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Title:

International labour migration and the many forms of poverty

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Abstract:

The discourse on migration and poverty has largely shown that international labour migration reduces monetary poverty for the migrant-sending households. With the international consensus that poverty is multidimensional and goes beyond income alone, many studies evaluate the nexus between migration and non-monetary aspects of life, such as education and health. These show mixed evidence. Far fewer studies assess whether suffering from simultaneous deprivations in multiple indicators of wellbeing is affected by migration – which would be a full multidimensional poverty analysis at the household level. To assess the value added of the latter, we empirically compare three approaches to measuring poverty and the effect of migration on the three. These are i) a solely monetary approach, ii) a dashboard approach that considers several non-monetary wellbeing deprivations, and iii) a counting approach that evaluates whether the multiple deprivations manifest themselves jointly. Using household panel data for rural Bangladesh, we assess how the association between international labour migration and poverty among the stay-behind household members changes in light of the three approaches. The endogenous nature of migration in this connection is explicitly addressed by applying a Hausman-Taylor estimation procedure. We corroborate that poverty is related to a lower likelihood of being monetary poor, but we do not find that it is associated with an increased likelihood of exiting multidimensional poverty altogether. However, we do find that it is associated with a lower likelihood of facing simultaneous deprivations in terms of sanitation, electricity and asset-ownership among those who live in multidimensional poverty.

Key Words:

Bangladesh, International Labour Migration, Panel Data, Poverty

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International Labour Migration and the Many Forms of Poverty

1. Introduction

Many studies in the literature on wellbeing and international labour migration make a case for the poverty-alleviating effects of migration on the migrant-sending households (e.g. Adams & Page, 2005; Adams et al., 2008; Osili, 2007; Brown & Jimenez-Soto, 2015). This strand of literature focusses on remittances and considers poverty solely as a monetary deprivation, which is not fully aligned with modern development paradigms. According to the SDGs¹, poverty should be regarded as a *multifaceted* phenomenon². The SDGs cover many aspects of people's lives that go beyond monetary poverty alone. While some are closely related to lack of purchasing power, many others are tangible deprivations in non-monetary domains of health and education, and others are related to intangible aspects of life, such as social cohesion.

An increasing number of migration studies embraces this broader definition of poverty by analyzing the experience of multiple monetary and non-monetary wellbeing deprivations (e.g. Antman, 2013; Adams, 2011; McKenzie, 2005; Sasin & McKenzie, 2007; Yang, 2008). These analyses are more attuned with the notion of poverty embedded in the SDGs and the 2030 Agenda. By laying focus on several aspects of life, these studies provide useful insights on the connection between international labour migration and human deprivations. In that sense, these analyses are much closer to the notion of *multidimensional* poverty that is now powerfully applied in the development discourse (see e.g. Alkire & Jahan, 2018; World Bank, 2018; OPHI, 2018). Importantly, however, a full account of the multidimensional nature of poverty is not merely concerned with its manifold manifestations, but also their intrinsic interconnections (Atkinson, 2019). A 'full' multidimensional analysis requires more than simply analyzing several wellbeing indicators; it must also account for the *simultaneous manifestation of deprivations* in the same household. We argue that this is particularly relevant to better understand the connection between migration and wellbeing deprivations, as many livelihood aspects of the migrant-sending households may be *simultaneously* reconfigured by migration.

What is the value added of taking into account simultaneous deprivations to understand the connection between a broad notion of poverty and international labour migration? This question is relevant since several negative consequences of migration may counter-balance its potential positive effects. Largely, the literature agrees on the positive relation between international migration and purchasing power due to remittances. There is, however, mixed evidence on its relation to other non-monetary aspects of wellbeing. For instance, migration-induced improvements in education are documented for the Philippines (Yang, 2008), Fiji (Brown et al., 2006) and El Salvador (Edwards & Ureta, 2003). However, López-Córdova (2005) and McKenzie and Rapoport (2011) find that school dropout rates among the 12-18 years old Mexican youth is higher in migrant-sending households. Similarly, migration-induced improvements in health indicators are found in Mexico (Frank & Hummer, 2002; Duryea et al., 2005; Amuedo-Dorantes & Pozo, 2011), whereas Hildebrandt and McKenzie (2005) find that

¹ See <https://www.un.org/sustainabledevelopment/> for details.

² Explicitly, target 1 has two sub-targets, namely the eradicate monetary poverty (Target 1.1) and the reduction by half of the proportion of men, women and children that live in multidimensional poverty according to national definitions (Target 1.2).

children living in Mexican migrant-sending households are less likely to receive adequate preventive health care.

In order to provide an answer to the question above, we undertake an empirical comparison of three approaches to wellbeing deprivation and their connection to migration. The first is the traditional purely *monetary approach*. The second is a *dashboard approach*, which considers an array of non-monetary wellbeing indicators as the evaluative space. This approach, however, does not capture whether or not these deprivations manifest simultaneously in the same household (Ravallion, 2011). The third is a *counting approach*, which considers not only multiple wellbeing indicators, but also their simultaneous manifestation in the same household (Atkinson, 2019). To investigate the value added of the counting approach, we apply the Alkire-Foster method (Alkire & Foster, 2011). This method is also termed the dual cutoff counting approach (Atkinson, 2019) because it consists of applying two cutoffs to identify households suffering a ‘critical’ number of simultaneous deprivations – the first cutoff identifies the existence of a deprivation, and the second cutoff identifies the households suffering from a certain number of deprivations simultaneously. This method enjoys wide international acceptance, and it has been endorsed by the World Bank’s commission report on ‘Monitoring Global Poverty’ (Atkinson, 2017) as a valid method to measure multidimensional poverty. Furthermore, it is the methodological underpinning of state-of-the-art measures of this wide notion of poverty, including the UNDP’s Multidimensional Poverty Index (MPI), and the World Bank’s Multidimensional Poverty Measure. It thus has a long history of empirical implementation in development studies³, but is thus far disconnected from the migration literature.

To the best of our knowledge, this is the first study that empirically compares the different insights obtained in light of these approaches in the migration literature, and hence this is one of our main contributions. Additionally, we introduce a general framework to evaluate the connection between migration and poverty through the lens of a dual cutoff counting approach. Also, we generate novel empirical evidence of the value added of the counting approach. Our empirical application concerns Bangladesh, not only because it is one of the poorest and largest migrant-sending countries in the world, but also because there is a considerable dynamic mismatch between monetary and non-monetary wellbeing indicators.

With 7.8 million migrant workers, Bangladesh accounts for the sixth highest migrant stock globally in 2019⁴, and remittances have contributed more than 6% to Bangladesh’s GDP in recent years⁵. According to the UNDP-OPHI global MPI, the country was home to about 70 million multidimensionally poor people in 2018 – the fifth highest number globally (OPHI, 2018). While monetary poverty rates in Bangladesh have been decreasing over the last decades, improvements in health, education, and living standards have been improving at much a much lower pace (HIES, 2016). A thorough analysis of this context requires rich household level data. The Bangladesh Integrated Household Survey (BIHS) is, to the best of our knowledge, the only representative panel dataset of rural Bangladesh that includes information on both migration and various wellbeing indicators such as individual outcomes on nutrition, food security, education, living standards *as well as* consumption expenditure. Therefore, we make the case that

³ See Atkinson (2019) for a review of this approach and others.

⁴ <https://www.un.org/en/development/desa/population/migration/data/estimates2/estimatesgraphs.asp?3g3> (accessed in March 2020). Only India (17.5 million), Mexico (11.8 million), China (10.7 million), Russia (10.5 million), and Syria (8.2 million) account for more.

⁵ The World Bank Migration and Development Brief 27, 2017.

the two-wave BIHS (2011/2015) is the best source of data to operationalize the three approaches to wellbeing deprivations of interest.

In our empirical analysis, we exploit the BIHS panel data in two ways. One, we show descriptively how our understanding of the migration-poverty nexus depends heavily on the choice of the approach to wellbeing deprivations. Two, we develop an IV framework to estimate and compare the effects of migration for each of the three definitions of poverty. We apply a Hausman-Taylor estimation procedure to address a) the endogeneity issue inherent to the migration-poverty question and b) the limited within-household dynamics of migration in our data (Hausman & Taylor, 1981). This framework allows us to use the rich inter-household information in the dataset to minimize efficiency and consistency threats (Zhunio et al., 2012; Checchi et al., 2007; Balderas & Greenwood, 2010).

Supporting the relevance of our comparative analysis, we find that non-migrant households that are monetary non-poor face a likelihood of only 3.5% of being exempt of any non-monetary deprivations. Taking solely a monetary approach would thus overlook a considerable number of non-migrant households that face joint non-monetary deprivations in several indicators. For migrant households that are monetary non-poor, the likelihood of not facing any deprivation is higher (6.1%). Thus, we show that a sole reliance on the monetary approach is insufficient not only in comparing general patterns of poverty, but also in uncovering important differences between migrant and non-migrant households that are non-poor in monetary terms. In addition, we present compelling evidence showing that a full multidimensional analysis must capture the simultaneous nature of multiple deprivation. For instance, 15.8% of the pooled households in our data are deprived in nutrition, but only 4.93% of these deprived households are free of any other deprivation. In fact, more than 60% of the nutrition-deprived households face between two and four additional deprivations.

In our model-based analysis, we corroborate that the association between international labour migration and the poverty vary depending on the approach taken to the latter concept. Migration is associated with a lower likelihood of being monetary poor, as well as the likelihood of facing deprivations in flooring, electricity, and sanitation. Conversely, we do not find that migration can be associated with a higher likelihood of exiting multidimensional poverty. However, migration is associated with a lower likelihood of being multidimensionally poor *and* deprived in sanitation or electricity or asset ownership. Therefore, even if migration cannot be associated with better chances of exiting multidimensional poverty altogether, it is related to livelihood improvements among the poor.

The paper is structured as follows. We begin with by laying out the theoretical framework and terminology of poverty measurement in the context of migration (Section 2). Based on this, we present the data and a discussion of the indicators of choice (Section 3). In Section 4, we provide a descriptive analysis of the migration-poverty nexus for rural Bangladesh. In Section 5, we present both the econometric framework (5.1) and the estimation results along with a discussion (5.2). We conclude in Section 6 with suggestions for further research.

2. Poverty and Migration: A Counting Framework

2.1. A General Counting Approach-based Framework

The counting approach to measure wellbeing shortfalls (i.e. deprivations) is a prominent feature in many contemporary development analyses (Atkinson, 2003, 2019). This approach consists of identifying wellbeing deprivations across an array of indicators. After identifying these deprivations at the household level, this approach consists of constructing a household-specific deprivation score that reflects the multiple deprivations people face at the same time. This score thus quantifies the intensity of *simultaneous* shortfalls in multiple wellbeing indicators.

This approach has attractive features for international migration studies. It is not too farfetched to imagine that migration can reconfigure many aspects of the migrant's household in the home country simultaneously, such as school dropout, housing conditions and purchasing power. In the development economics literature, applying the counting approach to wellbeing shortfalls offers a quantitative representation of *multidimensional* poverty. The latter concept is deeply entrenched in the SDGs rationale and the 2030 Agenda. It is the methodological underpinning of many influential wellbeing and poverty assessments worldwide.

Arguably, the most prominent operationalization of the counting approach is the Alkire-Foster method (Atkinson, 2017, 2019). It was pioneered by Alkire and Foster (2011) and it is often referred to as the dual cutoff counting approach; it identifies people living in multidimensional poverty by applying a one set of indicator cutoffs to determine wellbeing deprivations, and the second to identify a 'critical' number of joint deprivations. Although many poverty measures around the world use this method, the most well-known application of the dual cutoff counting approach is the global Multidimensional Poverty Index (MPI), developed in 2010 by UNDP and the Oxford Poverty & Human Development Initiative (OPHI) at the University of Oxford (Alkire & Santos, 2014). Since then, it has been annually computed for more than 100 countries and published in the UN's Human Development Reports (HDR).

2.1.1. Essential features of the dual cutoff approach

Formally, let us consider a set of d wellbeing indicators that are related to international migration and that we observe at time t for n households. We refer to the households, that live in the country of origin and that have a household member who is a migrant labourer as *migrant households*. The rest of the households are considered as *non-migrant households*. If household i fails to meet a minimum standard in indicator j at time t , then it is deprived in indicator j . For example, a household may be deprived in nutrition if there is at least one child that is malnourished, or the household may be deprived in housing if it uses a dirt floor. Following the notation in Alkire and Foster (2011), a binary deprivation score denoted as g_{ijt}^0 takes the value of unity in this case: $g_{ijt}^0=1$; otherwise, $g_{ijt}^0 = 0$. For generality, we allow each deprivation to have a different importance with respect to the others (Atkinson, 2003, 2019). For instance, being deprived in nutrition may be deemed more important than the lack of adequate housing. This can be operationalized by assigning time-invariant weights to each deprivation, $w_1 \dots w_d$ such that $\sum_{j=1}^d w_d = 1$. This allows us to construct a weighted deprivation score for household i at time t , denoted as c_{it} :

$$c_{it} = \sum_{j=1}^d w_d g_{ijt}^0, \quad \forall i, t$$

The c_{it} values for all households at time t may be denoted as c_t . It allows us to empirically test the association between facing simultaneous deprivations and international migration in a straightforward manner. Let us assume that there are n_m and n_{nm} migrant and non-migrant households in our dataset, respectively. Naturally, $n = n_m + n_{nm}$. Let us denote the expected number of weighted deprivations among migrant and non-migrant households at time t , conditional on a set of observed control variables X_t as $E_m[c_t|X_t]$ and $E_{nm}[c_t|X_t]$, respectively. These control variables may include household or environmental characteristics, such as size of the household, ethnicity or the level of economic activity in the region of residence. Several testable hypotheses can be studied in this setting:

- If $E_m[c_t|X_t] < E_{nm}[c_t|X_t]$, then one can state that, after controlling for X_t , migrant households have an average static advantage over non-migrant households at time t . In effect, this means that, on average, migrant households face a lower number of (weighted) simultaneous deprivations. The converse is true if $E_m[c_t|X_t] > E_{nm}[c_t|X_t]$.
- If $E_m[c_s|X_s] > E_m[c_t|X_t]$ with $s > t$, then one can state that after controlling for X_s and X_t , on average, the migrant households' wellbeing advantage has increased between periods t and s . A similar assessment can be made to assess the situation of non-migrant households.
- If $E_m[c_s|X_s] - E_m[c_t|X_t] > E_{nm}[c_s|X_s] - E_{nm}[c_t|X_t]$, with $s > t$, then one can state that after controlling for X_s and X_t , on average, the reduction of simultaneous deprivations over time for migrant households (if any) have been greater compared to non-migrant households. In that sense, migrant households would have a dynamic advantage over non-migrant households between periods t and s .

In a general way, these differences in expected conditional outcomes can be interpreted as causal effects for migration if they are computed using experimental data in which households were exposed to migration at random (see e.g. Vaz, Malaeb & Quinn, 2019). In absence of these data, such causal links may also be uncovered by applying a quasi-experimental methodology, such as an IV framework, which is precisely the route that we take in this study.

3. An Empirical Analysis: The Case of Bangladesh

In order to operationalize the dual cutoff counting approach, we require household level data. Additionally, for the purpose of our study, these data must contain sufficient information to measure monetary and non-monetary deprivations. The Bangladesh Integrated Household Survey (BIHS) is one of the very few representative panel datasets that fulfills these requirements. These data include information on migration and several wellbeing indicators such as individual outcomes on nutrition, food security, education, living standards. It also includes enough information to gauge consumption expenditure.

The BIHS was conducted as a household panel survey in two waves during 2011 and 2015⁶. The data are representative at the national and divisional level for rural Bangladesh. It is established that standard poverty-related measures based on the BIHS, including as consumption per capita align with official estimates of the Bangladesh Bureau of Statistics (BBS). According, to Ahmed et al. (2016), attrition between the two waves was exceptionally low, at just 1.26 percent per year. One limitation of the BIHS is that it is only representative for rural areas of Bangladesh. However, for the purpose of this paper, this is not a significant drawback, as 81% of Bangladeshi international migrants have rural home families (Bangladesh Bureau of Statistics, 2015). This dataset has been successfully used to assess wellbeing deprivations in previous studies, including food insecurity – and its connection to remittances (Regmi et al. 2018), asset-based poverty (Hoque, 2014), and a comprehensive study about low consumption, lack of social acceptance and women’s (dis)empowerment (Hassan & Jebin, 2018).

Our panel consists of a sample of 5050 households in the first wave (2011) and 4892 households in the second wave (2015). In 2011, 383 households (7.58% of the household sample) had a family member working abroad, i.e. they were a migrant household. Similarly, in 2015, 431 households (8.81%) were migrant households.

3.1. The variables of interest

We use three continuous indicators to measure monetary poverty: monthly per-capita food consumption (7-day recall period), non-food consumption (30-day recall period) and total consumption. In order to compare 2011 and 2015 figures coherently, we monetize item quantities using 2010 prices provided by Bangladesh Bureau of Statistics (BBS, 2016). The interpretation of these variables is straightforward: lower values depict wellbeing disadvantages in monetary terms. We identify households falling below the minimum district-specific consumption poverty lines defined by BBS as being monetary poor. Clearly, this approach lays focus on people’s capacity to acquire goods and services through market-based mechanisms.

Naturally, many other aspects of people’s wellbeing are not necessarily acquired through market mechanisms. In order to capture these complementary aspects, a host of indicators are available in our data. Here we draw inspiration from UNDP and the University of Oxford (Alkire & Jahan, 2018) to focus on a parsimonious, theoretically sound set of non-monetary indicators that are routinely reported in the Human Development Reports since 2010. These indicators pertain to the domains of health, education and living standards, and they mimic as close as possible those forming the global MPI (see Table 1, Alkire & Jahan, 2018). These wellbeing indicators are firmly established in academic and political spheres at the international level, as they are the result of thorough scrutiny of alternative options (Alkire & Santos, 2014; Atkinson, 2019). In that sense, they reflect a somewhat tacit consensus about relevant dimensions and indicators of wellbeing at the global level. We explore how these indicators complement the money metrics.

The BIHS dataset allows us to operationalize this multidimensional vision of wellbeing in two different ways. The first is the dashboard approach, which consists of analyzing one indicator at

⁶ Funded by the U.S. Agency for International Development (USAID), designed by the Bangladesh Policy Research and Strategy Support Program (PRSSP), implemented by IFPRI, and administered by Data Analysis and Technical Assistance (DATA) (Ahmed et al., 2016), the data are openly available in the Harvard and IFPRI Dataverse Repository at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/BXSYEL>

a time. The second consists of accounting for the interconnections between these indicators by applying the dual cutoff counting approach. While the dashboard approach is straight forward – choices only pertain to indicators and indicator cutoffs – the counting approach also relies on a selection of indicator weights. For this, we rely on common practice and follow UNDP’s and the University of Oxford’s guidelines: we attach equal weights across dimensions – 1/3 each for health, education, and living standards – and apply equal weights to the indicators within each dimension.⁷ The last column of Table 1 presents the indicator weights, which, as per our discussion in Section 2, underpin the subsequent analyses of household-specific deprivation scores (c_{it}). We acknowledge that our results are dependent on the underlying structure of the multidimensional poverty index. As a robustness test, we have computed the results under alternative weighting schemes and poverty cut-offs and find that they are stable across an array of alternative specifications (see Appendix B).

[TABLE 1 HERE]

4. Migration and Poverty in Bangladesh: A Descriptive Assessment

In this section, we first compare the monetary and dashboard approaches to highlight the complementary nature of the two. We then go on to show that neither one of the two allow us to uncover important poverty differentials between migrant and non-migrant households related to the simultaneous experience of multiple deprivations. This lends support to our analysis of the relationship between migration and variables obtained through the dual cutoff counting approach. From a static perspective, we assess the differences of average outcomes between migrant and non-migrant households at one particular point in time. We complement this analysis by using the dynamic information in our data to compute the differences of outcome dynamics of migrant and non-migrant households over time. This effectively amounts to computing difference-in-difference coefficients, although the observational (non-experimental) nature of our data prevents us from claiming any causality.

4.1. Monetary and Dashboard Approaches

In Table 2, we present monetary-based measures of poverty for migrant and non-migrant households. In a nutshell, the monetary approach clearly shows that wellbeing is higher for migrant households, regardless of the chosen money-metric. However, monetary poverty evolves differently over time depending on the chosen indicator.

We find that there is a marked wellbeing disadvantage for non-migrant households in both 2011 and 2015. By comparing their respective average consumption levels in logs, non-migrant households had a consumption level around 34% and 41% in 2011 and 2015, respectively, compared to migrant households. In light of a means t-test, this increased disadvantage over time is found to be statistically significant. Largely, this is due to non-food consumption following the same qualitative pattern. This is not the case of food consumption, which is indeed lower, on average, in non-migrant households in both 2011 and 2015 (see Table 2), but it has remained constant over time.

[TABLE 2: HERE]

⁷ This corresponds to a nested-weighting structure (Alkire & Santos, 2014; Atkinson, 2003).

We now complement the monetary analysis by including the dashboard approach to multidimensional poverty, with results presented in Table 3. We stress that, in this analysis, each indicator is assessed separately. Focusing on health, as measured by the nutrition indicator, we find statistically non-significant differences between migrant and non-migrant households in 2011. The headcount ratio in nutrition is 21% for non-migrant households and slightly over 18% for migrant households. By 2015, this indicator dropped to 16% for the former and to 12% for the latter, which suggests that migrant households have acquired a relative advantage in terms of health over time.

In terms of the education dimension, we examine headcount ratios in years of schooling and school attendance. We do not find statistically significant differences across groups in the former. In terms of school attendance, however, non-migrant households are much worse off in 2011 (14% vs. 10%) and, despite considerable progress over time for both groups, the relative advantage for migrant home families remains statistically significant in 2015 (4% vs. 2%).

[TABLE 3 HERE]

Regarding the five living standards indicators, migrant households have a considerable and statistically significant advantage over non-migrant households in every indicator. Most notably, the likelihood of being deprived in electricity for non-migrant households in 2011 (54%) is twice as high as the one for migrant households (27%), and the same relative pattern is observed in 2015 (43% vs. 20%). We find similar advantages for all the other living standard indicators, albeit with a lower relative magnitude. In fact, the likelihood of being deprived in flooring has substantially decreased for migrant households (76% in 2011 to 62% in 2015). These deprivation headcount ratios are high, but they are even higher for non-migrant households, and have reduced at a much slower pace (90% in 2011 to 87% in 2015). Thus, the relative advantage for migrant households in terms of living standards seems to have increased over time only via better flooring.

4.2. What are we missing out?

Although insightful, the above description is only a partial representation of the actual differences between migrant and non-migrant households. To see this, let us identify monetary poor households by applying the official monetary poverty lines for rural areas. For non-migrant households that are monetary non-poor, the likelihood of being exempt of any non-monetary deprivation is only 3.5% (see Figure 1, right panel, bar corresponding to zero deprivations). It is most likely for such households to experience simultaneous deprivations in three out of the eight indicators (22.6%), followed by suffering from four simultaneous deprivations (21.5%). Taking solely a monetary approach would thus overlook a considerable number of non-migrant households that face joint non-monetary deprivations in several indicators. The same pattern holds true for migrant households, albeit to a lesser extent. For migrant households that are monetary non-poor, the likelihood of not facing any deprivation is higher (6.1%, see Figure 1, left panel), and they are most likely to experience two simultaneous deprivations (26.7%). Thus, a sole reliance on the monetary approach is insufficient not only in comparing general patterns of poverty, but also in uncovering important differences between migrant and non-migrant households that are non-poor in monetary terms.

[FIGURE 1 HERE]

The dashboard approach alone also hides important information about the difference between migrant and non-migrant households. In Figure 2, we illustrate the extent of the mismatch between the dashboard approach and the one that considers the joint deprivations - i.e. a counting of simultaneous deprivations. By taking one indicator at a time and counting the number of additional deprivations, it is evident that several deprivations from the dashboard tend to manifest jointly. For instance, 15.8% of the pooled households are deprived in nutrition, but only 4.93% of these deprived households are free of any other deprivation. In fact, more than 60% of the nutrition-deprived households face between two and four additional deprivations. Focusing only on deprivation in flooring, which affects more than 69% of the pooled households, one would fail to uncover that households deprived in flooring are likely to be deprived in at least two additional deprivations. Finally, it is interesting to notice that being deprived in walls, which affects more than one-quarter of the pooled households, never manifests on its own but occurs jointly with other deprivations.

[FIGURE 2 HERE]

4.3. Data description based on the dual cut-off

For In 2011 and 2015, the distributions of deprivation scores, c_{it} , are systematically concentrated in the lower values for migrant households compared to non-migrant ones (see Figure 3a, and first column of Table 4). Non-migrant households face unambiguously more simultaneous deprivations in both periods of time. In fact, we can see that the distribution of c_{it} in 2011 and 2015 for non-migrant households first-order stochastically dominates the one for migrant households. Non-migrant households always find themselves at a disadvantage in terms of their propensity to suffer a higher number of weighted deprivations.

[FIGURE 3 HERE]

Turning to the description of dynamics, we find that the evolution of the c_{it} distribution is not statistically different between the two types of households. This is quite a powerful result, as it means that the advantage of migrant households is persistent over the entire period that we cover. This is not to say that every household has experienced a reduction in the number of simultaneous deprivations. It rather reflects that positive and negative changes over time have taken place for both migrant and non-migrant households in similar proportions. 58.5% of the migrant households and 54.6% of the non-migrant households have experienced a reduction in the sum of weighted deprivations. At the same time, 22.2% and 22.6% of the migrant and non-migrant households, respectively, have experienced an increase in the sum of weighted deprivations.

In a nutshell, based on the descriptive analysis, non-migrant households suffer a higher number of weighted deprivations in both periods of time than migrant households. This relative disadvantage has remained stable between 2011 and 2015. In that sense, the counting approach-based analysis corroborates and complements the limited descriptive evidence of dynamic effects of migration as measured via the monetary and dashboard approaches to wellbeing.

[TABLE 4 HERE]

5. A Model-Based Discussion

Following the descriptive discussion above, we now assess the differences in terms of conditional expectations in these outcomes, after controlling for other household and environmental characteristics. We investigate the extent to which the different poverty patterns may be linked to the fact that a household member is an international labour migrant. Applying a quasi-experimental approach allows us to detect whether a causal relationship can be uncovered. In the following, we propose and justify a Hausman-Taylor estimation technique as our econometric framework (Section 5.1) and present the model-based results in Section 5.2.

5.1. Econometric Framework

Isolating migration induced effects is complex for two reasons. First, there is the evident endogenous nature of migration in its connection to poverty-related variables of the stay-behind household members' (see e.g. Brown & Jimenez-Soto, 2015; Bodvarsson et al., 2015). Most studies use IV procedures to address this problem, but the bar for valid instruments is high and this has often proven to be troublesome (Antman, 2013; Adams, 2011). This issue is amplified in our study, as our comparative assessment requires us to deal with multiple poverty indicators as outcome variables, for which different instruments are likely needed. Thus, it is hardly possible to identify the migration effects on *all* the poverty-related variables that we analyze simultaneously; this is beyond the scope of our study. Second, the data contains very limited dynamic information about migration. Only 84 households (or 1.8% of the total sample) have changed their migrant-household status between 2011 and 2015. The average likelihood of observing the same migration status in both waves is above 98%. This may be due to the relatively short period covered between the two waves.

We argue that these great challenges may be addressed by applying a Hausman-Taylor estimation procedure (Hausman & Taylor, 1981; Baltagi et al., 2003). It consists of an IV-GLS framework with noteworthy features about the way it identifies structural equations using panel data. Unlike the more traditional fixed effects fit, this procedure avoids relying solely on intra-household variations for identification – which are quite limited in our data. Rather, it combines this dynamic information with inter-household variations and exploits the exogenous nature of the control variables to derive suitable IVs to tackle the migration endogeneity problem (Baltagi et al., 2003). The control variables provide enough information to construct internally valid instruments without having to be excluded from the model. Thus, our main hypothesis is that the control variables are strictly exogenous. In this framework, this hypothesis can be tested allowing us to determine which associations between poverty indicators and migration may have a causal interpretation.

In the following, we briefly explain our empirical strategy; more details can be found in the Appendix and in Hausman and Taylor (1981) and Baltagi et al. (2003). We define a time-invariant dichotomous variable, M_i , indicating whether household i has a family member working abroad in 2011 or 2015. In this case, $M_i = 1$ (9% of the total sample) and the household is defined as a *migrant household*. Otherwise, $M_i = 0$ (91% of the total sample) indicating a *non-migrant household*.

Let us denote a generic poverty indicator for household $i = 1 \dots N$ at time $t = \{2011, 2015\}$ as y_{it} . Our model is:

$$y_{it} = \alpha + \delta_i M_i + \beta X_{it} + \gamma Z_i + u_i + e_{it}, \quad \forall i, t \quad (1)$$

where, α is a constant term, u_i are household fixed effects (with variance σ_u^2), and e_{it} are unobserved time-varying unobserved factors affecting y_{it} (with variance σ_e^2). Our time-invariant migration indicator, M_i , is posited to be endogenous in the sense that it is correlated with household fixed effects. X_{it} and Z_i are, respectively, vectors of time-varying and time-invariant observed poverty determining factors that are assumed to be exogenous; these are the control variables.

Equation (1) makes it clear that it is impossible to estimate the coefficient associated to M_i by applying a fixed effects fit, as this variable is wiped out of the equation by the fixed effects transform. However, the Hausman-Taylor procedure allows us to estimate this coefficient (and all the others) while taking into account the endogenous nature of M_i . Let us denote as $w_{it}^* = w_{it} - \hat{\theta} \bar{w}_i$ the random effects-GLS transformation of any variable w_{it} , where \bar{w}_i is the time-mean of w_{it} and $\hat{\theta} = 1 - (\hat{\sigma}_e^2 / (\hat{\sigma}_e^2 + 2\hat{\sigma}_u^2))^{1/2}$. $\hat{\sigma}_u^2$ is a consistent estimate derived from a fixed effects fit of Equation (1). $\hat{\sigma}_e^2$ is computed after regressing the fixed effects residuals on Z_i and M_i , using \bar{X}_i as instruments for the latter.

Using these estimates for the variance components, it is possible to derive the random effects GLS-transformed version of equation (1) as follows:

$$y_{it}^* = \alpha^* + \delta_i M_i^* + \beta X_{it}^* + \gamma Z_i^* + u_i^* + e_{it}^*, \quad \forall i, t \quad (2)$$

All the coefficients in the above equation can be estimated applying an IV fit using \bar{X}_i as instruments for M_i , while X_{it}^* and Z_i^* serve as their own instruments. We re-emphasize that this procedure allows us to estimate the coefficient related to M_i *as well as* the direct effects of the control variables, which need not be excluded from the above equation (see Hausman & Taylor, 1981 p. 1386).

Based on data availability, we pay particular attention to include a parsimonious and carefully selected set of elements in X_{it} and Z_i , which are identical in all variants of our model. This allows us to investigate whether some control variables, that have been extensively posited in the related literature as exogenous determining factors of an array of monetary and non-monetary poverty measures, are indeed exogenous in our context.

The included time-varying covariates in X_{it} are i) household composition as measured by the number of children under 5 years of age, and number of members aged 15-44 and 45-65, and ii) distance (in minutes) to a market, public transportation and a hospital. Similar household composition variables have been used as controls to assess the connection between migration and education outcomes (Jaupart, 2018, Amuedo-Dorantes & Pozo, 2010), expenditure/consumption (Adams & Cuecuecha, 2010; Yang, 2008; Lokshin et al., 2010); child health (Hildebrandt & McKenzie, 2005); business ownership (Amuedo-Dorantes & Pozo, 2006), and durable good ownership (Yang, 2008). These controls are important because, following

these studies, households with more young children tend to have lower expenditure per capita and may be more prone to face non-monetary deprivations. Conversely, more working age members may counterbalance these negative associations. Distance to a bus station is used in Howell (2017), and distance to the market in Du et al. (2005) to control for general economic environment that is common to both migrant and non-migrant household members.

In the same spirit, our time-invariant covariates in Z_i are i) the distance to a city with more than 20K, 50K, 250K and 500K habitants (akin to Howell, 2017; Zhu & Luo, 2010 and related to overall regional development indicators in Hanson & Woodruff, 2011); ii) indicators of the economic activity in the households' most proximate area (akin to Lokshin et al., 2010; Shi et al., 2019; Du et al., 2005), which in our case is the past rice-yield (pre-migration); and finally iii) division dummies. We test the null hypothesis of exogeneity of these control variables using a Hausman contrast between the Hausman-Taylor estimates of β and γ and their counterparts obtained, respectively, through the models used to estimate $\hat{\sigma}_e$ and $\hat{\sigma}_u$ (see Hausman & Taylor, 1981 pp. 1388-89). A causal interpretation of the coefficients is justified only when we fail to reject the null (high p-value); otherwise, we can only interpret the coefficients as associations.

5.2. Results

We estimate several versions of Equation (2); each one corresponds to a different dependent variable and they include identical control variables. In Table 5, we present the Hausman-Taylor estimates of the coefficient associated with migration. In order to have a clear idea of the magnitude of each effect, we also report the model-estimates of each dependent variable's mean in 2011 for a non-migrant household. For analytical purposes, this is the baseline value of the dependent variable. We also present the estimates of the variance components in each case, as well as the result of the Hausman specification tests. All the standard errors used to assess the significance of these coefficients are cluster robust. The coefficients of all the control variables included in the models have the expected intuitive signs in every single variant (see Appendix A).

[TABLE 5 HERE]

Before analyzing the coefficients, let us mention that we reject the null of the Hausman specifications tests for the monetary poverty-related variables, as well as for asset ownership. Thus, the coefficients relating migration to material aspects of wellbeing only depict associations and do not have a causal interpretation. All other estimates allow us to infer causality.

Monetary approach

Taking money metrics as the outcome variable, we find that migration has a weak association with consumption (total, food or non-food). Although, on average, migration can be associated with an 18% increase in non-food consumption expenditure, we detect high heterogeneity around this value, resulting in statistical non-significance. The absence of compelling and strong empirical evidence of an association between migration and consumption expenditure after controlling for additional characteristics may be related to the rapid overall economic progress in rural Bangladesh before 2011, for both migrant and non-migrant households. For instance, Sen (2003) and Sen & Ali (2017) stress that a large part of the Bangladeshi rural population has managed to successfully overcome structural obstacles to increase their purchasing power.

Besides migration, this consists of crop intensification, agricultural diversification and a boost of off-farm activities in general.

Interestingly, we do find that migration is associated with a lower likelihood of suffering *extreme* monetary poverty (-13 pp, from a 42% baseline). Indeed, migration has been found to increase chances of exiting monetary poverty in rural Bangladesh by promoting land acquisition, entrepreneurship and debt payment (Mamun & Nath, 2010; Siddiqui & Abrar, 2003). It is also congruent with cross-country evidence. Adams & Page (2005), for example, who find that a 10% increase in the share of international migrants in a country's population could be associated to a 2.1% decline in the share of people living on less than \$1.00 per person per day, which effectively reflects extreme poverty by international standards.

Dashboard Approach

To complement these results on monetary poverty, we now turn to the multidimensional dashboard approach. Let us recall that this analysis considers the prevalence of deprivations among the entire population, and not only among those who are poor. We find strong statistical evidence of migration being associated with a lower propensity to be deprived in flooring (-16 pp, from an 88% baseline), electricity (-11 pp, 47% baseline) and sanitation (-12 pp, 66% baseline). Overall, migration benefits are associated with improvements in the home family's living standards. In that sense, these results are in line with the reduced propensity to suffer monetary poverty as discussed earlier. The results on flooring and sanitation may be very intuitive as they relate to goods and services that can be acquired via market-based mechanisms. In this connection, Palit & Chaurey (2011) document the successful market-based approach in fostering off-grid electrical power undertaken by the private sector and micro-finance institutions. In summary, the migration-induced reduction in tangible deprivations of living standards, may lend support to the 'increasing aspiration in rural Bangladesh to progress and access more comfortable lifestyles' (Mapril, 2014).

We find no evidence of migration being associated with education or health-related indicators when additional characteristics are included. This may have a two-fold explanation. On the one hand, it may be due to the limited timeframe that we consider in our analysis – a four-year time span, which may not allow sufficient time for such associations to become visible. On the other hand, the estimated average associations may not capture fully the inherent complexities that lie behind the relationship between these dimensions and migration. For instance, Kuhn (2006) finds migration-induced positive effects on schooling only for male Bangladeshi children. Also, there is a vast literature - see. e.g. Hildebrandt and McKenzie (2005); Biggeri & Mehrotra (2011) – suggesting that there are conflicting effects on child health indicators depending on whether the international migrant is the mother or the father. We argue that these important nuances should be the object of in-depth studies adopting a 'full' multidimensional approach in the future, thus complementing the rich existing literature on these issues.

Counting Approach

In terms of empirical results for the counting approach, we find that migration is related to a shift in the deprivation scores (c_{it}) towards lower values. The average number of weighted deprivations reduces by more than 10% - a reduction of 0.037 points from a 0.350 baseline. This result conveys insights that are different from the other two approaches. It shows that migration can be associated with a reduction of the experience of simultaneous deprivations for the entire rural population - and not only the poor. This contrasts with the absence of a clear similar effect

on total consumption expenditure discussed above. To the best of our knowledge, this is the first empirical evidence on migration and simultaneous deprivations of this kind for rural Bangladesh.

In the following, we highlight some results that are visible only through the lens of a counting based approach to poverty (see coefficients for the likelihood of being multidimensionally poor *and* deprived in each indicator as dependent variables in Table 5). We focus on the population suffering from acute multidimensional poverty, i.e. those that are deprived in at least one third of the weighted indicators⁸. This allows us to test the extent to which migration is associated with being deprived in the different indicators *while* being poor (this is termed the censored headcount ratio in the multidimensional poverty literature, see Alkire & Foster, 2011). We find that migration is associated with a lower likelihood of being poor *and* deprived in sanitation (-13.8 pp from a 60.2% baseline), electricity (-16.3 pp, 45.4% baseline), and asset ownership (-11.6 pp, 51% baseline). This means that, even if migration cannot be associated to exiting multidimensional poverty altogether, it is related to livelihood improvements among the poor.

Even if migration is related to a reduction in extreme monetary deprivations, we do not find evidence for a lower likelihood in experiencing other forms of extreme multidimensional poverty, as defined by facing deprivations in more than one-half of the considered indicators (OPHI, 2018). This mismatch indicates that improving the lives of the most disadvantaged households - as per the broader notion of multidimensional poverty that we make a case for here - requires much more than market driven mechanisms or increased purchasing power alone. Martin & Hulme (2003) argue that reaching the 'hardcore poor' in Bangladesh requires multifaceted programs combining elements of food aid, skills training and micro-finance. Following Collier (2017), it may be a combination of market mechanisms and policy efforts that needs to be at play in order to effectively enhance livelihoods of 'the poorest of the poor'. Reducing the likelihood of facing simultaneous deprivations in, say, sanitation, school attendance, years of schooling and electricity requires an improved set of capabilities that will then give access to such services. Many studies argue that providing these services are still a pending task in Bangladesh (see e.g. Mahmood (2010) and Elias-Sarker (2006)). Our results reinforce the idea that people suffering the most from simultaneous deprivations deserve policy priority. Drastic efforts at the individual or household level - such as international labour migration - are insufficient to lift the poorest out of the precarious situation that entails living in severe multidimensional poverty. In a sense, our results reflect that migration can be associated to a reduction of simultaneous deprivations among the whole population (intensive margin), but we do not find that it can be associated to an increased likelihood of exiting poverty altogether (extensive margin).

6. Concluding Remarks

International labour migration and the stay-behind household members' livelihoods are deeply interconnected. These linkages, however, are quite complex in that they cover monetary and non-monetary (often intangible) wellbeing aspects at the same time. In this paper, we have shown that the discussion on the migration-poverty nexus can benefit from a more comprehensive perspective on the chosen evaluative space and the conceptualization of wellbeing. It is indeed possible to better align the migration-poverty literature with the modern

⁸ According to UNDP and OPHI, these people are deemed as multidimensionally poor (OPHI, 2018).

development paradigm that unanimously advocates for a wide notion of wellbeing and lack thereof, which is often referred to as *multidimensional* poverty.

Throughout our study, we make the case that an exclusive focus on monetary considerations offers only a thin informational basis to understand the connection between migration and poverty. A host of complementary studies on international migration consider an array of material *and* non-material deprivations including health, education and entrepreneurship, as the relevant evaluative space. However, we also emphasize that a ‘full’ multidimensional poverty analysis requires both considering several wellbeing deprivations and an explicit account of the simultaneous experience of multiple deprivations. We also show compelling empirical evidence supporting these statements. We have also shown that the dual cutoff counting approach to poverty (namely the Alkire-Foster method) is one suitable way for taking into account not only the many dimensions of poverty, but also their inter-linkages, in migration studies. By doing so, we empirically demonstrate that there is a benefit in exploring combinations of the literature on the migration-poverty nexus with that of multidimensional poverty analyses.

In our empirical analysis with the BIHS 2011-2015 panel data set for rural Bangladesh, we highlighted differences in unconditional (descriptive) and conditional (model-based) expected outcomes for migrant and non-migrant households. We estimate the extent to which having a household member working abroad is associated with the many forms of poverty among the stay-behind household members. The endogenous nature of the migration-poverty nexus is explicitly addressed by applying a Hausman-Taylor estimation procedure. We find that there are associations between international labour migration and the reduction of wellbeing deprivations that vary depending on the approach taken to the latter concept. Migration is associated with a lower likelihood of being monetary poor, as well as a lower likelihood of facing deprivations in flooring, electricity, and sanitation. Conversely, we do not find that migration can be associated with a higher likelihood of exiting multidimensional poverty, but we do find that it is associated with a lower likelihood of being multidimensionally poor *and* deprived in sanitation or electricity or asset ownership. We emphasize that this goes on to show that, even if migration cannot be associated to better chances of exiting multidimensional poverty altogether, it is related to livelihood improvements among the poor.

Thus, our results show that a counting approach to poverty sheds a novel and useful light on the migration-poverty nexus. It allows to uncover some elements of this nexus that may be overlooked by other, arguably more traditional approaches. Based on these results, we propose that future research can and perhaps should focus on migration-induced effects on multidimensional poverty in other empirical contexts. The unavailability of household level data for such detailed studies may be a limiting factor, but we have shown that there are ways to overcome potential data deficiencies.

Understanding the relationship between migration and multidimensional poverty is still a pending challenge in spheres of academia and policymaking spheres, and we believe our study takes us one step further in this direction. While migration may not end poverty in itself – as we find in this paper - the intensity of multidimensional poverty is indeed reduced. From this result, one can envision several research questions for future studies. From a methodological perspective, it is important to investigate plausible ways to arrive at consistent identification of migration effects in settings with more dynamic variation than our current data allow. For such a purpose, additional instrumental variable procedures need to be explored and compared

against other structural, theory-based frameworks. From a theoretical and policy perspectives, it is vital to uncover the causal mechanisms linking migration and the simultaneous experience of deprivations, which are evidently powerful in light of our empirical analyses. Arriving at sound theories of change in this respect would be an important step towards improved policymaking to battle poverty and meet the SDG targets timely.

It is important to acknowledge that international labour migration is a natural and permanent demographic process, with ever-varying causes and effects that are highly context-dependent. It is undeniable that these permanent human movements will always reconfigure livelihoods and affect poverty in complex and multifaceted ways.

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Tables

Table 1: Dimensions, indicators, deprivation cutoffs and weights

Dimension	Indicator	A household is deprived if...	Weight
Health	Nutrition	There is at least one child under 6 that is either underweight or stunted ^a	1/3
Education	School Attendance	not all school-aged children are attending school ^b	1/6
	Years of Schooling	the household head does not have at least 5 years of education ^c	1/6
Living Standards	Electricity	there is no electricity in the dwelling	1/15
	Floor	it does not have a durable, solid floor ^d	1/15
	Walls	it does not have walls made out of a durable material ^e	1/15
	Sanitation	it does not have SDG-compliant sanitation facilities ^f	1/15
	Asset Ownership	it does not own a TV (communication assets) or a bicycle (mobility asset) ^g	1/15

Notes:

^aWe calculate weight-for-age and height-for-age z-scores using the standard WHO ado-file for calculating anthropometrics (available at: <https://www.who.int/childgrowth/software/en/>) and determine anyone as underweight or stunted that has z-scores of -2 or less.

^bWe consider 6 to 14 years as the compulsory school age.

^cFive years of education are equivalent to primary education.

^dA solid floor is “concrete”, whereas floor material of “wood”, “mud”, or “bamboo” is considered as deprived.

^eWalls are considered solid if they are: “concrete/brick” or “ tin/ci sheets”; walls are inadequate if they are of: “wood”, “mud or unfired mud brick”, “bamboo”, “jute stick”, “plastic sheeting (polythene)”, “golpaata/palm leaf”, “grass/straw”, or “other”.

^fSanitation is according to SDG standards if categories are: “sanitary without flash (water sealed)”, “sanitary without flash (water sealed)” ; and not if categories are : “none (open field)”, “kutcha (fixed place)”, “pucca (unsealed)”, “community latrine”, “other”.

^gWe consider these assets from the global MPI assets indicator to capture basic mobility and information.

Table 2: Monetary indicators, levels and trends

	Consumption per capita (log)			Pov. Headcount (%)	
	Food	Non-Food	Total	Mod.	Ext.
Non-migrant HHs, 2011	6.917	5.414	7.165	61.0	49.5
Migrant HHs, 2011	7.235	5.878	7.508	37.9	25.1
Difference	-0.318	-0.464	-0.343	23.2	24.4
p-value	0.000	0.000	0.000	0.000	0.000
Non-migrant HHs, 2015	7.11	5.69	7.377	46.3	33.8
Migrant HHs, 2015	7.426	6.411	7.786	25.5	15.8
Difference	-0.316	-0.721	-0.409	20.7	18
p-value	0.000	0.000	0.000	0.000	0.000
Time diff. non-migrant	0.198	0.249	0.211	-14.6	-15.5
Time diff. migrant HHs	0.225	0.568	0.307	-14.2	-10.8
Difference	-0.028	-0.319	-0.097	-0.4	-4.6
p-value	0.387	0.000	0.001	0.891	0.119
Number of households			9942		
Migrant households, 2011			383		
Migrant households, 2015			431		

Notes: Standard paired t-tests are performed to compare means. Consumption is evaluated using 2010 real Thaka prices.

Table 3: Dashboard deprivation headcount ratios, by dimension (%), levels and trends

	Health	Education		Living Standards				
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Non-migrant HHs, 2011	20.8	13.7	51.1	54.0	89.9	39.3	75.5	60.4
Migrant HHs, 2011	18.3	9.9	50.9	27.2	75.7	26.6	57.4	47.5
Difference	2.5	3.8	0.1	26.9	14.2	12.7	18.1	12.8
p-value	0.243	0.035	0.956	0.000	0.000	0.000	0.000	0.000
Non-migrant HHs, 2015	16	3.8	46.9	42.7	86.7	27.7	57.6	52.8
Migrant HHs, 2015	11.6	2.1	48.5	19.5	61.5	19.7	45.5	39.9
Difference	4.4	1.7	-1.6	23.2	25.2	8	12.1	12.9
p-value	0.017	0.066	0.526	0.000	0.000	0.000	0.000	0.000
Time difference non-migrant HHs	-2.3	-9.7	-4.6	-10.9	-3.3	-11.2	-17.8	-6.6
Time difference migrant HHs	-6.4	-8.3	-1.7	-11.6	-16.3	-10.1	-14.2	-8.0
Difference	4.1	-1.5	-3.0	0.6	13	-1.0	-3.6	1.4
p-value	0.081	0.425	0.129	0.753	0.000	0.614	0.248	0.522
Number of households	9942							
Migrant households, 2011	383							
Migrant households, 2015	431							

(a): Nutrition; (b)=School Attendance; (c)=Years of Schooling; (d)=Electricity; (e)=Floor;
(f)=Walls; (g)=Sanitation; (h)=Asset Ownership.

Notes: Standard paired t-tests are performed to compare means.

Table 4: Mean levels and trends of the number of simultaneous weighted deprivations

	$E(c_t)$
Non-migrant households, 2011	0.390
Migrant households, 2011	0.319
Difference	0.071
p-value	0.000
Non-migrant households, 2015	0.316
Migrant households, 2015	0.247
Difference	0.069
p-value	0.000
Time difference, non-migrant households	-0.065
Time difference, migrant households	-0.078
Difference	0.013
p-value	0.176
Number of households	9942
Migrant households, 2011	383
Migrant households, 2015	431

Note: Standard paired t-tests were performed to compare means

Table 5: Hausman-Taylor estimates of the coefficient associated to migration

Dependent variable	Coef.	Baseline mean	$\hat{\sigma}_u^2$	$\hat{\sigma}_e^2$	Hausman test
Monetary approach					
-Food consumption per capita (log)	-0.029	7.014	0.401	0.413	***
-Non-food consumption per capita (log)	0.182		0.541	0.645	***
-Total consumption per capita (log)	-0.023	7.283	0.424	0.378	***
-Extremely monetary poor (yes=1)	-0.132 *	0.420	0.318	0.409	***
-Moderate monetary poor (yes=1)	-0.119	0.549	0.411	0.404	**
Dashboard approach					
-Deprived in nutrition (yes=1)	-0.052	0.180	0.126	0.291	
-Deprived in schooling (yes=1)	0.048	0.490	0.439	0.259	
-Deprived in school attendance (yes=1)	0.002	0.082	0.115	0.249	
-Deprived in sanitation (yes=1)	-0.116 *	0.663	0.175	0.435	
-Deprived in electricity (yes=1)	-0.108 **	0.468	0.390	0.285	
-Deprived in flooring (yes=1)	-0.157 ***	0.881	0.266	0.212	
-Deprived in walls (yes=1)	0.005	0.343	0.366	0.274	
-Deprived in asset ownership (yes=1)	-0.078	0.531	0.380	0.314	***
Counting approach					
-Multidimensionally poor, acute: k=33.33% (yes=1)	-0.103	0.490	0.310	0.374	
-Multidimensionally poor, severe: k=50% (yes=1)	-0.043	0.231	0.202	0.325	
-c-vector score	-0.037 **	0.348	0.125	0.124	
-Multid. poor and deprived in nutrition (yes=1)	-0.052	0.180	0.126	0.291	
-Multid. poor and deprived in schooling (yes=1)	0.029	0.464	0.420	0.281	
-Multid. poor and deprived in school attendance (yes=1)	0.001	0.082	0.116	0.248	
-Multid. poor and deprived in sanitation (yes=1)	-0.138 **	0.602	0.229	0.424	
-Multid. poor and deprived in electricity (yes=1)	-0.163 ***	0.454	0.379	0.295	
-Multid. poor and deprived in flooring (yes=1)	-0.092	0.761	0.300	0.304	
-Multid. poor and deprived in walls (yes=1)	0.011	0.324	0.350	0.289	
-Multid. poor and deprived in asset ownership (yes=1)	-0.116 *	0.510	0.378	0.316	***

Notes: ***: p-value<0.01; **: p-value<0.05; *: p-value<0.10. Linear probabilities are assumed for binary dependent variables.

Figures

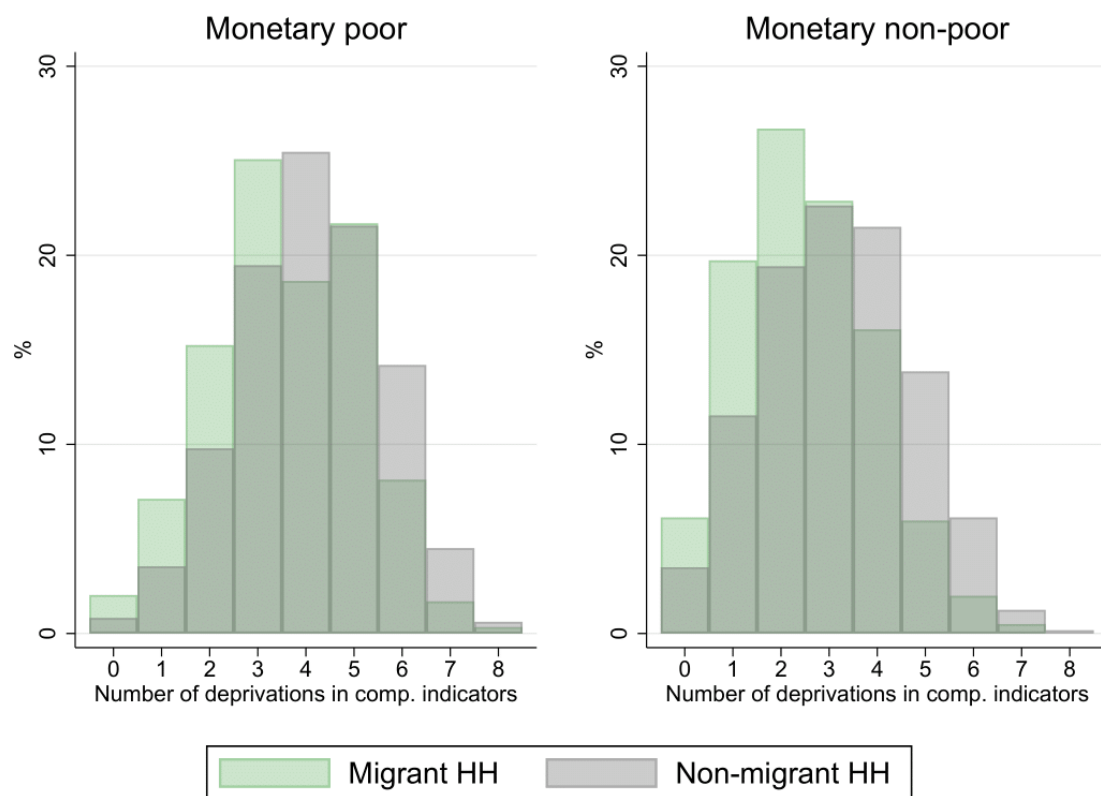


Figure 1: Frequency of simultaneous non-monetary (or complementary) deprivations, by monetary poverty and migration status

Note: These figures have been computed using pooled data.

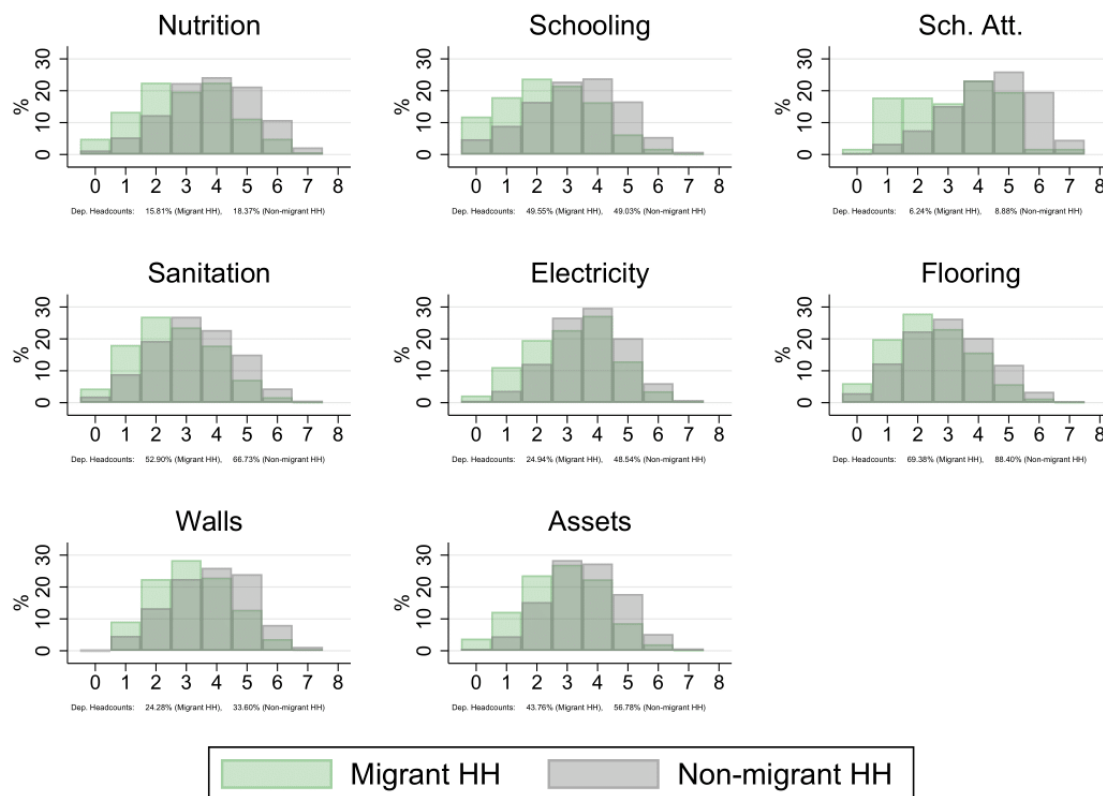
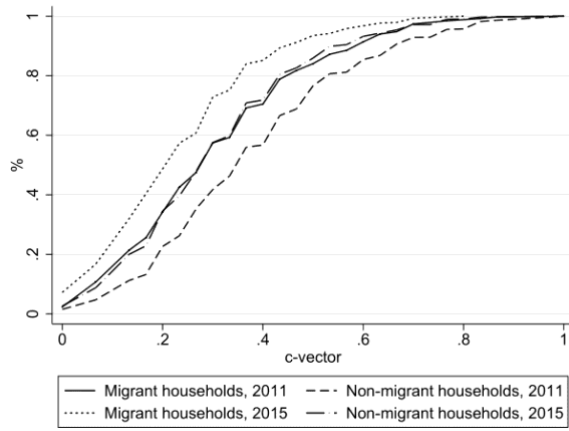
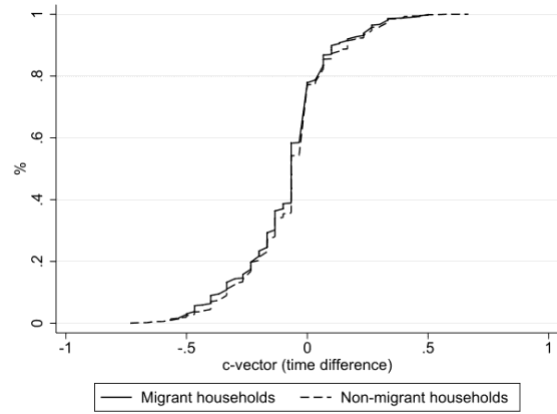


Figure 2: Frequency of Additional Simultaneous Deprivations, by Indicator and Migrant Status
 Note: These figures have been computed using pooled data



(a) Levels



(b) Changes over time

Figure 3: Cumulative Distribution Functions of c-vectors

Appendix A: Full Estimation Results

Table A1: Hausman-Taylor Estimates: Monetary approach models, full results

Variable	Model				
	(a.1)	(a.2)	(a.3)	(a.4)	(a.5)
Migrant household	-0.029 (0.072)	0.182 (0.122)	-0.023 (0.074)	-0.132* (0.077)	-0.119 (0.081)
Members, aged <6	-0.022** (0.009)	-0.125*** (0.013)	-0.038*** (0.009)	-0.006 (0.009)	-0.018* (0.010)
Members, aged 15-44	0.061*** (0.008)	0.173*** (0.011)	0.089*** (0.008)	-0.064*** (0.007)	-0.065*** (0.008)
Members, aged 45-65	0.067*** (0.010)	0.091*** (0.015)	0.076*** (0.010)	-0.032*** (0.011)	-0.039*** (0.012)
Dist. Market (min.)	-0.001* (0.001)	0.002** (0.001)	-0.000 (0.001)	0.002*** (0.001)	0.002*** (0.001)
Dist. Pub. Trans. (min.)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.000)	0.000 (0.000)	0.001 (0.000)
Dist. Hospital (min.)	0.000 (0.000)	-0.001** (0.001)	-0.000 (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Muslim HH _a	0.092*** (0.024)	0.002 (0.034)	0.082*** (0.023)	-0.016 (0.020)	-0.055*** (0.020)
Barisal _b	0.029 (0.036)	0.009 (0.055)	0.035 (0.037)	-0.007 (0.031)	-0.015 (0.032)
Chittagong _b	0.155*** (0.039)	0.342*** (0.058)	0.204*** (0.040)	-0.057* (0.035)	-0.030 (0.036)
Khulna _b	-0.074* (0.043)	0.053 (0.061)	-0.023 (0.043)	-0.022 (0.037)	-0.007 (0.038)
Rajshahi _b	-0.252*** (0.028)	-0.050 (0.041)	-0.215*** (0.028)	0.059** (0.026)	0.078*** (0.026)
Rangpur _b	-0.342*** (0.031)	-0.302*** (0.046)	-0.347*** (0.031)	0.168*** (0.032)	0.190*** (0.031)
Sylhet _b	0.167*** (0.057)	0.045 (0.086)	0.125** (0.058)	-0.161*** (0.052)	-0.269*** (0.052)
Dist. City >50K Hab. (Km, log)	0.019 (0.021)	0.005 (0.034)	0.024 (0.022)	0.001 (0.019)	-0.014 (0.020)
Dist. City >100K Hab. (Km) log)	0.011 (0.019)	-0.003 (0.028)	0.008 (0.019)	-0.019 (0.016)	-0.015 (0.017)
Dist. City >250K Hab.(Km) log)	-0.025 (0.024)	-0.043 (0.037)	-0.031 (0.025)	0.021 (0.021)	-0.000 (0.022)
Dist. City >500K Hab.(Km) log)	-0.000 (0.024)	-0.031 (0.037)	0.013 (0.025)	0.006 (0.023)	0.021 (0.024)
Dist. City >20K Hab.(Km, log)	-0.024 (0.019)	0.018 (0.029)	-0.023 (0.019)	0.006 (0.016)	0.017 (0.016)
Rice harvested area (H, log)	0.203** (0.096)	0.137 (0.134)	0.224** (0.094)	-0.120+ (0.080)	-0.137* (0.080)
Rice physical area (H, log)	-0.231*** (0.085)	-0.241** (0.122)	-0.240*** (0.085)	0.163** (0.074)	0.165** (0.074)
Rice production area (Tn, log)	0.013 (0.038)	0.119** (0.053)	0.001 (0.037)	-0.035 (0.029)	-0.024 (0.029)
Rice yield area (Tn/H, log)	0.017 (0.019)	-0.029 (0.028)	0.026 (0.019)	-0.006 (0.017)	-0.005 (0.017)
Baseline Mean	7.01	5.60	7.28	0.42	0.55

Notes:

- Dependent variable by model: (a.1)=Food consumption per capita (log); (a.2)=Non-food consumption per capita (log); (a.3)=Total consumption per capita (log); (a.4)=Extremely monetary poor (yes=1); (a.5)=Moderate monetary poor (yes=1)
- ***: p-value<0.01; **: p-value<0.05; *: p-value<0.10
- Standard errors in parentheses
- Linear probabilities are assumed for binary dependent variables.

Variable	Model							
	(b.1)	(b.2)	(b.3)	(b.4)	(b.5)	(b.6)	(b.7)	(b.8)
Migrant Household	-0.052 (0.047)	0.048 (0.050)	0.002 (0.039)	-0.116* (0.071)	-0.108** (0.047)	-0.157*** (0.048)	0.005 (0.045)	-0.078 (0.058)
Muslim Muslim Household _a	-0.014 (0.011)	0.013 (0.023)	0.019** (0.009)	-0.028 (0.018)	-0.133*** (0.022)	-0.012 (0.015)	-0.098*** (0.021)	0.063*** (0.021)
Members, aged <6	0.300*** (0.007)	-0.035*** (0.007)	-0.007* (0.004)	0.013* (0.008)	0.016** (0.007)	0.005 (0.006)	0.004 (0.007)	0.044*** (0.009)
Members, aged 15-44	-0.006* (0.003)	-0.075*** (0.006)	-0.006** (0.003)	-0.033*** (0.006)	-0.037*** (0.006)	-0.026*** (0.005)	-0.015*** (0.005)	-0.094*** (0.007)
Members, aged 45-65	-0.021*** (0.005)	-0.045*** (0.009)	-0.022*** (0.004)	-0.033*** (0.008)	-0.033*** (0.008)	-0.025*** (0.008)	-0.026*** (0.008)	-0.076*** (0.011)
Dist. Market (min.)	0.000 (0.000)	0.001** (0.000)	-0.000 (0.000)	0.000 (0.001)	0.003*** (0.000)	0.001* (0.000)	0.000 (0.000)	0.002*** (0.001)
Dist. Pub. Trans. (min.)	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)	0.001* (0.000)	0.000 (0.000)	0.001** (0.000)	-0.000 (0.000)	-0.000 (0.000)
Dist. Hospital (min.)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.002*** (0.000)	0.000 (0.000)	-0.000** (0.000)	-0.000+ (0.000)	-0.000 (0.000)
Barisal _b	0.017 (0.019)	-0.119*** (0.035)	-0.028+ (0.017)	-0.038 (0.028)	-0.141*** (0.032)	-0.057*** (0.021)	0.024 (0.029)	-0.018 (0.033)
Chittagong _b	0.009 (0.025)	0.007 (0.040)	0.000 (0.022)	-0.092*** (0.031)	-0.061* (0.036)	-0.018 (0.025)	0.254*** (0.034)	0.064* (0.037)
Khulna _b	-0.015 (0.025)	-0.007 (0.045)	-0.071*** (0.021)	-0.093*** (0.031)	-0.065 (0.041)	-0.070*** (0.026)	0.413*** (0.038)	-0.228*** (0.041)
Rajshahi _b	0.016 (0.015)	0.045+ (0.028)	-0.017 (0.013)	-0.125*** (0.022)	0.108*** (0.027)	-0.020 (0.017)	0.185*** (0.027)	-0.115*** (0.029)
Rangpur _b	0.029* (0.017)	0.027 (0.031)	0.004 (0.015)	-0.028 (0.025)	0.294*** (0.027)	0.029* (0.018)	0.076*** (0.027)	-0.072** (0.033)
Sylhet _b	0.039 (0.035)	-0.011 (0.057)	0.013 (0.031)	-0.139*** (0.046)	0.199*** (0.054)	-0.063* (0.034)	0.112** (0.050)	0.128** (0.055)
Dist. City >50K Hab. (Km, log)	-0.003 (0.012)	0.015 (0.022)	-0.003 (0.011)	0.014 (0.017)	-0.010 (0.020)	-0.002 (0.015)	0.094*** (0.019)	-0.030 (0.020)
Dist. City >100K Hab. (Km, log)	0.006 (0.010)	-0.026 (0.019)	0.005 (0.010)	0.022 (0.015)	0.059*** (0.016)	0.023* (0.013)	-0.012 (0.015)	0.055*** (0.018)

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Dist. City >250K Hab.(Km, log)	0.014 (0.012)	0.073*** (0.023)	0.011 (0.012)	0.013 (0.020)	0.092*** (0.021)	0.017 (0.016)	-0.216*** (0.021)	0.047** (0.022)
Dist. City >500K Hab.(Km, log)	-0.015 (0.013)	-0.031 (0.024)	-0.007 (0.011)	-0.026 (0.019)	-0.124*** (0.023)	-0.014 (0.018)	0.175*** (0.023)	-0.034 (0.025)
Dist. City >20K Hab.(Km, log)	-0.006 (0.009)	-0.013 (0.018)	-0.012+ (0.008)	-0.019 (0.014)	0.036** (0.017)	0.007 (0.013)	-0.006 (0.017)	-0.004 (0.017)
Rice harvested area (H, log)	-0.003 (0.057)	-0.034 (0.096)	-0.054 (0.050)	-0.151** (0.068)	0.143* (0.087)	0.070 (0.053)	0.307*** (0.078)	0.077 (0.086)
Rice physical area (H, log)	-0.002 (0.053)	0.059 (0.088)	0.046 (0.046)	0.103+ (0.064)	0.008 (0.079)	0.003 (0.049)	-0.368*** (0.072)	0.062 (0.080)
Rice production area (Tn, log)	0.004 (0.019)	-0.011 (0.037)	0.003 (0.018)	0.041+ (0.027)	-0.140*** (0.034)	-0.071*** (0.020)	-0.047+ (0.033)	-0.134*** (0.031)
Rice yield area (Tn/H, log)	-0.002 (0.011)	-0.008 (0.019)	0.003 (0.010)	0.005 (0.014)	-0.030+ (0.019)	-0.001 (0.014)	0.092*** (0.021)	0.002 (0.017)
Baseline mean	0.180	0.490	0.082	0.663	0.468	0.881	0.343	0.531

Notes:

- Dependent variable by model: (b.1)=Deprived in nutrition (yes=1); (b.2)=Deprived in schooling (yes=1); (b.3)=Deprived in school attendance (yes=1); (b.4)=Deprived in sanitation (yes=1); (b.5)=Deprived in electricity (yes=1); (b.6)=Deprived in flooring (yes=1); (b.7)=Deprived in walls (yes=1); (b.8)=Deprived in asset ownership (yes=1)
- ***: p-value<0.01; **: p-value<0.05; *: p-value<0.10
- Standard errors in parentheses
- Linear probabilities are assumed for binary dependent variables.

Table A2: Hausman-Taylor Estimates: Counting approach models, full results

Variable	Model										
	(c.1)	(c.2)	(c.3)	(c.4)	(c.5)	(c.6)	(c.7)	(c.8)	(c.9)	(c.10)	(c.11)
Migrant household	-0.037*	-0.103	-0.043	-0.052	0.029	0.001	-0.138**	-0.163***	-0.092	0.011	-0.116*
	(0.019)	(0.065)	(0.050)	(0.047)	(0.051)	(0.039)	(0.067)	(0.051)	(0.061)	(0.045)	(0.063)
Members age < 6	0.096***	0.159***	0.214***	0.300***	-0.027***	-0.007	0.028***	0.022***	0.034***	0.010	0.042***
	(0.003)	(0.008)	(0.007)	(0.007)	(0.008)	(0.004)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Member age 15-44	-0.032***	-0.082***	-0.047***	-0.006*	-0.086***	-0.006**	-0.053***	-0.046***	-0.058***	-0.021***	-0.087***
	(0.002)	(0.006)	(0.004)	(0.003)	(0.006)	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
Members age 45-65	-0.030***	-0.055***	-0.049***	-0.021***	-0.048***	-0.021***	-0.046***	-0.041***	-0.059***	-0.029***	-0.066***
	(0.003)	(0.009)	(0.006)	(0.005)	(0.009)	(0.004)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Dist. Market (min.)	0.001***	0.001**	0.001*	0.000	0.001**	-0.000	0.001	0.002***	0.001*	0.000	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Dist. Pub. Trans. (min.)	-0.000	-0.000	-0.001***	-0.000	0.000	-0.000*	0.001	0.000	0.001**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. Hospital (min.)	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.001***	0.000	-0.000	-0.001*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Muslim HH	-0.019**	-0.035*	-0.021	-0.014	-0.007	0.018**	-0.040**	-0.139***	-0.048***	-0.096***	0.045**
	(0.008)	(0.020)	(0.015)	(0.011)	(0.023)	(0.009)	(0.019)	(0.021)	(0.018)	(0.021)	(0.021)
Barisal	-0.033***	-0.085***	-0.015	0.017	-0.126***	-0.030*	-0.046	-0.143***	-0.077***	-0.011	0.002
	(0.011)	(0.030)	(0.024)	(0.019)	(0.034)	(0.017)	(0.029)	(0.032)	(0.027)	(0.029)	(0.032)
Chittagong	0.007	0.055	0.022	0.009	0.009	-0.001	-0.066**	-0.048	-0.024	0.211***	0.032
	(0.014)	(0.035)	(0.029)	(0.025)	(0.040)	(0.022)	(0.032)	(0.036)	(0.030)	(0.033)	(0.037)
Khulna	-0.022	-0.020	-0.035	-0.015	-0.014	-0.071***	-0.053	-0.069*	-0.017	0.365***	-0.156***
	(0.015)	(0.038)	(0.030)	(0.025)	(0.044)	(0.021)	(0.033)	(0.041)	(0.032)	(0.037)	(0.041)
Rajshahi	0.019**	0.031	0.034*	0.016	0.044	-0.017	-0.070***	0.087***	0.031	0.147***	-0.046*
	(0.009)	(0.025)	(0.019)	(0.015)	(0.028)	(0.013)	(0.023)	(0.027)	(0.022)	(0.026)	(0.027)

Rangpur	0.041*** (0.010)	0.075*** (0.027)	0.088*** (0.022)	0.029* (0.017)	0.036 (0.030)	0.005 (0.015)	-0.007 (0.026)	0.267*** (0.027)	0.090*** (0.022)	0.089*** (0.027)	-0.038 (0.029)
Sylhet	0.037* (0.020)	0.090* (0.050)	0.072* (0.043)	0.039 (0.035)	-0.008 (0.057)	0.012 (0.031)	-0.090* (0.048)	0.187*** (0.054)	0.027 (0.043)	0.080 (0.049)	0.163*** (0.054)
Dist. City >50K Hab. (Km, log)	0.004 (0.007)	0.019 (0.019)	-0.000 (0.015)	-0.003 (0.012)	0.015 (0.021)	-0.003 (0.011)	0.018 (0.018)	-0.021 (0.019)	0.007 (0.017)	0.099*** (0.018)	-0.029 (0.020)
Dist. City >100K Hab.(Km, log)	0.009 (0.006)	0.020 (0.016)	0.020 (0.013)	0.006 (0.010)	-0.021 (0.018)	0.006 (0.010)	0.022 (0.016)	0.054*** (0.016)	0.022 (0.015)	-0.011 (0.015)	0.068*** (0.018)
Dist. City >250K Hab.(Km, log)	0.018** (0.008)	0.024 (0.020)	0.009 (0.016)	0.014 (0.012)	0.069*** (0.023)	0.012 (0.012)	0.007 (0.020)	0.081*** (0.021)	0.043** (0.019)	-0.188*** (0.021)	0.061*** (0.022)
Dist. City >500K Hab.(Km, log)	-0.019** (0.008)	-0.020 (0.021)	-0.006 (0.016)	-0.015 (0.013)	-0.027 (0.024)	-0.008 (0.011)	-0.012 (0.020)	-0.118*** (0.023)	-0.027 (0.019)	0.156*** (0.022)	-0.049** (0.023)
ist. City >20K Hab.(Km, log)	-0.004 (0.006)	-0.011 (0.016)	-0.012 (0.013)	-0.006 (0.009)	-0.009 (0.018)	-0.011 (0.008)	-0.015 (0.015)	0.045*** (0.017)	-0.001 (0.015)	-0.014 (0.016)	-0.007 (0.017)
Rice harv area (H)	0.007 (0.032)	0.100 (0.081)	-0.028 (0.067)	-0.003 (0.057)	0.005 (0.095)	-0.055 (0.050)	-0.113 (0.072)	0.122 (0.087)	0.068 (0.069)	0.257*** (0.077)	0.116 (0.088)
Rice phy. area (H)	0.007 (0.030)	-0.035 (0.074)	0.023 (0.063)	-0.002 (0.053)	0.040 (0.087)	0.047 (0.046)	0.095 (0.068)	0.007 (0.079)	0.013 (0.064)	-0.276*** (0.071)	0.028 (0.081)
Rice prod. (Tn, log)	-0.017 (0.012)	-0.080*** (0.031)	-0.006 (0.025)	0.004 (0.019)	-0.033 (0.036)	0.002 (0.018)	0.021 (0.029)	-0.115*** (0.033)	-0.073*** (0.027)	-0.078** (0.032)	-0.138*** (0.034)
Rice yield (Tn/H, log)	-0.002 (0.007)	0.012 (0.017)	0.006 (0.014)	-0.002 (0.011)	-0.005 (0.018)	0.004 (0.010)	-0.010 (0.015)	-0.038** (0.018)	-0.013 (0.016)	0.090*** (0.020)	-0.003 (0.018)
Baseline Mean	0.350	0.490	0.230	0.180	0.460	0.080	0.600	0.450	0.760	0.320	0.510

Notes:

- Dependent variable by model: (c.1)=c-vector; (c.2)=Acutely poor (k=33.33%); (c.3)=Extremely poor (k=50%); (c.4)=Acutely poor and deprived in nutrition (yes=1); (c.5)= Acutely poor and deprived in schooling (yes=1); (c.6)= Acutely poor and deprived in school attendance (yes=1); (c.7)= Acutely poor and deprived in sanitation (yes=1); (c.8)= Acutely poor and deprived in electricity (yes=1); (c.9)= Acutely poor and deprived in flooring (yes=1); (c.10)= Acutely poor and deprived in walls (yes=1); (c.11)= Acutely poor and deprived in asset ownership (yes=1)
- ***: p-value<0.01; **: p-value<0.05; *: p-value<0.10
- Standard errors in parenthesis
- Linear probabilities are assumed for binary dependent variables.

Appendix B: Robustness Analyses

Our counting approach-based analyses consider the structure of the global MPI as undertaken by UNDP and OPHI. Even if this structure enjoys international acceptance, it still involves a set of inescapable normative decisions that underlie the results that we presented (see. e.g. Sen, 2002; Atkinson, 2003; Alkire et al., 2015). These include the relative importance given to each dimension (i.e. the weighting scheme) and the multidimensional poverty cutoff (i.e. the k value). We performed a set of robustness analyses of the associations that we detect with migration. These analyses show that not only are they robust to a wide array of alternative specifications, but the qualitative interpretations that we propose for them are actually reinforced.

We first examine the stability of our results under alternative weighting schemes. We defend that the considered indicators pertain to a dimension and they are not single, independent entities. Thus, we consider the following alternative schemes:

- Scheme 1: nested weights (Global MPI)
- Scheme 2: 50% (Health), 25% (Education), 25% Living Standard
- Scheme 3: 25% (Health), 50% (Education), 25% Living Standard
- Scheme 4: 25% (Health), 25% (Education), 50% Living Standard

The baseline specification, Scheme 1, assigns equal weights to each of the three dimensions and then equal weights within dimensions (nested weights). In Schemes 2, 3, and 4 nested weights are applied as well, but dimensions are not weighted equally. In turn, each one of them is given twice the importance of the others. In our view, these configurations imply considerable normative changes in terms of how we understand poverty, but one may potentially find reasons to justify them. In Scheme 2, the dimension of Health receives 50%, while the remaining receive 25% each. In Scheme 3, Education receives 50% and in Scheme 4 it is Living Standard with the major weight of 50%.

In Figure 4, while we see that even if the magnitude in the gap of c -vector levels between years may vary, the patterns and trend is largely the same across schemes. This is confirmed in Figure 5, where we plot the changes over time in the c -vector for each specification. The static advantage of migrant households that we found, as well as its time invariance are quite robust to distinct dimensional weights. Thus, even if one were willing to defend a normative priority of either one of the considered dimensions over the others, our results remain unchanged.

The weak evidence of migration-induced effects on the likelihood of suffering moderate multidimensional poverty is also a robust result with respect to changes in the weighing scheme. In Figure 6, we plot the regression coefficients of interest along with 95% confidence intervals for each of the Schemes. While on average, the migration effect is consistently negative, it is not statistically significant at this confidence level for any of the specifications.

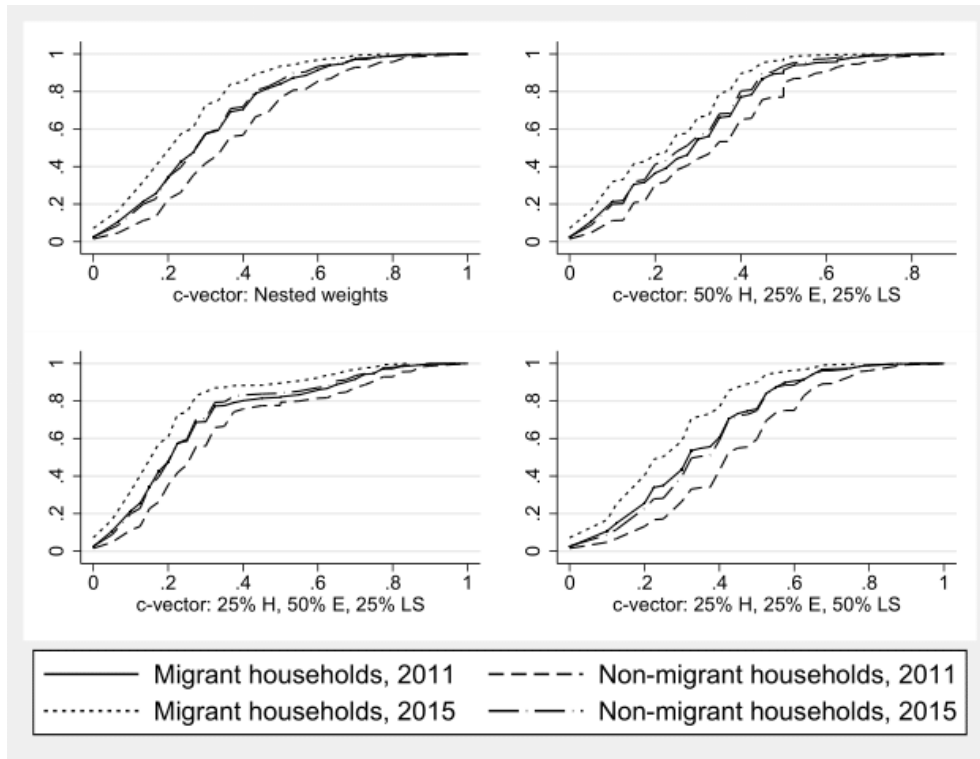


Figure 4: Levels of Cumulative Distribution Functions of c-vector, for four Weighting Schemes

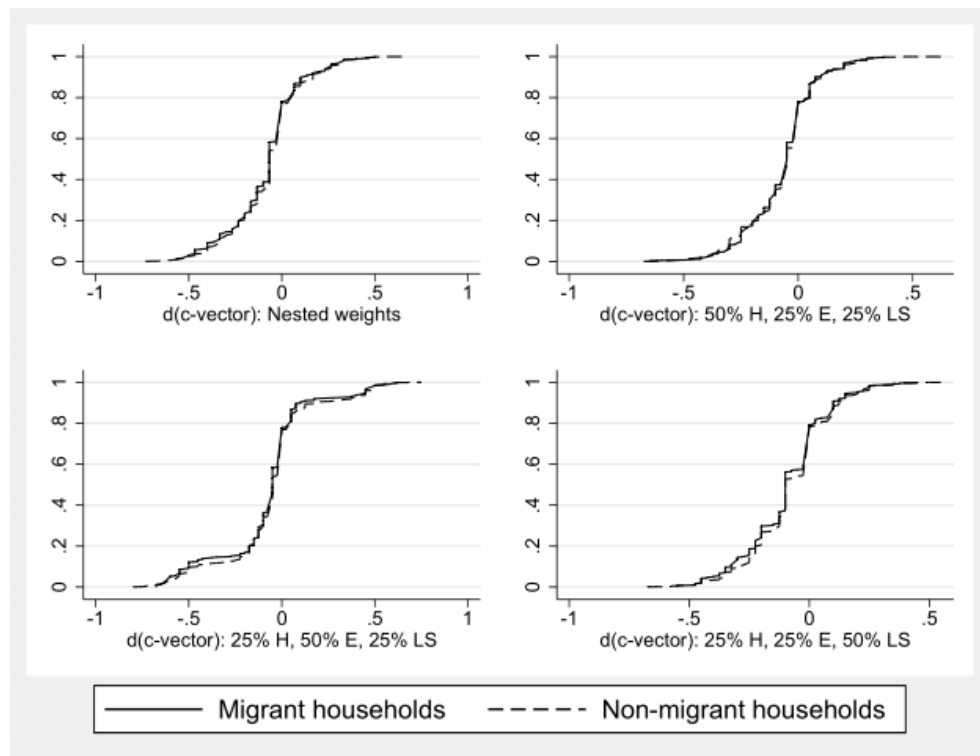


Figure 5: Changes over time of Cumulative Distribution Functions of c-vector, for four Weighting Schemes.

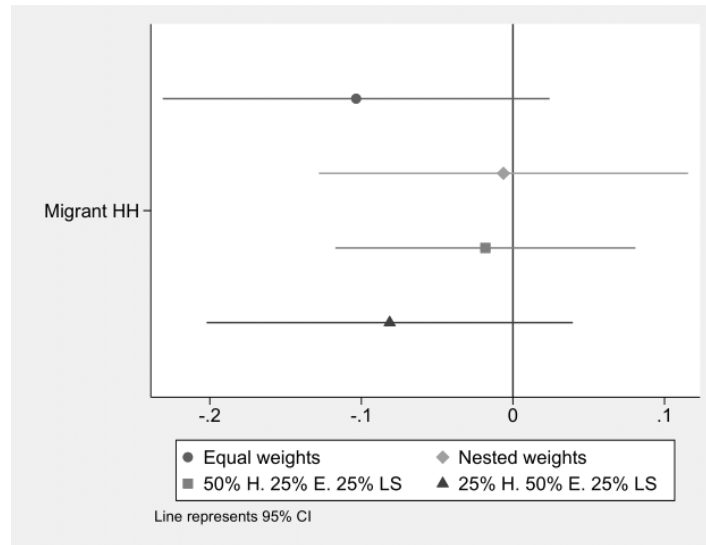


Figure 6: Regression Results for Changes in Multidimensional Headcount Ratio, for four Weighting Schemes, k Poverty Cut-off is 33%

Note: Line represents 95% confidence intervals

Similarly, our results and key message about the effects of migration on the likelihood of suffering extreme multidimensional poverty is strongly robust (see Figure 7). We don't find any evidence of migration-induced effects on the likelihood of being extreme multidimensionally poor. Even if distinct importance is given to any of the considered dimensions to identify people suffering this disadvantaged status, migration does not have an extreme poverty-attenuating effect.

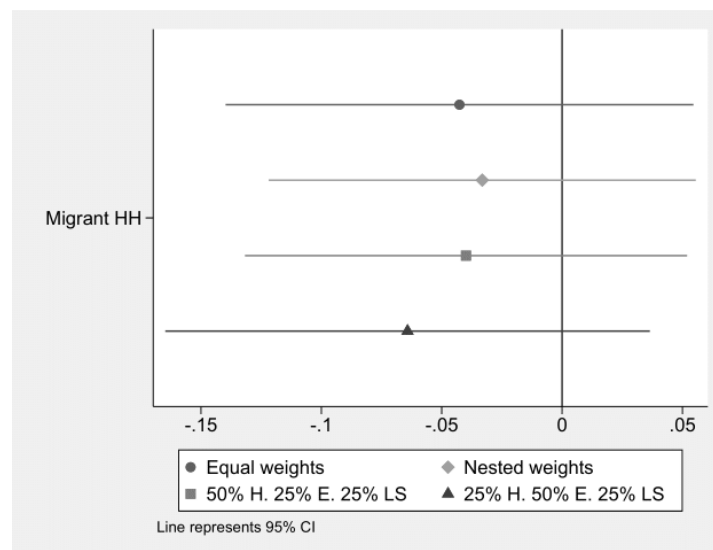


Figure 7: Regression Results for Changes in Multidimensional Headcount Ratio, for 5 Weighting Schemes, k Poverty Cut-off is 50%

Note: Line represents 95% confidence intervals

Finally, to test for robustness to poverty cutoff (k), we estimated the effects of migration under a parsimonious array of alternative procedures to identify people suffering multidimensional poverty. Let us recall that lower k values define less-demanding conditions to be identified as multidimensionally poor. We consider values from $k = 20\%$ to $k = 80\%$ in steps of 10 percentage points, but we include the preferred k -value, 33.33% , representing the baseline poverty cut-off.

Figure 8 shows that changing the poverty cutoff allows to uncover an interesting pattern of migration-induced effects on the likelihood of being multidimensionally poor. For lower values of k the migration effect is negative and statistically significant. As k increases the effect remains negative, on average, but reduces in magnitude and becomes statistically insignificant. This pattern reinforces key messages that we made a case for. We confirm that migration has a well-being improving effect over the entire rural Bangladeshi population, as it tends to reduce the weighted number of simultaneous deprivations that they face. However, it does not manage to reduce the likelihood of suffering multidimensional poverty for those sitting at the highest end of the c -vector, i.e. ‘the poorest of the poor’.

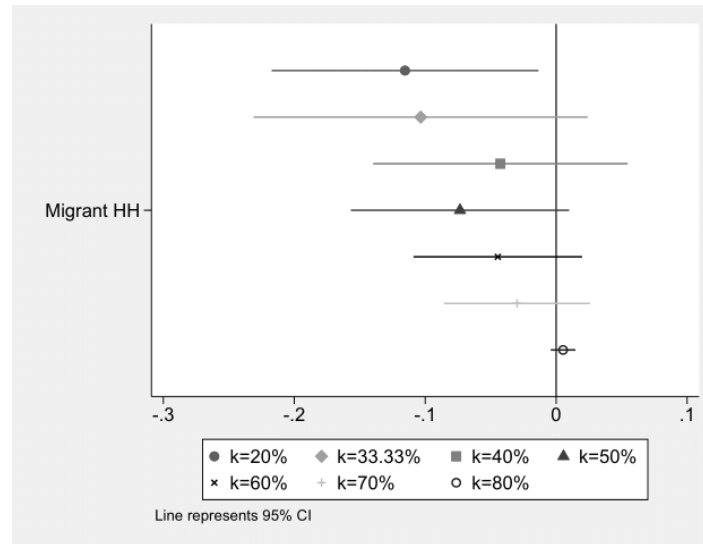


Figure 8: Regression Results for Changes in Multidimensional Headcount Ratio, for Weighting Scheme 2 (Global MPI), k Poverty Cut-off from 10% to 90%

Note: Line represents 95% confidence intervals