

Employing the Multidimensional Poverty Lens to Deliver Livelihood Support to the Urban Poor

Lessons from a UNDP Bangladesh intervention

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Impacts of crises on inequality and marginalization are more complex and layered in today's interconnected world than they were in the past, often manifesting through exacerbation of various pre-existing vulnerabilities of disadvantaged groups. Recovery strategies and efforts to build resilience thus require more multidimensional lenses for addressing secondary impacts of shocks, particularly on the most vulnerable. This brief explores whether multidimensional approaches to addressing issues related to poverty and vulnerability are more helpful in crisis contexts. Towards that end, the brief analyzes primary data on beneficiaries of UNDP Bangladesh's Livelihoods Improvement of Urban Poor Communities (LIUPC) project. The findings are expected to contribute to the conception, design and scaling-up of future initiatives and contextualized solutions to strengthen the resilience of urban poor communities in similar settings.

In Bangladesh, the national discourse and official statistics have historically focused on incomebased measures to understand poverty issues and design policies, including in crisis response.² The country's periodic Household and Income Expenditure Survey (HIES) uses income poverty as its focal lens for analysis. However, Global Multidimensional Poverty Index (MPI)³ scores of Bangladesh, which take into account measures of education, health and living standards, have

consistently outstripped national income-based estimations.⁴

The COVID-19-induced crisis has further revealed the shortcomings of a unidimensional metric for addressing poverty. Despite a decade of sustained economic growth and decline in income poverty, Bangladesh continues to face challenges linked to rising living costs, jobless growth and climate change, among others. The COVID-19

crisis has exacerbated these vulnerabilities in Bangladesh, especially for those living in low-income settlements in urban and peri-urban areas.⁵ According to estimates from various organizations, the pandemic has resulted in 17.5 to 20 million new poor in Bangladesh.⁶ The crisis's multifaceted impacts have further stressed the importance of pre-emptive measures and resilience-building efforts to address underlying multidimensional aspects of vulnerabilities beyond income.

Against this backdrop, this policy brief attempts to contribute evidence to shifting the emphasis on the discourse towards more multidimensional

perspectives for addressing issues related to poverty and vulnerability, especially in crisis contexts. The brief discusses results of a survey based on UNDP Bangladesh's LIUPC project's database of low-income urban households. It also offers important insights into the programmatic approach of delivering grants using the MPI with the potential to help the most vulnerable households get through unprecedented shocks like COVID-19. The emerging policy lessons can help development practitioners and policymakers at large in countries facing similar socio-economic vulnerabilities and recurring crisis situations.

Background of the survey

The LIUPC project is a multidimensional poverty reduction programme with interventions covering four million urban poor living in 19 cities and towns across Bangladesh. The project has been using the MPI metric to identify and deliver conditional cash support to members of eligible MPI-poor households to either start a new business or expand an existing one. The project maintains a database for MPI indicators⁷ of over 700,000 households.

The project considered households with MPI scores (the sum of weighted scores for deprivations) of 20 and above to be multidimensionally poor and eligible to receive 'business grants'. The beneficiary of the grant is a female member of the selected household. For this analysis, 360 households across seven cities in Bangladesh were randomly selected from the project's beneficiaries following certain criteria (for more details, see Box 1).

For comparison, sample households were categorized under three groups based on their pre-COVID MPI scores and whether or not they received business grants prior to the pandemic (i.e., during 2018–2019): (i) vulnerable non-poor households with pre-COVID MPI between 10 and 20; (ii) poor grantee households that received business grants with pre-COVID MPI between 20

and 40; and (iii) poor non-grantees with pre-COVID MPI between 20 and 40.8 The third category, poor non-grantee households, did not receive the grants based on a secondary vetting done by the project in consultation with community members to choose the neediest and most deserving households for the limited number of grants. All three groups of households benefitted from the project's common interventions (e.g., knowledge, information, participation in savings and credit group, etc.). Moreover, all three groups received (in varying degrees) COVID-response-related relief support, independent of their grant-receiving status, in the form of cash, food and preventive materials. This came from different sources, including the project, the government, non-governmental organizations and community members, etc.

The study uses a structured questionnaire to compare MPI scores across the three groups mentioned above over two periods—before the COVID-19 crisis and before receiving grants (applicable for grantees) and two years into the COVID-19 crisis and after receiving grants. The present multidimensional poverty situation of the households is assessed based on the same set of questions asked during their registration in 2018 and 2019, with some additional questions related to the use of business grants and COVID-19.9

Box 1: Note on Methodology

Sample design

A stratified random sampling method was used to randomly select 360 households registered with the LIUPC project in the years 2018 and 2019 across seven cities of Bangladesh.

The population was divided into the following strata:

- Year/phase: 2018, 2019
- Beneficiaries: Recipients of business grants (grantees) and those who did not receive any grants (non-grantees)
- •MPI score: 10–20 (non-grantees), 20–40 (both grantees and non-grantees)
- •Cities: Chandpur, Chittagong City Corporation, Dhaka North City Corporation, Khulna, Mymensingh, Narayanganj and Sylhet City Corporation

The minimum total sample size determined was 360, with 60 from each comparison group and with proportional representation from the seven cities, using the formula in **Equation 1** below (considering 10% of the sampled households are unreachable or fall out of the project over the course of time, known as attrition rate).¹⁰

Equation 1

$$N = \frac{2(z_{\alpha} + z_{\beta})^{2} (1 + (n-1)\rho)}{n[(\mu_{1} - \mu_{2})/\sigma]^{2}} \times attr,$$

where σ^2 is the assumed common variance in the two groups at two time points (before and after COVID), $\mu_1 - \mu_2$ is the difference in means of the two groups, \boldsymbol{n} is the number of timepoints, $\boldsymbol{\rho}$ is the assumed correlation of the repeated measures and **attr** is the attrition rate for possible dropout from project/non-response.

The sample size was drawn considering a 95% confidence interval, 80% power and an attrition rate of 10%. With a two-tailed 0.05 hypothesis test, \mathbf{z}_{α} value is 1.96. The value of \mathbf{z}_{β} is 0.842 with a power of 80%. The effect size, $(\mu_1 - \mu_2)/\sigma$, is chosen as 0.5, considering a medium effect.¹¹ The value of \mathbf{n} is 2 for the two time points and the correlation of the repeated measures is assumed as 0.7; i.e., the correlations between the MPI scores of the same households before and after covid is 0.7.

Data analysis

The data analysis is comprised primarily of descriptive analysis, comparative analysis and graphical presentations. For the comparative analysis, the most appropriate hypothesis test was performed to compare the MPI scores of the different groups registered in 2018 and 2019 over two different time points (before COVID and after COVID, around February 2022). Tests performed to check the 5% level of significance for different alternative hypotheses included the ANOVA test, paired T-test, and Welch two sample T-test.

Main findings of the survey

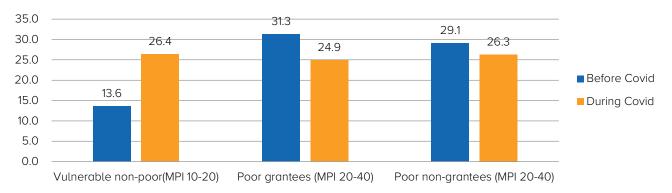
Within the above context, the following messages came out strongly from the data analysis.

Business grants helped poor households improve their MPI scores.

Among the three household categories, poor grantee households exhibited the most (statistically) significant decrease in their MPI scores over time,

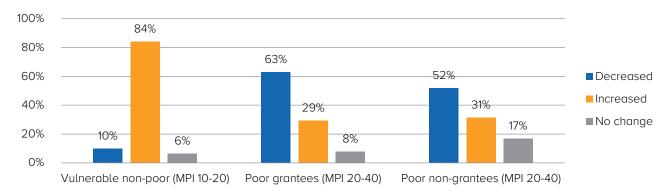
as reflected by 63 percent of such households with reduced MPI levels (see Figures 1 and 2). Figure 1 also depicts a decline in the MPI score among poor non-grantee households, albeit a smaller one than among poor grantees. This could be partly explained by variation in the nature of COVID relief received by the three groups from different sources (independent of their grant-receiving status from the project), as discussed later.

Figure 1: Change in MPI scores across three household groups



Source: Authors' own calculations

Figure 2: Percentage distribution of households with change in MPI score

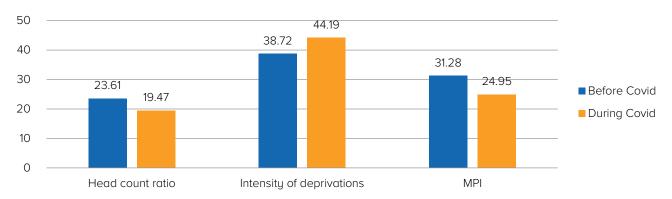


Source: Authors' own calculations

Moreover, MPI has two components: poverty headcount and intensity of deprivation.¹⁵ The poor grantees experienced a four-percentage point fall in multidimensional poverty headcount ratio (see Figure 3). However, the intensity of deprivation increased by 5.5 percentage points. This further reflects the multidimensional nature of crisis impacts on these households (see Box 2). Over a third of

grant-recipient households used the money to start a new business, and almost three-fourths expanded their existing business. Around 9 percent of the grant recipients were able to do both. They also reported that the grants i) helped them to increase their regular income, ii) allowed them to continue their children's education and iii) helped improve the overall family welfare.

Figure 3: Change in headcount, intensity and MPI of poor grantees (MPI 20-40)



Source: Authors' own calculations

Furthermore, 2018 grantees (who received the money sometime in 2019) show a 15 percent decrease in their MPI scores. In comparison, 2019 grantees (who received the money during the COVID-induced lockdown in 2020) exhibited a larger decline in MPI scores of around 28 percent. The relatively lower decrease for 2018 grantees raises concerns regarding the sustained benefits of the grants in terms of financial capital and income over an extended period for low-income households. Another possible explanation behind the better performance by 2019 grantees could be the fact that they received a slightly bigger grant amount (around US\$35 more) as cash. These households also received the money in the middle of the crisis, which may have allowed them to make more informed choices and better utilize the flexibility that came with cash grants.

Box 2: Socio-economic Impact of COVID-19 on the sample households under the LIUPCP

A socio-economic assessment was undertaken at the early stages of the pandemic (following a two-month countrywide lockdown) to determine the impact of COVID-19 and its containment measures on the project beneficiaries.¹⁶ Loss of employment, closing down of businesses, reduced income and consumption, depleted savings and assets and increased debt levels were among the economic impacts of the crisis. The most obvious social fallouts included the closing down of schools, a rising number of dropouts, early marriages and increased domestic violence. The assessment also estimated that in the low-income settlements in and around the 20 cities and towns where the project operates, 3.7 million people emerged as 'new income-poor' due to the effects of the COVID-19 lockdown. The assessment further looked at the changes in MPI indicators of beneficiary households and found a statistically significant increase in multidimensional poverty immediately following the lockdown as compared to a baseline study conducted before the onset of the pandemic. Both the headcount of multidimensional poor and the intensity of deprivation were affected by the crisis.

Vulnerable non-poor were the most affected in terms of multidimensional poverty.

Vulnerable non-poor (non-grantee) households with pre-COVID MPI scores between 10 and 20 fell just below the project's primary eligibility score of MPI 20 for grantees. Being so close to the poverty line, these households were not poor by definition but were vulnerable to falling into poverty if exposed to shocks. The COVID-19 crisis presented this exact external distress to these households, which made them the worst affected group in terms of change in MPI scores. The vulnerable non-poor group exhibited an increase in their MPI by almost 13 points (see Figure 1), reflecting 83 percent of households (see Figure 2) experiencing a deterioration in their multidimensional poverty.

The survey results corroborate the emergence of a significant number of 'new poor'. Other incomebased national assessments suggested an equally staggering number of non-poor people subsisting just above the income poverty line, falling into poverty following the onset of the COVID-19 pandemic.¹7 People in these vulnerable categories usually remain outside the purview of usual and emergency policy measures since they do not meet eligibility requirements under normal circumstances. As such, their vulnerabilities remain unaddressed and are brutally unveiled during crises.

Cash support helps in tackling MPI, especially during a crisis.

Containment measures (i.e., lockdown) severely constrained the livelihoods of the surveyed households (see Box 2). In response, COVIDrelated support measures were extended by the government, non-governmental organizations, local representatives, private philanthropy and friends and family of the households, mostly in the form of cash, food and preventives. The LIUPC project was also quick to respond to the situation, thanks to its readily available database on urban households. Households belonging to all three categories (vulnerable non-poor, poor grantees and poor non-grantees) benefitted from one or more forms of relief measures from the above-mentioned sources. According to survey data, larger shares of poor grantees (31.5 percent) and poor non-grantees (28 percent) received cash as a form of Covid relief. This is compared to only 10 percent of vulnerable non-poor households receiving the same (see Figure 4). Preventive materials were the most common form of support received by this group.

35% 31.46% 30.11% 27.74%_ 26.28% 28.09% 30% 25% Cash 20% 16.85% Food 15.33% 15.05% 15% ■ Preventive 9.68% materials 10% 5% 0% Vulnerable non-poor (MPI 10-20) Poor grantees (MPI 20-40) Poor non-grantees (MPI 20-40)

Figure 4: Share of households receiving different types of relief

Source: Authors' own calculations

As a result, non-grantee poor households saw a (statistically) significant decline in their MPI at the time of the survey (see Figure 1). The poor nongrantees were better off than poor grantees before the pandemic, as per community-level assessments, and they benefitted from the common programmes extended by the project. While these factors may have contributed to their resilience against the crisis, they do not explain why the poorer nongrantee households fared better than the non-poor vulnerable households. The explanation possibly lies in the differing nature and levels of COVID assistance received by the different groups.

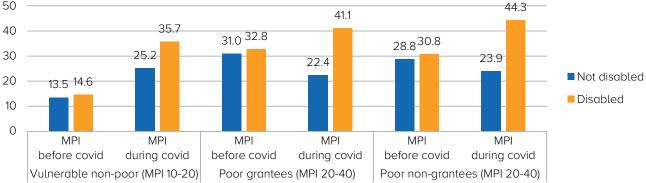
Unconditional cash support (as in the case of COVID response) is a key tool for social protection responses to shocks and has been widely known to be more effective in addressing the multifaceted needs of the poor during crisis situations. Direct cash to households provides the most flexibility for a family to utilize the money as per their specific needs. The better access to direct and unconditional cash during the crisis could be why poor non-grantee households performed well in retaining or improving their multidimensional poverty levels compared to non-poor households.

Aggregate changes in MPI masks disparities across households with vulnerabilities.

It is well known that the pandemic has disproportionately impacted households and individuals with distinct vulnerabilities related to, among others, their gender, disability status, geographic regions, etc.²⁰ A disaggregated look into the survey findings on how MPI scores have changed for different groups two years into the pandemic highlights a similar picture.

Disability status. The survey revealed that MPI scores have increased for all households with one or more persons with disability (PwD) regardless of which category among the three household groups they belong to (see Figure 5). Despite an overall decline in MPI scores in poor grantee households, the improvement in multidimensional poverty was not reflected for those grantees with PwD members. While these grantee households had a slightly higher pre-COVID MPI score compared to their counterparts with no PwD members, the crisis has widened this difference by a big margin. This implies that business grants were not adequate in addressing the distinct and disproportionate challenges that households with PwD members had to endure during the COVID-19 crisis.





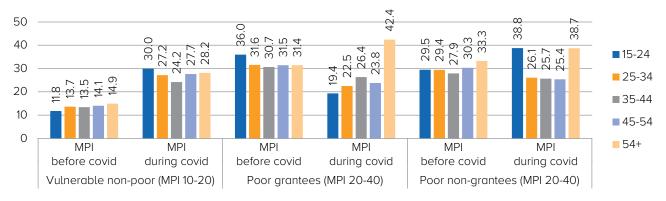
Source: Authors' own calculations

Demographic groups. Direct beneficiaries (all of whom are female) falling in the youth age group of 15–24 belonged to the most vulnerable households even before the pandemic. This is indicated by the high pre-COVID MPI scores of all three categories of households for this age group (see Figure 6). This is particularly true for the poor grantee households. The post-COVID MPI scores suggest that, overall, the pandemic has hit households belonging to the youngest and the oldest age groups the hardest, as indicated by the highest increases in MPI scores. This is a concerning trend because the youth in Bangladesh, particularly female youth, are considered a systemically vulnerable category. Female youth in Bangladesh are characterized by highly disproportionate rates of

labour force participation, unemployment, and being 'not in education, employment or training' (NEET).²¹

The only exception to the above pattern related to post-COVID MPI is the poor grantee households, where the MPI scores have improved for households with youth beneficiary members (see Figure 6). Grants seemed to be most effective in improving MPI for these households. This is an interesting insight, as it implies that despite the potential of young women to effectively use cash and positively contribute to their families, lack of access to finances often impedes their chances of overcoming multidimensional poverty (as was the case for both vulnerable non-poor and poor non-grantees).

Figure 6: Change in MPI scores by current age of direct beneficiary

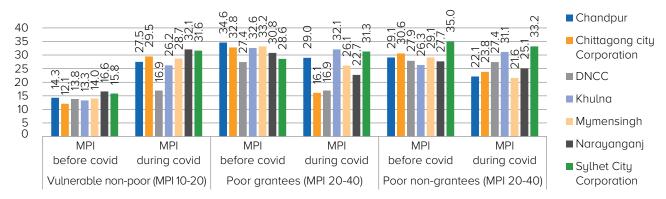


Source: Authors' own calculations

Geographic region. The implications of the COVID-19 crisis on multidimensional poverty have not been uniform across different cities. The impacts have been particularly harsh on low-income urban settlements in cities that are comparatively less socio-economically developed, e.g., Chandpur, Mymensingh, Sylhet,²² Narayanganj and Khulna compared to more advanced metropolitan areas like the capital city of Dhaka and the main seaport city of Chittagong (see Figure 7). This pattern was reflected in the uneven improvement in MPI for poor

grantee households across the seven cities. Much of the overall decrease in MPI scores for this group was influenced by the progress made by households residing in Dhaka and Chittagong. Sylhet is the only city where multidimensional poverty deteriorated for grantee households. Besides the fact that some cities are scarcely endowed, poor local governance, conservative contexts and limited mobility for women in many of these cities are likely to have contributed to the comparatively underwhelming performance of grantees.

Figure 7: Change in MPI score by city



Source: Authors' own calculations

Gender. While all direct beneficiaries considered in the sample were women, the heads of their respective households were, in most cases, male members. Only 28.5 percent of the total sample households were headed by female members. Across all three groups, female-headed households exhibited higher MPI scores on average during COVID (see Figure 8). For vulnerable non-poor households, the increase in MPI score was higher for female-headed households. On the other hand, for poor grantee households, the decline in MPI scores was lower for female-headed households compared to when the head was a male member. In fact, the slight decline in MPI scores for poor grantee female headed-households was almost

similar to the decline in MPI scores experienced by non-grantee poor female-headed households. This may imply that business grants had a marginal role to play in addressing the unique vulnerabilities of female-headed households and improving their multidimensional poverty levels. Female-headed households in Bangladesh are predominantly 'male-absent' households and do not necessarily represent more empowered women. Historically and traditionally, women in Bangladesh have had lower educational attainment, asset holdings, access to credit, connectivity to markets, and higher levels of malnutrition and risks of mortality.²³ The limited access to community support and social capital also makes them more vulnerable to crises and shocks.

31.1 31.6 35 28.4 29.3 25.7^{27.6} 25.8 30 23.1 25 20 ■Not female headed 13.6 13.6 15 Female headed 10 5 0 MPI MPI MPI before covid during covid before covid during covid before covid during covid Vulnerable non-poor (MPI 10-20) Poor grantees (MPI 20-40) Poor non-grantees (MPI 20-40)

Figure 8: Change in MPI scores by gender of household head

Source: Authors' own calculations

Key Policy Messages

The findings above evince some interesting results. The impact of the business grants among UNDP's LIUPC project beneficiaries' MPI scores in the context of the COVID-19 crisis has varied across different socio-economic groups. The results show that policymakers should pay more attention to not just income but also broader issues of deprivation to help achieve accelerated poverty reduction across different dimensions to achieve balanced spatial development and ensure that no vulnerable groups are left behind. The policy messages below are based on the survey results, a review of the related literature and the authors' observations on the usefulness of MPI.

i. Adopt MPI-based programming in addressing resilience during crises.

Since multidimensional poverty measures deprivations across a range of indicators, MPI-based programming can help identify vulnerabilities that go beyond income. MPI indicators can be

further disaggregated to see which dimensions contribute the most to poverty. This is especially useful during crisis periods, where deprivations often occur due to not just income but to various other factors. It also helps policymakers to differentiate between deprivations across different chronically vulnerable groups, e.g., disabled, women, senior citizens, etc., as well as newly impoverished groups. In light of this, there is a need for a more multidimensional lens in development programming in Bangladesh in line with the existing National Social Security Strategy²⁴ and for greater emphasis on the collection of non-income data from households. Further, national-level poverty measurements often overlook regional disparities that can exist in the living, education and health standards that can exist in a country. The beauty of the MPI metric is that it allows a certain level of contextualization to be more locally relevant. As such, it would make programming more effective if the MPI used was further adopted to capture spatial differences and regional realities within a country.

ii. Consider vulnerable non-poor in program design and crisis response

The starkest finding of the survey is how the vulnerable non-poor fared worst during the pandemic. They were worse-off than poor nongrantees because they were largely left out when it came to receiving adequate COVID relief, especially cash, that could address their loss of livelihoods. From the project's perspective, the disbursement of COVID relief among the surveyed households was largely based on MPI scores registered before COVID (during 2018–2019), which did not take into account the impact of the crisis. A similar pattern was observed in the national policy response to the COVID crisis using income-based approaches. Vulnerable populations subsisting just below the poverty line before the pandemic, and thus considered non-poor, were grossly unidentified and left out of the government's cash transfer programme during the initial response. It is imperative that both the government and development programming do not neglect the vulnerable non-poor. Not including them in programs will decrease their coping mechanisms in response to crises, adding to their risk of falling into more extreme multidimensional poverty.

iii. Continue to prioritize cash programs and focus on efficiency

Cash-based support should continue to be among the primary responses to address shocks. As is evident from the survey, it seems to be effective in addressing multidimensional poverty. However, there is a need for cash-based programs to be more efficient, especially in light of the leakages and irregularities that often occur. For instance, in 2020, the government of Bangladesh announced a cash grant equivalent to \$30 to five million poor families as part of its COVID recovery stimulus measures.²⁵ However, even three months into the program, two-thirds of the target beneficiaries had not received the funds amidst allegations of widespread leakages and irregularities in disbursement.²⁶ Thus, the efficiency of delivering cash programs should be prioritized. The ultimate goal should be universal coverage. But before that is reached, a reliable and functional national database of poor and vulnerable non-poor households with relevant information (personal, income, number of members, etc.) needs to be in place to quickly and effectively mobilize cash transfers and improve coverage.²⁷

iv. Invest in youth and other vulnerable populations and in cities with fewer economic opportunities

The survey shows that business grants were more effective in reducing the MPI of households when the beneficiary member was a youth. While grants and other measures also help people when targeted to higher-age groups, from specifically a poverty reduction point of view, it would be more useful to spend resources and create investment and credit opportunities for the younger population to increase their opportunities and market access. This is also in line with the national priority of harnessing the demographic dividend that Bangladesh is currently undergoing. Further, even though the current social protection regime has programs catering to vulnerable populations (such as PwDs, senior citizens, women, children, etc.), the grant amounts are usually too small to make any discernible livelihood changes. As such, emphasis should be on delivering programs that address the unique vulnerabilities of these groups. The results also show that the reduction in MPI was significantly lower in cities with lower economic opportunities. So, there is a case to be made for reducing spatial disparities and prioritizing the resilience-building and sustainability of less developed cities.

v. Encourage use of new data and technology to improve multidimensional poverty tracking

Static data (as used in this survey) cannot account for real-time changes. For example, migrants may move from one slum to another, or some beneficiaries may get multiple livelihood improvement supports from different development interventions. The use of big data, dynamic data, artificial intelligence (AI) and machine learning could address these inconsistencies and help attain the most updated information on households through remote sensing, mobile data, and other means for better evidence-based decision-making. For example, mobile data could be used to track the movements of project beneficiaries in realtime moving between different slums or areas or update their information against MPI indicators. A monitoring mechanism based on such technology could be more efficient in evaluating crisis response and quickly provide recommendations to improve the effectiveness of programmatic interventions. There is need for advocacy around promoting substantive investments in developing the capacity, infrastructure and regulatory environment required for new technology to be adopted by development programmes.

Endnotes

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- 2 The government of Bangladesh committed to developing a national MPI, acknowledging the need to explore poverty multidimensionally to create apt policies in the 2019 Voluntary National Review. Since then, it has taken steps to estimate the MPI of the country's population using the Multiple Cluster Indicator Survey of 2019. Source: Bangladesh Voluntary National Review 2020—Accelerated action and transformative pathways.
- 3 The Multidimensional Poverty Index (MPI), launched in 2010 by the Human Development Report Office of the United Nations Development Programme and the Oxford Poverty and Human Development Initiative at the University of Oxford, goes beyond a traditional focus on income to reflect the multiple deprivations faced by a poor person, usually across dimensions: health, education and standard of living.
- 4 The Global MPI for Bangladesh is estimated periodically by the Oxford Policy and Human Development Initiative.
- 5 PPRC-BIGD (2020), "PPRC-BIGD Rapid Response Research: Livelihoods, Coping and Recovery During COVID-19 Crisis", Dhaka: BIGD and PPRC.
- 6 https://www.thedailystar.net/opinion/the-overton-window/news/yearwhen-poverty-increased-and-so-did-misery-2020909
- 7 The project measured MPI across 10 indicators under three dimensions: i) Education (school attendance; years of schooling); ii) Health (disability status; infant mortality); Standard of Living (access to electricity; quality of sanitation facility; quality of flooring of the house; cooking fuel; asset holding; proximity to safe drinking water).
- 8 Households with MPI scores below 10 or above 40 were considered to be too comfortably non-poor and extremely/ultra-poor, respectively, to draw any reasonable comparisons.
- 9 The survey data was collected at a time when a third wave of the pandemic caused by the Omicron variant was taking over the country with reasonable social restrictions in place.
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- 14 Rasch, D., Kubinger, K. D., & Moder, K. (2011). "The two-sample t test: Pretesting its assumptions does not pay off." Statistical papers, 52(1), 219-231.

- 15 Headcount ratio refers to the share of the population that is multidimensionally poor—in this case, those with an MPI score equal to or above 20. The intensity of deprivation refers to the average percentage of dimensions in which poor people are deprived.
- 16 Barkat, A., et al. (2020). "Socio-economic assessment of COVID-19 under National Urban Poverty Reduction Programme." Dhaka: HDRC and UNDP. https://www.hdrc-bd.com/socio-economic-assessment-of-covid-19-under-national-urban-poverty-reduction-programme-conducted-for-undp-year-2020/
- 17 PPRC-BIGD (2020). "Livelihoods, coping and recovery during COVID-19 crisis: Evidence from three rounds of PPRC-BIGD Survey." Dhaka: Power and Participation Research Centre.
- 18 The project used households' MPI scores at the time of registration to determine the nature of relief extended as a COVID response. As such, more households with a pre-COVID initial score of above 20 were offered cash and food relief compared to those in the non-poor category, who primarily received preventive materials. Since the COVID response was independent of a household's grant-receiving status, there was not much difference in the type of relief received between poor grantees and non-grantees.
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- 21 Bangladesh Bureau of Statistics (2018). Labour Force Survey (LFS) 2016-17.
- 22 Mymensingh, Sylhet and Chandpur are among the most multidimensionally poor regions in the country. (Source: https://bids.org.bd/uploads/research/completed_research/FINAL_Challenges%20 of%20Inclusion_With%20LOGOS%20_28%20September%202021_Revised.pdf.)
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- 24 See General Economic Division (2015). "National Social Security Strategy (NSSS) of Bangladesh." Dhaka: General Economics Division, Bangladesh Planning Commission, Ministry of Planning, Government of the People's Republic of Bangladesh. https://socialprotection.gov. bd/wp-content/uploads/2018/09/National-Social-Security-Strategy-Enalish.pdf
- 25 https://home.kpmg/xx/en/home/insights/2020/04/bangladeshgovernment-and-institution-measures-in-response-to-covid.html
- 26 https://archive.dhakatribune.com/bangladesh/corruption/2020/11/10/tib-covid-19-exposed-created-opportunities-for-corruption
- 27 The Bangladesh government's Bureau of Statistics and Department of Disaster Management started working on a National Household Database in 2013 to streamline beneficiary selection for social protection programs by gathering household data for every household. However, the process has faced several delays and is yet to be completed.