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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 income-based 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 indicators[7] 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,* n *is the number of timepoints,* ρ *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, z_α *value is 1.96. The value of* 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* 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,[12] *paired T-test,*[13] *and Welch two sample T-test.*[14]

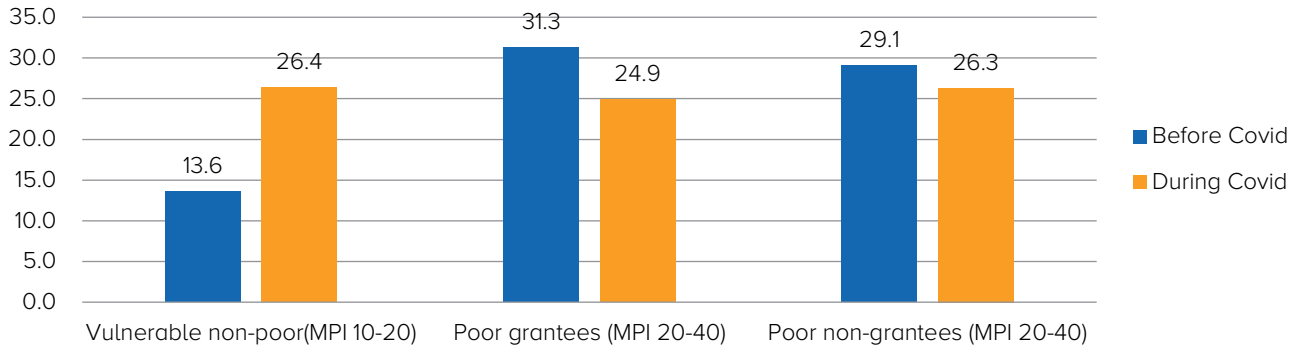
Main findings of the survey

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

Business grants helped poor households improve their MPI scores.

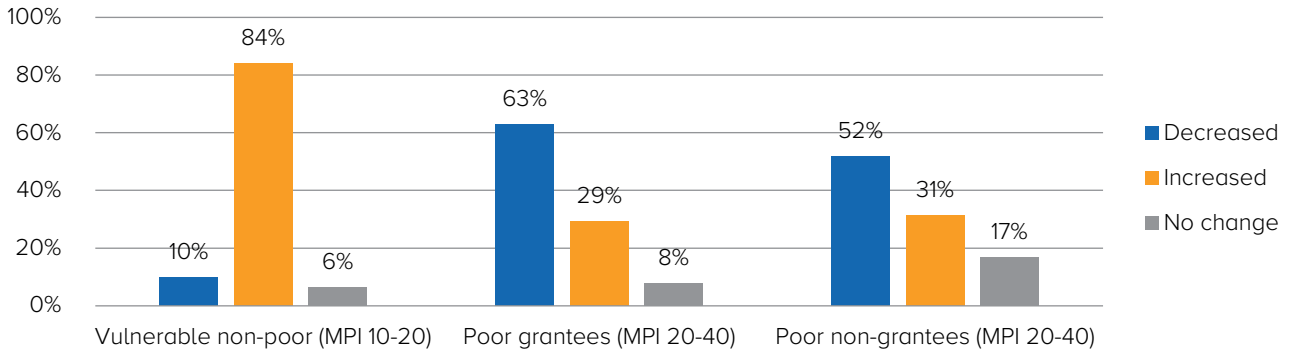
Among the three household categories, poor grantee households exhibited the most (statistically) significant decrease in their MPI scores over time, as reflected by 63 percent of such households with reduced MPI levels (see Figures 1 and 2). Figure 1 also depicts a decline in the MPI score among poor 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

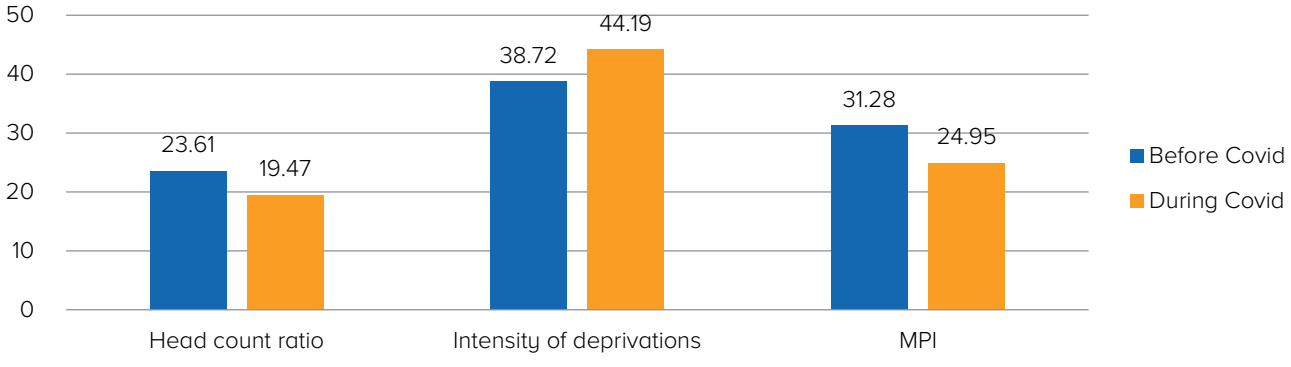
Figure 2: Percentage distribution of households with change in MPI score



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.

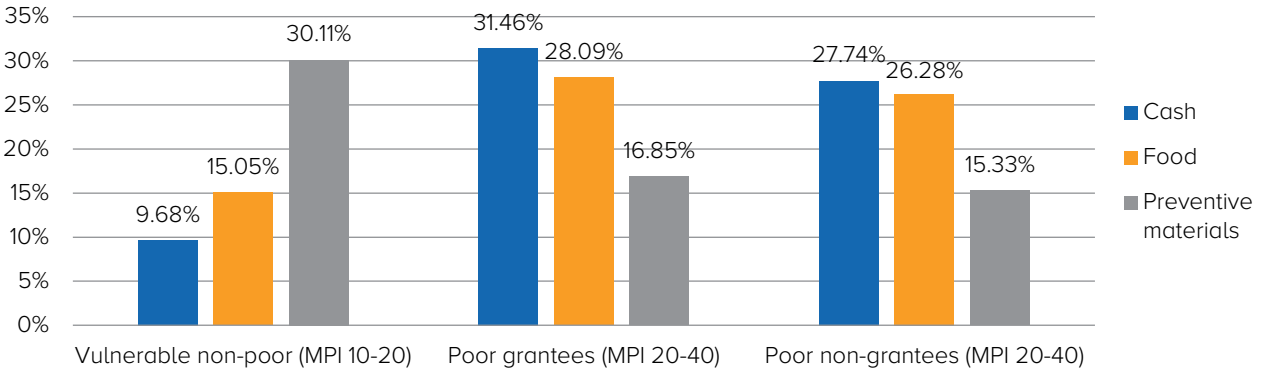
Vulnerable non-poor (non-grantee) households with pre-COVID MPI scores between 10 and 20 fell just below the project's primary eligibility score of MPI 20 for grantees. Being so close to the poverty line, these households were not poor by definition but were vulnerable to falling into poverty if exposed 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 income-based 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, COVID-related 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.[18] 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.

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 non-grantees 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 non-grantee 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.[19] 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

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