FIVDB
Friends In Village Development Bangladesh (FIVDB)

# Reflections on research processes in a development NGO:

## *FIVDB's survey in 2013 of the change in household conditions and of the effect of livelihood trainings*

A research note

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# Summary

### *What this is about*

This is a note with a double purpose:

- It reports findings from a survey of households in Jonoshilon villages regarding changes in their overall conditions and the effect of livelihood skills training. The findings are presented chiefly in statistical models, with a technical appendix (A companion note reports the same findings in a more accessible language, including a number of trainee case studies).
- Second, it prefaces the technical chapters with an introduction that offers reflections on the research process. The survey was in the works for over a year, from design and piloting in autumn 2012 to the date of this writing in November 2013. While the work intensity varied over time, the total effort was considerable, measured by the volume of data collected and processed. Dynamics and issues were not atypical of NGO-led surveys; they thus merit some afterthoughts.

### *The occasion for a survey*

With the Jonoshilon program in its fifth year, FIVDB has a heightened interest in documenting welfare changes in the program area and particularly in households participating in key program components. This note reports on the extent and direction of the overall change that households have experienced since the beginning of the program. It is based on a special survey taken in spring 2013.

The survey used a method known as "community-based change ranking (CCR)", which researchers in BRAC had validated. FIVDB had already applied it in an earlier sample survey in Jonoshilon villages in 2011. Besides evaluating their overall change in welfare, the interviewed households, on average, volunteered four specific changes in their lives. The patterns of these changes are strongly associated with the overall outcomes.

Baseline surveys had fully enumerated all households in 362 Jonoshilon villages in 2009-2010. From the 362, 70 were selected for this survey. They were from every one of the eight working districts. In every sample village, 30 households were interviewed, a total of 2,100 households. The interviews took place in meetings of ten households each drawn from the same neighborhood, as prescribed by the CCR method.

The analysis concentrates on differences in changes of household conditions in terms of:

- household wealth rank and education at baseline
- clusters of specific changes in the households
- participation in Jonoshilon livelihood trainings.

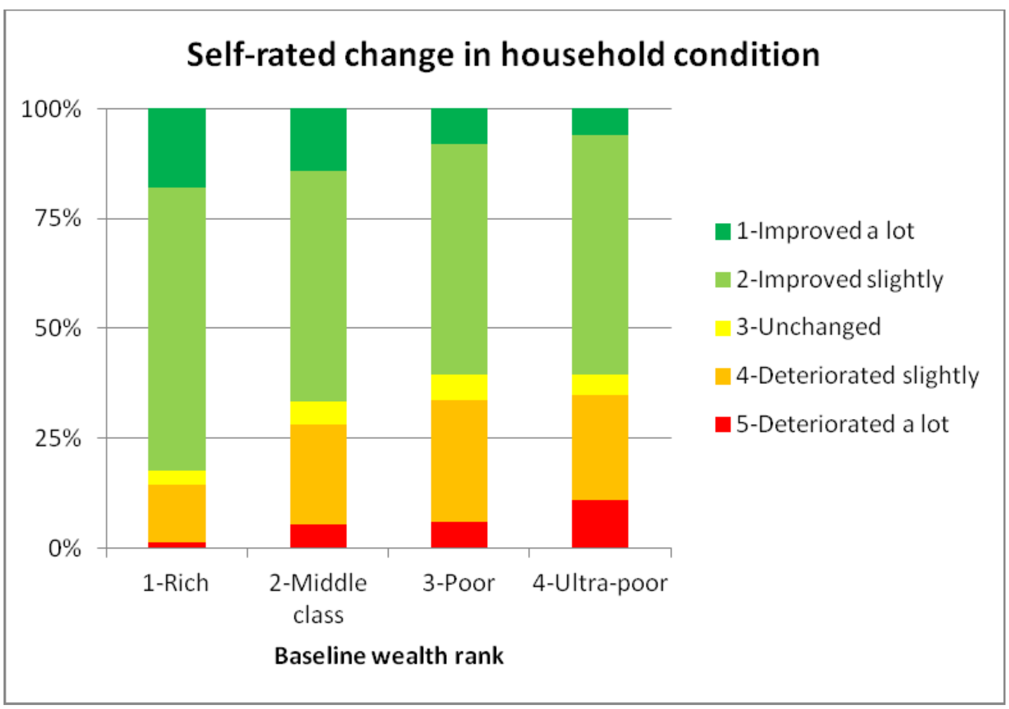
### *Changes in household conditions*

We find that a majority of households have slightly improved their overall condition during the Jonoshilon years. The best estimate for this group is 54 percent. Another 10 percent improved a lot, 5 percent lived in basically unchanged conditions, 24 percent deteriorated slightly, and 5 percent deteriorated a lot.

There are differences among the districts regarding the proportions of households with positive changes, but not all are statistically significant. At the extremes are Brahmanbaria and Joypurhat, each with an estimate of 79 percent households improving "a bit" or "a lot", and Habiganj with only 48 percent.

The association between baseline wealth rank and improvement during Jonoshilon is significant. But the major difference is between the rich and the rest. The middle class, on some indications, fares more closely with the poor. Yet, the association is weaker than it was in the 2011 sample. Much of this seems due to the fact that in 2013 relatively fewer among the rich reported substantial improvements, and fewer of the poor and ultra-poor reported deterioration. The two surveys are comparable within limits only; the looser association, as we move further away from the baseline years, should not be read as a catch-up effect directly attributable to Jonoshilon interventions. But the scenario looks rosier for the poor and ultra-poor than it did in the 2011 survey.

**Figure 1: Change in household conditions, by baseline wealth rank**



Significant changes over 2011 happened also in the *relative* importance of the major concerns in life that can be inferred from the distribution of specific changes reported. Housing and education are up. Food and clothing are down. The importance of health is as low as it was in the first survey; in both health-related changes were probably underreported. When asked what caused them most joy or sorrow, the interviewees placed illness and disability in the second rank, behind the death of family members.

The impression that conditions have improved for many is reinforced when we look into the pattern of specific changes. Across the spectrum of over 9,000 changes highlighted by the interviewees, five household types are discernible. Such a household typology had already been created in the 2011 survey. Then, as expected, the clustering algorithm produced two types with predominantly positive changes, a change-neutral type, and two with negative changes. This time, surprisingly, the neutral type was replaced by households that have *improved* their nutrition and clothing. In other words, "neutral" was replaced by positive changes in basic needs.

Above this type we find another type, with stronger positive changes of various kinds, in income and assets, housing and education. And on top yet another, with positive changes in remittance income, access to loans and savings, as well as in lifestyle and family situations. However, in contrast to the pattern in 2011, this group of households, capable of accumulating wealth, is less strongly defined by remittance income. The sources of strong positive change in the 2013 sample are more diverse.

There are two household types characterized by negative changes. In one of them, food and clothing have deteriorated. This is the least prevalent type, touching an estimated 6 percent of households in the 362 villages only. But these 6 percent are more sharply set off from the rest of the population that was the case in the 2011 survey.

As one expects, the five types of household change are clearly associated with the five steps of the change rank ladder. This is a sign that the change rank measure has good validity.

We noted that the interviewees in 2013 pointed out education-related changes much more often than those in 2011 had done. We therefore investigated also the influence of pre-existing education on changes in household conditions. For this purpose, for each household the maximum number of years of schooling among its members at baseline was computed. Surprisingly, it turns out that, when we control for education, middle-class, poor and ultra-poor households have virtually the same rates of improvement - only the rich improved faster. To the extent that the poor can get access to education, they should thus experience improvements at a rate similar to the middle class.

### *The effect of livelihood training*

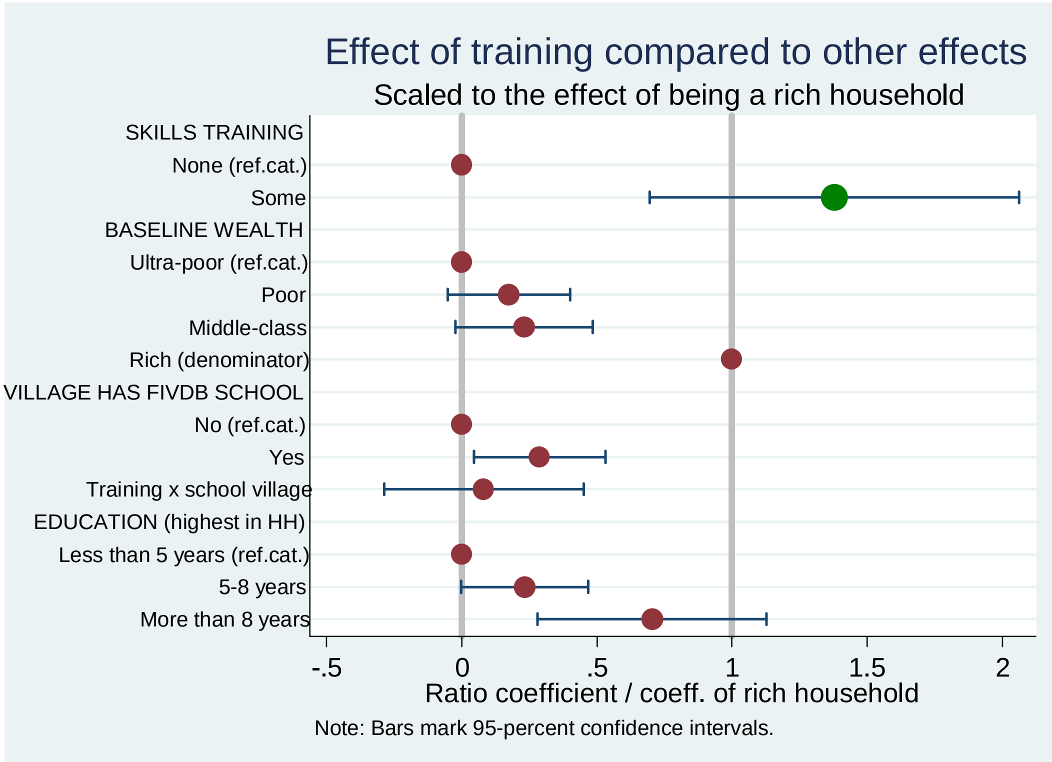
A second objective of the CCR 2013 survey was to gauge the impact of livelihood trainings imparted under Jonoshilon. This question had been investigated to some extent already in 2011. The data in 2011 suggested that, adjusting for the development level of the village and the primary education of the household head, households that had received training were more likely to report that conditions had improved over the previous two years. The survey in 2013 reinforces this finding, with more emphasis placed on its robustness.

In the 362 baseline villages, an estimated 37 percent of the households attended livelihood trainings during the Jonoshilon years. An estimated 69 percent of the trainee households improved their conditions, versus 61 percent of the non-trainee households. The eight-percent difference is statistically significant. For six percent, the improvement was "a lot", for two it was "a bit".

This proportion of households in improved condition by itself means little. Access to training depended to some degree on socio-economic and program factors. For example, households with someone who had five to eight years of schooling participated more readily than those with a maximum of four years (+ 6 percent); those with someone with at least nine years were 10 percent points ahead.

The correct approach to control for differences in access to training is to simultaneously estimate the barriers to access and the effect of the training. To make this graphic, we compare the relative effects of training, of baseline education and of the wider Jonoshilon environment to the effect of baseline poverty. Rich households saw their conditions improve with a probability of 82 percent, ultra-poor ones with 60 percent. So this difference of 22 percent between top and bottom of the wealth ranks makes for an intuitive comparison base. This figure visualizes this intuition in a more analytic way. The effects of various factors, particularly training, have been scaled to the effect of being rich (rather than ultra-poor). The coefficient ratios are subject to error. They are therefore represented together with their confidence intervals.

**Figure 2: Effects on the change rank, scaled to the effect of baseline wealth**




The key statistic - the relative effect of livelihood training - has a 95-percent confidence interval ranging all the way from 70 to 206 percent. Therefore we are confident that such trainings had an effect on improving household conditions *at least* 70 percent as strong as that of being rich at baseline.

That is an indication that the livelihood training part of Jonoshilon was effective. Skeptics may argue that cause and effect have not been established. Villages that were enjoying strong socio-economic development may have set many poor residents on a path of improvement while at the same time encouraging some of them to enroll in Jonoshilon trainings. Stagnating communities, by contrast, may have constrained their poor both from local advantage and from participation in programs like Jonoshilon. While that is conceivable, it is not very likely because only communities that had actively invited FIVDB to bring Jonoshilon services were in the baseline population.

### *What to take home from this survey*

In conclusion we may say this about the CCR 2011 survey:

It measured improvement in household conditions during the Jonoshilon years with a *valid* tool. Whether the measurements were highly *reliable* is more difficult to ascertain. The neighbors overhearing the interview limited gross error. Yet the scale of change was open to local interpretation in every group interview. Moreover, change-ranking, by nature, is not *precise*. It does not produce financial, calorie-intake, school success or any other exact statistics. It only says whether the change is negligible, slight or substantial.

Nevertheless, there is much internal coherence in the data that lets us affirm two overall findings:

1. The condition of the majority of households, across wealth ranks, improved.
2. Households with livelihood training were significantly more likely to improve.

The reader is advised to register these findings with caution and with appreciation. With caution, due to the triple uncertainty from measurement error, sampling and limited information. With appreciation because they hint at a globally positive evolution of a complex rural development program, and because they bring to the point thousands of changes that the participants reported from their own lives.

# Introduction

FIVDB has tried to shed light on the conditions of the populations it support using the tool of sample surveys at various occasions. Within the Jonoshilon program, it conducted two large baseline surveys in 2008 - 2010, for which villages were sampled, yet within sampled villages the households and household members were fully enumerated. With a view to assessing changes in the conditions of these households, another two sample surveys were taken in 2011 and 2013.

The most recent of these surveys sought to answer a double question: how has the overall condition of the households changed during the Jonoshilon years (2009 - 2013)? And: have the livelihood trainings offered under this program helped to improve conditions?

The survey produced a number of results, which we detail in this note. In addition, it invites us to reflect on the process in which the survey was designed, conducted, analyzed and absorbed within FIVDB. These reflections are not exhaustive; there could be more or more profound ones. But they speak to challenges and achievements that are not atypical of the experience that FIVDB has made with other surveys, or other NGOs in Bangladesh have made with theirs. They are primarily written down in the perspective of the expatriate consultant who assisted with part of the design, did a major part of the analysis and wrote up the findings. But they do reflect numerous discussions that he and the responsible unit in FIVDB had had in training sessions, remotely as well as during analysis and the discussion of tentative findings.

# Reflections on the survey process

The reflections bear on several stages of the survey process. They address social, conceptual as well as didactic aspects. An overarching question is how much complexity the research and monitoring unit of a mid-sized NGO can generate and manage in the early stages of a sample survey, and how productively this complexity can be preserved and/or reduced in the later stages.

The survey was carried out by FIVDB's Policy, Planning and Research Unit (PPR), with considerable assistance from other departments and individuals. Besides the large sample survey, the unit conducted 44 case studies of trainees. These combined qualitative aspects with estimates of the additional monthly incomes. These case studies are reported and discussed in a companion note.

## *Design phase*

The instrument to measure the change in the overall conditions of households closely followed the 2011 survey. This survey had adapted a method that researchers in the large NGO BRAC had pioneered and validated. FIVDB's own experience with the instrument in 2011 had been positive. Despite considerable staff turnover, the PPR unit had several associates who had taken part in that survey, and thus were in a position to train the new colleagues.

The measurement of training exposure and participation could not rely on an already validated tool. Training participation in 2011 was measured as the number of trainings that the interviewee recalled for her household. Some of these data were disputed when it turned out that households that were not members of the local Community Learning Centers had participated in considerable numbers. The questions in 2013 simply aimed to establish whether the household had ever attended skills trainings, and if any of these were about income-generating activities. The participants, number of trainings attended, and the specific trades were not investigated because additional detail would have overwhelmed the group interview format. Similarly, the distinction between exposure to training offers and actual participation, while theoretically important, was not practical.

There were changes in the sampling design over 2011. The number of sample households per village was to be lower, to reduce the design effect, and therefore more villages had to be sampled (70, up from 20). There needed to be a sampling stage between village and household because group interviews had to take place in compact neighborhoods. De facto, this required clustering of households in distinct corners of the village. On the basis of the village map drawn originally by CLC volunteers and of household lists from the baseline survey database, interviewer teams were to determine three neighborhoods with maximum physical separation and with a mixture of several wealth ranks. In each of these clusters, they were to interview representatives of ten households. The community-based change method required these ten interviewees to sit as a group while the team interviewed each of them individually, in presence of the other interviewees.

In addition, it was anticipated that households with trainees needed to be oversampled in order to obtain robust estimates of the training effect. The plan was to identify trainees and their households using trainee registries at FIVDB field offices, which thus would serve as a second household sampling frame.

## *Data collection and data entry*

The interviews were conducted during a five-month period from March to July 2013. The teams adhered strictly to the plan of interviewing representatives of thirty households each in seventy villages. The 2,100 sample households therefore form a perfectly balanced panel.

Two things did not work out exactly as planned. These deviations illustrate a general rule: In the actual field operations, the initial design gets stripped of some of its complexity for sheer practical necessity. Changes during execution can happen also for lack of conceptual understanding. Specifically, in this survey, the interviewer teams did not note - or the questionnaire did not enjoin them to do so - to which of the three clusters in the village the sampled households belonged. As a result, this second-stage cluster aspect goes unaccounted in the survey settings. The standard errors are therefore underestimated.

Second, the way the three clusters, and then the ten households within each cluster in the third stage, were selected added an element of convenience sampling (described in detail further below). The proportion of households with trainees is thus impossible to estimate, and the likely overrepresentation of such households may bias the proportion of households reporting improved conditions upward.

The first of these shortcomings is due more to oversight than impracticality. The second one reflects poor judgment at the design stage. The decision to oversample households with trainees implied a double sampling frame (the list of households from the baseline surveys as well as a complete list of trainees, traceable to the households). It should have been obvious that the survey workers would not be able to draw the sample on this basis, and PPR would not have lists of household with trainees for post-estimation purposes.

These details are now of historic interest only, but they reaffirm the need for clarity and optimal simplicity in design. They also demonstrate the necessary place of improvisation when sample members have to be replaced, or when they can be selected only upon arrival of the interviewer team in the village.

The PPR associates entered the data into Excel spreadsheets. They did this in their field offices during the interviewing months. The coding of the free-text statements of specific household changes was also done by them, during initial entry, supported by the spreadsheet template. Village-wise batches of data records were forwarded to the central unit. Three persons here reviewed the interviews and specifically all the coding decisions and appended the batches into a combined dataset.

## *Data reduction*

The core variables included the rating of the overall change in household conditions on a five-level scale, the illustrations that the interviewees gave in terms of specific changes and their causes, and of the participation during the Jonoshilon years in livelihood skills trainings of any sort.

The free-text entry of 9,310 specific change statements and the concurrent categorization using a coding table with 98 change types was the most labor-intensive part of the data entry and quality control.

Since coding and recoding are eminently important, if under-appreciated tasks in social research, a few remarks are due:

- First of all, the fact that the teams were able to collect an average of 4.3 specific statements per sample household reflects a very high level of community and interviewee cooperation with this survey. The richness of the information is fairly consistent across locations and wealth ranks, with only one district (Brahmanbaria) appearing less loquacious. Naturally, households reporting a lot of change (improvement or deterioration) elaborated more than those experiencing no change or slight change only.

- Second, the entry, coding and quality control of this rich information represents a Herculean labor on the part of the survey workers. This has to be acknowledged with due respect. However, it was time consuming. This change-ranking method, accompanied by the elicitation and use of detailed change information, is not feasible for rapid survey needs. It works in survey environments and for purposes with long, patient timelines.

- Third, the initial coding deliberately used a large category set - as many as 98 options. This had two advantages. It made extensive use of the interviewers' fresh memories. They were able to assign highly specific codes, looking at the written notes but also recalling the total ambiance of the interview. Moreover, the large number of codes left numerous possibilities for recombining them in smaller category sets. This recoding was subsequently done by the expatriate consultant, with input from the PPR coordinator regarding categories that were not straightforward to recode.

- Fourth, by coding the specific changes in 98 categories, the information was still far too scattered in order to produce manageable summaries. It was reduced to 30 categories in a further step, and then used to assign the 2,100 sample households to a typology of five household types. This condensation - from an average 4.3 specific changes per household, each in one of 98 categories, to one five-valued variable (the membership of the household in exactly one household type) - was not straightforward. It zigzagged across social, conceptual and software boundaries. Some steps depended entirely on the expatriate consultant; it is unlikely that many Bangladeshi NGOs with their limited monitoring and research resources would be able to replicate a similar process. Some operations could have been carried out by the PPR team in Excel (recoding, and the creation of so-called indicator variables). They had been the subject of earlier trainings, but in the event it proved more efficient to let the consultant do them in a statistical application. This has consequences for the degree of belief in some of the results; for example, the PPR team took note of the household typology, but it cannot revise it with its own means.

- Fifth, also from a research ethics viewpoint, if the information reduction was accomplished effectively, this does not mean that the detailed information was used to the extent and in the depth of interpretation that it deserved[1]. 9,310 statements reduced to a five-value variable is a poor bargain. Ideally, the original verbatim information should have been reviewed once or twice more in a meaningful filter grid. For example, a grid could have been spanned, using the thirty interim categories and the four wealth ranks. Subsets of those categories could then have been assigned to associates, who each would then review the statements within a given change category for patterns across wealth ranks. What did the ultra-poor, poor, etc. have to say about positive changes in food and nutrition? What was the pattern among those who reported negative changes in this regard? The set-up for this is easy in Excel. It was not done for lack of time and, plausibly, an excessive focus on information reduction. One comes away with a feeling that both interviewees and interviewers had deserved better.

[1] We are grateful to our colleague Bazle Mostafa Razee for this observation.

In sum, the data reduction process was integrated with the data entry in a clever way. However, more stringent reductions were required and were achieved in the division of labor between FIVDB's team and the expatriate consultant. This had consequences for the ownership of some of the results as well as for the under-utilization of the rich original information. The challenges of disciplined data reduction and, simultaneously, of creative re-cycling of the detailed original information are ever present in survey research. Development NGOs meet them with their limited research resources, which can be made more effective, to a degree, by prior or concurrent training emphasizing these points.

## *Analysis*

### Survey estimation

Survey results are uncertain. The uncertainty comes from three sources:

- model error,
- measurement error, and
- sampling variance.

Explanations are incorrect when the underlying model leaves out important variables or connects variables incorrectly. For example, one may think that the fraction of households improving their overall condition during the Jonoshilon years depended on the wealth rank. A simple cross-tabulation of this rank with the level of change would indeed confirm this. However, when we include in the model also the education level of the household, the difference in improvement reduces to one between the rich and the rest. Conditional on education, middle-class, poor and ultra-poor households show the same rates of change.

Measurement error is usually considerable in survey research. Unless specific errors can be identified, or the distribution of errors can be somewhat precisely assumed, there is little that can be done about it after the fact (sample members with gross outliers in some key variables can be excluded, but this too may be problematic). Prevention is everything.

The third source of uncertainty results from sampling. The typical NGO research unit has a minimal awareness of this. Often, sample size is determined on the basis of the desired precision of an estimate of a particular key variable, without reference to specific hypotheses or to design elements such as clustering. Just as often, confidence intervals are not computed during the analysis of the collected data.

The first stage of the sampling in this survey stratified the selection of villages by literacy and poverty rates. This provided an incentive to go all the way to gather the elements of survey estimation, including probability weights and finite population correction. This caused considerable additional work since these elements had to be calculated in a combined baseline survey file into which the sample membership was merged back.

Was it worth the trouble? The answer is a disappointing "no". It would have been sufficient to calculate confidence intervals on simple random sample assumptions, i.e. assuming identical probability weights. The differences would have been minimal. Moreover, one of the key analysis modules in the statistical software unexpectedly rejected probability weights. It did work without weights, which is to say that it produced confidence intervals on simple random sample assumptions.

Did it damage the ownership of results by FIVDB? Not really. It is unlikely that the PPR unit, analyzing the data on their own, would have computed measures of uncertainty. Thus, orthodox survey estimation using probability weights vs. simple random sample assumptions did not matter.

### Analytic models

The same cannot be said of the choice of analytic models. Some of the methods used - cluster analysis, multiple correspondence analysis as well as two regression-based estimates of the effect of livelihood skill trainings - are available in statistical applications only. They are beyond the descriptive statistics that Excel or other spreadsheet software offer.

Was their use justified? Whatever analytic gains they promised has to be weighed against the loss in local ownership and the sustainability in the NGO's own analytic capacity.

The answer here is "yes and no". With more time on their hands, the PPR team could have pursued a narrative analytic style in unlocking patterns of specific changes. Time pressure privileged a rapid and radical compression via cluster analysis. The result - the identification of five types of households - is not necessarily robust. Robustness checks of the clusters (or, for that matter, of the coordinates of the multiple correspondence analysis) were not done. They would have been tedious to program. Thus, in terms of model and sampling uncertainty, these two methods do not necessarily give us more confidence than simple descriptive statistics of the sample data only.

The case of the livelihood skills training is different. Here we are interested in the difference in improved conditions between households with trainees and those without. This is ultimately a program evaluation question. The differences have to be robust to sampling variance. For this, probabilistic methods are necessary. We used two such methods (see the concerned section further below), with different strengths and limitations. They both pointed to significantly more frequent improvement of overall conditions in households with trainees.

## *Dissemination*

In sharing the major findings of this study with other colleagues in FIVDB, two problems of communication emerged. These are not unknown in research communication. One is to find meaningful measures and units in which to express change or causation. The other has to do with the human preference for certainty. They deserve brief comment here.

## Intuitive metrics

To say that *"x percent of the households in y baseline wealth rank reported that their household conditions had improved"* was unproblematic. Similarly, specifying change to households with some livelihood skill training participation vs. those without was well understood.

The problem was that the effect of training seemed tiny. Roughly eight percent more among than households with trainees than among those without had improved their conditions "slightly" or "a lot".

The figure as such is almost meaningless. It means little even when compared to the overall proportion of households reporting improvement (71 percent in the sample). The reason is that the training measure is informationally weak. It did not capture the specific trades and whether the households actually used the new skills. The average training effect has been attenuated by types of trainings that attracted large numbers of participants, but created little income for individual trainees. This is true of homestead gardening, which accounted for almost three quarters of all livelihood skills trainees.

A more meaningful way to express the training effect is to scale it to the effect of some other factor. Ideally, this would be one that captures the hard realities of the social structure in which households are exposed to training opportunities, may avail some, and may then benefit from the new skills - or not.

FIVDB routinely observes the village environment for indicators of welfare in the ultra-poor. It interprets these observations in comparison to those of other groups. A natural candidate for a yardstick, therefore, is the difference in reported improvements between the extremes of the wealth rank scale - the rich and the ultra-poor.

Scaling the training effect to this difference has other advantages. It allows us to compare regression coefficients. These kinds of quantities are hard to explain, particularly in non-linear models. This changes when we scale one coefficient to another. It is particularly helpful that the explanatory variables are categorical and can be transformed into sets of dichotomous ones. The ratio between the coefficients of two dichotomous variables is dimensionless. Therefore it can simply be expressed as *"the effect of the training is x percent of the effect of being rich rather than ultra-poor"*.

Moreover, the second of our regression models returned a training effect much stronger than the naïve comparison of sample frequencies. The reason is that the model controls for several other factors that influence access to training, as well as factors that influence improvements and deterioration.

So far, so good. Understanding these results hit a wall when it came to the "effect *on what?"* The difference in the *rates of improvement* between rich and ultra-poor households tended to be misunderstood as the difference of *being* rich rather than ultra-poor. In other words, the proposed metric failed the expectation of the user to be told the training effect in his language. It is not sufficiently intuitive.

## Communicating uncertainty

The descriptive statistics of the sample values give point estimates. They do not convey a sense that frequencies, means and proportions are imprecise because of the sampling variance. Survey estimation supplies measures of the uncertainty. For example, 9.2 percent of the sample households reported significant improvements during the Jonoshilon years. The percentage using survey estimation is 10.3. This proportion is, with 95 percent confidence, between 7.9 and 13.3 percent. Here "95 percent confidence" means that if repeated samples of 2,100 were drawn from a population of households with 10.3 percent significant improvement, in 19 out of 20 samples the mean would fall into this interval.

A single point estimate can be communicated with its attendant confidence interval if formulated in appropriate language. Multiple point estimates with overlapping confidence intervals are much harder to popularize. The point is well illustrated by the frequent comparisons that are made in NGO reports of some quantity of interest across geographical areas (we demonstrate this further below). Usually subsample averages are placed in the same table, in ways that are suggestive of a clearly established order among areas. The differences between areas of neighboring ranks may be statistically insignificant, but in the absence of measures of dispersion or uncertainty the viewer may take them as population rather than sample values.

Our impression, when talking about this survey, is that in particular program managers do not want to hear about a forest of findings with variable uncertainty. They want to be shown the few big trees that stand out tall from the undergrowth, at a height that is distinctly above the teeming undergrowth. This makes for sharp, selective summaries. The problem is that the paths connecting the tall trees can be muddy; if users are not warned, they can get stuck.

## *Looking back on the whole process*

Our point of departure on these reflections was the feasible complexity of the survey design and execution. We have seen that certain components of this complexity were generated and subsequently transformed in productive and efficient ways. Others were aborted by field realities. In yet other perspectives, the complexity reduction was too rapid or too one-dimensional, giving away a large potential for interesting findings. The researchers struggled with these opportunities and conflicts throughout the process, from the design to analysis and to the (as yet very limited) communication of findings.

A particular element of the complexity needs to be mentioned again. The survey had two main purposes. It was to estimate the changes in overall household conditions in the Jonoshilon population. And it was to test if participation in livelihood skills trainings improved those conditions. The survey has provided estimates answering both questions. These answers are, as far as we can judge, reliably positive. Still they are less precise than one might wish. In the case of the change ranking, a weak measure was chosen deliberately (with a strong rationale - see the appendix). The measure of training participation, from an information perspective, was even weaker. This weakness was less desirable; it was accepted as a limitation of the community-based change ranking method and of the group interviewing setup that this entailed. It is fair to say that the change ranking part of the survey dominated at the expense of the livelihood skill training part. At this point, it is an open question whether the trade-off could have been milder.

## The occasion for a survey

With the Jonoshilon program (FIVDB 2008) in its fifth year, FIVDB has a heightened interest in documenting welfare changes in the program area and particularly in households participating in key program components. This note reports on the extent and direction of the overall change that households have experienced since the beginning of the program. The sample includes 70 villages. These are part of the 362 villages with full household enumeration in baseline surveys during 2009-10. Some of the findings can be generalized to this larger set of villages. Generalizing to the entire set of Jonoshilon program villages seems plausible, but the precision of estimates for this level is unknown. There are about 690 villages in total if we go by the number of Community Learning Centers (CLCs). A CLC was founded in every Jonoshilon program village.

The major thrust of this survey was to gauge the extent and direction of the overall change in household conditions. Jonoshilon is a multi-sectoral program; many of its villages had been exposed to earlier FIVDB programs. A neat distinction between participant and other households was not feasible. However, differences in overall change ratings were observed for households that at some point had been involved in livelihood trainings (organized by FIVDB's Livelihood Enhancement Program [LEP], which takes care of this wing of Jonoshilon activities) and others who did not report such involvement.

A household could have several members attending trainings, at different points in time and for different trades. This complexity was reduced to the simple distinction between households ever attending some livelihood training in the Jonoshilon period and others who did not. This attribute is informationally weak. Yet it is manageable in group interviews and in simple flat-table data management. Part of the training complexity was recaptured through case studies. A secondary objective, therefore, was to estimate the impact of livelihoods trainings. The impact was defined, for purposes of this survey, as the difference in overall household conditions between households reporting any such training and others.

The survey applied the so-called community-based change ranking (CCR) method. CCR was pioneered by BRAC researchers (Sulaiman and Matin 2007); FIVDB used it in a previous, smaller survey in twenty Jonoshilon villages in 2011. For readers not familiar with CCR, we reproduce, in the appendix, part of an earlier note that details rationale and key elements. This tool has the advantage that it has been validated by others (as well as by the 2011 survey). Its strength is to capture small improvements in the lives of the poor, changes that would be missed by unreliable income and expenditure measures.

### *Population and sample*

FIVDB research and monitoring associates conducted the CCR 2013 survey in seventy villages. The villages were drawn from a grid based on village literacy and poverty rates calculated for the 362 baseline villages; each cell in the grid was based on 10-percent intervals. Villages within each cell were randomly drawn with probability roughly proportionate to the number of villages in the cell. In a second round, some draws were replaced with villages from the same or from adjacent cells such that desired sample sizes by district were attained. This was done also for workload considerations.

**Table 1: Jonoshilon baseline villages and CCR survey**

| District | Population: Jonoshilon baseline survey 2009-10 | Sample: CCR survey 2013 |
|---|---|---|
| Brahmanbaria | 24 | 8 |
| Habiganj | 15 | 6 |
| Joypurhat | 7 | 3 |
| Kishoreganj | 12 | 6 |
| Maulvibazar | 23 | 9 |
| Netrakona | 42 | 8 |
| Sunamganj | 130 | 15 |
| Sylhet | 109 | 15 |
| **Total** | **362** | **70** |

Because the replacements were non-random and sometimes from adjacent strata, we simplified the strata used for the analysis. We made the grid wider, also in order to avoid singleton strata (strata with only one sample village). We thus collapsed the initial 36 strata into eight, reducing also the number of cross-strata replacements. The effective stratification is detailed in the statistical appendix.

In each of the 70 sample villages, the associates conducted interviews with representatives of 30 households. The interviewees met in groups of ten. The three groups in a village were convened in different neighborhoods (in three or four small villages, the teams met the thirty interviewees in just two clusters). These two stages of the sampling were carefully prepared; nevertheless they did not follow a strict probability sampling protocol.

**Figure 3: Three sample household clusters in Moshuria village, Maulvibazar District**

**The 30 sample households (marked green) roughly form three clusters. The cluster membership was not noted. At least one household must have been grouped with more distant neighbors, in order to form clusters of equal size. This segment is from an A4-size village map replica kept in the regional field office.**

The teams prepared for their visits to sampled villages taking help from the social organization and livelihood support colleagues in their field offices. The field offices had A4-size replicas of the village maps drawn by Community Learning Center volunteers, with locations and numbers of dwellings. To these, the teams could match their own household lists with the baseline wealth rank. The livelihood support unit had lists of trainees. These were incomplete as far as household numbers were concerned, but the program assistants generally knew where inside the villages many of "their" trainees lived. All this information was taken into account in order to determine three cluster locations in the village from where to recruit ten interviewees on arrival. The clusters were generally selected such that they promised a mixture of household of different wealth and were physically separated from each other.

In some villages, program assistants from the cooperating departments would visit the village ahead of the interview day, requesting households with trainees to be available. On the day itself, they accompanied the teams, who improvised on the spot, asking people in the cluster locations which households had in fact received livelihood training, and ensuring that members of several such households would be among the ten interviewees. In some clusters, when the teams found that the quality of the interviews varied, they continued interviewing more households until they had ten interviews with notes that they considered reasonably complete and meaningful.

Of the effective sample households, 49 percent reported prior involvement in LEP trainings of any kind, and 37 percent in livelihoods trainings. This proportion is higher than the 26 percent with a livelihood training history in the CCR survey in 2011. While the number of households touched by LEP has since gone up, there may be some overrepresentation of households with trainees. In 2011 no efforts were made to oversample such households. Similarly, 83 percent of the interviewees were from households with CLC members. In the 2011 sample, they made up 44 percent. Thus CLC member households in 2013 probably were overrepresented; this is so because, among other factors, a significant number of non-member households refused interviews.

The interviews were done with individual households, in the presence of the other interviewees in the group, all of whom typically were seated around a poster-size visual that expressed steps of positive or negative change (the schematic is shown in the appendix). The associates typically worked in teams of three, with one of them leading the conversation, and the other two taking notes and seeing to an orderly sequence of interviews. The interviewee's challenge was to rate the changes that her household had undergone during the Jonoshilon years on this five-step ladder.

### *Information collected*

The interviews gravitated around the question whether the condition of the household had improved significantly, improved somewhat, basically stayed the same, deteriorated somewhat, or deteriorated significantly.

The interviewees were encouraged to specify particular changes, positive or negative or both, that led them to the summary change assessment. They were asked to supplement the noted changes with their perceived causes. The statements were recorded in short free-text notes.

The interviewees could also say, if they wanted, what had caused them particular joy or particular sorrow in recent times. These statements were recorded in separate spaces.

Information was collected about whether any household member was a CLC member, and whether anyone had previously taken part in an LEP-run training course, and if any of those trainings were about livelihoods. The specific trades were not noted. Trying to record training histories for individual households would have overwhelmed the group interview format.

The wealth rank of the household, as assigned by CLC volunteers at the time of the baseline survey, was retrieved from baseline datasets. The identification relied on the household numbers in the CLC-drawn village maps. An updated wealth ranking was not attempted, chiefly because the associates did not meet the interviewees in their individual homesteads.

Other household baseline information was later imported from the same baseline datasets. This data from 2009 and 2010 concerned the gender, age and years of schooling of the household head, the maximum years of schooling among the household members, household size and earning members, and annual household income. Information was imported also about the sample villages: population, literacy and poverty rate, the presence of an FIVDB (and specifically a Jonoshilon-built) school. Only four percent of the sample households had been identified as female-headed at baseline. The gender distribution of the interviewees or of the livelihood trainees in the sample is not known;

the use of personal pronouns in text fields recording specific changes suggests a much higher participation of women in the interviews.

In addition, the associates conducted case studies of over forty LEP livelihoods trainees. These represented a variety of trades, with mobile phone servicing, sewing and traditional midwifery being the largest groups. This dataset allows analysis by gender. Findings from the case studies are presented in a companion note.

### *From speech to text to numbers*

The interviewees were asked to elaborate on the overall change that they claimed with examples of specific changes. They were also asked about the causes of change. Both questions were entirely open. The answers were noted in free-form, if significantly abbreviated text. This raw material called for categorization and coding, a process that absorbed a large part of the total survey effort. FIVDB had learned already in 2011 that it was not possible to elaborate two distinct category sets, one for the reported changes in household conditions, and the other for the causes of those changes. Thus, while changes and causes were coded into different sets of fields, the same set of categories were used for both. The associates initially worked with 98 categories. Subsequently, the categories were mapped onto three valuation levels (positive, neutral, negative), 13 subject areas, and 30 combinations of valuation levels and subject areas (30, rather than 3 * 13 = 39, because not all logical combinations were needed to code the interviewee statements).

An example will help. Access to food was one the subject areas:

- An interviewee in Sunamganj related that her household (ranked "poor") depended on a food catering business; lately this had not been running well. Also, they now had two children in school. As a result, they could no longer afford "quality food" (sl. no. 26). This statement was categorized as **"Food-negative".** Out of the 2,100 sample households, 279 made such statements.
- A rich household in Habiganj described itself as "slightly deteriorated" after its head had died and the extended household had been divided. The interviewee mentioned difficulties in meeting education expenses and a lower budget for clothes. But she made a point that the family were eating the same way as before. This is a **"food-neutral"** case, one of 98 in the sample (sl. no. 1664).
- From Netrokona District, an ultra-poor household reported decreased indebtedness after the husband increased his earnings, and the wife found work as a helper in other households. As a result, the family ate as well as dressed better. This is a **"food-positive"** case, one of 411 in the sample (sl. no. 1176).

This is the complete list of the subject area-valuation categories, in alphabetical order, and the number of statements received against them.

**Table 2: Change statements categorized**

| Change categories | Statements |
|---|---|
| AssetsProductive_1-Negative | 249 |
| AssetsProductive_3-Positive | 631 |
| Clothing_1-Negative | 190 |
| Clothing_2-Neutral | 65 |
| Clothing_3-Positive | 257 |
| Education_1-Negative | 243 |
| Education_3-Positive | 573 |
| FamilySituat_1-Negative | 401 |
| FamilySituat_3-Positive | 193 |
| Food_1-Negative | 279 |
| Food_2-Neutral | 98 |
| Food_3-Positive | 411 |
| Health_1-Negative | 185 |
| Health_3-Positive | 59 |
| Housing_1-Negative | 183 |
| Housing_2-Neutral | 42 |
| Housing_3-Positive | 931 |
| IncomeEarner_1-Negative | 348 |
| IncomeEarner_3-Positive | 544 |
| IncomeGeneral_1-Negative | 237 |
| IncomeGeneral_2-Neutral | 15 |
| IncomeGeneral_3-Positive | 915 |
| IncomeRemit_1-Negative | 54 |
| IncomeRemit_3-Positive | 161 |
| Lifestyle_1-Negative | 33 |
| Lifestyle_3-Positive | 361 |
| LoansSavings_1-Negative | 401 |
| LoansSavings_3-Positive | 323 |
| Other_1-Negative | 29 |
| Other_3-Positive | 4 |
| **Total changes reported** | **8,415** |

The initial 9,310 specific change statements were shrunk, in the process of data reduction, to 8,415 (because of redundancies as subsequent levels of categorization used fewer, but broader categories). This works out as almost exactly four statements on average for each of the 2,100 interviewees.

## *Need for a household typology*

Using the 30 distinct subject area-valuation categories, we arrive at 975 different combinations into which the change and cause statements of the 2,100 interviewees fit.

This is a tremendous diversity. It cannot be summarized at this level of detail. Therefore we split the 2,100 households into a small number of homogenous groups. Each group is characterized by relatively high frequencies of certain categories, and relatively low frequencies of others, compared to the other groups. This grouping is one of the key methods of processing this CCR data. We will give details after presenting the overall direction and extent of change, its association with poverty (as measured by household wealth rank and income at baseline) and with the sample districts.

### *Sampling weights*

Our sample is not a simple random sample from for the entire 60,119 households in the 362 baseline villages. The raw sample statistics, therefore, do not provide the best estimates of quantities of interest in the population (the population here are the 60,119 households). To reduce the risk of potentially serious bias, sampling weights were needed. These were computed by multiplying the probability that a given village was in the sample by the probability that a given household in the village was among the 30 households interviewed, then taking the reciprocal of the product. These values were scaled such that they summed to 60,119. Population estimates were then computed using sampling weights, the stratification and an adjustment for the relatively small number of villages in each stratum.

Sampling weights range from 4.25 to 138.8, with a mean of 28.6281. As explained, 70 villages * 30 households / village * 28.6281 = 60,119, the total number of households enumerated in the baseline surveys. In other words, each case in the 2013 CCR survey represents, on average, 28.6 households in the population. The average sampling weight varies considerably among districts; in Brahmanbaria, each case represents 60.7 households, in Habiganj only 17.0. This is not surprising; in the sample, the mean number of households per village is 392 in Brahmanbaria, and 124 in Habiganj.

## Overall change

"Slightly improved" and "slightly deteriorated" were by far the most used options by which the interviewees described the overall change of their households. Roughly half of the households experienced slight improvements; a quarter deteriorated slightly. One in ten households improved a lot. One in twenty reported an unchanged situation. The proportion of seriously deteriorated households was similarly low.

As always in sample surveys, there is uncertainty due to sampling, and extrapolations to the entire 362 baseline villages have to be made with care. For example, the best estimate is that 54 percent of its households saw slight improvement. The true value of this proportion may be different. Statistically, all we can say is that with 95 percent confidence it is somewhere between 49 and 59 percent.

**Table 3: Direction and extent of change in household conditions**

A. Raw sample means

| Change rank | Freq. | Percent | Cum. |
|---|---|---|---|
| 1-Improved a lot | 194 | 9.2 | 9.2 |
| 2-Improved slightly | 1,111 | 52.9 | 62.1 |
| 3-Unchanged | 119 | 5.7 | 67.8 |
| 4-Deteriorated slightly | 542 | 25.8 | 93.6 |
| 5-Deteriorated a lot | 134 | 6.4 | 100.0 |
| **Total** | **2,100** | **100.0** | |

B. Population estimate with confidence intervals

| Change rank | Percentage | 95% confidence interval | |
|---|---|---|---|
| | | Lower bound | Upper bound |
| 1-Improved a lot | 10.3 | 7.9 | 13.3 |
| 2-Improved slightly | 54.0 | 49.4 | 58.6 |
| 3-Unchanged | 5.2 | 4.0 | 6.8 |
| 4-Deteriorated slightly | 24.3 | 20.9 | 28.0 |
| 5-Deteriorated a lot | 6.2 | 4.6 | 8.4 |
| **Total** | **100.0** | | |

The change in comparison to the CCR 2011 sample is major. At that time 11 percent of the sample households reported substantial improvements, 34 percent slight ones, 17 percent unchanged conditions, 26 percent slight deterioration, and 12 percent substantial deterioration. In the 2013 sample (and the population estimate based on it), the proportion of households reporting slight improvements has gone up significantly, by 20 percent points. This caused all the lower categories to shrink. The proportion of households in substantially deteriorated conditions fell by half.

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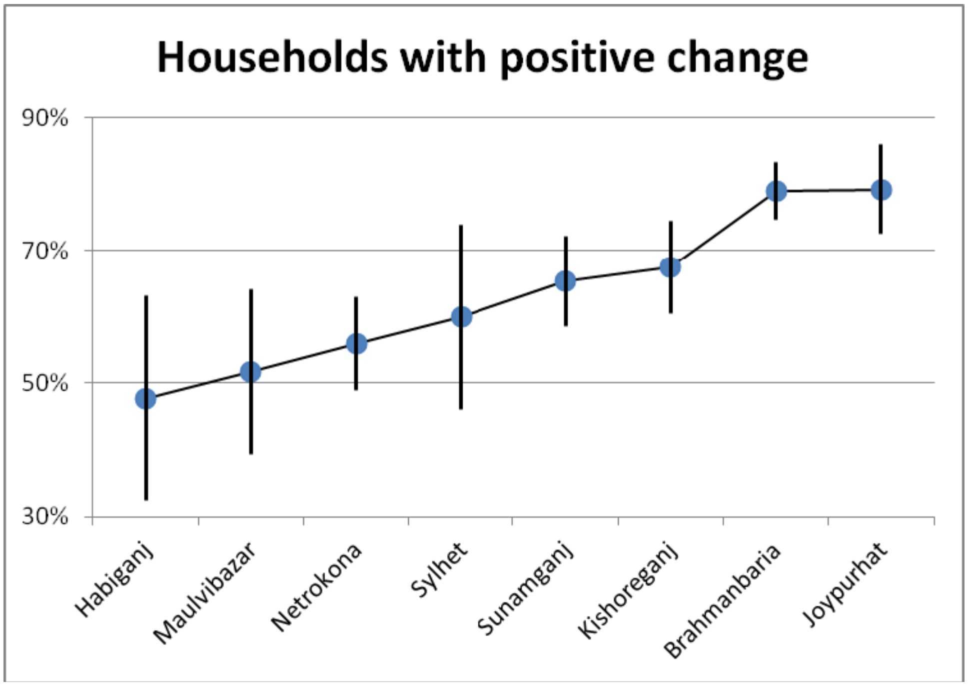
## [Sidebar:] Differences among Jonoshilon districts

There are considerable differences among the eight districts in terms of how the situation of households changed in the Jonoshilon period. Because this is a sample survey, simply comparing the raw statistics may be misleading. The estimates differ in precision from district to district. To simplify matters, we compare districts on the proportion of households whose condition improved - either "a bit" or "a lot". We put these two levels together and simply call this "positive change".

**Figure 4: Households reporting positive overall change, by district**




The estimated proportions range from 48 percent for Habiganj to 79 percent for Brahmanbaria and Joypurhat. The vertical sticks in this graph designate the extent of the 95-percent confidence intervals. It is obvious that Brahmanbaria and Joypurhat are distinct - their confidence intervals barely overlap with the others. Whether this better position is real or due to undetected measurement error, the data do not tell.

Thus one has to be careful not to make too much of the differences between any two districts, nor of the absolute value for a single district. For example, Kishoreganj has a statistically significantly higher proportion of improved households than Habiganj; but Sylhet does not (Sylhet's and Habiganj's blue dots bounce into each other's bars; Kishorganj's and Habiganj's don't).

It would also be incorrect to claim that "Habiganj is the only district that has less than half of the households seeing positive change". This would be incorrect in two ways: The raw sample proportion for Habiganj is 45 percent; the estimate, adjusted for the sample structure, is 48 percent, with the confidence interval going far above 50 percent. Second, the confidence intervals for Maulvibazar, Netrokona and Syhet all reach below the 50-percent line. Thus it is possible, given our sample, that as many as four districts have their true percentages of households with positive change below 50.  But it is even more likely that all eight districts saw improvements in the lives of more than half of the households. The uncertainty is the price we pay for sampling.

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## *Poverty and change*

The baseline wealth rank influences the direction and extent of the self-reported change of household conditions. Among the rich households in the 362 villages, an estimate 85 percent reported improved conditions (slight or substantial). The proportion among middle-class households was 68 percent, among the poor 61 percent, among the ultra-poor 63 percent, differences that are not statistically significant. These statistics contain two findings. First, in all four baseline wealth strata, a majority of the households have improved their overall conditions. Second, growing inequality may increasingly separate the rich (approx. 8 percent of the households) and the rest. Part of the middle class may participate in this growth - the proportion of middle-class households saying they "improved a lot" is closer to the rich than to the poor and ultra-poor -, but the downwardly mobile middle-class households are a sizeable group, similar in proportion to the deteriorating poor and ultra-poor households.

This table gives the proportions of change ranks in the households in the 362 baseline villages, by wealth rank. The population estimates come with considerable uncertainty, which we show by the 95-percent confidence intervals for each point estimate. This makes the table more informative, but also unwieldy to read. The point estimates are the same as those in Figure 1 in the summary, which can be understood at one glance.

**Table 4: Change by baseline wealth rank, with confidence intervals**

| Wealth rank at baseline | Change rank: 1-Improved a lot | 2-Improved slightly | 3-Unchanged | 4-Deterior. slightly | 5-Deterior. a lot | Total |
|---|---|---|---|---|---|---|
| 1-Rich | 18.01 | 64.43 | 3.173 | 13.05 | 1.341 | 100 |
| | [12.17,25.82] | [57.12,71.13] | [1.534,6.449] | [8.768,18.98] | [.4178,4.221] | |
| 2-Middle class | 14.26 | 52.45 | 5.081 | 22.94 | 5.273 | 100 |
| | [10.39,19.26] | [46.02,58.8] | [3.595,7.136] | [17.87,28.94] | [3.139,8.728] | |
| 3-Poor | 8.126 | 52.37 | 5.988 | 27.7 | 5.821 | 100 |
| | [5.115,12.67] | [46.58,58.1] | [4.385,8.126] | [23.51,32.31] | [4.012,8.375] | |
| 4-Ultra-poor | 6.046 | 54.45 | 4.652 | 23.83 | 11.03 | 100 |
| | [3.54,10.14] | [46.91,61.79] | [2.335,9.056] | [18.59,30] | [7.288,16.35] | |
| Total | 10.28 | 53.99 | 5.219 | 24.28 | 6.237 | 100 |
| | [7.865,13.33] | [49.36,58.55] | [4.011,6.764] | [20.94,27.96] | [4.616,8.378] | |

Key: row percentages
[95% confidence intervals for row percentages]

Compared to the 2011 CCR sample, the association between wealth rank and improvement / deterioration seems to have somewhat softened. Gamma, a statistical measure of how strongly the former determines the latter, went down from 0.30 to 0.21, a reduction by approximately one third. Much of this seems due to the fact that in 2013 relatively fewer among the rich reported substantial improvements, and fewer of the poor and ultra-poor reported deterioration.

## *Importance of change areas*

The over 9,000 change and causes-of-change statements were categorized into 12 subject-matter areas, or short: change areas (not counting the residual category "other"). These same change areas had been used in the 2011 CCR survey. This table, broken down by household wealth ranks, reports the percentages of sample households that talked about changes in the particular areas during the interviews. These statistics, at his point, make no distinction between positive, neutral and negative changes.

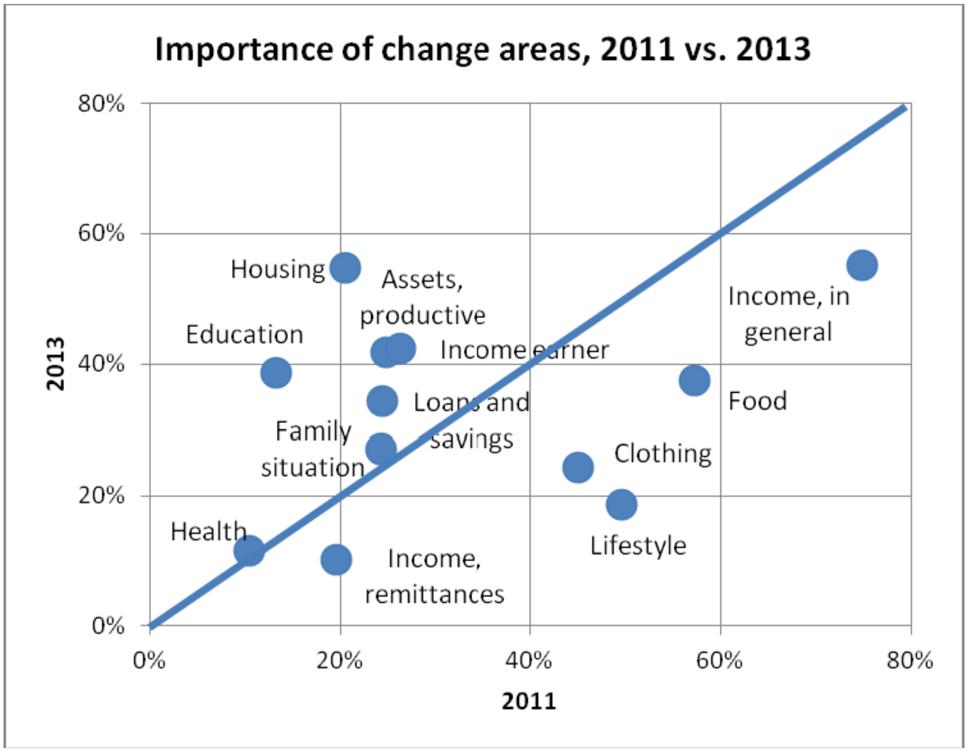
**Table 5: Sample households reporting changes in 12 change areas**

| Change area | Wealth rank at baseline | | | | |
|---|---|---|---|---|---|
| | 1-Rich | 2-Middle class | 3-Poor | 4-Ultra-poor | Total |
| Income, in general | 67% | 58% | 52% | 50% | 55% |
| Housing | 59% | 57% | 54% | 51% | 55% |
| Income earner | 31% | 37% | 45% | 51% | 42% |
| Assets, productive | 54% | 48% | 36% | 38% | 42% |
| Education | 43% | 38% | 40% | 33% | 39% |
| Food | 31% | 32% | 41% | 41% | 38% |
| Loans and savings | 23% | 38% | 36% | 34% | 34% |
| Family situation | 23% | 24% | 28% | 33% | 27% |
| Clothing | 20% | 19% | 28% | 25% | 24% |
| Lifestyle | 30% | 20% | 16% | 15% | 19% |
| Health | 9% | 9% | 13% | 14% | 12% |
| Income, remittances | 20% | 16% | 7% | 3% | 10% |

The table has been sorted by the overall proportion of households mentioning changes in the various areas. Income dominates, particularly when all three income-related categories are considered together. This is not surprising; we expect income, the wherewithal of survival and wellbeing, to be prominent in people's stories of change. Yet, there are important differences among the three income-related categories and the poverty groups. The gain or loss of an income earner hits the poor harder than the better-off; therefore they mention the related changes more often. Income changes not tightly connected with earner changes and particularly those coming from remittances are more frequently reported by the better-off.

The rest of the categories are more fruitfully discussed if we compare the frequencies with those of the previous survey. The relative changes in importance are dramatic for several categories.

**Figure 5: Importance of change areas, 2011 vs. 2013**




The changes, between two surveys less than two full years apart, are particularly strong in the areas far from the blue line of equality. Some of the differences may be artificial. Thus, the drop from "income in general" is offset by "Income, earner". This may be due to different coding behavior by the 2011 and 2013 data entry teams. The increased importance of productive assets may be put down to the overrepresentation of LEP trainee households in 2013; the livelihood training experience encourages people to talk about their productive assets.

Other changes in importance may be genuine. Of particular note are the substantial increases for housing and education, and the equally significant drops for food, clothing and other lifestyle elements. It is hard to believe that they can be the result of sampling and coding behavior. It is more likely that, with the more numerous general improvements reported in 2013, many interviewees were less concerned with basic needs such as food and clothing, *relatively* to a heightened affordability of housing and education.

The relative importance of two change areas stayed nearly the same: health and family situations. That people speak relatively little about these things may have to do with the interview setting; interviewees may be avoiding references to very personal matters, of which their neighbors may be broadly informed, but on which they have no desire to elaborate in front of others.

## [Sidebar:] Joy and sorrow

The associates invited the interviewees to share what had caused them particular joy or sorrow in recent years. The question was motivated by the experience of the 2011 CCR survey. This fielded a question about "most important changes". Most of the replies concerned financial changes. In order to probe for what people see as particularly significant in their lives, beyond financial concerns, the question was reformulated using the emotive terms "joy" and "sorrow".

Fewer than ten percent of the interviewees volunteered changes that they had greeted with joy. Slightly more told us episodes of sorrow. These statements were noted in free text and were entered into the dataset in various degree of compression. We categorize them. A few statements were of a complex nature that made the use of more than one category necessary. The two tables below are sorted mainly by descending frequency of the type of change. A few categories closely related were moved together.

**Table 6: Changes that gave us joy**

| | Frequency | Percent of responses | Percent of cases |
|---|---|---|---|
| Daughter married | 43 | 20.57 | 21.72 |
| Self or other member married | 34 | 16.27 | 17.17 |
| Family harmony | 41 | 19.62 | 20.71 |
| Education advantage | 34 | 16.27 | 17.17 |
| Financial or job improvement | 21 | 10.05 | 10.61 |
| Housing improved | 9 | 4.31 | 4.55 |
| Altruism | 7 | 3.35 | 3.54 |
| Social position improved | 7 | 3.35 | 3.54 |
| Migration benefit | 5 | 2.39 | 2.53 |
| Conflict reduced | 3 | 1.44 | 1.52 |
| Debt decreased | 2 | 0.96 | 1.01 |
| Health improved | 1 | 0.48 | 0.51 |
| Hard to classify | 2 | 0.96 | 1.01 |
| Total | 209 | 100.00 | 105.56 |

Valid cases: 198
Missing cases: 1902

Marriages clearly lead the list, with 77 out of 209 statements. The ability to marry away girls is critical for family well-being; successful arrangements are cause for joy. "Family harmony" is a broad category; most often it was used in the advent of a new child. Other examples include the peaceful cohabitation in extended families, the birth of a grandchild, even, in one case, the reassurance that comes from having five brothers established in America. "Education advantage" too comprises of several things; someone is happy with her own adult literacy studies; others are grateful that they have the means to defray the cost of their children's education. After "financial and job improvement" there is a steep drop in frequency. "Altruism" is a cover for the happiness, expressed mainly by literacy shebika and birth attendants, of serving the community. Note that health improvements - many household members must have gone through illnesses and recovered - were almost never mentioned in this context.

**Table 7: Changes that caused us sorrow**

| | Frequency | Percent of responses | Percent of cases |
|---|---|---|---|
| Death in the family | 94 | 32.30 | 33.22 |
| Health problem or disability | 63 | 21.65 | 22.26 |
| Household breakup | 30 | 10.31 | 10.60 |
| Abandonment, divorce | 22 | 7.56 | 7.77 |
| Conflict and police | 17 | 5.84 | 6.01 |
| Education barrier | 15 | 5.15 | 5.30 |
| Migration loss | 11 | 3.78 | 3.89 |
| Marriageability of daughter | 8 | 2.75 | 2.83 |
| River erosion, other disasters | 7 | 2.41 | 2.47 |
| Financial burden, debt, job loss | 6 | 2.06 | 2.12 |
| No home of their own | 6 | 2.06 | 2.12 |
| Has no child | 3 | 1.03 | 1.06 |
| Has no sons | 3 | 1.03 | 1.06 |
| Has no grandchild | 1 | 0.34 | 0.35 |
| Social position weakened | 2 | 0.69 | 0.71 |
| Hard to classify | 3 | 1.03 | 1.06 |
| Total | 291 | 100.00 | 102.83 |

Valid cases: 283
Missing cases: 1817

That death ranks first among the causes of sorrow is in the nature of human life. However, numerous statements of the kind "my husband (or child) died three (or four) years ago" lead one to think that the loss of family members is noted also in the context of persistent grieving, lingering depression and the struggle with the financial consequences from losing breadwinners. Second in number were statements to do with health problems and disability; the two should be kept separate, but many formulations do not allow such a neat distinction. The steep drop in frequency happens here; the third-ranked category, the breakup of households (alada), was less than half the number of health and disability statements.

The willingness to share such statements has some vague social correlates. Surprisingly, they are not the same for joy and for sorrow. Naturally, both correlate with the direction of the overall change of the households. Households with improved conditions tended to report more joyful experiences; those in deteriorating conditions had more sorrowful things to share.

However, the baseline wealth rank had no influence on the frequency of joyful statements. What made these more likely was a higher education level in the household, as measured by the highest number of years of schooling among its members.

The voluntary sharing of sorrow followed the obverse pattern, although with a surprising sign: it was interviewees from rich and middle-class households that were more forthcoming about sad events. The education level of the household was irrelevant for this. This may hint at cultural patterns in which the poor and ultra-poor are very reticent about sharing their life difficulties; the middle-class and richer people may feel less inhibition to complain. If this is so, we should re-think the ability of particular interviewing tools to measure positive and negative changes across social classes.

## *A household typology*

The change areas that we presented in the previous section indicate broad areas of concern in terms of which the interviewed households formulated important changes over the past few years. As noted, those statistics did not take account of the value of the changes - whether they were positive, neutral or negative.

Here we offer a typology of households that looks at the changes by subject matter and by value simultaneously. With over 900 combinations of various categories among the 2,100 sample households, dividing the households in neatly distinct, mutually exclusive groups is difficult. Only an approximate solution is feasible. Groups of households should be distinguished if their members experienced certain types of change at much higher, or much lower, frequencies than the sample average.

To give an example: Only 8 percent of the households reported increased income from remittances (perhaps as a result of a household member finding a job overseas). This is thus a small minority; it could well serve as a criterion for household types. The problem is that we have to assess household types on many more changes. Moreover, households with increased remittance income may not be very different from others regarding other changes.

The solution is to train the analytical lens on household types that are dramatically different from others on one or two criteria, or, if those are not always available, are *sufficiently* different *on several criteria*. A statistical procedure known as "cluster analysis" proposes such typologies. We present one in the next table, then explain it further.

**Table 8: Household types according to multiple changes**

| Categories | Types of households 1 | 2 | 3 | 4 | 5 | Total |
|---|---|---|---|---|---|---|
| | Mainly distinguished by changes in: | | | | | |
| | Family situation, loans and savings, lifestyle, remittances | Various income and assets | Food and clothing positive | Various negative | Food and clothing negative | |
| IncomeRemit_3-Positive | 25% | 0% | 9% | 0% | 0% | 8% |
| FamilySituat_3-Positive | 20% | 0% | 5% | 7% | 15% | 9% |
| LoansSavings_3-Positive | 39% | 16% | 13% | 1% | 0% | 15% |
| Lifestyle_3-Positive | 43% | 18% | 16% | 1% | 0% | 17% |
| IncomeGeneral_3-Positive | 80% | 57% | 61% | 5% | 1% | 44% |
| Housing_3-Positive | 72% | 76% | 56% | 3% | 1% | 44% |
| AssetsProductive_3-Positive | 47% | 65% | 24% | 3% | 1% | 30% |
| IncomeEarner_3-Positive | 19% | 61% | 47% | 1% | 0% | 26% |
| Education_3-Positive | 35% | 45% | 46% | 4% | 1% | 27% |
| Clothing_3-Positive | 5% | 1% | 59% | 0% | 1% | 12% |
| Food_3-Positive | 3% | 5% | 97% | 0% | 0% | 20% |
| Health_3-Positive | 6% | 3% | 5% | 0% | 0% | 3% |
| Clothing_2-Neutral | 0% | 0% | 0% | 11% | 0% | 3% |
| Food_2-Neutral | 1% | 0% | 0% | 15% | 0% | 5% |
| Housing_2-Neutral | 1% | 1% | 0% | 5% | 1% | 2% |
| Lifestyle_1-Negative | 0% | 0% | 0% | 5% | 0% | 2% |
| IncomeRemit_1-Negative | 0% | 0% | 0% | 8% | 1% | 3% |
| Housing_1-Negative | 1% | 1% | 1% | 25% | 8% | 9% |
| AssetsProductive_1-Negative | 2% | 0% | 0% | 34% | 17% | 12% |
| Education_1-Negative | 0% | 0% | 0% | 34% | 18% | 12% |
| Health_1-Negative | 0% | 0% | 0% | 25% | 20% | 9% |
| IncomeGeneral_1-Negative | 1% | 0% | 0% | 31% | 27% | 11% |
| FamilySituat_1-Negative | 8% | 3% | 3% | 46% | 35% | 19% |
| LoansSavings_1-Negative | 2% | 1% | 1% | 52% | 39% | 19% |
| IncomeEarner_1-Negative | 1% | 0% | 1% | 41% | 54% | 17% |
| Clothing_1-Negative | 0% | 0% | 0% | 7% | 86% | 9% |
| Food_1-Negative | 0% | 0% | 0% | 19% | 96% | 13% |
| **Cases** | **501** | **438** | **383** | **610** | **168** | **2,100** |

The table presents five types of households. The column headings say by which type of changes each household type is chiefly distinguished. These distinctions are based on the relative frequencies of the changes.

To illustrate by example:

- Among Type-1 households, 25 percent reported increased remittance income. This is three times more than the sample average (8 percent). Similarly, for this type, positive family changes were more than three times as frequent as the average (20 vs. 9 percent). Strong differences also apply to access to loans and savings (39 vs. 15 percent) and to lifestyle improvements (43 vs. 17 percent). On all those criteria, the advantage of this group of households over the sample average is by a factor of more than two. This is an example of "sufficiently different on several criteria".

- The third group too deserves special mention. This is the group of households defined by high prevalence of positive changes in clothing and food. On both criteria, the changes were about 4.5 times more frequent than in the sample average. This is an example of a household type "dramatically different on one or two criteria".

- Finally, let us point out that there are two household types - Type 4 and 5 - that are defined by negative changes. The major difference between the two is that Type 5 is high on negative changes in clothing and food, and Type 4 is low on them. Type 4 households suffered several other negative changes more frequently.

Once the basic distinctions among those five types are noted, we can now proceed to a more daring interpretation: There is an *ordering* among the household types, based on positive vs. negative changes and on basic vs. less basic needs.

**Table 9: Household types, ordered**

| Household type | Overall direction of change | Basic vs. other needs | Distinguishing changes in: | Sample households |
|---|---|---|---|---|
| 1 | Positive | Accumulating | Family situation, loans and savings, lifestyle, remittances | 501 |
| 2 | Positive | Intermediate | Various: income and assets, housing and education | 438 |
| 3 | Positive | Basic needs | Food and clothing | 383 |
| 4 | Negative | Intermediate | Various: income and assets, housing and education, etc. | 610 |
| 5 | Negative | Basic needs | Food and clothing | 168 |
| **Sample** | | | | **2,100** |

Two features in this table leap to the eye:

- First, there is no household type with a neutral direction of change. Households which reported changes of a neutral kind (in clothing, food and housing) were mostly those who also reported a number of negative changes. Most of them belong to household type no. 4. Neutral changes in other areas were hardly ever described and thus are not included in this table.

- Second, among both positively and negatively affected households, the number of those emphasizing changes in basic needs is smaller than those less focused, in the interviews, on food and clothing. This distribution may indicate a very favorable development in poverty reduction: It *could* (but need not necessarily) mean that the larger part of those experiencing greater difficulties were still able to meet their basic needs. Also, among those reporting positive changes, the majority made progress beyond the fulfillment of their families' basic needs.

The best way of testing these assumptions is, of course, to correlate the five household types with the direction and extent of the overall change that the interviewees evaluated for their households. This we shall presently do, after briefly pointing to some differences vis-à-vis the cluster analysis of the 2011 sample. Three are noteworthy:

- In 2011, about 10 percent of the sample households formed a neutral category regarding their various detailed changes. These household were about 5 to 8 times more likely to note neutral changes in income generation, food, clothing and lifestyle elements than the sample average - enough to establish them as a neutral type. In 2011, such statements were so few that the households that made them were absorbed into the intermediate negative type.

- The first household type in 2011 was much more sharply defined by increased remittance incomes than it is in 2013. The Type-1 households then reported this change six times more frequently than the sample average. In 2013, this factor is close to three. Interestingly this same group in 2011 emphasized also improvements in food and clothing - changes which in 2013 are almost entirely replaced by positive family and lifestyle developments and by greater savings and credit. By relying less on remittance income, this group has become much larger in 2013 than it was in 2011(approx. 25 percent, up from 8 percent of the sample).

- The opposite is true at the lower end of the change order - among households defined by a worsening of their basic needs. In 2011, Type 5 households were five times more likely to report negative changes in food and clothing than the sample average. In 2013, these factors were nine for clothing and seven for food. Yet, the group has also shrunk in size, from 19 percent of the sample to 8 percent.

In other words, there has been a hardening of the distinction between those experiencing the most difficult change - deterioration in basic needs - and the rest of village society. Among the group defined by frequent increased remittance income, there has been a diversification of the other criteria, away from basic needs and towards more accumulative-economic as well as lifestyle changes. But let us remind ourselves that these distinctions are construed on the basis of what people elected to note in the interviews; "in reality" (if we could observe their daily lives) the lines of distinction may run elsewhere.

## *Household types and overall change*

As announced, this table presents the association between household types and overall change for the 2013 sample. In order to read the table both ways, we present the counts of households, rather than row- or column-wise percentages.

**Table 10: Household types and overall change**

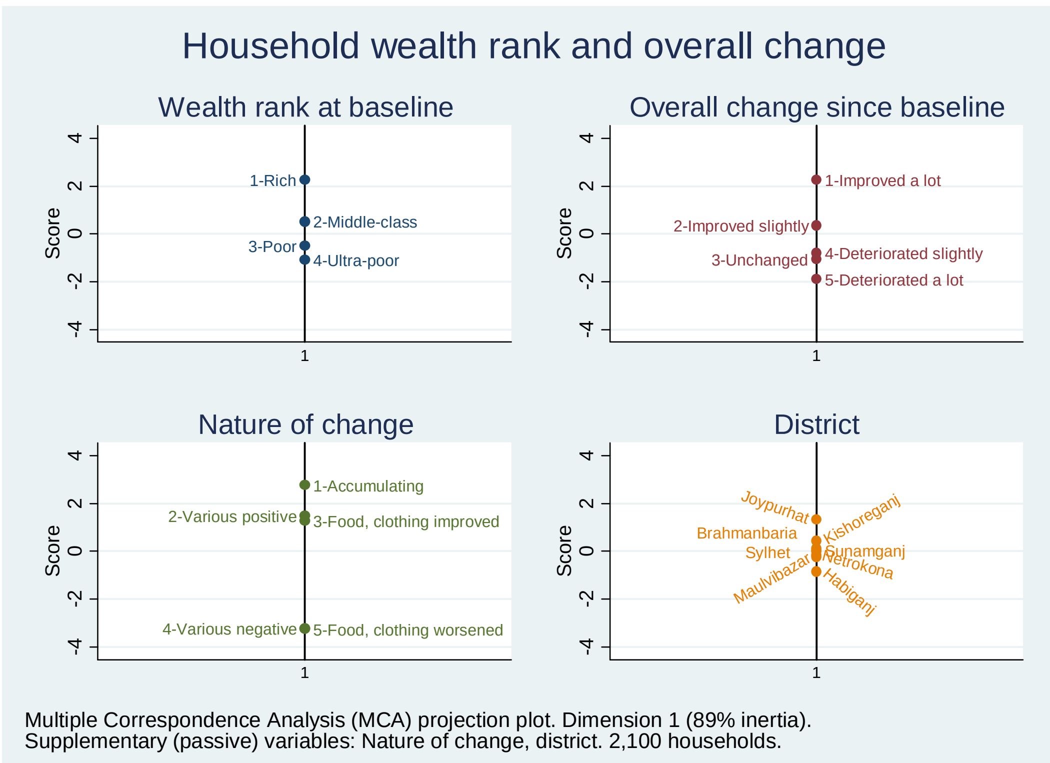
| Self-ranked overall change | Household type | | | | | Total |
|---|---|---|---|---|---|---|
| | Improvement | | | Deterioration | | |
| | 1-Family situation, loans and savings, lifestyle, remittances | 2-Various: income and assets, housing and education | 3-Food and clothing | 4-Various: income and assets, housing and education | 5-Food and clothing | |
| 1-Improved a lot | 107 | 58 | 28 | 1 | 0 | 194 |
| 2-Improved slightly | 377 | 373 | 352 | 5 | 4 | 1,111 |
| 3-Unchanged | 13 | 6 | 2 | 97 | 1 | 119 |
| 4-Deteriorated slightly | 4 | 1 | 1 | 401 | 135 | 542 |
| 5-Deteriorated a lot | 0 | 0 | 0 | 106 | 28 | 134 |
| **Total** | **501** | **438** | **383** | **610** | **168** | **2,100** |

As expected, the correlation between the ordered overall changes and the ordered household types is strong. This is hardly a structural finding; it basically says that the interviewees were consistent in basing their overall change evaluations on the types and combinations of specific changes that they emphasized. The structural content is basically limited to the (unsurprisingly) stronger association between substantial overall improvement and Type-1 households. In other words, positive changes like increased remittance income tend to prompt an "improved a lot" evaluation. Things are not that clear at the other end; Type-5 households are not much more likely to rate their conditions as "deteriorated a lot" than Type-4 households.

Comparing this table to its equivalent in the analysis of the 2011 survey data does not provide much new insight. As already noted, Type 3 at that time comprised of a cluster of neutral changes. Assuming that the five household types in 2011 formed an ordered sequence too, from positive-accumulating to negative-basic needs, we find that the strength of association between overall change and household types is virtually the same in both samples (gamma = 0.87 in 2013; 0.93 in 2011). To repeat, these strong associations are a sign of validity of the change measurement, and much less so a structural property of the households themselves.

Finally, we represent the mutual determination of wealth rank and overall change on a common dimension. The graph below is the result of such a statistical procedure. The distances between the categories are of the most interest. In terms of improving their situation, the distance between rich and middle-class is larger than that between middle-class and poor. The distance between poor and ultra-poor is even smaller. We find similar relations in the overall-change panel. In terms of reflecting wealth rank, the difference between "Improved a lot" and "Improved slightly" is larger than any of the other intervals. In fact, by sampling accident, "Deteriorated slightly" is even a tiny bit above "Unchanged".

**Figure 6: MCA projection plot of wealth rank and overall change**




On this same dimension, we subsequently calculated the average position of the five household types as well as of the eight Jonoshilon districts. The position of "accumulating" households - among which, as we recall, those receiving remittance income are frequent - stands out on top of the line. But the major difference is between households with positive changes and those with negative ones. There is no neutral category. On either extreme, the differences between those defined by "various" criteria and those precisely defined by changes in nutrition and clothing are vanishingly small. This is surprising. It means that in terms of wealth rank and, simultaneously, of overall change, the difference between basic and other needs matters less than expected.

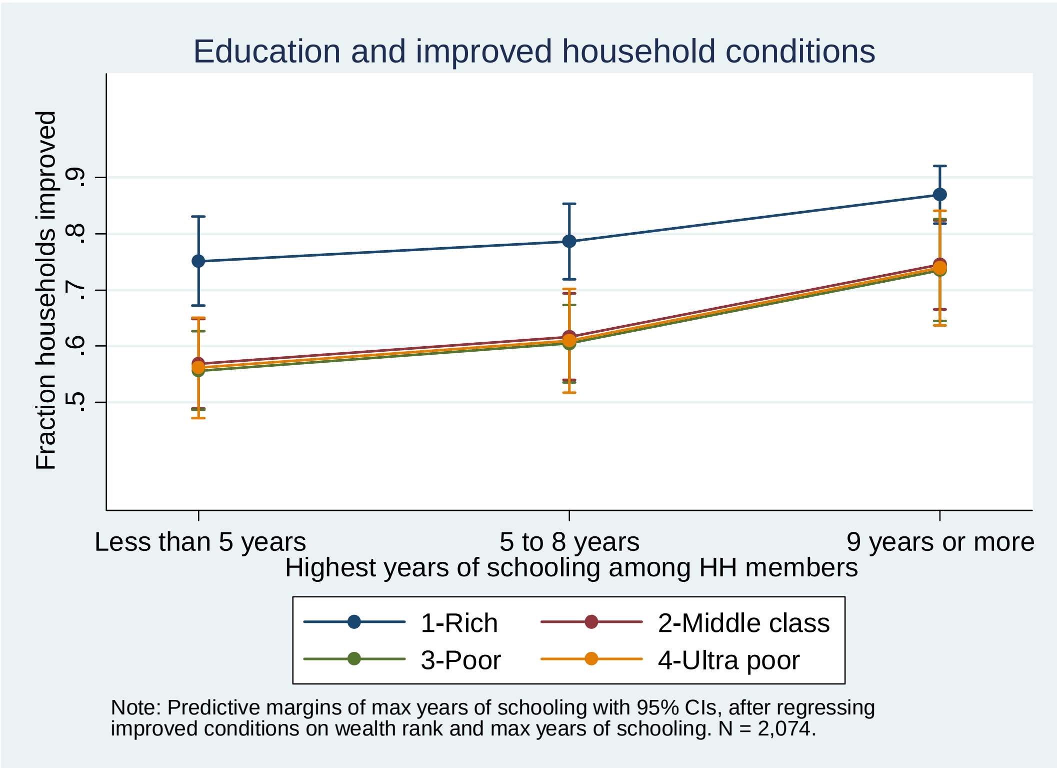
The differences between districts are relatively small. Still the difference between the extremes - Joypurhat and Habiganj - is significant. It is due mainly to the fact that Joypurhat had a lot of households with positive change; this district did not report a single household deteriorating a lot. This is unlikely the case in real life; there may be measurement bias at play in this and perhaps other districts.

## Education and positive change

Finally, for an NGO with a deep, longstanding involvement in education like FIVDB, it should be interesting to know how increased education is associated with improved household conditions. We measure the education level of a household as the maximum number of years of schooling among the household members, at the time of the baseline survey. This assumes that not only the education of the head, but also the education of any members contribute to household welfare.

As is well known, socio-economic status and education are correlated. In this sample, the percentage of households with at least one member with nine or more years of schooling is 57 for the rich, 39 for the middle class, 18 for the poor and 13 for the ultra-poor. The question of interest then becomes: "What is the effect of education on improved conditions when we control for the wealth rank?" This chart visualizes a statistical answer. It is derived from a model that estimates the effects of wealth rank and of education simultaneously.

**Figure 7: Education and improved conditions, by wealth rank**



Three points are worth noting:

- Across all the education levels, rich households report improved conditions more frequently, over the other three wealth rank groups. The advance diminishes a bit as the education level moves up.
- Once the effect of education is considered, the differences among middle-class, poor and ultra-poor virtually disappear. Except for the rich, education is an equalizer, regarding the ability to improve one's conditions.
- The difference in reported improved conditions, for middle-class, poor and ultra-poor households, is about 5 percent between those with maximum 4 years of schooling and those with 5 to 8 years. Statistically, this is weakly significant. The difference between the first group and those with 9 or more years is 18 percent. This is highly significant (for the rich, the differences are 4, respectively 12 percent).

Education, obviously, cannot on its own reverse social inequality. To the extent that the poorer sections get access to education, it may slow down the growth of inequality. At the very least, it gives those at the bottom the force to advance, by whatever small steps.

## The impact of livelihood trainings

Both the 2011 and the 2013 CCR survey collected minimal data on livelihood trainings that the interviewed households had received. The data in 2011 suggested that, when we adjusted for the development level of the village and the primary education of the household head, households that had received training were more likely to report that conditions had improved over the previous two years. CLC member households that had received three or more trainings were about ten percent more likely to report improvements, compared to (member or non-member) households without training.

In 2013, the information collected differed slightly. The interviewees were simply asked whether anyone in the household had attended any training under Jonoshilon, and if so, whether the training was about livelihoods. The number of trainings, the specific trades, and the members attending were not investigated. Instead, the associates conducted 40 small case studies of livelihood trainees. These provide information also on the specific trades and on the estimated additional monthly incomes.

With one exception, only CLC member households reported ever attending trainings[2]. For the survey analysis, the consequence is that we are no longer concerned with who chose to join the local CLC, and then who was chosen for trainings, but only and directly with the selection of trainees. An estimated 51 percent of the households had attended some training (to be precise: trainings given by staff of the Livelihoods Enhancement Program, not adult literacy classes), and 37 percent had attended livelihood trainings.

[2] In 2011, about a quarter of the trainee households were not CLC members. This finding was contested.

The question of interest here is: How did livelihood training affect changes in household conditions? Did trainee households experience positive change more often than other households? Are the differences statistically significant? Are they robust when we take into account that participation in trainings may be determined by the prior wealth rank and the education of the household?

We present results step by step because the raw sample figures can be misleading. The population estimates - the estimates for all the 362 baseline villages - reveal considerable uncertainty. The reader should take into account that, while the impact of the training is significant, the exact estimate of its size falls into a wide confidence range.

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## [Sidebar:] The structure of LEP trainings 2009 - 2013

An internal study (Chowdhury and Khan 2013) estimated that between January 2009 and August 2013 FIVDB's Livelihood Enhancement Program had extended training to 66,716 beneficiaries. Almost half of the participants (26,304) attended awareness-raising trainings, particularly in water and sanitation. The others attended trainings with an income-generating intention. Of these, 25,184 learned better homestead gardening.

We need to see the commercial training repertory to get a handle on the scope of the training effort that may have had the most noticeable effects on household conditions. Thus we remove from the training lists homestead gardening and smokeless ovens (because they are not meant as major-time earning trades). Similarly, traditional birth attendant training should be removed because its rationale is essentially social (fighting bad practices), not income generation. Thus we are left with 7,490 trainees in 14 on-farm trades and 857 trainees in 9 off-farm trades. Trainee recruitment into these was strongly gender-segregated for on-farm trainings, and almost completely so for the off-farm trainings. For both men and women each, 13 different on-farm training types were conducted during this period. The diversity of off-farm trainings was smaller; 6 types of training for men and 3 for women.

The most popular trainings included:

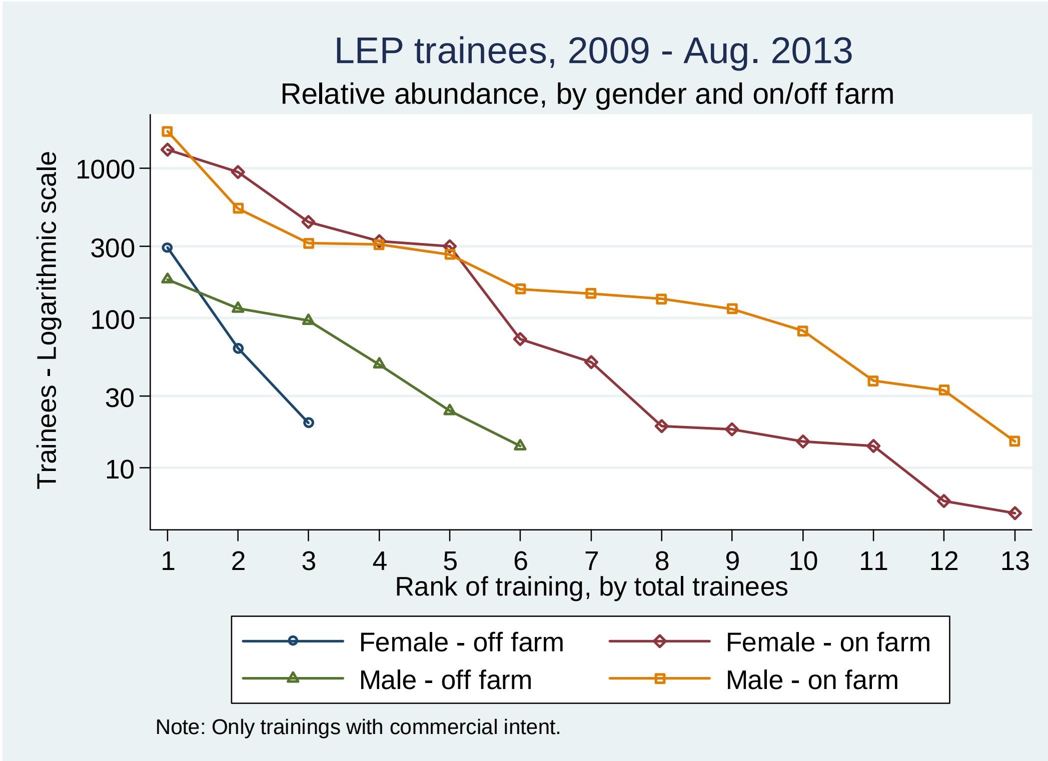
- Men - on farm: Commercial vegetable gardening (1,765 trained)
- Women - on farm: Goat rearing (1,335 trained)

- Men - off farm: Mobile phone servicing (181 trained)
- Women - off-farm: Sewing (294 trained)

The overall distribution of trainee statistics suggests that

- developing a greater diversity of off-farm trainings is difficult
- it is particularly difficult for trades that are accessible for women
- even in on-farm trainings, for most trades it is hard to recruit substantial numbers of women trainees.

**Figure 8: Abundance diagram of trainings, by gender and on/off-farm type**




The abundance-plot method (Cox 2005) is indifferent to the specific trainings; it summarizes the shape of the entire portfolio, broken down by criteria of interest such as gender and on/off farm. For comparison, FIVDB was able to conduct on-farm activity trainings with more than a total of 100 participants in 9 types for men, and in 5 for women. The diversity in off-farm activity trainings was smaller: the threshold of 100 trainees was reached in just two activity types for men and in one for women.

Moreover, the drop-off in training abundance is steeper for training types for women than for men. This is so in both on- and off-farm types. It suggests that FIVDB did try to elaborate more training types suitable for women, but could not multiply participation in them to levels achieved with the men.

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## *Size of the training effect*

### Raw sample statistics

The raw figures suggest a modest increase in those reporting improvements in association with livelihood trainings, with about 68 percent of the trainee households improving (slightly or a lot), as opposed to 59 percent among the others. This is a difference of roughly 9 percent.

**Table 11: Change rank, by IGA trainee households vs. others - SAMPLE ONLY**

| Change rank | LEP trainee household No | Yes | Total |
|---|---|---|---|
| 1-Improved a lot | 102 | 92 | 194 |
| | 7.70 | 11.86 | 9.24 |
| 2-Improved slightly | 679 | 432 | 1,111 |
| | 51.28 | 55.67 | 52.90 |
| 3-Unchanged | 82 | 37 | 119 |
| | 6.19 | 4.77 | 5.67 |
| 4-Deteriorated slight. | 372 | 170 | 542 |
| | 28.10 | 21.91 | 25.81 |
| 5-Deteriorated a lot | 89 | 45 | 134 |
| | 6.72 | 5.80 | 6.38 |
| Total | 1,324 | 776 | 2,100 |
| Percent | 100.00 | 100.00 | 100.00 |

**Estimate for all 362 baseline villages**

In the population estimate, the proportions are slightly different from the raw figures. For all the 362 baseline villages 69 percent of the trainee households are estimated to have improved their conditions during the Jonoshilon period, as different from 61 percent by the others, an eight-percent difference. The difference is statistically significant (p = 0.005).

Here is the breakdown by change rank, with percentages of households in improved conditions, depending on whether any of their members were in livelihood trainings:

**Table 12: Change rank, by IGA trainee households vs. others - POPULATION ESTIMATE**

| Change rank | LEP trainee household No | Yes | Total |
|---|---|---|---|
| 1-Improv. a lot | 8.174 [6.344,10.47] | 13.83 [9.504,19.71] | 10.28 [7.865,13.33] |
| 2-Improv. slightly | 53.19 [47.83,58.48] | 55.33 [49.79,60.74] | 53.99 [49.36,58.55] |
| 3-Unchan. | 5.407 [3.878,7.491] | 4.901 [3.347,7.124] | 5.219 [4.011,6.764] |
| 4-Deterio. slightly | 26.48 [22.74,30.59] | 20.56 [16.46,25.37] | 24.28 [20.94,27.96] |
| 5-Deterio. a lot | 6.747 [5.097,8.883] | 5.375 [3.405,8.384] | 6.237 [4.616,8.378] |
| Total | 100 | 100 | 100 |

Key: column percentages
[95% confidence intervals for column percentages]

Note that the confidence intervals are quite wide. For example, the best estimate of having significantly improved their conditions for households who received training is 14 percent. The confidence interval ranges from 10 to 20 percent, a fairly imprecise estimate. Also it overlaps with the confidence interval for those who did not receive training (6 to 10 percent). Nevertheless, all these differences are significant - in this table, the question is what change rank training generates, not how many in a given change rank had training.

These estimates clearly are useful to know, but they are not satisfactory as an explanation. Clearly, other factors have to be considered, including wealth rank and education at baseline. They have to be considered both for access to training, and for the outcomes - the improved household conditions.

## *Two analytic models to estimate the training effect*

### Controlling for access factors

Households of different wealth rank and of different education levels may have different chances to be selected into livelihood trainings. The sample figures suggest that middle-class and ultra-poor households participate more often than the rich and poor. Households that have more highly educated members avail trainings more easily. However, population estimates correct that picture somewhat. Wealth rank has no significant influence on participation. Households with someone who had five to 8 years of schooling participated more readily than those with a maximum of four years (+ 6 percent); those with someone with at least 9 years were 10 percent points ahead. These differences are small, but they are statistically significant.

We therefore want to control for differences in wealth rank and in education while we estimate the effect of livelihood trainings on changes in household conditions. One way of doing so is by rebalancing the sample. We treat households with trainees as an experimental treatment group, and those without as control group. We form narrow strata of households with similar values on socio-economic variables. We use the annual household income and the maximum years of schooling among household members. Income has more distinct values than wealth rank, which has four levels only. Income thus can be cut up into finer strata. We then reweight the households without trainees such that their relative frequency in each stratum is the same as that of the households with trainees.

In this way we can estimate the effect of the livelihood training uncontaminated by differences in training participation. For the 362 baseline villages, we estimate that 69 percent of the households with livelihood trainees have improved their situation. This estimate may vary with the 95-percent confidence interval from 63 percent to 75 percent. For those without trainees, the best estimate is 61 percent in improved situations. We have confidence that its true value is between 55 and 68 percent. Although the confidence intervals overlap, the 8-percent difference (69 - 61 = 8) is statistically significant ($p < 0.01$).

We can refine the effects, by showing the different effects on each of the five change levels:

**Table 13: Effect of livelihood training on changes in household conditions**

| Change during Jonoshilon period | Households with | | Total | Difference |
|---|---|---|---|---|
| | No trainees | Trainees | | |
| 1-Improved a lot | 8% | 14% | 10% | 6% |
| 2-Improved slightly | 53% | 55% | 54% | 2% |
| 3-Unchanged | 5% | 5% | 5% | 0% |
| 4-Deteriorated slightly | 27% | 21% | 24% | -6% |
| 5-Deteriorated a lot | 7% | 5% | 6% | -1% |
| **Total** | **100%** | **100%** | **100%** | **0%** |

Finally, we tabulate the association between livelihood training participation and the types of households that we earlier were able to distinguish on the basis of various specific changes. The pattern of differences is almost the same as in the previous table. This is not surprising, given the strong association between change rank and household type.

**Table 14: Association between livelihood training and household change type**

| Household type by dominant changes | | Households with: No trainees | Households with: Trainees | Total | Difference |
|---|---|---|---|---|---|
| Positive | Family situation, loans and savings, lifestyle, remittances | 22% | 29% | 24% | 7% |
| Positive | Various income and assets | 24% | 26% | 25% | 1% |
| Positive | Food and clothing | 16% | 16% | 16% | 0% |
| Negative | Various changes | 31% | 25% | 29% | -6% |
| Negative | Food and clothing | 7% | 5% | 6% | -2% |
| **Total** | | **100%** | **100%** | **100%** | **0%** |

The gist of this section is the *estimate* that households with livelihood training were 8 percent more likely to have improved their condition during the Jonoshilon years, than those with such training. The estimate adjusts for differences in access to training, based on baseline wealth and education.

These estimates are based on the so-called "coarsened exact matching" method described in the appendix, starting on page 64.

This method does not reveal how the training effect compares to the effects of wealth and education on the outcome itself. To present such a model, is the next step.

## Training in the wider Jonoshilon context

The livelihood trainings are only one of several major Jonoshilon program outputs. Others include primary school construction and operation, CLC support and adult literacy training. It is plausible that these reinforce each other.

It would be intriguing to estimate the interaction between livelihood training and other Jonoshilon components in their effects on improved household conditions. However, the CCR survey offers little in the way of supportive data for this endeavor. There is an analytic opportunity, though, provided by FIVDB's primary education involvement:

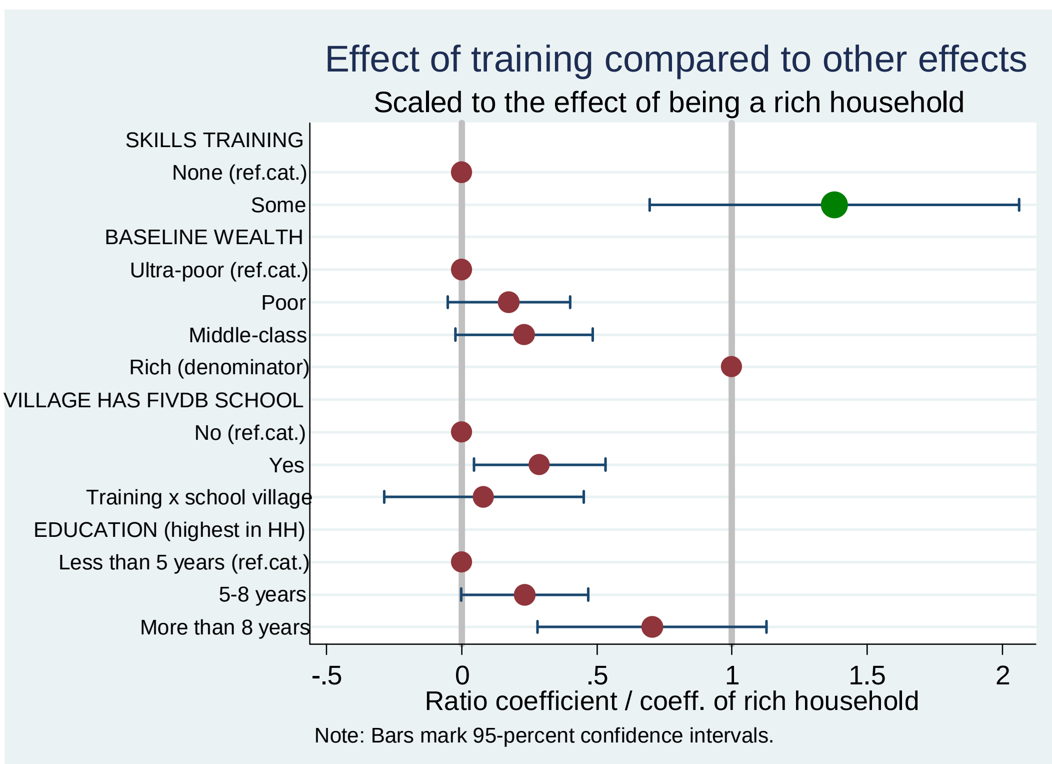
We can estimate the livelihood training effect on household conditions in the context of FIVDB school villages. These are villages in which FIVDB operates schools, not necessarily villages in which the majority of primary school age children are attending these schools. The point is to find out how the effects of training and of living in an FIVDB school village compare, and whether there is an interaction between them. To have a reasonable standard for these comparisons, we gauge them to the effect on the change rank of being a rich household rather than an ultra-poor one. Thus expressing the training effect as a multiple of the wealth effect may make it more meaningful. This ratio compares a program effect to an initial endowment effect.

Households in FIVDB school villages are more likely (39 percent) to have had livelihood training than those outside (33 percent). We therefore estimate a model that adjusts for different training access due to wealth rank, household education as well as FIVDB school location.

The type of model that achieves that is known as an "endogenous switch regression" and is described in the appendix starting on page 67.

We then divide the effects of these variables on improved conditions by the effect of being rich rather than ultra-poor. Since we are concerned with the uncertainty concerned by the sampling, we want confidence intervals for the ratios. The variables compared are all dichotomous. All we have to do, therefore, is to estimate the ratios between the coefficients of interest and the coefficient on the wealth rank "rich". "Ultra-poor" is our reference category. This calls for a non-linear combination of estimators as detailed starting on page 70.

**Figure 9: Effects on the change rank, scaled to the effect of baseline wealth**




**Note: This figure is a copy of one used in the summary.**

The results are instructive. As noted before, once education is taken into account, the advantage of being middle-class or poor rather than ultra-poor are not that massive (in reality, the problem is that most ultra-poor cannot afford much education!). The education effect on improved conditions during the Jonoshilon period is strong; being a household in which a member studied for nine years or more makes up for 70 percent of the difference between ultra-poor and rich.

In the Jonoshilon context, the mere fact of living in an FIVDB school village imparts an advantage regarding improved conditions of about a quarter of the effect of being rich rather than ultra-poor. This only concerns where the household lives; it assumes equal education at baseline; it does not say whether a particular household's own children ever attended the local FIVDB school.

The most stunning effect, however, comes from the training side. The best estimate of the effect of having had some member undergo livelihood training has an effect about 138 percent of the effect of being a rich household. Note that this assumes equal education for rich and ultra-poor; in real life, the rich are massively better educated than the ultra-poor. Thus we speak about the effects of training and of wealth ranks in statistical isolation, not in real-world embedding in the lives of rich and poor. Also, as all estimates, this one is uncertain; the 95 percent-confidence interval ranges from 70 to 206 percent.

The key finding of this section is: The effect of livelihood training on improved household conditions is, with high certainty, at least 70 percent of the effect of being rich at baseline, at constant education and school village status.

The extra effect of livelihood training and living in an FIVDB school village is minor. Being only 8 percent of the ultra-poor vs. rich effect, it is not statistically significant. This is not surprising; if you get training, improved conditions of your household depend on how successfully you practice your skill; this has little to do with the presence or not of an FIVDB school in your village. The small advantage may be the result of stronger post-training support that some enjoy due to shorter distances from school villages to FIVDB field operation centers.

# Conclusion

### *Ranking overall change*

The 2013 Community-Based Change Ranking (CCR) Survey collected data on 2,100 households in a sampling process that lets us generalize findings to the 362 villages of the earlier Jonoshilon baseline surveys. The validity of the findings is challenged by certain features of the survey, and strengthened by others:

- **Limitation:** Households with livelihood training experience were oversampled. Additional households were recruited for interviews in many or most sample villages. We do not think that this convenience-sampling element is strong enough to distort the overall findings about the direction and extent of the changes in household conditions. But it rules out estimates of CLC membership and livelihood training prevalence in the population.

- **Added strength:** The community-based change ranking method allowed us to capture improvements and deteriorations in household conditions even where they were too small to be reliably registered through questions aimed at income and expenditure. The ranking of the overall changes that the interviewees offered appears to be valid, judging by the strong association between change ranks and the types of households that we constructed from the pattern of specific changes.

Overall, positive change dominates although most of it is at the level of "Our condition improved a bit". Fewer than one in six of the households claiming improved conditions felt they had improved "a lot". Yet, improvement was wide-spread; in all wealth ranks, from the rich to the ultra-poor, the statistical estimates point to a majority of households that saw their conditions improve during the Jonoshilon period.

Change ranks were still significantly associated with baseline wealth ranks. Thus, rich households were three times more likely to experience "a lot of improvement" than ultra-poor households. Yet, to the extent that comparisons with the earlier CCR survey in 2011 are permissible, this association has weakened. In support of that, we no longer find a change-neutral category in our household typology. The clustering algorithm instead replaced it (compared to 2011) with a group of households that found ways to better meet some of their basic needs in food and clothing. Equally noticeable is the household type on top of the change ladder. It is less strongly defined by access to remittance income than in 2011; the specific changes that are prevalent in this group increasingly concern developments at home: family and lifestyle changes, changes in income of any kind, access to loans and savings, and housing.

### *The major concerns of the people*

The major concerns that speak through the enumerations of specific changes have seen their relative ranks go up and down, compared to findings in 2011. Housing and education grew to be far more important in 2013. Food and clothing have lost importance in the change narratives (lifestyle elements too are far down, but it is less clear what this actually involves).

Education is particularly noteworthy. When we estimate the proportion of households in improved conditions as a function, not only of the wealth rank at baseline, but also of education, the differences among middle-class, poor and ultra-poor disappear. Those between the rich and the rest remain. But it does suggest that, if the poor can get access, education is a vehicle to betterment, if not always to lasting upward mobility.

As in 2011, health-related changes were reported rarely, by a mere 12 percent of the 2013 sample households. They may be underreported. On this point the survey format may be inadequate, in the sense that most recoveries from illness went unmentioned.

### *Livelihood training*

The survey was done with a second ambition, of gauging the effect that livelihood trainings extended under Jonoshilon had on household conditions. This objective enriched the scope of findings, but it also introduced methodological complications, particularly in sampling. The associates who organized the group interviews made special efforts to recruit households with livelihood trainees from the same neighborhoods. Since there were no lists of households with or without training histories, we are at a loss of how to re-weight the sample. Re-weighting is required in this situation if we want to estimate the proportion of households ever participating. Non-trainee households were further underrepresented because of more frequent refusals by non-CLC households to be interviewed.

These technicalities have to be noted in the conclusions; they illuminate a more general problem. Development NGOs often find it difficult to maintain the kind of stable monitoring environment that makes for reliable and comparable findings of interest over time. Jonoshilon is no exception. However, our data are good enough to estimate the difference in improved conditions between households with and without livelihood trainings. The best estimate for the 362 baseline villages is that households with livelihood trainings were 8 percent more likely to improve their overall condition than those without such training.

This difference may appear small. It would be larger if measurement error were eliminated, and more precise if the kinds of trades were known in which household members underwent training.

Under this qualitative definition - "did your condition improve, stay the same, deteriorate in the past few years?" -, the relative contribution of livelihood trainings to improvements is considerable. When we control for some of the factors that influence access to training, the training effect measures up favorably to the effects of baseline conditions. It measures up favorably also to the general Jonoshilon environment, proxied by living in an FIVDB school village.

### *Qualitative and quantitative*

This survey database has relatively few variables. The major thrust of the data collection was towards the elicitation of specific changes by which the interviewees would illustrate, temper or reinforce their claims to the overall household change. Over 9,000 such specific changes were recorded. This was done in interviews with individuals witnessed (and sometimes corrected) by their neighbors. The coding and condensation of this information was a significant achievement of the survey team. The coded information was subsequently reduced with the help of quantitative methods. FIVDB did not invent the Community-Based Change Rank method, but has applied it for the second time in a manner that combined qualitative and quantitative research.

# Appendices

## *The community-based change ranking method*

This is a segment from a note written in 2011 (Benini, Chowdhury et al. 2011). BRAC researchers pioneered the method. It would be more correct to call it "community-based change *rating*" because no ranking takes place of the households represented in a group interview; each household situates itself on a five-level scale. To avoid confusion, we abide by the term that the pioneers chose.

### *Rationale*

The logframe included in the Jonoshilon project document obliges FIVDB to report on *activities* in skills training as well as on consequent *outcomes* in the use of skills and *impact* in terms of increased household incomes. The trainees are supposed to come from poor and very poor households. The table gives a condensed view of the concerned key logframe elements.

**Table 15: Selected Jonoshilon logframe elements (condensed)**

| | | |
|---|---|---|
| Poor and extreme poor households in 850 villages have acquired sustainable means for increasing their income<br>46,180 community members trained to improve their income earning capacity | 80% of trained community members will use the new skills learned, and<br><br>80% of them will have achieved improvements in their livelihoods | • # of trained members, segregated by gender, initiating income augmenting activities<br><br>• # of members, segregated by gender, increasing their income |

In terms of evaluation logic, the reporting requirement is mild. The current formulation is not concerned with the measurement of exposure and selection effects, except that the trainees should be from the target group of poor and extremely poor households. The donor solely wants information on those selected into the program. Comparisons with non-exposed or exposed, but not selected households are not requested.

The major challenge arises from the metric of change, which is household income. It is true that the baseline survey elicited a household income estimate from the interviewees, and thus there would be an income baseline of sorts. However, household income estimates are highly problematic, on two counts. Substantively, due to fluctuations of various kinds, income as a household welfare measure is inferior to expenditure. Formally, income estimates are notorious for their elevated measurement errors. These errors lead to overestimates of transition rates in and out of poverty (Baulch and Hoddinott 2000).

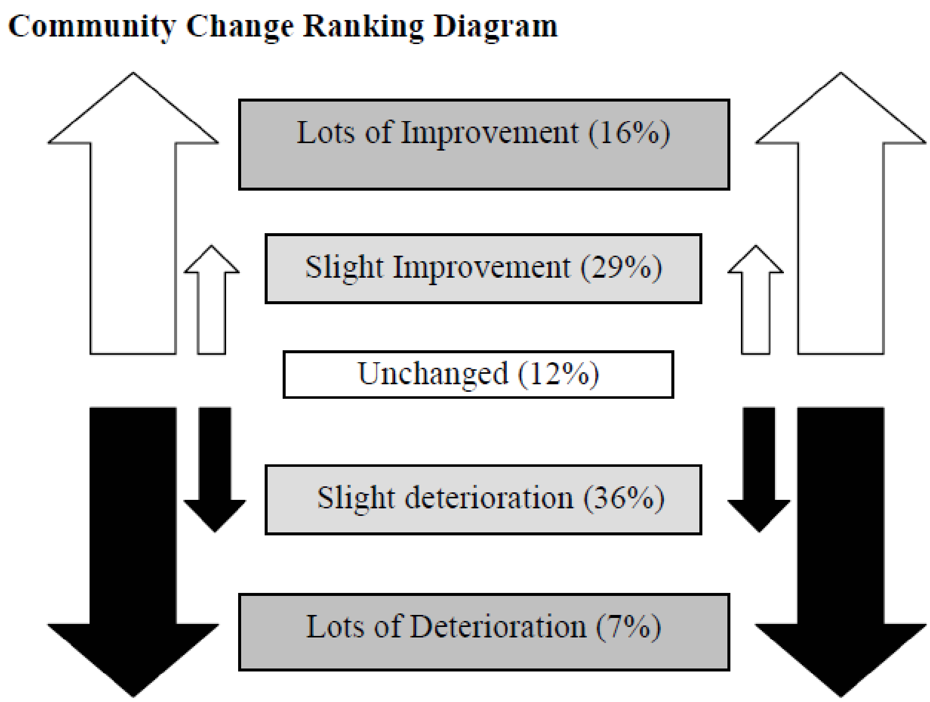
Particularly among the poor and very poor, the actual changes in terms of incomes are often smaller than the typical measurement error inherent in summary income elicitation. Yet, small changes, positive or negative, are important in their own right. Moreover, the poor may single out changes in their welfare as the most important ones that are currently non-pecuniary, such as the continued schooling of children, or an equally paying, but more secure job.

Required, therefore, are two change measurement devices: a substitute for household income that is less error-prone; and an elicitation mode that generates information also about the types of changes and their causes specific of each observed household.

### *Key elements*

Developing this rationale further, researchers in BRAC devised and successfully applied a change measuring tool that they called "Community-based Change Ranking" (Sulaiman and Matin 2007). Its embedding in a particular BRAC program in northwestern Bangladesh and the detailed analysis of changes and their associated causes defy brief summary. Essentially, interviewers invite household representatives meeting in small neighborhood-based groups to self-rate their changes (over a meaningful period of time). The group format is meant to improve the reliability of estimates and the identification of causes, under the watchful eye of neighbors who know each attending household's situation from dense personal acquaintance. A five-level change diagram, understandable to barely literate persons, is displayed conspicuously, to help focus the discussion and to ensure that ratings be expressed in comparable terms. The figure below is from the Sulaiman-Matin paper, with percentages computed for their sample households.

**Figure 10: Poster-size diagram used in group interviews in the BRAC project**




The Sulaiman Matin change rank measure may be characterized as a

- Non-income based
- Total household welfare
- Measure using an ordinal scale
- Ranging from -2 [deteriorated a lot] to +2 [improved a lot] (5 levels)
- Comparing current conditions to conditions at some meaningful earlier point in time,

notably before the household was selected into the project being assessed. An important detail is that the earlier condition need not be known to the researchers; it is enough that those who rank the change know it. This can make for significant information economy, differently from income change measurements, which generally depend on baseline incomes recorded during previous survey waves.

## *Statistical appendix*

Tables and figures in this section are not captioned.

## Population and sample

### *Stages of sampling*

The population covered in the CCR 2013 survey consists of the households in 362 villages in eight Jonoshilon working districts. The households were enumerated in two baseline surveys in 2009-10, the first covering 98 villages, the second 264. The data tables of the two surveys were appended for the purposes of computing the sampling weights. The combined table holds records of 60,119 households. The common identifier between the baseline survey data table and the CCR 2013 survey data is provided by the village code and by the number that the local Community Learning Center (CLC) assigned to the household on the village map drawn in the early stage of Jonoshilon.

The 362 villages, scattered in 107 Unions in 29 Upazilas in eight districts, are themselves a sample, out of the approximately 690 villages in which the Jonoshilon program has been active. We do not generalize to these for technical reasons (we lack the information to compute the finite population correction on the basis of all), but there is no reason to assume that conditions in villages not surveyed at baseline were significantly different.

The sampling went through three stages, two of which are documented:

1. From the list of 362 villages, 70 were selected, stratified in rough proportion to the frequencies in a 10-percent interval grid of poverty and literacy rates.
2. In each sample villages, three physically distinct neighborhoods were selected. In each neighborhood, ten households were recruited for group meetings.
3. In the group meetings, representatives of each household were interviewed individually, in the presence of, and with variable participation by, the other interviewees (and assorted bystanders, one may think).

The process of selecting neighborhoods, the households belonging to them, and the membership of the selected households in particular clusters of ten households were not recorded. As a result, corrections for clustering at that level cannot be made, and standard errors are likely somewhat underestimated.

Also, at that second stage, it appears that some convenience oversampling of households with livelihood training took place. These households had earlier been planned as additions from a second sampling frame, the list of trainees kept by FIVDB's Livelihood Enhancement Program department (LEP), to be documented and marked. In the event, they were done ad-hoc. Also, the interviewers reported a significant number of refusals to be interviewed by non-CLC member households. Since trainees had been selected by the CLCs, both these deviations are liable to create upward bias in the estimated rates of training participation and of households with improved conditions. Models of training impact are less likely to be biased because for them the sample can be rebalanced, or, alternatively, access to training can be modeled simultaneously with the impact.

The effective sample consists of 2,100 households, 30 from the 70 sample villages each.

### *Stratification and sampling weights*

For workload and representativeness (districts, school / non-school villages) reasons, at stage 1, some villages initially drawn were replaced by others from the same grid cell. In rare cases where replacements from the same cell were not available, they were replaced with villages from adjacent cells. This initial arrangement created 36 strata in the sample from 53 strata in the sampling frame. The number of villages in the sample strata ranged from 1 to 8 (mean = 1.94), with 23 singleton strata (a singleton stratum has one member only). The corresponding range in the frame was 1 to 36 (mean = 6.83; 17 singletons).

In order to reduce the number of replacements across grid cells and to avoid singleton strata (which result in failure to compute standard errors), we collapsed the initial strata, by making the grid wider, as follows (we present also the STATA command code):

```
. des povrategroup litrategroup stratumcomb2

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------------------
povrategroup    float  %9.0g                  Village poverty rate, ceil(rate in percent /10)
litrategroup    float  %9.0g                  Village literacy rate, ceil(rate in percent /10)
stratumcomb2    float  %9.0g                  Stratum, no singleton PSU, broader literacy and
                                                poverty rate intervals
-------------------------------------------------------------------------------------------

. summ povrategroup litrategroup if villagecodetag

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
povrategroup |       362    6.831492    1.459254         1         10
litrategroup |       362    4.748619    1.468152         1         10


. gen stratumcomb2 = .
(60119 missing values generated)

. * Define new strata

       . * Stratum 1
       .  replace  stratumcomb2  =  1  if  povrategroup  >  0  &  povrategroup  <=  5  &
       litrategroup > 0 & litrategroup <= 3
       (962 real changes made)

       .
       . * Stratum 2
       .  replace  stratumcomb2  =  2  if  povrategroup  >  0  &  povrategroup  <=  5  &
       litrategroup > 3 & litrategroup <= 6
       (5563 real changes made)

       .
       . * Stratum 3
       .  replace  stratumcomb2  =  3  if  povrategroup  >  0  &  povrategroup  <=  5  &
       litrategroup > 6 & litrategroup <= 10
       (1945 real changes made)

       .
       . * Stratum 4
       .  replace  stratumcomb2  =  4  if  povrategroup  >  5  &  povrategroup  <=  8  &
       litrategroup > 0 & litrategroup <= 3
       (6758 real changes made)

       .
       . * Stratum 5
       .  replace  stratumcomb2  =  5  if  povrategroup  >  5  &  povrategroup  <=  8  &
       litrategroup > 3 & litrategroup <= 6
       (33591 real changes made)
```

```
.
. * Stratum 6
.  replace  stratumcomb2  =  6  if  povrategroup  >  5  &  povrategroup  <=  8  &
litrategroup > 6 & litrategroup <= 10
(4585 real changes made)

.
. * Stratum 7
.  replace  stratumcomb2  =  7  if  povrategroup  >  8  &  povrategroup  <=  10  &
litrategroup > 0 & litrategroup <= 3
(2189 real changes made)

.
. * Stratum 8
.  replace  stratumcomb2  =  8  if  povrategroup  >  8  &  povrategroup  <=  10  &
litrategroup > 3 & litrategroup <= 6
(4526 real changes made)

.
. * Stratum 9
.  replace  stratumcomb2  =  9  if  povrategroup  >  8  &  povrategroup  <=  10  &
litrategroup > 6 & litrategroup <= 10
(0 real changes made),
```

resulting in eight strata (Stratum 9 is empty).

| Stratum | Population | | | Sample | | |
|---|---|---|---|---|---|---|
| | Villages | Poverty rate (mean) | Literacy rate (mean) | Villages | Poverty rate (mean) | Literacy rate (mean) |
| 1 | 7 | 43.7% | 22.9% | 4 | 44.9% | 20.5% |
| 2 | 32 | 39.2% | 44.3% | 6 | 38.8% | 47.7% |
| 3 | 14 | 38.9% | 67.1% | 6 | 32.8% | 66.2% |
| 4 | 42 | 69.0% | 24.2% | 7 | 69.3% | 23.8% |
| 5 | 199 | 64.8% | 42.9% | 33 | 60.2% | 45.4% |
| 6 | 28 | 61.0% | 66.6% | 4 | 62.1% | 69.1% |
| 7 | 13 | 84.7% | 22.3% | 2 | 90.5% | 18.8% |
| 8 | 27 | 85.3% | 42.8% | 8 | 85.0% | 43.3% |
| **Total** | **362** | **63.7%** | **42.5%** | **70** | **60.9%** | **44.1%** |

***Sampling probabilities***

The sampling probabilities were calculated as the product of two probabilities and an adjustment factor. The first was the probability for a village, given its stratum, to be in the sample. The second was the probability for a household, given the village (and the number of households in the village), to be in the sample. The adjustment factor was chosen such that the products would sum to 2,093, the number of households whose household codes in the CCR and baseline survey tables matched. Since the probabilities do not vary within a village, those for the 7 other sample members were subsequently assigned after matching these probabilities to the CCR data table (similarly, the village-level baseline covariates of interest were assigned whereas the baseline household-level covariates could not). Thus sampling weights thus became computable for all 2,100 sample members.

```
.  des  IsInSampleVillage  IsInCCRsample  villagecodetag  households2  stratumcomb2tag
villbystratcomb2 samplevillbystratcomb2 pVillInSample2 pHHInVillQuota2 pHHInSample2adj

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------------------
IsInSampleVil~e float  %9.0g                  Household is in a sample village
IsInCCRsample   byte   %8.0g                  Household is in the sample
villagecodetag  byte   %8.0g                  tag(villagecode)
households2     float  %9.0g                  Households, as counted in HH level table
stratumcomb2tag byte   %8.0g                  tag(stratumcombtag)
villbystratco~2 float  %9.0g                  Villages by stratum, from all 362 villages
samplevillbys~2 float  %9.0g                  Sample villages, by stratum
pVillInSample2  float  %9.0g                  Prob village is in sample, by stratum
pHHInVillQuota2 float  %9.0g                  Prob HH in sample in given sample village
pHHInSample2adj float  %9.0g                  Prob HH in sample, adj. to sum to 2,093
-------------------------------------------------------------------------------------------
```

**Villages per stratum**

In the frame

```
. summ villbystratcomb2 if stratumcomb2tag

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
villbystra~2 |         8       45.25    63.17267          7        199
```

In the sample

```
. summ samplevillbystratcomb2 if stratumcomb2tag & IsInSampleVillage

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
samplevill~2 |         8        8.75    9.982127          2         33
```

**Households per village**

In the frame

```
. summ households2 if villagecodetag

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
 households2 |       362    166.0746    95.27367         26        787
```

In the sample

```
. summ households2 if villagecodetag & IsInSampleVillage

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
 households2 |        70       187.1    138.1647         38        787
```

**Probabilities**

For the village to be selected

```
. summ pVillInSample2 if stratumcomb2tag [Mean by stratum]

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pVillInSam~2 |         8    .2641244     .157848   .1428571   .5714286

. summ pVillInSample2 if villagecodetag [mean by village]

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pVillInSam~2 |       362    .1933702    .0804205   .1428571   .5714286
```

[Obviously, 362* 0.19337 = 70]

For the household to be selected, given the village, sample only

```
. summ pHHInVillQuota2 if  IsInSampleVillage

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pHHInVillQ~2 |     13097    .1598076    .0956859   .0381194   .7894737
```

For the households to be in the sample

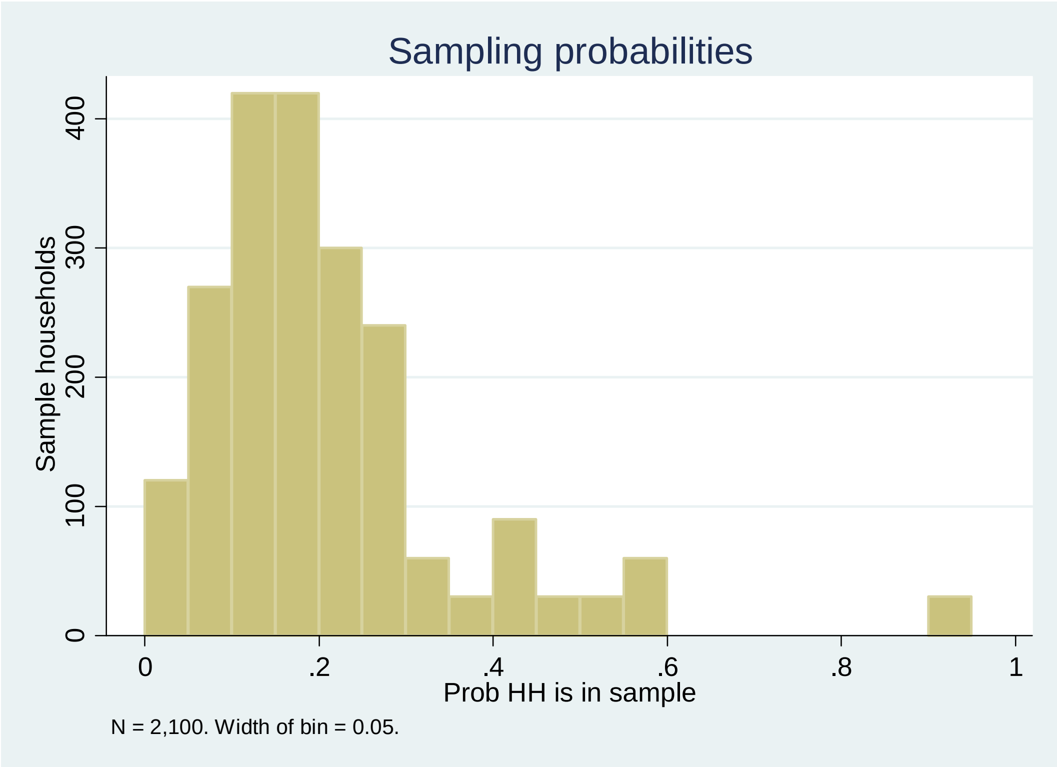
Frame

```
. summ pHHInSample2adj

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pHHInSampl~j |     60119    .0348143    .0899059          0   .9106646
```

Sample only (sample members with recognized household code)

```
. summ pHHInSample2adj if IsInCCRsample

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
pHHInSampl~j |      2093    .2134041    .1479633   .0278715   .9106646
```

Histogram, incl. the six households with assigned probabilities




with one outlier village:

```
. list District Upazila Union Village villbystratcomb2 samplevillbystratcomb2 households2
if villagetag & pHHInSample2adj > 0.8, noobs

  +-----------------------------------------------------------------------------------+
  |  District    Upazila         Union        Village   villby~2   sample~2   househ~2 |
  |-----------------------------------------------------------------------------------|
  | Sunamganj   Tahirpur   Uttar Badal   Maharam Tila          7          4         83 |
  +-----------------------------------------------------------------------------------+
```

### *Sampling weights and survey analysis settings*

#### Weights

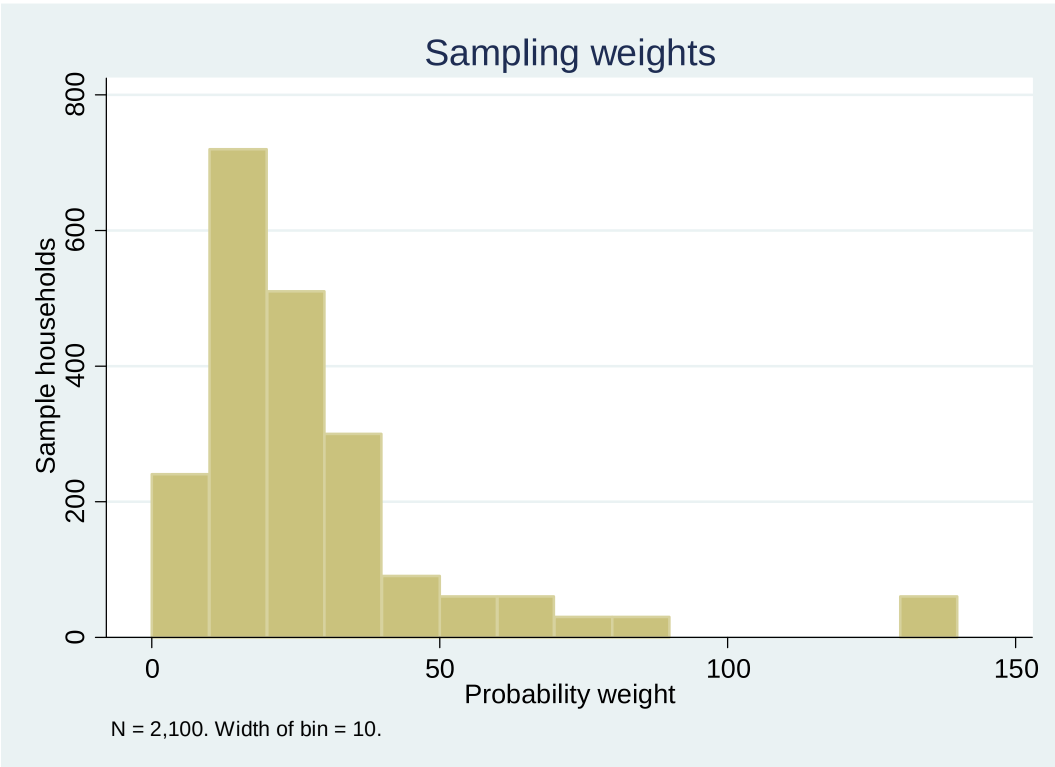
The sampling weights ("probability weights" means the same) are calculated as the product of

1. the inverse of the sampling probabilities and
2. an adjustment factor, such that

the weights sum to the population, the 60,119 households of the baseline surveys:

```
. des pweight

              storage  display     value
variable name   type   format      label      variable label
-----------------------------------------------------------------------------------------
pweight         float  %9.0g                  Probability weight

. summ pweight

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
     pweight |      2100     28.6281    24.62613   4.247218   138.7721

. di r(N) * r(mean)
60119.001
```

Histogram:




with a list of these sample villages with extreme values: in these villages one sample household represents either:

fewer than 10 population households, or
more than 70:

```
. list District Upazila Union Village pweight if villagetag & (pweight < 10 | pweight >
70), noobs sep(0)

  +------------------------------------------------------------------------------+
  |     District        Upazila            Union              Village    pweight |
  |------------------------------------------------------------------------------|
  |    Sunamganj       Tahirpur      Uttar Badal         Maharam Tila   4.247218 |
  |     Habiganj      Madhabpur          Noapara   Shahapur (Dakshin)   6.549926 |
  |       Sylhet   Sylhet Sadar      Khadimnagar            Hana Para    6.70056 |
  |     Habiganj     Baniachong         Makrampur             Kabilpur   7.675694 |
  |  Maulvibazar       Barlekha         Barlekha          Satkarakandi   8.392093 |
  | Brahmanbaria     Nasirnagar            Kunda     Mahishber Paschim   8.801463 |
  |  Maulvibazar       Barlekha   Nij Bahadurpur       Purba Maijgram   8.893219 |
  |  Maulvibazar       Rajnagar         Rajnagar             Moshoriya   9.572688 |
  |------------------------------------------------------------------------------|
  | Brahmanbaria     Nasirnagar        Burishwar              Ashurail     77.371 |
  |       Sylhet       Zakiganj        Sultanpur             Sayedabad   80.85065 |
  | Brahmanbaria     Nasirnagar       Nasirnagar             Dantmandal   135.5982 |
  | Brahmanbaria     Nasirnagar        Burishwar             Burishwar   138.7721 |
  +------------------------------------------------------------------------------+
```

## Survey design settings

Setting used for most survey estimates:

```
. . svyset villageenc [pw = pweight], strata(stratumcomb2) fpc( villbystratcomb2)  ||  _n

      pweight: pweight
          VCE: linearized
  Single unit: missing
     Strata 1: stratumcomb2
         SU 1: villageenc [i.e., the encoded version of the village variable]
        FPC 1: villbystratcomb2
     Strata 2: <one>
         SU 2: <observations>
        FPC 2: <zero>

                                          #Obs per Unit
                                  ----------------------------
Stratum    #Units     #Obs      min       mean      max
--------  --------  --------  --------  --------  --------
       1         4       120        30      30.0        30
       2         6       180        30      30.0        30
       3         6       180        30      30.0        30
       4         7       210        30      30.0        30
       5        33       990        30      30.0        30
       6         4       120        30      30.0        30
       7         2        60        30      30.0        30
       8         8       240        30      30.0        30
--------  --------  --------  --------  --------  --------
       8        70      2100        30      30.0        30
```

As mentioned earlier, the within-village clustering was not documented. These settings go directly from the village as the primary sampling unit to the sample household.

We used another setting exceptionally for models that balance the sample between a treatment group (households with livelihood training) and a control group (those without training) on baseline annual income and education. The weights in this setting are the product of the Coarsened Exact Matching weights (Blackwell, Iacus et al. 2009) and the original probability weights, adjusted, as before, so that they sum to 60,119, the number of households in the 362 baseline villages.

```
. des probcemweights

              storage  display     value
variable name   type   format      label      variable label
-----------------------------------------------------------------------------------------
probcemweights  float  %9.0g                  Probability weights adjusted for CEM weights

. summ probcemweights

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
probcemwei~s |      2100     28.6281    27.45645          0   227.3348

. di r(N) * r(mean)
60119

. count if probcemweights==0
   46
```

with 46 observations lost due to matching problems.

Design setting:

```
. svyset villageenc [pw = probcemweights ]  || _n
Note: stage 1 is sampled with replacement; all further stages will be ignored

      pweight: probcemweights
          VCE: linearized
  Single unit: missing
     Strata 1: <one>
         SU 1: villageenc
        FPC 1: <zero>
```

without strata or finite population correction.

## Descriptive statistics for some variables of interest

### *Household, at baseline*

```
. des econstatusenc IncAnnualCPIadjLog10 YSchoolHighestInHH IsMaleHHhead ageHHhead

              storage  display     value
variable name   type   format      label      variable label
------------------------------------------------------------------------------------
econstatusenc   long   %14.0g      econstatusenc
                                              Poverty rank
IncAnnualCPI~10 float  %9.0g                  Annual household income (log10) (adj.
                                                for 1 year betw. the 2 surveys)
YSchoolHighes~H float  %9.0g                  Maximum years of schooling among
                                                household members
IsMaleHHhead    byte   %8.0g                  Household head is male (=1, female = 0)
ageHHhead       int    %8.0g                  Age of the household head

. summ econstatusenc IncAnnualCPIadjLog10 YSchoolHighestInHH IsMaleHHhead ageHHhead

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
IncAnnualC~0 |      2079      4.7889     .293082   3.439541   6.982271
YSchoolHig~H |      2074    6.059788    3.695513          0         17
IsMaleHHhead |      2074    .9585342     .199413          0          1
   ageHHhead |      2074    44.29171    14.28324         14        110
-------------+--------------------------------------------------------
```

and

```
. tab econstatusenc

  Poverty rank |      Freq.     Percent        Cum.
---------------+-----------------------------------
        1-Rich |        254       12.10       12.10
2-Middle class |        551       26.24       38.33
        3-Poor |        949       45.19       83.52
  4-Ultra poor |        346       16.48      100.00
---------------+-----------------------------------
         Total |      2,100      100.00
```

The maximum number of years of schooling among household members was calculated using the household member data tables in the baseline surveys. In some models a recoded version was used:

```
. des YSchHHmaxCateg

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------
YSchHHmaxCateg  byte   %17.0g      YSchHHmaxCateg
                                              Highest years of schooling among HH
                                                members

. tab YSchHHmaxCateg

 Highest years of |
  schooling among |
       HH members |      Freq.     Percent        Cum.
------------------+-----------------------------------
Less than 5 years |        634       30.57       30.57
     5 to 8 years |        874       42.14       72.71
  9 years or more |        566       27.29      100.00
------------------+-----------------------------------
            Total |      2,074      100.00
```

### *Village, at baseline*

```
. des povertyrate literacyrate

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------
povertyrate     double %10.0g                 Poverty rate in the village (from
                                                table all villages)
literacyrate    double %10.0g                 Literacy rate in the village (from
                                                table all villages)

. summ povertyrate literacyrate if villagetag

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
 povertyrate |        70    59.80797    17.98545       6.25   94.14226
literacyrate |        70    44.31378    15.65584   8.333333   87.48044
```

### *Household, in the 2013 survey*

```
. des CLCMembership crenc improved IsLEPtrainee IsLEPtraineeIGA IsLEPtraineeAny

              storage  display     value
variable name   type   format      label      variable label
-------------------------------------------------------------------------------
CLCMembership   byte   %8.0g                  Is a member of the local CLC
crenc           long   %23.0g      crenc      Change rank (encoded)
improved        float  %9.0g                  Condition of the household improved
IsLEPtrainee    byte   %8.0g                  LEP trainee
IsLEPtraineeIGA float  %4.2f                  LEP trainee in livelihood skills
IsLEPtraineeAny byte   %8.0g                  LEP trainee, any type

. summ CLCMembership crenc improved IsLEPtrainee IsLEPtraineeIGA IsLEPtraineeAny

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
CLCMembers~p |      2100    .8319048    .3740399          0          1
    improved |      2100    .6214286    .4851466          0          1
IsLEPtrainee |      2100    .4895238    .5000093          0          1
IsLEPtrain~A |      2100    .3695238    .4827908          0          1
IsLEPtrain~y |      2100    .4895238    .5000093          0          1
-------------+--------------------------------------------------------
```

and

```
. tab crenc

  Change rank (encoded) |      Freq.     Percent        Cum.
------------------------+-----------------------------------
        1-Improved a lot |        194        9.24        9.24
     2-Improved slightly |      1,111       52.90       62.14
             3-Unchanged |        119        5.67       67.81
 4-Deteriorated slightly |        542       25.81       93.62
    5-Deteriorated a lot |        134        6.38      100.00
------------------------+-----------------------------------
                   Total |      2,100      100.00
```

In the following section, we present only a small segment of the models investigated in this research.

## A selection of models used

### *Cluster analysis for household types*

Cluster analyses do not take probability weights. We employed a Ward's linkage model with the Jaccard measure. Ward's method has been recommended for binary data. The Jaccard measure seems especially suited in data situations where for most cross-tabulations of two binary variables the case of both being zero is the most frequent (Jaccard does not include this count in the denominator).

```
. des rsubjval3 rsubjval4 rsubjval5 rsubjval6 rsubjval7 rsubjval8 rsubjval9 rsubjval10
rsubjval11 rsubjval12 rsubjval13 rsubjval14 rsubjval15 rsubjval16 rsubjval17 rsubjval25
rsubjval26

              storage  display     value
variable name   type   format      label      variable label
-----------------------------------------------------------------------------------------
rsubjval3       byte   %8.0g                  Clothing_1-Negative
rsubjval4       byte   %8.0g                  Clothing_2-Neutral
rsubjval5       byte   %8.0g                  Clothing_3-Positive
rsubjval6       byte   %8.0g                  Education_1-Negative
rsubjval7       byte   %8.0g                  Education_3-Positive
rsubjval8       byte   %8.0g                  FamilySituat_1-Negative
rsubjval9       byte   %8.0g                  FamilySituat_3-Positive
rsubjval10      byte   %8.0g                  Food_1-Negative
rsubjval11      byte   %8.0g                  Food_2-Neutral
rsubjval12      byte   %8.0g                  Food_3-Positive
rsubjval13      byte   %8.0g                  Health_1-Negative
rsubjval14      byte   %8.0g                  Health_3-Positive
rsubjval15      byte   %8.0g                  Housing_1-Negative
rsubjval16      byte   %8.0g                  Housing_2-Neutral
rsubjval17      byte   %8.0g                  Housing_3-Positive
rsubjval25      byte   %8.0g                  Lifestyle_1-Negative
rsubjval26      byte   %8.0g                  Lifestyle_3-Positive
```

[The frequencies are given in the main text body.]

```
. cluster wardslinkage rsubjval3 rsubjval4 rsubjval5 rsubjval6 rsubjval7 rsubjval8
rsubjval9 rsubjval10 rsubjval11 rsubjval12 rsubjval13 rsubjval14 rsubjval15 rsubjval16
rsubjval17 rsubjval25 rsubjval26  rsubjval1 rsubjval2 rsubjval18 rsubjval19 rsubjval20
rsubjval22 rsubjval23 rsubjval24 rsubjval27 rsubjval28 , measure(Jaccard) name(combined2)
```

```
. cluster stop

+---------------------------+
|             |  Calinski/  |
|  Number of  |  Harabasz   |
|  clusters   |  pseudo-F   |
|-------------+-------------|
|      2      |   557.15    |
|      3      |   385.48    |
|      4      |   299.67    |
|      5      |   256.77    |
|      6      |   218.58    |
|      7      |   205.51    |
|      8      |   187.63    |
|      9      |   173.34    |
|     10      |   164.55    |
|     11      |   157.55    |
|     12      |   149.47    |
|     13      |   140.13    |
|     14      |   135.44    |
|     15      |   131.35    |
+---------------------------+

. cluster gen cls = gr(2 3 4 5 6 7 8)

. renvars cls?, postf(combined)
```

As before, we first settled on a six-cluster solution, then, after inspection, combined two of the clusters.

```
. gen cls6combInto5 = cls6combined

. replace cls6combInto5 = cls6combInto5 - 1 if cls6combInto5 > 2
(1435 real changes made)

. tab cls6combInto5

cls6combInt |
         o5 |      Freq.     Percent        Cum.
------------+-----------------------------------
          1 |        501       23.86       23.86
          2 |        438       20.86       44.71
          3 |        383       18.24       62.95
          4 |        610       29.05       92.00
          5 |        168        8.00      100.00
------------+-----------------------------------
      Total |      2,100      100.00
```

Association with the change rank:

```
. tab crenc cls6combInto5, gamma

                      |                     cls6combInto5
Change rank (encoded) |         1          2          3          4          5 |     Total
----------------------+-------------------------------------------------------+----------
     1-Improved a lot |       107         58         28          1          0 |       194
  2-Improved slightly |       377        373        352          5          4 |     1,111
          3-Unchanged |        13          6          2         97          1 |       119
4-Deteriorated slight |         4          1          1        401        135 |       542
 5-Deteriorated a lot |         0          0          0        106         28 |       134
----------------------+-------------------------------------------------------+----------
                Total |       501        438        383        610        168 |     2,100

                    gamma =   0.8714  ASE = 0.010
```

### *Coarsened exact matching, to control for differential access to training*

Coarsened exact matching reweights the observations of a control group so that treatment and control group are balanced on variables important for comparability (Blackwell, Iacus et al. 2009: op.cit.). We used this facility to balance on baseline wealth and education. Instead of the categorical wealth rank, we used the information-richer annual household income (in its logarithmic version). Between the two baseline surveys, roughly a year elapsed; we adjust the earlier of the survey members' income by the CPI factor.

```
. des IncAnnualCPIadjLog10 YSchoolHighestInHH

              storage  display     value
variable name   type   format      label      variable label
--------------------------------------------------------------------------------
IncAnnualCPI~10 float  %9.0g                  Annual household income (log10)
                                                (adj. for 1 year betw. the 2
                                                surveys)
YSchoolHighes~H float  %9.0g                  Maximum years of schooling among
                                                household members

. summ IncAnnualCPIadjLog10 YSchoolHighestInHH

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
IncAnnualC~0 |      2079      4.7889     .293082   3.439541   6.982271
YSchoolHig~H |      2074    6.059788    3.695513          0         17
```

Matching:

```
. cem IncAnnualCPIadjLog10 YSchoolHighestInHH, treatment( IsLEPtraineeIGA) showbreaks
(using the  break method for imbalance)

Cutpoints:
IncAnnualCPIadjLog10: (sturges)
                  1
     +---------------+
   1 |  3.439541101  |
   2 |  3.734768609  |
   3 |  4.029996117  |
   4 |  4.325223625  |
   5 |  4.620451132  |
   6 |   4.91567864  |
   7 |  5.210906148  |
   8 |  5.506133656  |
   9 |  5.801361163  |
  10 |  6.096588671  |
  11 |  6.391816179  |
  12 |  6.687043687  |
  13 |  6.982271194  |
     +---------------+
YSchoolHighestInHH: (sturges)
                  1
     +---------------+
   1 |            0  |
   2 |  1.416666667  |
   3 |  2.833333333  |
   4 |         4.25  |
   5 |  5.666666667  |
   6 |  7.083333333  |
   7 |          8.5  |
   8 |  9.916666667  |
   9 |  11.33333333  |
  10 |        12.75  |
  11 |  14.16666667  |
  12 |  15.58333333  |
  13 |           17  |
     +---------------+
```

It can be seen that each variable was cut into slices of equal thickness. For a count variable like years of schooling, this may be correct, but not intuitive. What are 1.4166 years of schooling? In the end, 87 CEM strata were generated:

```
Matching Summary:
-----------------
Number of strata: 87
Number of matched strata: 58

              0     1
      All  1324   776
  Matched  1281   773
Unmatched    43     3


Multivariate L1 distance: .20974174
```

```
Univariate imbalance:

                  L1     mean      min      25%      50%      75%      max
IncAnnualC~0  .07925  .00033  .30103        0        0  .01773        .
YSchoolHig~H  .01479  .00205        0        0        0        0        .
```

which produces three new variables:

```
. des cem_*

              storage  display     value
variable name   type   format      label      variable label
-----------------------------------------------------------------------------------
cem_strata      int    %8.0g                  Coarsened exact matching stratum
cem_matched     double %10.0g                 Matched by coarsened exact matching
cem_weights     double %10.0g                 Coarsened exact matching weight

. summ cem*

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
  cem_strata |      2100     48.4719    13.29486          1         87
 cem_matched |      2100    .9780952    .1464075          0          1
 cem_weights |      2100    .9780952    .3228461          0   4.971539
```

To illustrate with the first six strata:

```
. table cem_strata IsLEPtraineeIGA if cem_strata < 7 , c(freq mean cem_weights)

--------------------------------
Coarsened |
exact     |
matching  |  LEP trainee in IGA
stratum   |      0          1
----------+---------------------
        1 |          3          5
          | 2.7619664          1
          |
        2 |          1
          |          0
          |
        3 |                     1
          |                     0
          |
        4 |          2
          |          0
          |
        5 |          2          1
          |  .82858991          1
          |
        6 |          2          1
          |  .82858991          1
--------------------------------
```

where the upper number in a cell is the number of observations, the second is the CEM weight. As one can see, where there is no observation either in the control or the treatment group, the weight is set to zero. Observations in the control group in stratum 1 are weighted upwards, in strata 5 and 6 downwards.

```
. tab cem_matched

 Matched by |
  coarsened |
      exact |
   matching |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |         46        2.19        2.19
          1 |      2,054       97.81      100.00
------------+-----------------------------------
      Total |      2,100      100.00
```

with 46 observations lost for models using the weights based on the CEM weights. These were already noted before, in the segment on probability weights:

```
. des probcemweights

              storage  display     value
variable name   type   format      label      variable label
---------------------------------------------------------------------------
probcemweights  float  %9.0g                  Probability weights adjusted
                                                for CEM weights
```

Example of a model using these weights: The difference in the proportion of households with improved conditions, by livelihood training status:

```
. svy: mean improved, over(IsLEPtraineeIGA)
(running mean on estimation sample)

Survey: Mean estimation

Number of strata =       1          Number of obs    =    2100
Number of PSUs   =      70          Population size  =   60119
                                    Design df        =      69

            0: IsLEPtraineeIGA = 0
            1: IsLEPtraineeIGA = 1

--------------------------------------------------------------
             |             Linearized
        Over |       Mean   Std. Err.     [95% Conf. Interval]
-------------+------------------------------------------------
improved     |
           0 |   .6139822   .0324218      .5493024     .678662
           1 |   .6917539    .029794      .6323164    .7511914
--------------------------------------------------------------

. lincom [improved]1 - [improved]0

 ( 1)  - [improved]0 + [improved]1 = 0

------------------------------------------------------------------------------
        Mean |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         (1) |   .0777716   .0287364     2.71   0.009     .0204442    .1350991
------------------------------------------------------------------------------
```

where .07777 stands for the 8-percent difference discussed in the main text. This estimate is robust to differences in income and education between trainee and other households.

### *Simultaneous estimation of training access and impact*

Access to, and impact of, livelihood training was simultaneously modeled using endogenous switch regression. STATA's *ssm* (Miranda and Rabe-Hesketh 2006) offers such estimators for binary, ordinal, and count variables. Unfortunately, although the help file says that probability weights are allowed, this is not the case in practice; our results, therefore, are valid on simple random sample assumptions only. Since our sample is not simply random, the extent of bias and standard error distortion in the results is unknown.

```
. des improved revcrenc IsLEPtraineeIGA iEconStatus1 iEconStatus2 iEconStatus3 YSchHHmax5To8 YSchHHmaxMoreT8 School_Village TrainIgaXschoolVill
```

```
                  storage  display     value
variable name     type     format      label      variable label
------------------------------------------------------------------------------------------------
improved          float    %9.0g                  [binary:] Condition of the household improved
revcrenc          byte     %23.0g      revcrenc   [ordinal:] Change rank (encoded) [reverse encoding]

IsLEPtraineeIGA   float    %4.2f                  LEP trainee in IGA
TrainIgaXscho~l   byte     %8.0g                  Household had livelihood training and is in an
                                                    FIVDB school village
iEconStatus1      byte     %8.0g                  EconStatus==1-Rich
iEconStatus2      byte     %8.0g                  EconStatus==2-Middle class
iEconStatus3      byte     %8.0g                  EconStatus==3-Poor
YSchHHmax5To8     byte     %8.0g                  Highest years of schooling among HH members: 5 to 8
YSchHHmaxMoreT8   byte     %8.0g                  Highest years of schooling among HH members: More than 8
School_Village    byte     %8.0g                  FIVDB school village
TrainIgaXscho~l   byte     %8.0g                  Household had livelihood training and is in an
                                                    FIVDB school village [interaction term]
------------------------------------------------------------------------------------------------
```

```
. summ improved IsLEPtraineeIGA iEconStatus1  iEconStatus2 iEconStatus3 YSchHHmax5To8 YSchHHmaxMoreT8
School_Village TrainIgaXschoolVill

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
    improved |      2100    .6214286    .4851466          0          1
IsLEPtrain~A |      2100    .3695238    .4827908          0          1
iEconStatus1 |      2100    .1209524    .3261496          0          1
iEconStatus2 |      2100     .262381    .4400334          0          1
iEconStatus3 |      2100    .4519048       .4978          0          1
YSchHHmax5~8 |      2100    .4161905    .4930433          0          1
YSchHHmaxM~8 |      2100    .2695238    .4438181          0          1
School_Vil~e |      2100    .5428571    .4982785          0          1
TrainIgaXs~l |      2100    .2152381    .4110853          0          1
-------------+---------------------------------------------------------
```

Note that *Ultra-poor* for wealth rank and *Highest years of schooling among household members: 0 to 4* for education are not listed among these model variables. Here they are the reference categories of these categorical variables, i.e. they are not entered in the estimation command, to avoid linear dependency. All variables are binary.

The ordinal version of the dependent variable has been reverse-encoded for more intuitive positive model coefficients. Substantively, the recoding does not matter:

```
. label list revcrenc
revcrenc:
           1 5-Deteriorated a lot
           2 4-Deteriorated slightly
           3 3-Unchanged
           4 2-Improved slightly
           5 1-Improved a lot

. tab revcrenc

  Change rank (encoded) |      Freq.     Percent        Cum.
------------------------+-----------------------------------
   5-Deteriorated a lot |        134        6.38        6.38
4-Deteriorated slightly |        542       25.81       32.19
            3-Unchanged |        119        5.67       37.86
     2-Improved slightly |      1,111       52.90       90.76
        1-Improved a lot |        194        9.24      100.00
------------------------+-----------------------------------
                  Total |      2,100      100.00
```

**Dependent variable binary**

```
. ssm improved IsLEPtraineeIGA TrainIgaXschoolVill iEconStatus1 iEconStatus2 iEconStatus3
YSchHHmax5To8 YSchHHmaxMoreT8 School_Village , switch(IsLEPtraineeIGA = iEconStatus1
iEconStatus2 iEconStatus3 YSchHHmax5To8 YSchHHmaxMoreT8 School_Village ) robust
family(binomial) link(logit)
```

```
Endogenous Switch Logit Regression (6 quadrature points)

                                                    Number of obs  =      2100
                                                    Wald chi2(14)   =    328.80
Log likelihood = -2699.6414                         Prob > chi2    =    0.0000

------------------------------------------------------------------------------
         improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------
improved           |
   IsLEPtraineeIGA |     .83155   .0855875     9.72   0.000     .6638015    .9992984
TrainIgaXschoolV~l |   .0493114   .1136121     0.43   0.664    -.1733642    .2719871
      iEconStatus1 |   .6032537   .1364866     4.42   0.000     .3357449    .8707626
      iEconStatus2 |   .1390272   .0897508     1.55   0.121    -.0368813    .3149356
      iEconStatus3 |   .1053857   .0787979     1.34   0.181    -.0490554    .2598268
     YSchHHmax5To8 |   .1407057   .0704586     2.00   0.046     .0026094     .278802
   YSchHHmaxMoreT8 |    .424774   .1010309     4.20   0.000     .2267571    .6227909
    School_Village |   .1741391   .0755507     2.30   0.021     .0260624    .3222158
             _cons |  -.4335868   .0895063    -4.84   0.000    -.6090159   -.2581577
-------------------+----------------------------------------------------------
switch             |
      iEconStatus1 |  -.2718989    .111582    -2.44   0.015    -.4905956   -.0532022
      iEconStatus2 |  -.0638367   .0894459    -0.71   0.475    -.2391473     .111474
      iEconStatus3 |  -.1874669    .080597    -2.33   0.020     -.345434   -.0294997
     YSchHHmax5To8 |   .1035062    .067206     1.54   0.124    -.0282151    .2352274
   YSchHHmaxMoreT8 |   .2526435   .0780901     3.24   0.001     .0995898    .4056972
    School_Village |   .1624145   .0566363     2.87   0.004     .0514094    .2734195
             _cons |  -.4024981   .0847205    -4.75   0.000    -.5685473   -.2364489
-------------------+----------------------------------------------------------
               rho |    -.39876   .0744184    -5.36   0.000    -.5118409   -.2134397
------------------------------------------------------------------------------
Likelihood ratio test for rho=0: chi2(1)= 0.00 Prob>=chi2 = 1.000
Robust Standard Errors presented.
```

The interaction term was not used in the switching equation. Rich and poor households accessed trainings significantly less often than the ultra-poor did; households in the highest education bracket significantly more than the lowest group; households in FIVDB school villages more than those in non-school villages.

#### Dependent variable ordinal

Some readers may wonder why, for the model presented in the main text, we did not take advantage of *ssm*'s ordinal regression feature. This would make use of the much richer information in the change rank, compared to the simple "improved or not". We present output from such a model here. As one can see, the point estimate for the training coefficient is larger than that for "being rich rather than ultra-poor" (iEconStatus1). However, it is no longer significantly larger than zero. Moreover, *rho* has become completely unstable, and the confidence intervals of some of the auxiliary cut level variables overlap.

The root cause for this instability plausibly is the low frequency of three of the five change ranks.

```
. ssm revcrenc IsLEPtraineeIGA TrainIgaXschoolVill iEconStatus1 iEconStatus2 iEconStatus3
YSchHHmax5To8 YSchHHmaxMoreT8 School_Village , switch(IsLEPtraineeIGA = iEconStatus1
iEconStatus2 iEconStatus3 YSchHHmax5To8 YSchHHmaxMoreT8 School_Village ) robust
family(binomial) link(ologit)
```

```
Endogenous Switch Ordered Logit Regression
(6 quadrature points)

                                                     Number of obs  =     2100
                                                     Wald chi2(14)   =   204.07
Log likelihood = -3906.409                           Prob > chi2    =   0.0000

------------------------------------------------------------------------------------
           revcrenc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
revcrenc            |
    IsLEPtraineeIGA |   .6694048   .7443118     0.90   0.368    -.7894195    2.128229
TrainIgaXschoolVill |   .0746814   .1032635     0.72   0.470    -.1277112    .2770741
       iEconStatus1 |   .5926843   .1279047     4.63   0.000     .3419958    .8433729
       iEconStatus2 |   .2137429   .0973771     2.20   0.028     .0228873    .4045985
       iEconStatus3 |   .1450044   .1083429     1.34   0.181    -.0673439    .3573527
      YSchHHmax5To8 |   .1096941   .0755713     1.45   0.147     -.038423    .2578112
    YSchHHmaxMoreT8 |   .4134624   .1412451     2.93   0.003     .1366271    .6902976
     School_Village |   .1523209   .0650926     2.34   0.019     .0247416    .2799001
--------------------+---------------------------------------------------------------
switch              |
       iEconStatus1 |  -.2707036   .1113208    -2.43   0.015    -.4888883   -.0525189
       iEconStatus2 |  -.0664655   .0896837    -0.74   0.459    -.2422424    .1093114
       iEconStatus3 |  -.1874928   .0805441    -2.33   0.020    -.3453563   -.0296293
      YSchHHmax5To8 |   .1027602   .0683086     1.50   0.132    -.0311223    .2366427
    YSchHHmaxMoreT8 |   .2511989    .079079     3.18   0.001      .096207    .4061908
     School_Village |   .1646722     .05751     2.86   0.004     .0519547    .2773897
              _cons |    -.40161   .0848214    -4.73   0.000    -.5678568   -.2353632
--------------------+---------------------------------------------------------------
aux_revcrenc        |
              _cut1 |  -.8794397   .3860002    -2.28   0.023    -1.635986   -.1228932
              _cut2 |   .2340562   .2823114     0.83   0.407     -.319264    .7873764
              _cut3 |   .3853513    .280175     1.38   0.169    -.1637816    .9344842
              _cut4 |   2.061452   .2091819     9.85   0.000     1.651463    2.471441
--------------------+---------------------------------------------------------------
                rho |   -.309985   .4404911    -0.70   0.482    -.6421651    .5420729
------------------------------------------------------------------------------------
Likelihood ratio test for rho=0: chi2(1)= 0.00 Prob>=chi2 = 1.000
Robust Standard Errors presented.
```

### *Tests of nonlinear combinations of estimators*

Going back to the model with the binary dependent variable:

The key of the model is the fact that the effect of training persists in positive and highly significant way in the presence of the other factors. In the interpretation, we scaled this and other effects to the effect of being rich (rather than ultra-poor) on improving one's conditions. The ratios are based on these tests using STATA's *nlcom*:

**Trainee household vs. being rich**

```
. nlcom ([improved]IsLEPtraineeIGA  / [improved]iEconStatus1)

       _nl_1:  [improved]IsLEPtraineeIGA  / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   1.378441   .3481459     3.96   0.000      .696088    2.060795
------------------------------------------------------------------------------
```

**Interaction of training and FIVDB school village vs. being rich**

```
. nlcom ([improved]TrainIgaXschoolVill   / [improved]iEconStatus1)

       _nl_1:  [improved]TrainIgaXschoolVill   / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .0817424   .1883479     0.43   0.664    -.2874126    .4508975
------------------------------------------------------------------------------
```

**Being middle-class vs. being rich**

```
. nlcom ([improved]iEconStatus2  / [improved]iEconStatus1)

       _nl_1:  [improved]iEconStatus2  / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2304621   .1295234     1.78   0.075    -.0233991    .4843234
------------------------------------------------------------------------------
```

**Being poor vs. being rich**

```
. nlcom ([improved]iEconStatus3  / [improved]iEconStatus1)

       _nl_1:  [improved]iEconStatus3  / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .1746955   .1155045     1.51   0.130    -.0516891    .4010801
------------------------------------------------------------------------------
```

**Being in an FIVDB school village vs. being rich**

```
. nlcom ([improved]School_Village  / [improved]iEconStatus1)

       _nl_1:  [improved]School_Village  / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2886665   .1244074     2.32   0.020     .0448324    .5325005
------------------------------------------------------------------------------
```

**Highest educated HH member has 5 to 8 years of education vs. being rich**

```
. nlcom ([improved]YSchHHmax5To8  / [improved]iEconStatus1)

       _nl_1:  [improved]YSchHHmax5To8  / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .2332446   .1202069     1.94   0.052    -.0023566    .4688458
------------------------------------------------------------------------------
```

**Highest educated HH member has more than 8 years of education vs. being rich**

```
. nlcom ([improved]YSchHHmaxMoreT8  / [improved]iEconStatus1)

       _nl_1:  [improved]YSchHHmaxMoreT8  / [improved]iEconStatus1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .7041382   .2160424     3.26   0.001     .2807029    1.127573
------------------------------------------------------------------------------
```

The first of those tests established the claim that the best estimate of the training effect was 138 percent of the effect of being rich. This and the confidence interval [70%, 206%] are discussed in the main body. Some readers may be under the impression that the training effect is significantly larger than the wealth effect. To refute this, it is enough to subtract one from the ratio and run the test again:

```
. nlcom ([improved]IsLEPtraineeIGA  / [improved]iEconStatus1 - 1)

       _nl_1:  [improved]IsLEPtraineeIGA  / [improved]iEconStatus1 - 1

------------------------------------------------------------------------------
    improved |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |   .3784415   .3481459     1.09   0.277     -.303912    1.060795
------------------------------------------------------------------------------
```

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