranking for all three specifications: 1, 2, 3, 5, 7, 8, 17, 18, 24, 33, 34, 35, 36. Furthermore, the same eight districts were considered least poor and the same six districts are considered poorest, with differences of rank never more than one place. The intermediate poverty ranks are also largely consistent, but with a few visible discrepancies. The highest variation is for the district of Attock and Mandi Bahauddin, which ranks 9 and 11 according to the Child MPI, but 14 and 16 according to the Child-disaggregated MPI$_p$, respectively. Only one district has a difference of four places between the two child measures. Overall, out of 108 comparisons in rank across the three distributions, 54 had exactly the same rank in all three measures while 28 had one place change difference. So, 76% of comparisons only changed zero or one rank. 15 comparisons changed two places, four comparisons changed three places, five changed four places, and two five places. The child-disaggregated and Proxy MPI differ by a maximum of two places, whereas the Child MPI and Proxy MPI differ four times by 4 places and once by three; the remaining 31 districts have the same or at most two place difference.[21] According to incidence, the five least poor regions and the seven poorest are both the least and poorest according to all measures with differences of at most one rank. Further, the ranks exactly matched for districts 1, 7, 18, 20, 27, 34, 35, and 36. The districts of Mandi Bahauddin, Khushab and Mianwali have afive or four , while Attock, TT Sindh, Khanewal, Chiniot and Jhang have a three-rank difference between the two child MPIs. The remaining 28 districts differ in incidence by one or two ranks for Child-disaggregated MPI_P and the Child MPI.

Table 10. District rankings based on MPI, H and A, according to the Proxy MPI_P the Child-disaggregated MPI_P and the Child MPI, 2017/18

	MPI			Incidence (H)			Intensity (A)		
	CMPI	**MPIp**	**MPIpAge**	**CMPI**	**MPIp**	**MPIpAge**	**CMPI**	**MPIp**	**MPIpAge**
Gujrat	1	1	1	1	1	1	3	8	10
Jhelum	2	2	2	3	3	2	1	1	1
Lahore	3	3	3	2	2	3	7	11	9
Rawalpindi	4	4	6	4	5	5	4	5	5
Sialkot	5	5	5	5	4	4	6	9	8
Narowal	6	6	4	8	6	6	2	2	2
Gujranwala	7	7	7	7	7	7	5	6	6
Chakwal	8	8	8	6	8	8	9	13	22
Attock	9	12	14	11	12	14	11	15	15
Faisalabad	10	10	11	9	10	10	13	19	17
Mandi Bahauddin	11	15	16	10	14	15	14	20	18
Sheikhupura	12	11	9	13	11	11	8	4	3
Tt Singh	13	9	10	12	9	9	18	27	27
Nankana Sahib	14	14	12	15	15	13	12	3	4
Hafizabad	15	13	13	14	13	12	15	21	19
Sargodha	16	16	15	17	16	16	10	7	7
Sahiwal	17	17	17	16	17	17	22	22	23
Multan	18	18	18	18	18	18	19	10	11
Mianwali	19	23	23	19	21	23	16	18	20
Okara	20	21	22	21	22	22	17	14	14
Vehari	21	20	19	20	20	20	21	16	13
Chiniot	22	22	21	24	23	21	20	12	12
Khanewal	23	19	20	22	19	19	25	29	29
Kasur	24	24	24	23	24	24	26	25	25
Layyah	25	25	26	26	25	26	23	23	24
Pakpattan	26	26	27	27	27	27	24	17	16
Jhang	27	27	25	28	26	25	28	28	28

21 There are of course a few exceptions in the middle of the distribution like Pakpattan which consistently ranks 25 in these three measurements according to M_0.

Khushab	28	29	30	25	29	29	30	31	31
Bahawalnagar	29	28	28	29	28	28	27	24	21
Bhakkar	30	30	29	31	30	30	29	26	26
Bahawalpur	31	32	32	30	31	32	33	33	33
Lodhran	32	31	31	33	32	31	31	30	30
Ry Khan	33	33	33	32	33	33	34	34	34
Muzaffargarh	34	34	34	34	34	34	32	32	32
Dg Khan	35	35	35	35	35	35	35	35	35
Rajanpur	36	36	36	36	36	36	36	36	36

Note: each column shows independent rankings taking a different variable at time in each column.

Source: Authors' calculations based on data from MICS 2017–18.

Table 11. Rank and values of MPI and H for all three measures for districts with minimum and maximum rank differences

	Rank by MPI					
	CMPI	**Child-disagg**	**MPIP**	**CMPI**	**Child-disagg**	**MPIP**
Faisalabad	10	11	10	0.156	0.095	0.072
				(0.142-0.171)	(0.082-0.111)	(0.061-0.085)
Attock	9	14	12	0.155	0.105	0.079
				(0.136-0.177)	(0.085-0.130)	(0.064-0.098)
Sheikhopura	12	9	11	0.160	0.091	0.072
				(0.142-0.179)	(0.076-0.109)	(0.060-0.087)
Mandi Bahauddin	11	16	15	0.159	0.113	0.085
				(0.144-0.176)	(0.096-0.132)	(0.072-0.100)
Mianwali	19	23	23	0.216	0.158	0.126
				(0.192-0.242)	(0.130-0.191)	(0.102-0.153)
	Rank by Incidence					
	CMPI (H)	Child Disagg	MPI_P	Child (H)	National H	Child Disagg
Mandi Bahauddin	10	15	14	39.4%	24.5%	18.8%
				(35.9-43.0)	(21.0-28.3)	(16.1-21.9)
Khushab	25	29	29	57.1%	43.3%	36.4%
				(51.5-62.6)	(36.9-50.0)	(30.7-42.4)
Mianwali	19	23	21	52.9%	34.3%	27.9%
				(48.1-57.6)	(28.7-40.3)	(23.3-33.1)
T T Singh	12	9	9	40.1%	19.6%	14.9%
				(0.351-0.452)	(0.154-0.246)	(0.117-0.189)

Source: Authors' calculations based on data from MICS 2017–18

Table 11 above provides examples the furthest distant rankings. It is not possible to directly compare the point estimates across measures. However, it is possible to compare point estimates across the same districts. So, we see that in Mandi Bahauddin the national MPI_P confidence intervals overlap with those of Faisalabad with five points rank difference. We further see that the confidence intervals of the MPI_P for Mandi Bahauddin and Sheikhupura overlap, although their ranks are four points different and furthermore the confidence intervals of Faisalabad and Sheikhupura overlap. Hence the apparent difference in rankings in MPI_P is not statistically significant. The same pattern can be observed for child disaggregated MPI_P and child MPI for these districts. Therefore, we can presume that these ranks are acceptable. Similarly, in terms of rankings by incidence, there is a four-rank difference between Mandi Bahauddin and TT Singh in the MPI_P (H), but the confidence intervals again overlap with each other. We can conclude that in this dataset, the three measures broadly agree on the district ordering.

In order to assess rankings more precisely, we assess the stability of the district poverty orderings by the Child MPI, the National MPI_P and the National MPI_P value for children. The district orderings can be considered robust if they are preserved according to the three specifications. This means that, largely, the poorest (or the least poor) districts by one specification remain among the poorest (or the least poor) by the other specifications.

The Spearman coefficient is at least 98% among all three specifications whereas the Kendall tau-b rank coefficient (which accounts for tied ranks so is more precise) is at least 93% for MPIp for other two specifications and around 91% for CMPI and age disaggregated MPIp for the children. This shows the district poverty orderings by the three specifications are largely congruent (Table 12).

Table 12. Correlation among district's Ranks for Different specifications

		National MPIp	**Child MPI**
Child MPI	Spearman	0.992***	
	Kendall's tau-b	0.947***	
Child-Disaggregated National MPIp:	Spearman	0.99***	0.984***
	Kendall's tau-b	0.964***	0.914***

Source: Authors' calculations based on data from MICS 2017–18.

The most precise examination of robustness, which considers standard errors, is to perform pairwise comparisons (see Alkire and Santos, 2014). This method consists of establishing the poverty ordering for each pair of districts by each MPI specification, and then assessing whether the ordering is consistent across the three specifications. For instance, if one establishes that poverty A is statistically significantly poorer than district B by the Child MPI and this statement holds true for the National MPI_P and the National MPI_P for children, then the pairwise comparison between A and B is robust. In this case, we see that of all the possible pairwise combinations among the 36 districts (i.e. 630 possible comparisons), 563 (89.4%) are robust (Table 13).

Table 13. Pairwise comparisons (PWC) of MPI using Child MPI, National MPI$_P$ and National MPI$_P$ for children

Number of districts	Possible comparisons	PWC consistent across all specifications	PWC significant by the Child MPI and consistent across all specifications
36	630	563/630= 89.4%	482/505=95.5%

Source: Authors' calculations based on data from MICS 2017–18.

Furthermore, we can limit ourselves to assess the stability only of the pairwise comparisons that result in a strict ordering at the baseline. This means focusing only on statistically significant poverty differences between districts in one distribution. Taking the Child MPI as the baseline specification to identify significant orderings, we find more than 95% are identical by the other specifications. This compellingly corroborates the rank correlation analyses showing the large stability of district orderings by the three specifications.

This section drew together the district level disaggregation that emerged from the Proxy MPI$_p$, a Child-disaggregated MPI$_p$ and the Child MPI, in order to ascertain the extent to which incorporating individual child analysis greatly changed the identification of the poorest districts. The resulting analysis showed clearly that, at least in this case, the district ranking was robust, with district ranks, Spearman's and Kendal Tau correlations as well as pairwise comparisons across the Proxy MPI$_p$ the Child-disaggregated MPI$_p$ and the new Child MPI all confirming congruence.

4.4.3 Nutrition and MPI

Table 14 presents the percentage of people living with a child under 5 that is either stunted or underweight. These indicators are components of the life-cycle indicator of Child nutrition and labour used in the Child MPI. In Punjab 26.4% of people have a stunted or underweight child in their household. At district level Rajanpur, firstly, and DG Khan, secondly, are the districts with the highest percentage of people who share their household with an undernourished child (48% and 47%). In the rest of districts this percentage is less than 35%, and in 18 districts, this share is smaller than Punjab's average.

The National and the Proxy MPI$_p$ lacks nutrition because this is not present in the PSLM survey. Yet nutrition deprivations are both destructive and high in Pakistan. Furthermore, many policy strategies rightly focus on nutritional interventions. There has therefore been a very keen interest in expanding the MPI to include direct measures of nutritional deprivations.

Table 14. Percentage of people with at least one child under 5 that is undernourished (underweight or stunted) by district, Punjab 2017/18

Districts	Value	lb	ub
Gujrat	17.5%	14.7%	20.3%
Jhelum	16.9%	13.6%	20.2%
Lahore	18.3%	16.5%	20.2%
Rawalpindi	17.6%	14.8%	20.3%
Sialkot	21.0%	18.6%	23.3%
Narowal	23.0%	18.7%	27.4%
Gujranwala	22.8%	20.3%	25.3%
Chakwal	17.8%	14.9%	20.7%
Attock	20.7%	17.4%	24.0%
Faisalabad	23.3%	21.2%	25.4%
Mandi Bahauddin	22.6%	19.8%	25.4%
Sheikhupura	25.3%	21.9%	28.7%
Tt Singh	25.6%	21.9%	29.3%
Nankana Sahib	24.1%	20.9%	27.4%
Hafizabad	22.5%	19.0%	26.0%
Sargodha	25.1%	22.5%	27.8%
Sahiwal	24.4%	21.0%	27.8%
Multan	30.2%	27.8%	32.7%
Mianwali	26.9%	23.8%	30.1%
Okara	29.1%	25.4%	32.8%
Vehari	28.1%	24.6%	31.5%
Chiniot	31.3%	28.0%	34.6%
Khanewal	29.3%	25.8%	32.7%
Kasur	27.7%	24.3%	31.0%
Layyah	26.0%	21.9%	30.1%
Pakpattan	27.5%	24.1%	30.9%
Jhang	34.4%	30.9%	37.8%
Khushab	28.2%	23.6%	32.7%
Bahawalnagar	29.0%	25.6%	32.4%
Bhakkar	34.0%	30.3%	37.7%
Bahawalpur	27.1%	24.2%	29.9%
Lodhran	34.7%	30.4%	39.1%
Ry Khan	36.8%	33.3%	40.4%
Muzaffargarh	34.2%	31.6%	36.9%
DG Khan	47.0%	42.6%	51.4%
Rajanpur	48.4%	43.6%	53.1%

Source: Authors' calculations based on data from MICS 2017–18.

Table 15 provides the correlation between the share of undernourished children and all three MPI measures examined in this study. The Child MPI is the only measure that includes nutrition. The other two lack this information. So, it would be expected that the correlation would be highest with the Child MPI and lower with the others. However, in fact, all three measures have an extremely high correlation. It is surprising, but reassuring, to discover, by using the MICS 2017–18 dataset that indeed does include child malnutrition, that even the National MPI and Child-disaggregated MPI, which completely lack nutrition data, nonetheless appear to provide a strong proxy of the nutritional status of a household. While this finding should not lessen the interest in obtaining direct anthropometric data where possible, it can increase the confidence in the use of the National and Child-disaggregated MPI, even if nutritional data are not available.

Table 15. Correlation between the percentage of people with undernourished children and the Proxy MPI_p, Child-disaggregated MPI_p and the Child MPI at district level.

	MPI (M_0)	H
Proxy MPI_p	0.929	0.921
Child-disaggr. MPI_p	0.919	0.909
Child MPI	0.939	0.900

Source: Authors' calculations based on data from MICS 2017–18.

4.5. Results at-a-glance: Convergent District Assessments

The analysis found that the pattern of poverty across Pakistan according to all three measures is convergent. From a geographic lens, all three measures find that multidimensional poverty in Punjab is higher in rural areas. All three suggest that the Southern divisions are poorer. Indeed, five southern divisions have larger MPI than average for all three measures. In terms of districts, the values of MPI across the three measures considering confidence intervals were compared for each district. The point estimates of the Child MPI are higher than the Proxy MPI for all of the districts. District rankings were then compared across all three measures. Although ranks are over-precise, because they do not consider standard errors, findings show that 14 of the districts had the exact same ranking: 1, 2, 3, 5, 7, 8, 17, 18, 24, 33, 34, 35, 36. The same eight districts were ranked as the least poor districts, and the same six districts ranked as poorest. Out of 108 comparisons in rank across the three distributions, 54 shared the same rank and 28 had one place change difference – so 76% of comparisons only changed zero or one rank. While comparing the rankings of the districts for two child measures, only one changed four places and two, five places – but on closer examination of confidence intervals, these apparent rank differences are not statistically significant. Across districts, 89.4% to 95,5% of pairwise comparisons of district values were convergent, considering 95% confidence intervals. Based on this exploration, we conclude that the Proxy MPI_p, the Child-disaggregated MPI_p and the Child MPI all provide strongly congruent information regarding the levels of poverty across the districts of Punjab.

Because data on child nutrition is expensive, but very serious and damaging, and because it shows high deprivations – 26% of people live in a household with at least one undernourished child at home in Punjab – the nutrition variable (which was also already included in the Child MPI) was separately probed by correlating the percentage of households with undernourished children and the levels of the Proxy MPI$_p$ the Child-disaggregated MPI$_p$ and the Child MPI. Correlations across MPI and nutrition by district were very high for all three measures at 0.92-0.94. Despite the fact that the Proxy MPI$_p$ and the Child-disaggregated MPI$_p$ lack nutrition, the identification of poverty levels across district is highly correlated with that which would be obtained if they had included nutrition data. This is reassuring, as it suggests that even when, unfortunately, child nutrition data are not available, the district rankings overall are not very different.

5. Concluding Remarks

According to the Proxy MPIP in 2017/18, a little less than one in four (23.6%) people in Punjab were multidimensionally poor. They were, on average, deprived in almost half (46.6%) of the weighted MPIP indicators. Deprivations in years of schooling, cooking fuel, and overcrowding, had the highest censored headcount ratios. Across Punjab, MPI values range from 0.026 in Gujrat and 0.033 in Jhelum (north) to 0.293 in DG Khan and 0.360 in Rajanpur (south).

Child-disaggregation of the MPIP finds that children (0–17) – who comprise 42.9% of the population – are disproportionately affected by multidimensional poverty. The headcount ratio of children who are poor was 29.5%, compared to adults 18-64 at 19.2%, and deprivations were significantly higher for children than adults in each of the MPIP indicators.

Using the additional information available from the MICS 2017–18, we estimated an individual level Child MPI for Punjab that is linked to the MPIP. The identification of poor children used a poverty cut-off equal to 25% so each child who is poor by the Proxy MPIP is also identified as poor, plus additional children. At the provincial level, the estimates for poverty incidence (47.1%.), intensity (42.8%) and the MPI for this innovation (0.202) are statistically higher than the Child-disaggregated MPIP by children. So, the two newly added indicators clearly identify a larger set of poor children than that currently observed by the MPIP with age desegregations. We then explored to what extent this affected the district rankings, because these rankings are the primary information source for district-wise budget allocation.

The findings delivered by this new Child MPI measurement are actually very similar to the proxy MPIP implemented in this study. Both confirm that rural areas and the Southern divisions usually have the highest levels of poverty. Within this set of constituencies, the ancient district of Rajanpur had the largest MPI and most poverty by all measures.

This study zoomed in to analyse the district-level analyses emerging from the three MPIs. Despite the fact that the provincial level of these measures is statistically different, the district-level rank differences between these measures are strikingly similar. This implies that while the new Child

MPI identifies a deeper and more refined deprivation profile at the individual level, the district (and Division) ranking are essentially convergent.

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