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What Is Behind the Decline in Poverty Since 2000?

Evidence from Bangladesh, Peru and Thailand

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Abstract

This paper quantifies the contributions of different factors to poverty reduction observed in Bangladesh, Peru and Thailand over the last decade. In contrast to methods that focus on aggregate summary statistics, the method adopted here generates entire counterfactual distributions to account for the contributions of demographics and income from labor and non-labor sources in explaining poverty reduction. The authors find that the most important contributor was the growth in labor income, mostly in the form of farm income in Bangladesh and Thailand and non-farm income in the case of Peru. This growth in labor incomes was driven by higher returns to individual and household endowments, pointing to increases in productivity and real wages as the driving force behind poverty declines. Lower dependency ratios also helped to reduce poverty, particularly in Bangladesh. Non-labor income contributed as well, albeit to a smaller extent, in the form of international remittances in the case of Bangladesh and through public and private transfers in Peru and Thailand. Transfers are more important in explaining the reduction in extreme compared with moderate poverty.

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WHAT IS BEHIND THE DECLINE IN POVERTY SINCE 2000?

EVIDENCE FROM BANGLADESH, PERU AND THAILAND

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1. Introduction

Despite the global financial crisis, the incidence and depth of poverty has fallen in the majority of countries over the past decade, whether one uses national or international poverty lines.[1] What are the factors behind the observed poverty and distributional changes? Was the reduction in poverty a result of higher employment, higher productivity or higher transfers from public or private sources? Was it the result of changes in the sector composition of employment? Were these changes the result of improved human capital characteristics or higher returns to those characteristics?

Answers to these questions can contribute to the evidence base for policy going forward. For example, in some countries in Latin America there is a debate around whether the reduction in poverty and inequality over the last decade can be attributed to better job opportunities or to the expansion of more effective transfer policies. Was Brazil's success in reducing poverty and inequality despite modest growth due to the availability of better jobs or thanks to social policies? In South Asia, some question whether the reduction in poverty was on account of better job opportunities at home, or due to higher remittances. In East Asia several countries have seen strong growth and poverty reduction, but are lately questioning whether social policy should have a stronger focus on redistribution.

In this paper we use decomposition methods to quantify the contribution of different factors towards poverty reduction in three emerging economies over the last decade. Standard decomposition methods include the Datt-Ravallion (1992) method, which split changes in poverty into distribution-neutral growth, a redistributive effect and a residual. Kolenikov and Shorrocks (2005) decompose changes in poverty into growth, distribution and price effects, while Ravallion and Huppi (1991) offer a way of decomposing changes in poverty over time into intrasectoral effects, a component due to population shifts and an interaction term between sectoral changes and population shifts. However, the usefulness of these decomposition methods is limited by the fact that they explain changes in poverty on the basis of changes in summary statistics (Ravallion 2001). In contrast, the methods adopted in this paper generate entire counterfactual distributions, allowing us to decompose the contributions of changes in different sources of income and in individual and household characteristics to the observed distributional changes. As such, these methods can capture the heterogeneity of impacts throughout the distribution and allow us to distinguish the forces behind the observed outcomes.[2]

[1] In a recent count of poverty episodes for 120 countries in the 2000s for which there is comparable data over time, shows that in 80 out of 105 countries, the annual average reduction in poverty was above 0.25 percentage points. Only eight countries had an increase in poverty.

[2] For a recent review of micro-decomposition methods see Essama Nssah (2012).

Two micro-decomposition approaches are explored. The first is a simple accounting approach, which adapts the Barros et al. (2006) method to quantify the contributions to distributional changes on account of changes in demographics, changes in employment and labor income and changes in non-labor income, including remittances, public transfers and other private transfers. The second approach adapts the Bourguignon, Ferreira and Lustig (2005) methodology to further distinguish between distributional changes on account of changes in endowments or/and returns to those endowments, changes in occupational choice and changes in geographical, age, and gender structure of the population, along with the non-labor dimensions mentioned above. These methods have been mostly used on income-based measures of poverty and inequality. Since most countries measure welfare through household expenditures or consumption, this paper modifies the existing methodologies to decompose consumption-based measures of poverty and inequality. These decompositions do not allow for the identification of causal effects, but they are useful to focus attention on the elements that are quantitatively more important in describing changes in poverty. In particular, we would like to capture the heterogeneity of impacts throughout the distribution and account for the contributions that demographics, sectoral, occupational and other labor and non-labor dimensions had in reducing poverty.[3]

As recognized in the literature (Bourguignon, Ferreira and Lustig, 2005), these decompositions are path dependent, and as such, sensitive to the order in which the variables are simulated to account for the overall changes in distribution. The best-known way to remedy path dependence is to calculate the decomposition across all possible paths and then take the average. These are also known as the Shapley-Shorrocks estimates of each component.[4] Although we do not propose to do this for all of the components, in this paper we group the variables into smaller sets, calculate the Shapley-Shorrocks estimates of these, and assess whether path dependence is indeed empirically important.

The paper focuses on Peru, Bangladesh and Thailand. These three economies have experienced fast poverty reduction during the last decade, with falls in the moderate national poverty headcount rate in each country of over 12 percentage points. Growth was very high during the decade in all three countries, well above 4 percent per annum during the period 2002-2008. In the case of Peru and Thailand, there was a sharp deceleration due to the financial crisis in 2009, only to rebound very fast the following year. Bangladesh came through the crisis unscathed.[5] In all countries employment and public social transfers increased, as did remittances. However,

[3] Panel data that can track the life and labor histories of households over time can be used to answer questions about economic mobility and poverty dynamics. However, panels are often not available with the frequency required. Moreover, panel data are often not representative of the population as a whole; and if they initially are, it is unlikely that over the course of a decade the panel would remain representative of the population. Alternative methods using repeated cross sections have been used. One approach is to construct pseudo panels, which can delve into some issues of economic mobility (Lanjouw et al., 2011). However, these models are often troubled by their lack of precision and the fact that they often do not measure the contributions of different factors to poverty reduction.

[4] See Shapley (1953) and Shorrocks (1999).

[5] See Bangladesh Poverty Assessment, World Bank (2012a).

specific patterns across the income distribution vary across countries, and the potential role of the different factors in reducing poverty is clearly different. Moreover the starting points are very different. Despite strong growth, Bangladesh is still a low-income country, with a GDP per capita of US$1,710, while Peru and Thailand are firmly in the middle-income country ranks with GDP per capita of US$10,439 and US$9,630, respectively (all figures in PPP terms). Peru is already highly urbanized, as opposed to Thailand and Bangladesh where the share of urban population is still below 30 percent.

The main result that emerges is that the largest contributions to poverty reduction in all three countries were labor market-related factors. The contributions to moderate poverty reduction on account of labor markets amount to 61 percent in Bangladesh, 75 percent in Peru and 65 percent in Thailand. Within this, the increase in the returns to endowments or characteristics explains most of the observed poverty reduction, pointing to an increase in real wages and higher productivity as the main contributors to poverty reduction in each case. While increases in farm income were mostly responsible for poverty reduction in Bangladesh and Thailand, non-farm income was mostly responsible in the case of Peru. Finally, while non-labor income played an important role in Thailand and Peru, particularly in reducing extreme poverty, the results show that labor income—from farm or non-farm sources—was the main contributor to poverty reduction.

The rest of the paper is organized as follows. Section 2 describes the evolution of poverty and economic growth in Bangladesh, Peru and Thailand, highlighting the similarities and differences in the initial and end period outcomes. Section 3 presents a simple approach, the results of which serve as a basis for the in-depth approach presented in Section 4. Section 5 concludes.

2. Country Context

Bangladesh, Peru and Thailand have one thing in common: they were able to drastically reduce poverty rates during the past decade. Using national moderate poverty lines, poverty fell by 1.8 percentage points per year in Bangladesh between 2000 and 2010, 2.7 percentage points per year in Peru between 2004 and 2010 and 1.6 percentage points per year in Thailand between 2000 and 2009.[6] Using an international poverty line of US$2.50 a day, these figures are -0.5, -1.4 and -0.6 percentage points annually for Bangladesh, Peru and Thailand respectively (Figure 1A).[7] Moreover, these countries all experienced strong growth over the decade, averaging 5.8 percent annually in Bangladesh, 6 percent in Peru and 4.4 percent in Thailand (Figure 1B). Greater volatility and vulnerability to the financial crisis was observed in Thailand and Peru, while Bangladesh enjoyed uninterrupted growth throughout the decade.

[6] To calculate the population below the poverty lines, the three countries use cost of basic needs approach, although baskets and specific lines are different.
[7] See Table 3 for changes in poverty rates using international poverty lines.

There is considerable evidence that economic growth is strongly and negatively correlated with changes in poverty (Ravallion and Chen, 2007). Using the standard Datt-Ravallion decomposition, growth does indeed explain most of the observed reduction in poverty in all three countries (Table 1). In each case, more than 90 percent of the observed change in poverty is explained by growth in mean income, while better distribution explains less than 10 percent of these changes.

Labor income, which has grown across the income distribution in all cases, could explain the transmission mechanism behind growth and the observed changes in poverty reduction (Figure 4). Those at the top of the income distribution in Bangladesh have seen their labor incomes grow faster than those at the bottom, while in Peru the opposite is true. In Thailand, incomes of the poor grow faster, except for those on the poorest decile. Given the magnitude of the changes, it is likely that growth in labor incomes did have an influence in moving people out of poverty.

Moreover, summary statistics show that labor force participation has remained relatively stable in Bangladesh and Thailand, while the employment population ratio increased slightly. On the other hand, in Peru both labor force participation and employment have increased, particularly for women (Figure 5 and Table 2). At the household level, we find that the share of occupied adults has increased in both Bangladesh and Peru (Table 2). However, in the case of Thailand, we find a slight decline in the share of occupied adults, possibly pointing to the impact of an aging population that could negatively affect consumption per capita.

But other structural factors might explain changes in poverty. First, demographics could play a role. Population growth has slowed considerably in each of the countries considered, and has been significant enough so that in the case of Bangladesh and Peru the youth bulge observed in earlier periods has now reached a working age,[8] meaning these are countries starting to enjoy a "demographic bonus" (Figure 2). This is also evident by the observed decrease in the average household size and a slight increase in the number of adults in each household (Figure 3 and Table 2). In principle, higher numbers of adults per household imply lower dependency rates, and therefore potentially higher consumption per capita. The question is how important this effect was in the observed changes in poverty during the past decade.

Another factor that could be behind the observed reductions in poverty is growth in non-labor income. Public and private transfers have been steadily increasing in Bangladesh, Peru and Thailand over the last decade (Figure 6). With regard to private transfers, international remittances have tripled in Bangladesh over the last decade, and have modestly grown in Peru. In Bangladesh, they amount to 5 percent of GDP, in Peru 2 percent and in Thailand 0.6 percent. They could be an important cushion to income shocks, but can also be greatly affected by conditions in the host country.

[8] Despite this deceleration, Bangladesh has added 19 million people to its total, a 15 percent increase between 2000 and 2010, while Peru has added 3.2 million (12 percent increase) and Thailand 6 million (9 percent increase) during the same time period.

While there are important differences in terms of the magnitude of public social spending across countries relative to the size of their economies, public spending has increased by at least 25 percent over the decade in each country. The importance of public transfers in explaining poverty reduction depends on its importance as a share of total consumption of the poor and the effectiveness of this spending, particularly in terms of targeting and in generating the right behavioral incentives among the poor.[9] Cash transfers, for example, may directly decrease monetary poverty through increasing disposable income. But they can also have an additional impact as they may allow credit constrained families to invest in productive assets.

Finally, in the context of growing incomes, households are likely to change the share of income they dedicate to consumption. The consumption-to-income ratio has fallen over the course of the decade in Bangladesh and Thailand, but it has increased in Peru (Figure 7). As a result, when undertaking the decompositions, this change will contribute to poverty reduction in the case of Peru (as a greater share of income is consumed), while it will imply a negative contribution to poverty reduction in the case of Bangladesh and Thailand, where the observed changes in consumption will seem less dramatic than what we would have otherwise expected had the consumption-to-income ratio remained constant. Since poverty is measured by consumption, actual poverty rates in Bangladesh and Thailand will be higher in the final period than they would have been had the consumption-to-income ratio remained constant.

3. A Simple Approach

While the standard Datt-Ravallion (1992) estimates of the reduced-form relationships between economic growth, inequality and poverty have been useful to identify empirical regularities, they are unable to make explicit links in how growth and poverty reduction are related (Ferreira, 2010). To go a bit beyond this, we begin with a simple approach, which requires only an accounting identity on household consumption and income, rather than a full behavioral model, but still allows us to distinguish the contributions to poverty reduction on account of changes in demographics, public and private transfers, labor income and changes in consumption patterns. Household consumption per capita is defined by:

$$C_{\square} = \theta_{\square} \frac{Y_{\square}}{n} \tag{1}$$

where $Y_{\square}$ is household income, n is the number of household members and $\theta_{\square}$ is the consumption-to-income ratio, which includes both the marginal propensity to consume and any measurement error.

[9] Figure 7 reports subsidies and transfers from the World Development Indicators, and includes all unrequited, non-repayable transfers on current account to private and public enterprises; grants to foreign governments, international organizations, and other government units; and social security, social assistance benefits and employer social benefits in cash and in kind.

Since the distribution of welfare depends on the distribution of consumption per capita, four forces could have a potential impact on poverty reduction: (1) a reduction in the number of household members, which, holding all else equal, could imply higher levels of consumption per member; (2) growth in labor income, which could lead to higher consumption; (3) growth in non-labor income; and (4) changes in the consumption-to-income ratio. We consider each of these in turn.

Decomposition Method

Given that household consumption identity in (1) above depends on household income per capita, following Barros et al. (2006) we re-write income per capita as the product of the share of adults in the household ($\frac{n_A}{n}$) and income per adult. Income per adult can be rewritten as the sum of labor and non-labor incomes per adult. Labor income per adult is just the product of the share of occupied adults ($\frac{n_o}{n_A}$) and the labor income per occupied adult $\left(\frac{1}{n_o}\sum_{i\in A}^{n} y_i^L\right)$ (Box 1, see Annex 1 for details). As a final step, we can then relate household consumption per capita to household income per capita as follows:

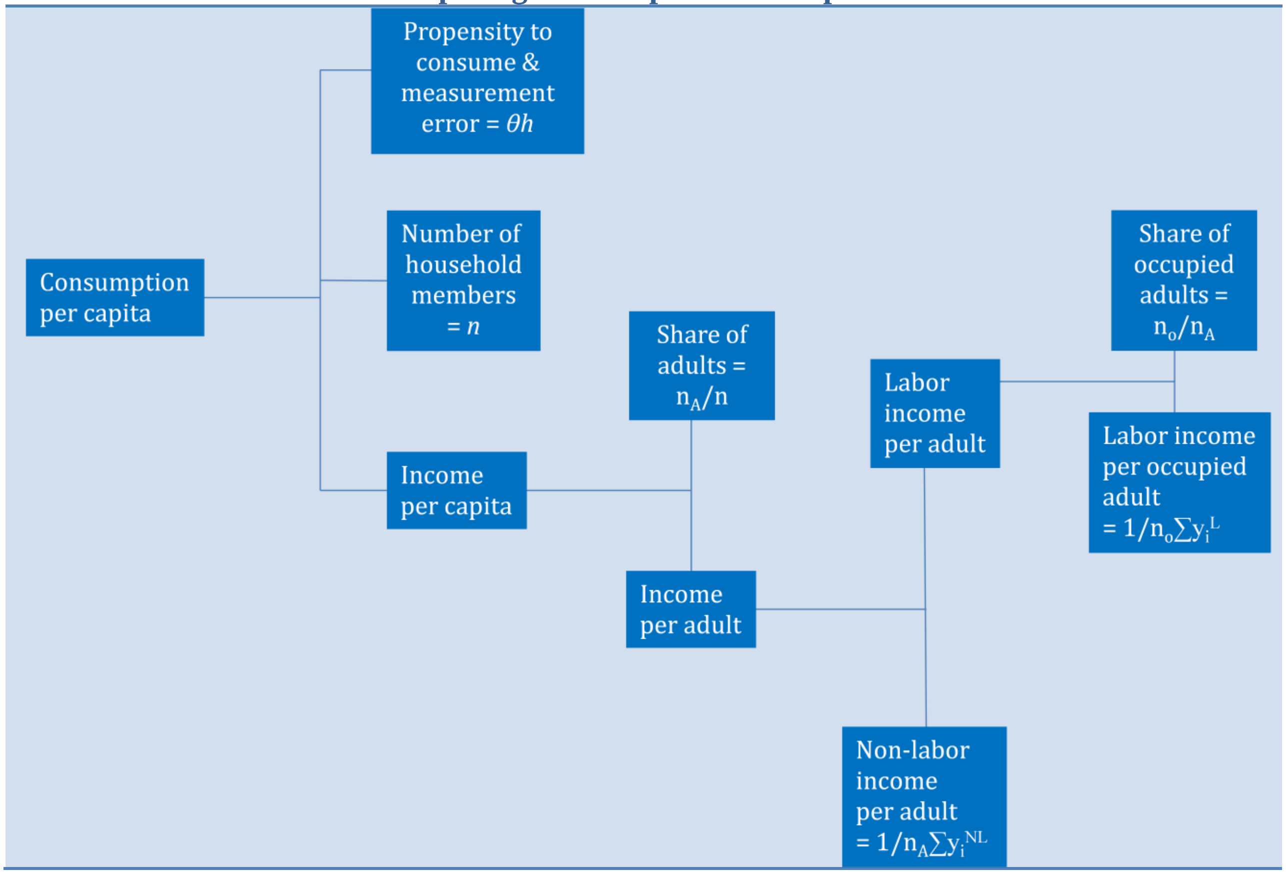
(2)

$$C_{pc} = \theta \left[\frac{n_A}{n}\left[\frac{n_o}{n_A}\left(\frac{1}{n_o}\sum_{i\in A}^{n} y_i^L\right) + \frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}\right]\right]$$

Since poverty depends on the distribution of consumption across households, it depends on each of the components outlined above. As a result, any poverty (or inequality) measure can be written as a function of each of these components. Therefore, the contribution of each component towards changes in poverty or distribution can be expressed as a function of changes in these indicators between the initial and end periods. Following Barros et al. (2006), we simulate changes in the distribution of welfare by changing each of these components one at a time, to calculate their contribution to the observed changes in poverty.

The result of this analysis is interesting from a policy perspective for various reasons. First, if demographic trends and declining dependency ratios were largely responsible for changes in poverty, population projections can help to distinguish whether this is likely to continue affecting poverty. Second, changes in labor income per occupied person or in the number of adults in the family who are working might explain the importance of work in moving people out of poverty. To the extent that poverty reduction has had more to do with employment and earnings rather than with public social transfers, this may indicate that greater effort should be placed in ensuring that the poor have access to good jobs. Or alternatively, one might question the effectiveness of transfers to redistribute and increase the incomes of the poorest. Third, to the extent that the observed reduction in poverty has been due to international remittances, this would point to the need for more concerted efforts to create employment opportunities domestically. Finally, to the extent that households change their consumption patterns and end up saving a greater share of their income, then we could observe fast income growth but moderate consumption growth.

Box 1. Decomposing Consumption Per Capita a la Barros



It is important to mention a few caveats with these methods from the outset. First, the counterfactual distributions on which these decompositions rely suffer from equilibrium inconsistency. Since we are modifying only one element at a time, the counterfactuals are not the result of an economic equilibrium, but rather a simulation exercise in which we assume that we can modify only one factor at a time and keep everything else constant. Second, as mentioned earlier, these decompositions are path dependent, and as such, sensitive to the order in which the variables are simulated. The best-known way to remedy path dependence is to perform the decomposition across all possible paths and then take the average, also known as the Shapley-Shorrocks values.[10] In other words, one would have to begin with each factor one at a time and follow every possible ordering of factors. To find the results, one would then take the average of the contribution of each factor across all possible paths. Since this grows very quickly with the number of factors, we group the variables into smaller sets, and calculate the Shapley-Shorrocks estimates.

[10] See Shapley (1953) and Shorrocks (1999).

We proceed in two steps. First we decompose the observed reduction in poverty into the simplest three elements: the consumption-to-income ratio, the number of adults as a share of the total number of household members and the income per adult. This allows us to explore all possible combinations and paths and to estimate Shapley values (Shapley value decomposition). We then further decompose the observed reduction in poverty by decomposing the elements of the income per adult in each case (Barros decomposition).

Results

The three countries we analyze, Bangladesh, Peru and Thailand, all experienced fast growth and poverty reduction. Panel A in Table 3 show the changes in poverty in the last decade for relevant international poverty rates[11] and the extreme and moderate poverty rates defined by the respective institutes of statistics. Panel B in Table 3 show the results of the most aggregate Shapley value decomposition. The most important contributor to poverty reduction in each country has been growth in income per adult (which captures all labor market outcomes without distinguishing if they are through earnings or more employment plus any non-labor income). Regardless of the decomposition path used, we find that growth in income per adult from all sources explains over 50 percent of the reduction in the Bangladesh poverty headcount using the national moderate and extreme poverty lines, and over 60 percent using the US$1.25 poverty line. Income per adult explains over 85 percent of the reduction in poverty observed in Peru and Thailand, regardless of which poverty line is used (Figure 8 and Table 3). Changes in the share of adults per household (i.e. the decline in dependency rates) are another important factor behind poverty reduction in Bangladesh and Thailand. Finally, these initial decompositions suggest that if households had continued to consume the same share of income in the final period as what was observed in the initial period, then poverty would have fallen even more in the case of Bangladesh and Thailand. In other words, the fact that households are consuming a smaller share of their incomes in the final period implies that poverty—as measured by consumption aggregates—is higher than if the consumption-to-income ratio had remained constant. This result is particularly important in Thailand. In the case of Peru, by contrast, a higher consumption-to-income ratio contributed to the observed decline in poverty.

Results using different decomposition paths are in most cases invariant to the order in which the decompositions are done. The differences are particularly small in terms of the contribution that income per adult has on observed poverty reduction.[12] These results give us some confidence to further decompose total income per adult into subcomponents using a single path, instead of calculating all potential paths—which would require 5,040 separate decompositions.

To explore the multiple channels behind the changes in poverty depicted in Figure 1, we further disaggregate total income per adult into its subcomponents. The key result that emerges is that

[11] The relevant international poverty lines are US$1.25 and US$2.50 for Bangladesh and US$2.50 and US$4 for Peru and Thailand.

[12] We found similar small differences in the results of alternative paths when decomposing the poverty gap and the severity of poverty.

the most important contributor to poverty reduction in each country has been improvements in labor market outcomes (Panel C of Table 3). First, more than 70 percent of the poverty reduction can be attributed to rising labor income per adult (Figure 9). Second, in line with the trends analyzed earlier, the increase in the share of adults per household and the share of occupied adults has also led to a reduction of poverty in Peru (accounting for 18 percent of moderate poverty reduction) and Bangladesh (accounting for 9 percent of moderate poverty reduction). By contrast, the aging population in Thailand led to more adults per household but fewer occupied adults, and therefore contributed to an increase in poverty.

In terms of non-labor income, public and private transfers play a relatively smaller role—between 7 and 34 percent—in explaining poverty reduction trends across these countries over the last 10 years. The importance of labor income tends to be lower for lower poverty lines in the case of Peru and Thailand, while the opposite is true for transfers. The finding that transfers are more important to explaining changes in extreme poverty compared to moderate poverty is non-trivial, as it indicates that these public programs are relatively well-targeted to the poorest and have a sizeable impact. But in all cases, the impact is significantly smaller than what is found for labor market outcomes.

The main result that comes out of these decompositions is that labor market-related outcomes have been the main contributor to poverty reduction during the last decade. This is true for moderate poverty lines and even extreme poverty lines in all cases. The next logical question is, what accounts for the increase in total labor income? Was it the result of more people working or higher earnings per worker? Was it the result of changes in occupation or changes in the sectoral composition of employment? Were these changes the result of improved human capital characteristics or higher returns to those characteristics? In order to answer these questions, a more complex model is needed.

4. An In-Depth Approach

Several potential reasons could explain why labor incomes had an important role in explaining reductions in poverty in these three countries. A look at cross tabulations reveals interesting patterns. First, there were changes in the occupational structure, with workers moving away from farm and daily work and toward salaried employment, which are likely to be economic activities with higher productivity (Figure 10A). In the case of Peru, there was a shift away from unpaid family employment towards self-employed and salaried work. There was also a sharp shift in employment away from agriculture and towards higher productivity manufacturing and services sectors (Figure 10B).

Moreover, there has been an improvement in the educational composition of the workforce over the last ten years in each of these countries as a consequence of higher investment in education in previous decades. A smaller share of the population was illiterate at the end of the decade in all countries, a higher share of the workforce had completed primary and lower secondary school in

Bangladesh and Thailand and a higher share of the population had completed secondary and tertiary school in Peru and Thailand (Figure 11A). Finally, there were population shifts across regions, through accelerated urbanization in Bangladesh and Thailand, countries at much lower level of urbanization than Peru (Figure 11B). In order to distinguish which of these changes has been most important in reducing poverty, a more detailed micro decomposition model is used.

Model

Again we begin with the household consumption identity presented earlier. Consumption per capita in household h is defined by:

$$C_h = \frac{1}{n}[\theta_h y_h] \tag{1}$$

where n is the number of people in household h, y_h is the total income of household h and θ_h is the consumption-to-income ratio, which includes the propensity to consume in household h and measurement error or underreporting of household income. If we further disaggregate income by its sources, we can rewrite (1) as:

$$C_h = \frac{\theta_h}{n}\left[y_h^w + y_h^d + y_h^{se} + \pi_h^F + y_h^{NL}\right] \tag{2}$$

where y_h^w, y_h^d and y_h^{SE} are household salaried labor, daily labor[13] and self-employed non-farm labor income respectively, π_h^F is the farm household net revenue function and y_h^{NL} is household non-labor income. We slightly modify the Bourguignon and Ferreira (2005) approach and model the household income generating function as:

(3)

$$y_h = \left[\sum_{i=1}^{n} I_{hi}^w y_{hi}^w(X_{hi}, \Omega^w) + \sum_{i=1}^{n} I_{hi}^d y_{hi}^d\left(X_{hi}, \Omega^d\right) + \sum_{i=1}^{n} I_{hi}^{se} y_{hi}^{se}(X_{hi}, \Omega^{se}) + \pi_h^F(W_h, \Omega^F) + y_h^{NL}\right]$$

where I_{hi}^w, I_{hi}^d, and I_{hi}^{se} are indicator variables that are equal to one if individual i in household h is a salaried, daily or self-employed worker, y_{hi}^w , y_{hi}^d, and y_{hi}^{se} are the corresponding earnings of individual i in household h that depend on individual and household endowments (X_{hi}) and the returns to those endowments (Ω), which vary across occupation types. In the rest of the paper we call people earning y_h^w, y_h^d and y_h^{SE} the "non-farm" sector, although it includes all dependent workers—including those in agriculture—plus the non-farm self-employed. π_h^F is household net revenue in farm activities, which depend on household endowments (W_{hi}) and the returns to

[13] Daily workers in Bangladesh are agricultural or non-farm workers who are hired on a daily basis rather than continually into one or more jobs. They are classified separately as they could potentially belong to multiple sectors, transitioning between agricultural and non-farm work. Note that they tend to be less educated and generally disadvantaged in terms of asset ownership compared to other types of workers.

those endowments (Ω^{F}). In the rest of the paper, this is the "farm" sector. Finally, y_{h}^{NL} is household non-labor income.

The allocation of individuals across occupations is modeled through a multinomial logit model (McFadden 1974a, 1974b), specified as follows:

$$I_{hi}^{s} = 1 \text{ if } Z_{hi}\Psi^{s} + v_{i}^{s} > Max\left(0, Z_{hi}\Psi^{j} + v_{i}^{j}\right), j = 1, \dots, J, \forall j \neq s \qquad (4)$$
$$I_{hi}^{s} = 0 \text{ for all } s = 1, \dots, J \text{ if } Z_{hi}\Psi^{s} + v_{i}^{s} \leq 0 \text{ for all } s = 1, \dots, J$$

where Z_{hi} is a vector of characteristics specific to individual i and household h, Ψ^{s} are vectors of coefficients for the following activities j={salaried, daily worker, non-farm self-employed, not employed} and v_{i}^{s} are random variables identically and independently distributed across individuals and activities according to the law of extreme values.[14] Within a discrete utility-maximizing framework, $Z_{hi}\Psi^{s} + v_{i}^{s}$ is interpreted as the utility associated with activity s, with v_{i}^{s} being the unobserved utility determinants of activity s and the utility of inactivity being arbitrarily set to 0. Following Bourguignon, Ferreira and Leite (2008), we estimate a multinomial logit model for the educational choice and sector in which individuals are employed. This allows for a representation of the occupational, sectoral and educational composition of the workforce.

We model the heterogeneity in individual earnings in each occupation type j by a log-linear Mincer model:

$$\log(y_{hi}^{j}) = X_{hi}\Omega^{j} + \varepsilon_{hi}^{j} \qquad (5)$$

for $i = 1, \dots, n_{h}$ and j = {salaried, daily worker, non-farm self-employed, not employed}. X_{hi} is a vector of individual characteristics, Ω^{j} a vector of coefficients and ε_{hi}^{j} a random variable supposed to be distributed identically and independently across individuals, according to the standard normal law. Farm net revenue is modeled as:

$$\log \pi_{h}^{F} = W_{h}\Omega^{F} + \varepsilon_{h}^{F} \qquad (6)$$

where $W_{h} = (K_{h}, X_{h})$ include endowments and household characteristics. As before, $\Omega^{F}$are vectors of coefficients and ε_{h}^{F} are random variables distributed as a standard normal.

[14] Individuals living in households where the head is a self-employed farmer can choose any of these states if they do not participate in the farm work or if they have a secondary job.

Implementation

The objective of this model is to distinguish the importance of changes in earnings due to changes in educational attainment, age, gender, occupation, sector and geographical distribution of the labor force. We implement the decomposition in four stages. First, we estimate the determinants of level of education for all individuals, as well as the sectoral and occupational choice for non-farm workers and for the secondary occupation of farm workers for two periods during the last decade. Second, we estimate the earnings regressions for each period for household heads and other household members, distinguishing between salaried, self-employed and daily workers, and for net farm revenue for farm households. Third, we use the coefficients from these regressions to simulate counterfactual distributions by moving one element at a time. Finally, we compare these counterfactuals to the observed changes in distribution in order to identify the contribution to changes in poverty.

We first estimate the education, occupation and sectoral choice models for each period for which data are available. Tables 4 and 5 present comparisons of simulated educational, occupation and economic sector structures using these regressions with the actual structures during the early and late part of the decade for household heads and other family members, respectively. In general, the simulated structures are close to the observed ones. However in some instances there are discrepancies. For instance, the simulated 2010 non-farm occupational structure in Bangladesh has slightly fewer salaried and more daily workers than the true values. In the case of Thailand the simulations underestimate the share of illiterate workers, overestimate the share of agriculture workers and underestimate the share of public sector workers. With the exception of Thailand, the simulated (predicted) structures are close to their true structures as shown by the Pearson Chi-squared test,[15] which gives confidence that we can use the coefficients from these regressions to simulate shifts in the labor force structure on at a time.

Tables A1-A3 in the appendix present the multinomial logit regression results for occupational choice.[16] The regression results show coefficients with the expected signs and a reasonable pseudo R^2. Given the considerable diversification of the sources of income that is common in rural households,[17] we estimate the sectoral choice model for the secondary occupation of individuals in farm households as well as for all non-farm work.[18]

Tables A4-A6 in the appendix present the earnings equation estimates for individuals engaged in non-farm activities. The results show that the models fit the data relatively well, with coefficients being statistically significant and of the right sign. In all cases, higher individual earnings are associated with being male, having higher education and experience, living in urban areas and

[15] P-values of Pearson Chi-squared tests confirm each simulated distribution is not statistically different from the actual distribution.
[16] Results for the other multinomial models are available from the authors upon request.
[17] See Davis et al. (2010).
[18] Results are available upon request.

working in the manufacturing sector. Tables A7-A9 present regression results for farm household net revenue functions.[19] Net revenue for farmers increases with experience, land holdings, access to irrigation and the number of members participating in farm work.[20]

The next step consists in using the estimated coefficients from these models to simulate counterfactual distributions. For instance, since we estimated the returns to education in two periods, we can take the estimated parameters in the first period and evaluate the earnings equations with the 2010 levels of education. This generates counterfactual earnings at the individual level, which can then be aggregated to get the corresponding household income using equation (3), which can then be used to get to a counterfactual level of consumption according to (1), and therefore a counterfactual poverty rate. In this way, changing one set of parameters at a time or one characteristic at a time, we obtain multiple counterfactual distributions and counterfactual poverty rates. The methodology for estimating each counterfactual distribution and the associated counterfactual poverty rate is detailed in Annex 2.

Finally, we compare these counterfactual poverty rates with the observed poverty rates to quantify the impact of each element being considered. Since replacing the first period parameters into last period data will yield results that are different from doing it the other way around, we calculate the counterfactual both ways and then take the average (in line with the literature). We first calculate these effects by changing one element at a time and leaving everything else constant. However, given that changes in multiple factors could have interaction effects, we also calculate the cumulative effect of these decompositions. For this purpose, we follow Bourguignon, Ferreira and Leite (2008), and begin by calculating the effects on poverty of changes in the characteristics of the population, beginning with age and gender, followed by changes in geographical, educational, occupational and sectoral structure of the population. With these results we then calculate changes in farm and non-farm earnings due to changes in the returns to these characteristics, followed by changes in non-labor incomes (first private and then public) and finally changes in the consumption-to-income ratio.

Results

Focusing on the contributions to the reduction of moderate poverty based on national poverty lines, Table 6 presents the results of each counterfactual distribution when simulating only one element at a time, and keeping everything else constant. We refer to these as the marginal contributions to poverty reduction. The main result that emerges is that the largest contributions to moderate poverty reduction in all three countries came from labor market-related factors: 61 percent in Bangladesh, 75 percent in Peru and 65 percent in Thailand. Within this, it was the increase in the returns to endowments or characteristics, rather than changes in these endowments or characteristics, that explain poverty reduction, pointing to an increase in real

[19] Net revenue was calculated using available information on total revenue stemming from agricultural production and the cost of inputs from detailed household enterprise modules included in the surveys.

[20] The Thai household survey does not contain information on land holding and access to irrigation.

wages and higher productivity as the main contributors to poverty reduction in each case (Tables 6 and 8). While increases in farm income were mostly responsible for poverty reduction in Bangladesh and Thailand, non-farm income was mostly responsible in the case of Peru (Table 6). Finally, while non-labor income played an important role in Thailand and Peru, the results presented here continue to reflect the fact that labor income, either from farm or non-farm sources, was the main contributor to poverty reduction. These main results are complemented by those in Table 7, which presents the contributions of each endowment and the returns to each one of those endowments.

Finally, since each change in endowment or characteristic is likely to be related with every other characteristic, we also compute the cumulative effect of each of these endowments in order to capture the interactions between each of the endowments, following Bourguignon, Ferreira and Leite (2008). Again, the main result that emerges is that the returns to endowments or characteristics were the largest contributors to poverty reduction in all three countries (Table 8). We look at these results in turn.

Occupation

Changes in the occupational structure were critical for poverty reduction in all countries for non-farm workers, pointing to shifts in employment as workers aimed to benefit from better work opportunities. This effect was most important in the case of Peru, where the shift in occupation from unpaid family workers into wage employment accounts for 21 percent of poverty reduction (Table 6). In the non-farm sector in Bangladesh, the shift from daily and self-employed work towards salaried employment contributed 9 percent of the observed poverty reduction.[21]

In contrast, changes in occupation for self-employed farmers had a negative impact on poverty, reflecting the fact that they were less likely to diversify into a secondary occupation, either because the returns to farm activities increased or because they lacked the skills to do so. For example, we calculated that Thai farmers with a secondary occupation declined from 32 to 23 percent between 2000 and 2009, while in Bangladesh the number of farmers with a secondary occupation fell from 30 to 10 percent between 2000 and 2010. This lower diversification resulted in a 10 and 3 percent increase in poverty in Thailand and Bangladesh respectively, as shown by the contribution of occupational choice in the farm sector (Table 6).[22]

Education and Experience

As would be expected, a more educated population helped to reduce poverty in all three countries, particularly in the non-farm sector (Table 7). In Thailand, wage premiums for education increased in both farm and non-farm households, so that the total contribution to poverty reduction on account of a better education amounted to 26 percent of the observed

[21] The cumulative effects shown in Table 8 are larger because they include all occupational changes, including the choice between daily-workers, salaried and self-employed work for non-farm workers and the choice to have a secondary occupation for farm workers.

[22] Note that this is consistent with the findings using the simple approach (see Table 4).

poverty reduction during the period. In contrast, the increase in educational attainment led to only a slight reduction in poverty in the non-farm sector in Peru and Bangladesh (as seen by the effect of changes in endowments); but this effect is countered by the decline in the educational premium, implying that the demand for more educated workers did not keep up with supply. However, the results also point to the fact that the incomes of the unskilled increased relatively faster in Bangladesh and Peru, contributing to poverty reduction (which we see in the constant). Therefore, while a more educated labor force deriving higher earnings made an important contribution to poverty reduction in Thailand, in the case of Peru and Bangladesh the rising incomes of the unskilled made a difference.[23] These results point to greater demand for specialized workers in the case of Thailand compared to Bangladesh and Peru.

Similarly, the returns to greater experience, proxied by age, fell in all cases (Table 7). This effectively means that the incomes of inexperienced, young workers increased relatively faster in Bangladesh and Peru, both in the farm and in the non-farm sector, which contributed to poverty reduction. In contrast, more average experience led to a reduction in poverty in Thailand, both due to greater share of working age population and due to a higher return to experienced workers.

For Bangladesh and Peru, these results point to the fact that there was a relative increase in earnings for workers with less education and experience, which strongly contributed to poverty reduction. In the case of Peru, this is consistent with recent evidence of reductions in returns to education and experience, which also had some impact in the reduction in inequality observed in the end of the 2000s (Jaramillo and Saavedra, 2011). Note that this effect is in part captured by a large contribution to poverty reduction in the constant, which includes the returns to labor for individuals with no schooling, the omitted category (Table 7). This implies that educational increases in the population have been faster than the rate at which job creation was able to absorb them. However, it also points to an important increase in the relative price of unskilled labor, which could at least partly be driven by higher productivity.

Sector of Work

Changes in the sector of work also mattered for poverty reduction, particularly shifts away from agriculture and into services. Panel B in Table 7 shows the impact on poverty of changing sectors within the non-farm sector (from salaried agriculture to services and manufacturing) and the impact of changing sectors in the secondary occupation for the farm sector. In both Bangladesh and Thailand, these effects were more than offset by reductions in the returns to working in those sectors. For instance, in the non-farm sector in Bangladesh, the shift into the service sector accounted for 3 percent of the observed poverty reduction. However, this was more than offset by a reduction the service sector wage premium, leading to a much higher poverty rate than would have otherwise been expected. Similarly, the movement into

[23] Note that the returns to education for salaried workers did increase in Bangladesh and Peru, but given the relatively size of this sector, this effect was small. See Table A4 of the appendix.

manufacturing and services in Thailand accounted for 9 percent of the reduction in poverty coming from farm households and 8 percent coming from non-farm households. However, these effects were countered by a decline in returns to working in those sectors, which led to a net increase in poverty. In contrast, despite the increasing share of workers in Peru's service sector, there were increases in returns to working in the service sector, which accounted for 9 percent of the reduction in poverty. This is astonishing, given that the share of service sector workers in Peru is much larger than in either of the other countries (see Table 2).

Regional Structure

One consistent result in all three countries is that the earnings penalty for living outside of the capital city (noted by the region dummy) fell over the last decade, pointing to an increase in real wages and/or higher productivity outside the main capital cities, which helped to reduce poverty. This is most evident in Peru, where the penalty for living outside of Lima declined, accounting for 31 percent of the reduction in poverty, mostly related to a smaller penalty in non-farm activities (Table 7).[24] In Bangladesh and Thailand, the penalty for living outside of the capital also declined, accounting for 15 percent of the reduction in poverty in each case (Table 7), despite the fact that the share of people living outside the capital remained more or less constant.

Rural Assets

There is also some evidence of increased returns to agriculture among farm households in Bangladesh and Peru. In particular, for farm households in Bangladesh, the most important change was the increase in returns to land, accounting for 42 percent of the reduction in poverty (Table 7). This is partly due to land becoming scarcer, as the average land size per capita declined from 0.8 to 0.6 acres per capita between 2000 and 2010. In contrast, the increase in the returns to land in Peru—where the average land size for farm households grew—accounted for 20 percent of the reduction in poverty.

This was complemented by better access to irrigation in the case of Peru, which accounted for 1 percent of the reduction in poverty. In Bangladesh, both access to irrigation and the number of workers in agriculture increased over the course of the decade, while the returns to irrigation and having additional household members employed in farming fell so that neither of these effects helped to reduce poverty.

It is important to mention that we cannot disentangle what fraction of the increase in returns to rural assets is due to an increase in real productivity (real output per worker) or due to an

[24] Although agricultural wage-workers outside of Lima saw a relatively higher increase in earnings, they represent a small share of the salaried labor force. As mentioned earlier, this method cannot identify the reason behind this change in the premium for living outside of Lima. However, one possible theory is that improvements in the road network reduced transactions costs and allowed for greater returns in investing outside the capital. An alternative explanation is that internal migration towards the capital led to a scarcity of workers in other regions, and therefore relatively better earnings. Given the size of this effect, further research would be useful to identify the source of change.

increase in relative prices. Indeed these returns measure the value of the marginal product, which is the product of changes in prices and quantities. Given that this period was characterized by an increase in the relative domestic prices of agricultural products,[25] this factor might have been an important driver of agricultural returns during the latter half of the decade, through its effect on the real value of agricultural production.

Non-labor Income

Changes in non-labor income had a very small role in explaining changes in poverty in Bangladesh, and a larger one in Peru and Thailand (Table 6). In Bangladesh, the increase in international remittances contributed 11 percent to the decline in poverty, but this effect was countered by a decline in domestic transfers, which led to a slightly higher poverty rate than if they had remained constant. Public transfers in Bangladesh increased from 0.9 percent to 1.9 percent of GDP between 2004 and 2010; however they had no impact on poverty reduction (Table 6). This is not surprising given that errors of inclusion are large and the expansion observed since 2004 has been larger among the non-poor (World Bank, 2012b). Moreover, only 34 percent of the poor receive any transfer and the amounts transferred by any of the programs is too small to have a significant impact on poverty.

In Peru, private transfers and donations accounted for 5 percent of the reduction in poverty, while public transfers and donations amounted to 9 percent, not negligible but much smaller than the role played by labor market factors. Conditional cash transfers, in kind transfer programs and social pensions in Peru are expanding, but coverage of these programs was still too small in 2010 to have made a significant impact on poverty.

In Thailand, growth in non-labor incomes was important in explaining reductions in poverty. This is particularly the case for pensions (possibly reflecting the introduction of the new pension scheme), which accounted for 20 percent of the reduction in poverty. Private transfers accounted for another 26 percent of poverty reduction (Table 6). These results are consistent with those using the simple approach, but have been further disaggregated to show the relative importance of the different sources.

5. Final Remarks

The last decade affords us a fantastic opportunity to study the most significant factors that were at work in favor of the poor. This paper has sought to account for the contributions of different factors to the very sharp reduction in monetary poverty that occurred in Thailand, Peru and Bangladesh—three countries with different levels of GDP per capita, urbanization, share of agriculture, employment patterns, social spending and reliance on remittances. In contrast to

[25] Average food inflation in Bangladesh went up from about 4.6 percent in 2000-2005 to an average of 8.9 percent in 2006-2010. Higher food prices could have substantially contributed to higher farm earnings and poverty reduction in rural areas of Bangladesh.

methods that focus on aggregate summary statistics, the methods adopted in this paper generate entire counterfactual distributions, allowing us to identify the contributions of various factors to the observed distributional changes and, in particular, to poverty.

The results show that in these three very different settings, the most important contributor to poverty reduction over the last decade has been the growth in labor income. In particular, growth in farm income has been critical in both Bangladesh and Thailand, while growth in the non-farm sector has been more important in the case of Peru.

In all cases, the observed growth in incomes was mainly due to higher returns to endowments: land and experience in the case of Bangladesh, nonfarm work in Peru, and education and experience in the case of Thailand. In each case the results signal an increase in the marginal value of work, either due to increases in productivity or higher real wages. In both Bangladesh and Peru, labor incomes of the poor, those in agriculture and those who were less educated all increased. In contrast, greater specialization and higher returns to human capital seem to have boosted the marginal value of work in Thailand, potentially through productivity increases.

One consistent result in all three countries is that the earnings penalty for living outside of the capital city fell over the last decade, which contributed to reducing poverty. A second consistent result is that each of these countries saw a shift in occupational choice into paid employment, away from daily and agricultural work, and towards salaried jobs, all of which contributed to poverty reduction, particularly in Peru.

Beyond the effects of labor income growth, both methods adopted in this paper showed that an increase in the number of adults per family and the number of them occupied helped to reduce poverty, particularly in the case of Bangladesh and to a lesser extent in Peru. International remittances also helped to reduce poverty in Bangladesh. Finally, transfers played a significant albeit smaller role in the observed poverty reduction in all three countries. In the case of Bangladesh, leakages and small size of individual transfers made their impact on poverty negligible, despite an expansion of transfers programs during the last decade. In Peru, the recent expansion in social expenditures and transfer programs had only a small impact on moderate poverty, but were relatively more important for extreme poverty. A larger impact of public transfers is found in Thailand, mostly related to the expansion of public pension programs. In general, public transfers had a larger role at lower poverty lines, but even there the impact of labor market outcomes in explaining changes in poverty were larger.

These results imply that jobs are responsible for moving the majority of people out of poverty. Job creation, higher productivity and growth in real wages at the bottom of the distribution are the main mechanisms to achieve sustained poverty reduction. Transfers, on the other hand, are especially important for the extreme poor.

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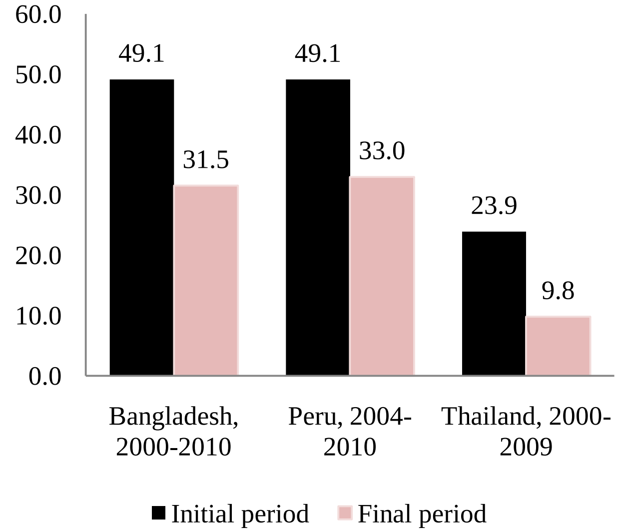
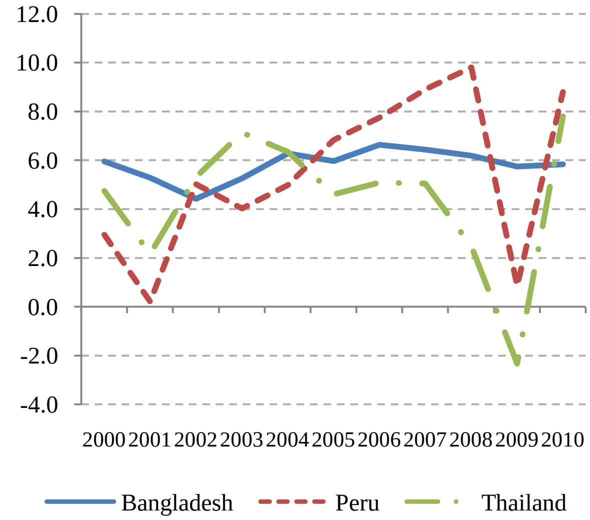
Figure 1. Growth and Poverty Reduction

A. Poverty Headcount
National Moderate Poverty Lines



B. Real GDP Growth
(annual percentage change)

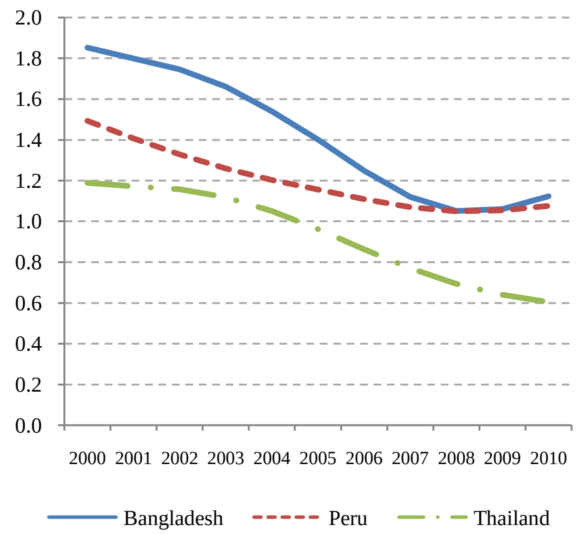


Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

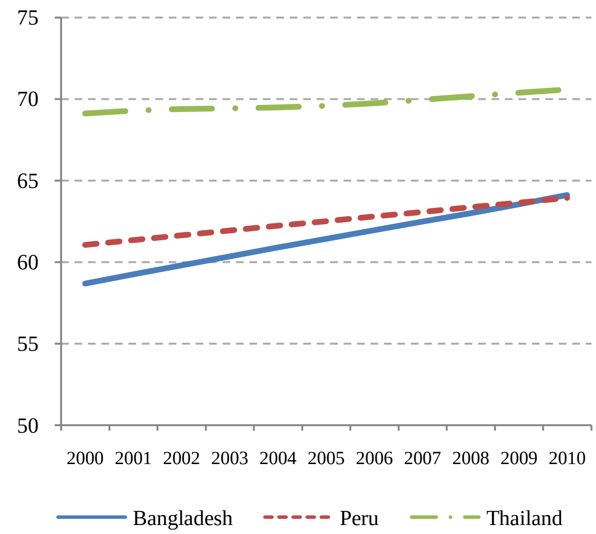
Source: WDI, 2011.

Figure 2. Demographic Changes

Population Growth
(annual percentage change)



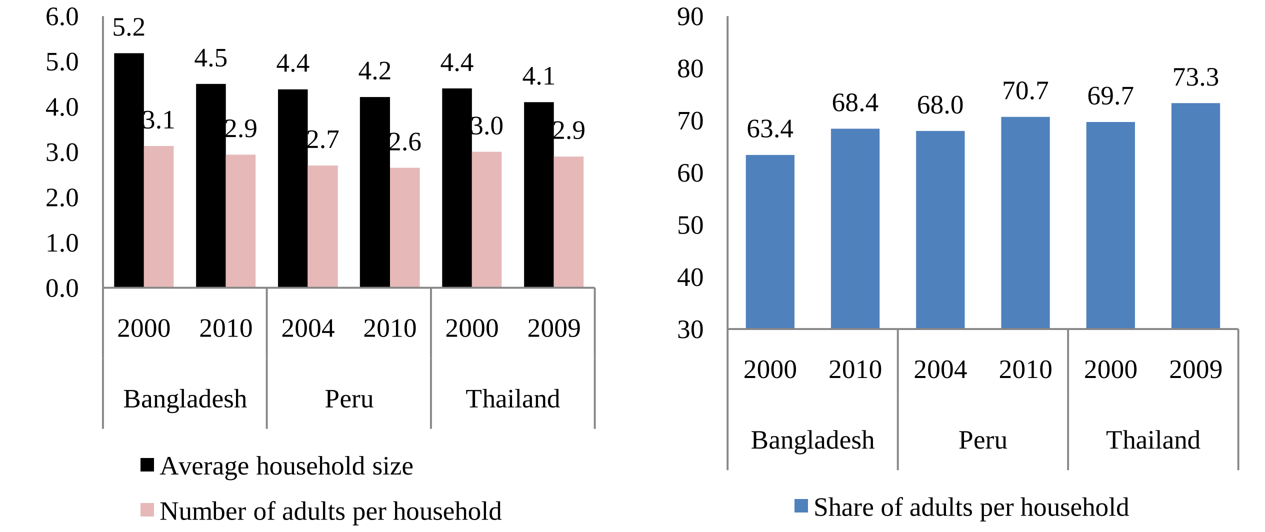
Population ages 15-64
(percent of total population)



Source: WDI, 2011.

Figure 3. Demographic characteristics

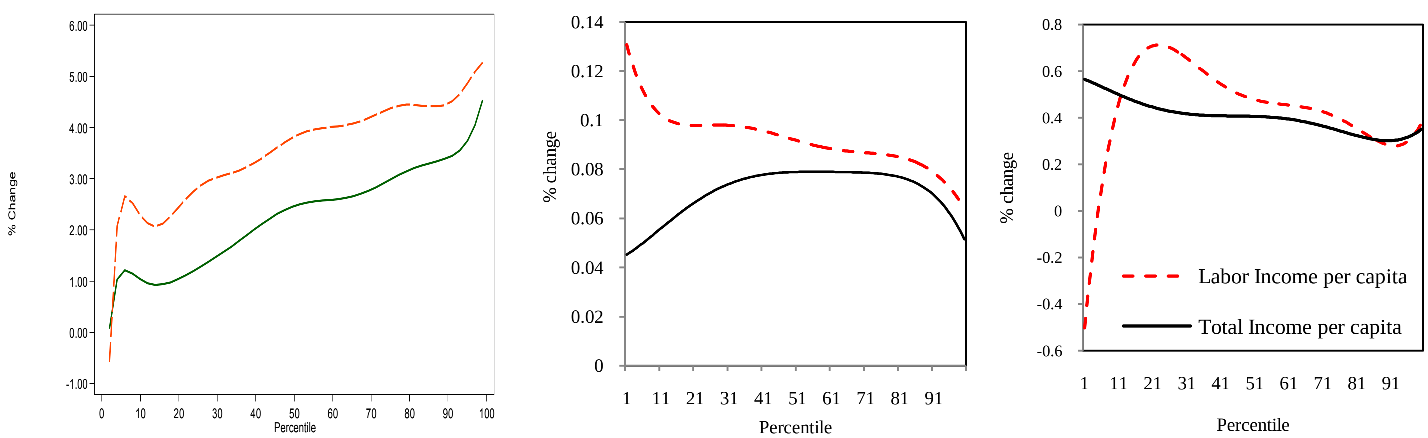
Household sizes have declined… ..while the share of adults has increased



Source: Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Figure 4. Labor Income Growth Incidence Curves

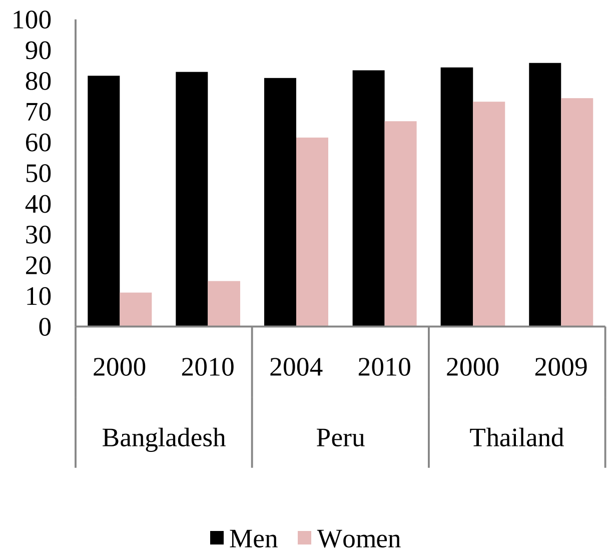
Bangladesh, 2000 to 2010 Peru, 2004 to 2010 Thailand, 2000 to 2009



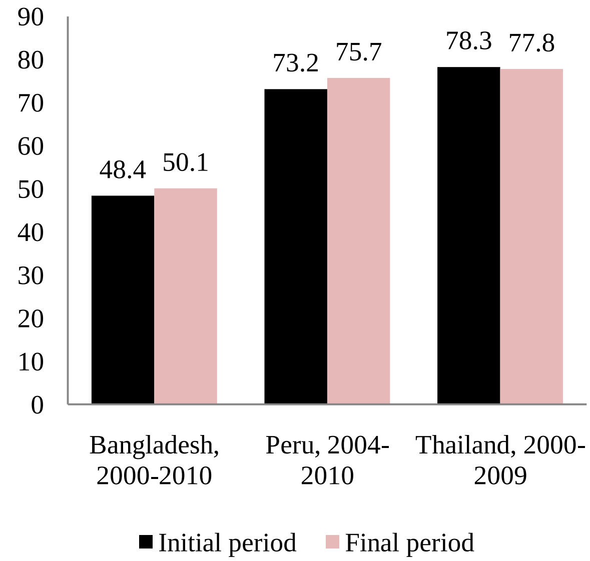
Source: Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Figure 5. Labor Force and Employment

Employment to Population Ratio
(% of total population ages 15-64)



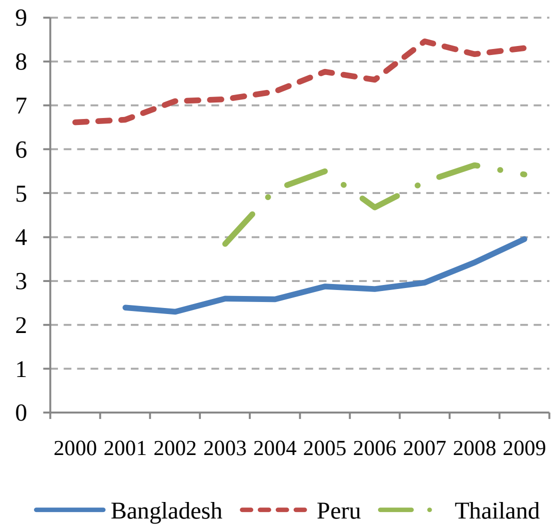
Occupied Adults
(as a share of number of adults)



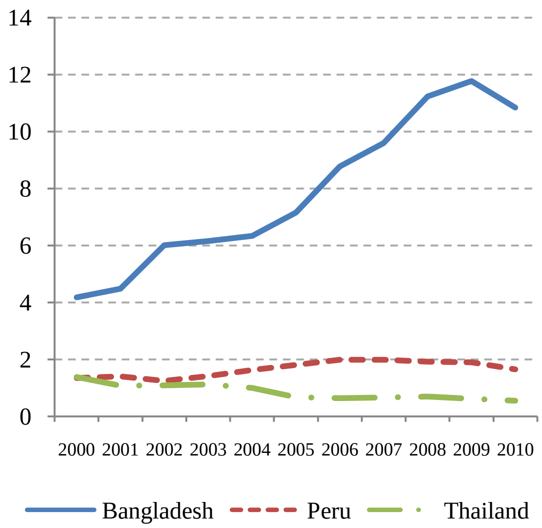
Source: Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Figure 6. Non-Labor Income Growth

Subsidies and Other Social Transfers
(percent of GDP)

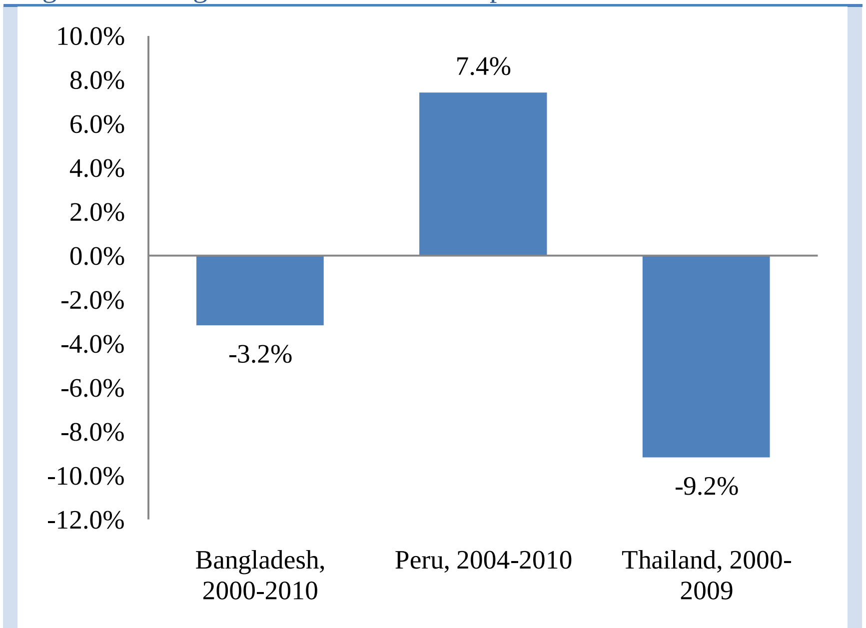


International Remittances
(percent of GDP)



Source: WDI, 2011.

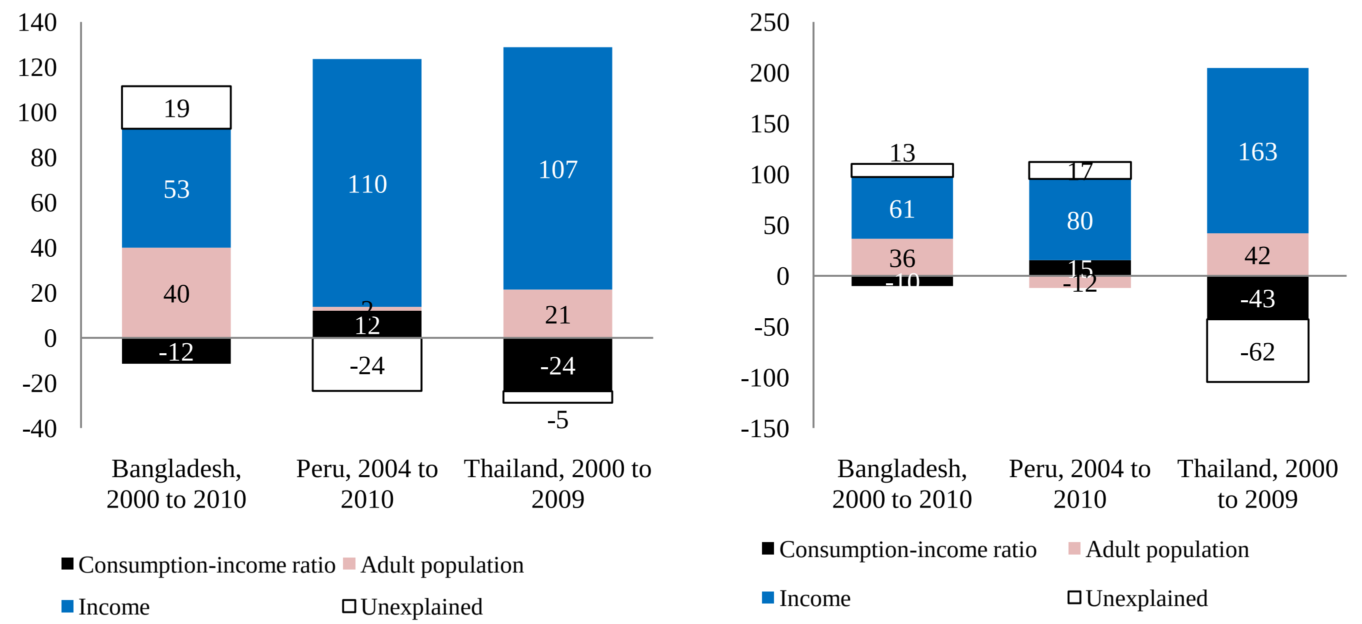
Figure 7. Change in Household Consumption to Income Ratio



Source: Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

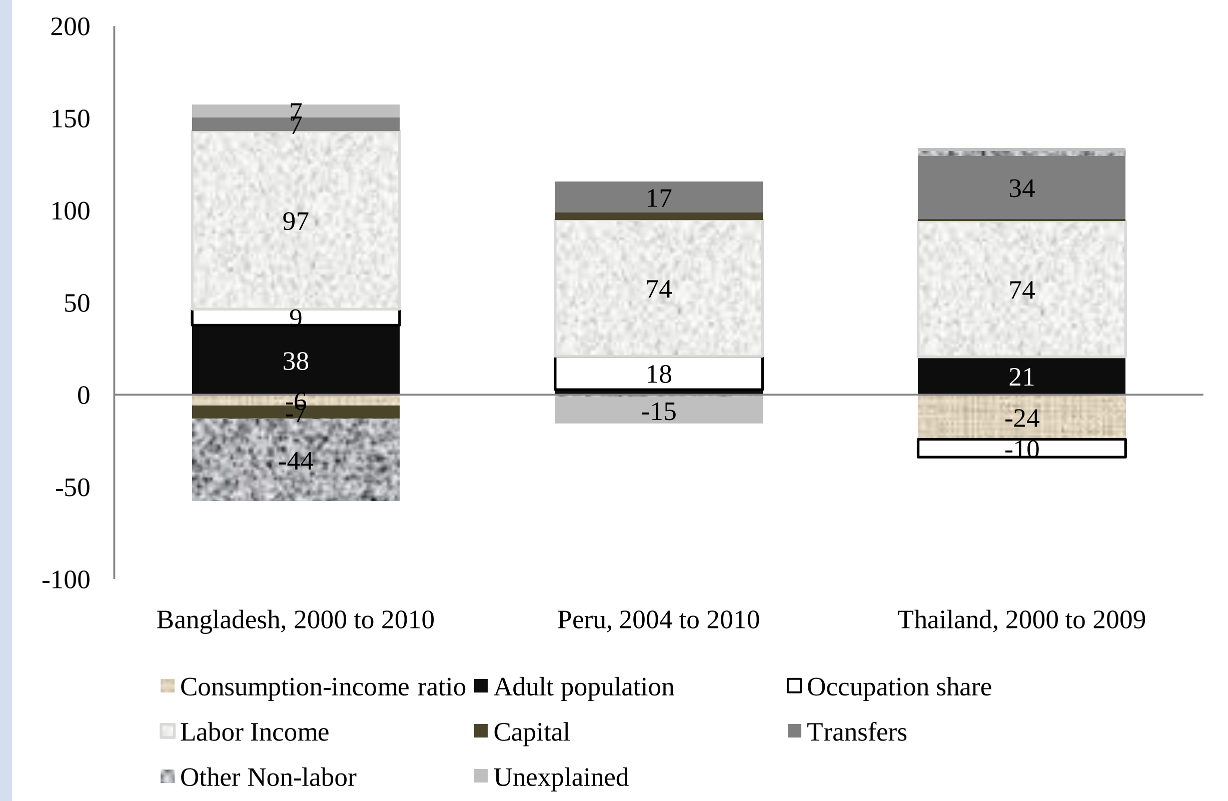
Figure 8. Contribution to the decline in Poverty

A. National Moderate Poverty Lines | B. USD 1.25 Poverty Line in PPP



Source: Shapely value estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

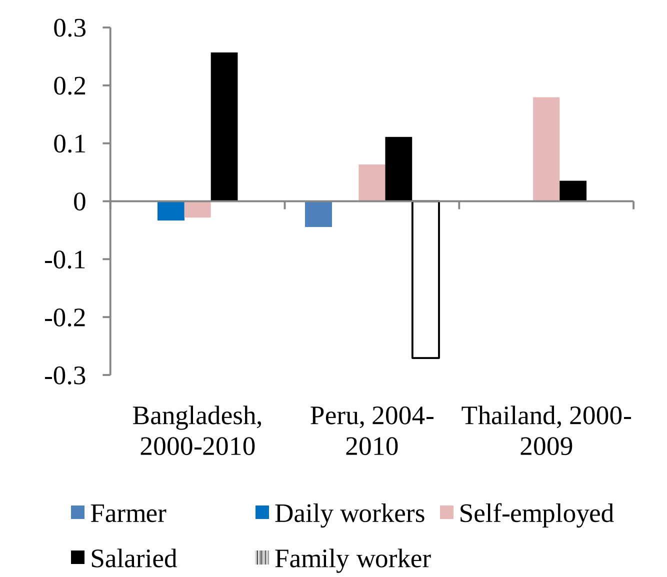
Figure 9. Contribution to the decline in National Moderate Poverty Headcount
(share of total decline in poverty)



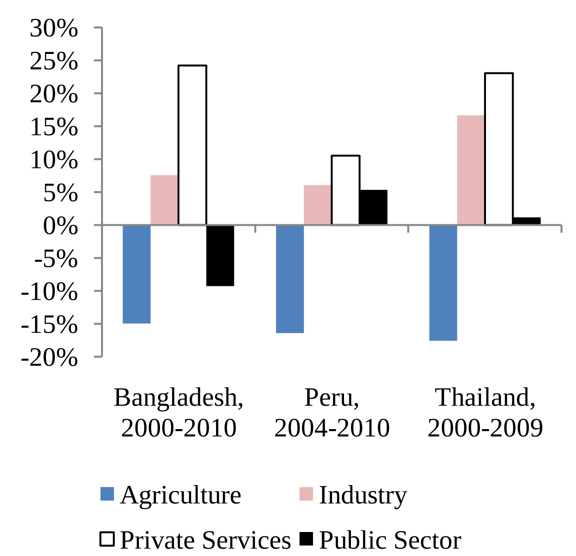
Source: Shapely value estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Figure 10. Changes in the Structure of Employed Population

A. Occupational Structure
(percent change in employed population)



B. Economic Sector
(percent change in employed population)

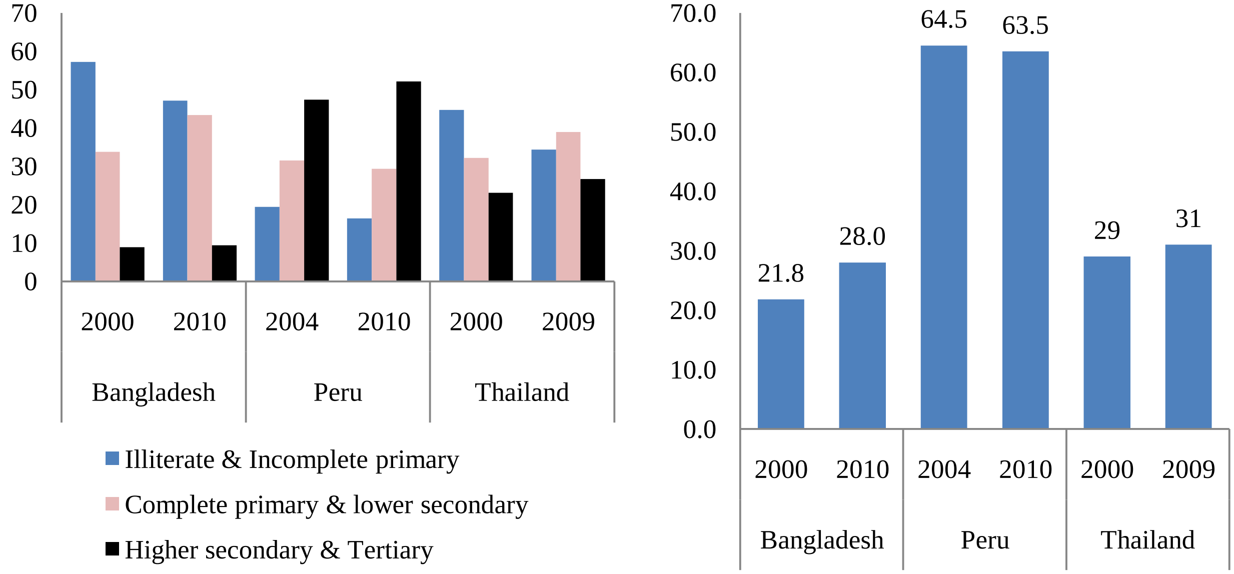


Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Figure 11. Changes in the Structure of Working Age Population

A. Education levels (percent of working age population)

B. Urban Population as a Share of Total (percent of working age population)



Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Table 1: Growth and redistribution decomposition of poverty changes

(Shapley approach - per capita consumption)

	Bangladesh	Peru	Thailand
	2000 vs 2010	2004 vs 2010	2000 vs 2009
Headcount rate FGT(0)			
t0	0.489	0.491	0.239
	(0.012)	(0.002)	(0.002)
t1	0.315	0.330	0.098
	(0.009)	(0.002)	(0.001)
Actual Δ%	-0.173	-0.161	-0.141
	(0.015)	(0.003)	(0.002)
Growth	-0.158	-0.138	-0.142
	(0.016)	(0.004)	(0.003)
Redistribution	-0.016	-0.024	0.001
	(0.015)	(0.003)	(0.003)
Contributions to the decline in FGT(0)			
Growth	91%	85%	101%
Redistribution	9%	15%	-1%
Poverty gap FGT(1)			
t0	0.128	0.164	0.055
	(0.005)	(0.001)	(0.001)
t1	0.065	0.093	0.018
	(0.002)	(0.001)	(0.000)
Actual Δ%	-0.062	-0.071	-0.036
	(0.005)	(0.001)	(0.001)
Growth	-0.056	-0.059	-0.037
	(0.006)	(0.002)	(0.001)
Redistribution	-0.006	-0.011	0.000
	(0.006)	(0.002)	(0.001)
Contributions to the decline in FGT(0)			
Growth	90%	84%	103%
Redistribution	10%	16%	0%

Source: Own estimations based on Peru's ENAHO 2005 -2009, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Standard errors for a two-sided 95% confidence interval shown in parentheses.

Table 2. Characteristics of the Population and Labor Force
(Individuals between 15 - 64 years old)

	Bangladesh		Peru		Thailand	
	2000	2010	2004	2010	2000	2009
Population and demographics						
Total (millions)	71.0	89.8	27.6	31.4	58.1	64.7
Men (percent of total)	50.4	48.4	49.7	49.2	47.9	47.9
Women (percent of total)	49.6	51.6	50.3	50.8	52.1	52.1
Urban (percent of total)	21.8	28.0	64.5	63.5	29	31
Rural (percent of total)	78.2	72.0	35.5	36.5	71	69
Average household size	5.18	4.5	4.4	4.2	4.4	4.1
Number of adults per household	3.13	2.94	2.7	2.6	3	2.9
Share of adults per household	63.4	68.4	68.0	70.7	69.7	73.3
Occupied adults (as a share of number of adults)	48.4	50.1	73.2	75.7	78.3	77.8
Labor force participation (percent of working age population)						
All	49.4	49.2	73.5	76.2	81.1	80.5
Men	83.3	84.9	83.1	84.4	87.6	86.7
Women	14.9	15.6	64.1	68.4	75.3	74.9
Employment (percent of working age population)						
All	46.6	47.8	71.2	74.9	78.5	79.8
Men	81.6	82.9	80.9	83.4	84.4	85.8
Women	11.1	14.8	61.6	66.8	73.2	74.4
Unemployment (percent of labor force)						
All	5.6	1.4	5.1	3.8	2	0.7
Men	2.0	2.0	4.5	3.3	2.6	0.9
Women	25.9	0.8	5.8	4.4	1.5	0.5
Education levels (percent of working age population)						
Illiterate & Incomplete primary	57.2	47.1	19.5	16.4	44.7	34.4
Complete primary & lower secondary	33.8	43.4	31.6	29.4	32.2	39
Higher secondary & Tertiary	8.9	9.4	47.4	52.2	23.1	26.7
Labor relation (percent of employed population)						
Farmer	28.6	25.0	17.2	16.4	40.1	36.0
Daily workers	33.5	32.4	…	…	…	…
Self-employed	17.8	17.3	25.2	26.8	12.1	14.3
Salaried	20.2	25.4	38.7	43.0	41.2	42.6
Family worker	…	…	18.9	13.8	6.6	7.1
Economic Sector (percent of employed population)						
Agriculture	49.0	41.6	35.9	30.0	49.3	40.6
Industry	22.2	23.9	9.8	10.4	17.3	20.1
Private Services	24.8	30.8	46.0	50.8	24.6	30.2
Public Sector	4.0	3.6	8.4	8.8	8.9	9.0
Area (percent of employed population)						
Rural	78.6	71.6	36.5	34.6	68.4	66.8
Urban	21.4	28.4	63.5	65.4	31.6	33.2

Source: Own estimations based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Table 3. Decomposition of Changes in Poverty Headcount

	Bangladesh, 2000 to 2010				Peru, 2004 to 2010				Thailand, 2000 to 2009		
Poverty Line	US $1.25	US $2.50	National Extreme	National Moderate	US $2.50	US $4.00	National Extreme	National Moderate	US $2.50	US $4.00	National Moderate
Poverty rate											
Initial period	57.7	89.2	34.5	49.1	22.9	45.8	17.4	49.1	7.9	31.4	23.9
Final period	40.3	84.0	17.6	31.5	11.7	30.0	10.5	33.0	2.5	16.6	9.8
Change	-17.4	-5.2	-16.9	-17.6	-11.2	-15.8	-6.9	-16.2	-5.3	-14.8	-14.1
Contributions to Poverty Reduction											
1. Shapely decomposition											
Consumption-income ratio	-10	-14	-11	-12	15	10	23	11	-30	-27	-24
Adult population	36	43	37	40	-5	1	-11	2	28	23	21
Income	61	119	53	53	88	90	137	111	126	117	107
Unexplained	13	-47	21	19	2	-1	-49	-23	-24	-13	-5
Total change	100	100	100	100	100	100	100	100	100	100	100
							0				
2. Full Barros decomposition											
Consumption-income ratio	-6	-23	-5	-6	0	0	-2	0	-31	-26	-24
Adult population	36	46	35	38	-1	2	-4	2	30	23	21
Occupation share	8	12	8	9	22	17	34	18	-14	-10	-10
Labor Income	95	132	99	97	82	67	128	74	76	81	74
Capital	-7	-8	-7	-7	4	3	6	4	1	1	1
Transfers	6	23	4	7	19	16	30	17	52	37	34
Other Non-labor	-41	-47	-40	-44	-1	-1	-1	-1	4	2	3
Unexplained	8	-35	7	7	-24	-4	-91	-15	-18	-8	2
Total change	100	100	100	100	100	100	100	100	100	100	100

Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh HIES 2000 -2010.

Poverty rates are own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010. International poverty lines are in US$ PPP terms. National lines are those establishes by the respective national statistical offices.

Table 4. Simulating the Characteristics of Household Heads

	Bangladesh				Peru				Thailand			
	2000		2010		2004		2010		2000		2009	
	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)
Education Structure												
Illiterate & Incomplete primary	63.2	61.9	57.0	57.8	55.3	55.4	49.7	49.9	59.7	64.8	46.9	40.8
Primary & Low Secondary	29.0	29.6	33.1	33.2	28.2	28.1	32.4	32.3	23.2	19.3	29.3	34.2
High Secondary & Terciary	7.7	8.5	9.9	9.0	16.5	16.5	18.0	17.8	17.1	15.9	23.8	25.0
P-value of Pearson chi-square		*94%*		*96%*		*100%*		*100%*		*56%*		*44%*
Occupation												
Non-employed	9.6	10.1	8.0	7.7	16.8	17.3	13.1	12.8	20.4	21.5	20.7	19.4
Self-employed - Non Agriculture	24.7	25.1	24.1	23.9	48.2	48.1	50.2	50.0	22.3	22.1	25.4	24.8
Salaried	20.2	24.2	24.5	18.6	35.0	34.5	36.7	37.2	57.3	56.4	53.9	55.7
Daily workers	45.5	40.7	43.4	49.9	…	…	…	…	…	…	…	…
P-value of Pearson chi-square		*72%*		*49%*		*99%*		*99%*		*96%*		*93%*
Economic Sectors for salaried workers												
-Manufacturing	27.7	26.8	33.4	34.3								
-Agriculture	8.6	7.3	5.4	6.9	31.8	29.9	25.9	27.6	20.6	16.5	11.6	15.1
-Industry	3.7	3.8	3.9	4.0	12.1	12.1	12.0	12.1	30.7	27.1	35.3	37.3
-Services	60.0	62.2	57.3	54.9	35.2	36.8	40.7	39.7	23.6	22.8	29.3	30.5
-Public Sector					20.9	21.2	21.5	20.5	25.1	33.5	23.8	17.2
P-value of Pearson chi-square		*99%*		*95%*		*98%*		*98%*		*26%*		*38%*

Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Table 5. Simulating the Characteristics of Other Household Members

	Bangladesh				Peru				Thailand			
	2000		2010		2004		2010		2000		2009	
	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)	Actual (1)	Simulated (2)
Education Structure												
Illiterate & Incomplete primary	54.4	54.5	42.1	42.3	50.3	50.8	45.4	44.6	36.6	42.3	27.3	22.1
Primary & Low Secondary	36.2	36.0	48.6	48.2	36.5	35.6	39.7	40.7	37.1	32.9	44.4	49.0
High Secondary & Terciary	9.5	9.6	9.3	9.4	13.3	13.6	15.0	14.7	26.3	24.8	28.3	28.9
P-value of Pearson chi-square		*100%*		*100%*		*98%*		*98%*		*49%*		*48%*
Occupation												
Non-employed	79.8	83.0	78.0	80.1	57.9	58.7	49.5	50.4	49.4	47.0	47.3	50.6
Self-employed - Non Agriculture	4.4	4.8	4.1	4.4	26.2	25.7	32.2	31.6	9.5	10.3	10.8	9.9
Salaried	7.2	7.5	9.7	9.9	15.9	15.6	18.3	18.0	41.0	42.8	41.9	39.5
Daily workers	8.6	4.7	8.2	5.6								
P-value of Pearson chi-square		*59%*		*81%*		*98%*		*98%*		*88%*		*81%*
Economic Sectors for salaried workers												
-Manufacturing	42.6	42.4	47.3	47.5								
-Agriculture	4.4	3.4	3.0	3.7	17.0	17.7	14.8	13.9	20.7	18.9	9.1	11.0
-Industry	2.5	2.0	2.6	2.7	13.2	12.8	13.2	13.9	36.0	32.2	38.8	41.2
-Services	50.5	52.2	47.2	46.0	52.8	51.4	56.7	58.3	27.2	25.6	34.7	35.9
-Public Sector					16.9	18.1	15.3	14.0	16.1	23.3	17.4	11.9
P-value of Pearson chi-square		*94%*		*97%*		*98%*		*97%*		*27%*		*52%*

Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Table 6. Marginal Contributions to the Change in National Moderate Poverty Head Count Ratio

Contribution to national moderate poverty reduction on account of changes in:	Bangladesh, 2000-10		Peru, 2004-2010		Thailand, 2000-2009	
	Percent point change	Share of total change	Percent point change	Share of total change	Percent point change	Share of total change
Non-Farm labor income	**-4.56**	**26%**	**-9.35**	**58%**	**-3.46**	**27%**
Returns to characteristics	-3.52	20%	-4.93	31%	-1.25	10%
Occupational-choice	-1.61	9%	-3.44	21%	0.08	-1%
Economic Sector	-0.48	3%	-0.08	1%	-1.01	8%
Education	-0.55	3%	-0.25	2%	-1.34	10%
Unobservables factors	1.59	-9%	-0.65	4%	0.06	0%
Farm income	**-6.02**	**35%**	**-2.74**	**17%**	**-4.91**	**38%**
Returns to characteristics	-6.98	40%	-2.04	13%	-4.83	38%
Occupational-choice (secondary occupation)	0.56	-3%	-0.25	2%	1.31	-10%
Economic Sector 1/			-0.14	1%	-1.11	9%
Education	0.13	-1%	-0.08	1%	-0.56	4%
Unobservables factors	0.26	-2%	-0.23	1%	0.28	-2%
Non-labor income	**1.05**	**-6%**	**-2.28**	**14%**	**-5.80**	**45%**
Private	1.05	-6%	-0.85	5%	-3.30	26%
Private Donations			-0.70	4%		
International transfers	-1.94	11%	0.19	-1%	-2.19	17%
Domestic transfers	1.10	-6%	0.24	-1%		
Other transfers	0.58	-3%	0.01	0%	-1.12	9%
Capital	1.31	-8%	-0.58	4%	0.02	0%
Public	0.00	0%	-1.38	9%	-2.51	20%
Public Donations			-0.45	3%		
Public transfers			-0.90	6%		
Pensions			0.01	0%	-2.51	20%
Other non-labor income			-0.04	0%		
Other	**-7.50**	**43%**	**-0.78**	**5%**	**2.50**	**-20%**
Age/gender	-3.48	20%	-1.17	7%	-1.18	9%
Consumption to income ratio	0.93	-5%	-1.73	11%	3.43	-27%
Unexplained	-4.95	29%	2.12	-13%	0.26	-2%
Total	**-17.34**	**100%**	**-16.13**	**100%**	**-12.84**	**100%**

Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

1/ Refers to the secondary occupation of individuals who work as self-employed agricultural workers.

Table 7. Contributions to the Change in Poverty Head Count Ratio- Returns to Characteristics

Contribution to national moderate poverty reduction on account of changes in:	Bangladesh, 2000-10 Percent point change	Bangladesh, 2000-10 Share of total change	Peru, 2004-2010 Percent point change	Peru, 2004-2010 Share of total change	Thailand, 2000-2009 Percent point change	Thailand, 2000-2009 Share of total change
Education	**2.14**	**-12%**	**0.21**	**-1%**	**-3.29**	**26%**
Nonfarm						
Change in endowment	-0.55	3%	-0.25	2%	-1.34	10%
Change in returns to endowment	1.77	-10%	0.54	-3%	-0.28	2%
Farm						
Change in endowment	0.13	-1%	-0.08	1%	-0.56	4%
Change in returns to endowment	0.78	-4%	0.00	0%	-1.11	9%
Sector	**5.58**	**-32%**	**-1.46**	**9%**	**1.71**	**-13%**
Nonfarm						
Change in endowment	-0.48	3%	-0.08	1%	-1.01	8%
Change in returns to endowment	5.85	-34%	-1.05	7%	3.50	-27%
Farm						
Change in endowment			-0.14	1%	-1.11	9%
Change in returns to endowment	0.21	-1%	-0.19	1%	0.32	-3%
Age/Gender	**4.01**	**-23%**	**1.45**	**-9%**	**-2.93**	**23%**
Change in endowment	-3.48	20%	-1.17	7%	-1.18	9%
Nonfarm						
Change in returns to age	3.94	-23%	0.97	-6%	-0.87	7%
Change in returns to gender	-0.44	3%	0.77	-5%	-0.01	0%
Farm						
Change in returns to age	4.19	-24%	0.96	-6%	-0.54	4%
Change in returns to gender	-0.20	1%	-0.08	1%	-0.33	3%
Returns to other characteristics						
Urban						
Nonfarm	0.11	-1%	0.20	-1%	-0.40	3%
Farm	0.45	-3%	0.12	-1%	-0.09	1%
Regions						
Nonfarm	-0.87	5%	-4.79	30%	-0.27	2%
Farm	-1.82	10%	-0.18	1%	-1.62	13%
Land (Farm)	-7.25	42%	-3.18	20%		
Irrigation (Farm)	0.30	-2%	-0.11	1%		
Other members (Farm)	1.48	-9%	1.07	-7%		
Constant						
Nonfarm	-14.87	86%	-3.38	21%	-2.71	21%
Farm	-7.74	45%	0.00	0%	-1.11	9%

Source: Own estimates based on Peru's ENAHO 2004 -2010, Thailand's SES 2000 -2009, and Bangladesh's HIES 2000 -2010.

Table 8. Cumulative Contributions to the Change in Poverty Head Count Ratio

Contribution to national moderate poverty reduction on account of cumulative changes in:	Bangladesh, 2000-10		Peru, 2004 - 2010		Thailand, 2000-2009	
	Percent point change	Share of total change	Percent point change	Share of total change	Percent point change	Share of total change
Population	-4.41	25%	-0.88	5%	-2.51	18%
Education	-0.88	5%	-0.31	2%	-1.94	14%
Occupation	-1.38	8%	-3.90	24%	0.40	-3%
Sector	-0.51	3%	0.02	0%	-1.40	10%
Returns Non-Farm	-2.93	17%	-1.95	12%	-1.34	10%
Returns Farm	-8.18	47%	-5.06	31%	-3.54	25%
Residuals	1.33	-8%	0.05	0%	0.25	-2%
Non-Labor income	-1.93	11%	-0.13	1%	-2.87	20%
Others	1.55	-9%	-3.96	25%	-1.15	8%
Total	-17.34	100%	-16.13	100%	-14.11	100%

Annex 1. Decomposing the changes in poverty a la Barros et al (2006)

In order to decompose the contribution of each factor to poverty reduction, we need some structure that would allow us to measure the contribution of each factor to the total change in poverty. We begin following Barros et al (2006), and model household per capita income as:

(1)

$$Y_{pc} = \frac{Y_h}{n} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

Income per capita is the sum of each individual's income and will depend on the number of household members, n. If in addition we recognize that only individuals older than age 15 contribute to family income, income per capita will in fact depend on the number of adults in the family, n_A, therefore income per capita can be written as:

(2)

$$Y_{pc} = \frac{n_A}{n}\left(\frac{1}{n_A}\sum_{i=1}^{n} y_i\right)$$

Income per adult, in turn, depends on labor income, y_i^L, and non-labor income, y_i^L, where nonlabor income includes public social transfers, pensions, remittances and other private transfers.

(3)

$$Y_{pc} = \frac{n_A}{n}\left(\frac{1}{n_A}\sum_{i\in A}^{n} y_i^L + \frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}\right)$$

Finally, recognizing that not all adults in the household are employed, we note that household labor income per capita depends on the income of employed adults. Therefore we can decompose the labor income per employed adult as:

(4)

$$Y_{pc} = \frac{n_A}{n}\left[\frac{n_o}{n_A}\left(\frac{1}{n_o}\sum_{i\in A}^{n} y_i^L\right) + \frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}\right]$$

where $n_o$is the number of occupied adults.

In some countries, official poverty rates are calculated on the basis of household income, so equation (4) is sufficient to decompose the contribution of demographic factors, labor and non-labor incomes towards observed poverty reduction. However, most countries measure the distribution of welfare, and poverty in particular using household consumption. Therefore, we modify the Barros et al (2006) approach by mapping consumption to income. In particular, we construct a household consumption model, where household consumption is defined by:

$$C_h = \theta_h Y_h \qquad (5)$$

where Y_h is household income, θ_h combines the marginal propensity to consume in household h, and measurement error or underreporting of household income, where $Log(\theta_h) = \Phi_h \sim F(.)$, and F(.) is the observed empirical distribution.

Combining (4) and (5) above, we can express household consumption per capita as:

(6)

$$C_{pc} = \theta_h \left[\frac{n_A}{n} \left[\frac{n_o}{n_A} \left(\frac{1}{n_o} \sum_{i \in A}^{n} y_i^L \right) + \frac{1}{n_A} \sum_{i \in A}^{n} y_i^{NL} \right] \right]$$

Measuring the Contributions to Poverty Reduction

The basic notion behind calculating the contributions to poverty reduction comes from the realization that poverty measurement depends on the distribution of the welfare aggregate (either income or consumption) across households. More specifically, let F(.) be the cumulative density function of the distribution of welfare. This density function will depend on either income or consumption, and therefore on each of the components outlined above. Since poverty rates depend on F(.), then we can decompose household consumption in each household by the factors in equation (6). As a result, any poverty or inequality measure can be written as a function of each of these components. Therefore the contribution of each component towards changes in poverty or distribution can be expressed as a function of these indicators in the initial and end periods.

Following Barros et al (2006), we can then simulate the distribution of welfare by changing each of these components one at a time, to calculate their contribution to the observed changes in poverty or inequality. In particular, let ϑ be a measure of poverty or inequality. Then, this measure will be a function of the cumulative density function, F(.), which in turn depends on each of the factors above:

(7)

$$\vartheta = \Phi\left(F\left(\theta_h, \frac{n_A}{n}, \frac{n_o}{n_A}, y_{PO}^L, y_{PA}^{NL} \right) \right)$$

where

$$y_{PO}^{L} = \frac{1}{n_o}\sum_{i\in A}^{n} y_i^L$$

and

$$y_{PA}^{NL} = \frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}$$

Given that the distribution of per capita consumption for period 0 and period 1 are known, we can construct counterfactual distributions for period 1 by substituting the observed level of the indicators in period 0, one at a time. For each counterfactual distribution, we can compute the poverty and inequality measures, and interpret those counterfactuals as the poverty/inequality that would have prevailed in the absence of a change in that indicator. For example, to see the impact of the change in the share of occupied adults, we can compute $\hat{\vartheta}$, where we substitute the value of $\frac{\mathrm{n_o}}{\mathrm{n_A}}$ observed in period 0 to the observed distribution in period 1. We can then compute:

(8)

$$\hat{\vartheta} = \Phi\left(F\left(\theta_h, \frac{n_A}{n}, \frac{\widehat{n_o}}{n_A}, y_{PO}^{L}, y_{PA}^{NL}\right)\right)$$

Such that the contribution of the share of occupied adults is the difference between the observed ϑ in period 1 and the estimated counterfactual, $\hat{\vartheta}$. Similarly, each of the other components in the consumption per capita distribution in period 1 can be substituted by their values in period 0 so that their contribution to changes in poverty can be computed.

Since panel data are not available, we follow the methodology proposed by Juhn, Murphy and Pierce (1993) to assign characteristics from the first period onto the second. More specifically, we first order households along the welfare distribution in each period and divide them into quantiles[26]. We then take the average value of the characteristic for each quantile in period 0 and assign it to each household in that same quantile in period 1. For example, if we are decomposing the effect of labor income, we order households into quantiles by their observed labor income in periods 0 and 1. Then for every quantile in period 1, we replace the period 1 labor income with the average labor income in period 0 from households who were in the same quantile.

Barros et al (2006) compute each counterfactual simulation in a nested fashion (as shown in Figure 9 and Table A1). They identify the contribution that interactions between variables have

[26] We use 200 quantiles, but some sensitivity analysis showed that changing this to 400 did not make much difference in the results. If the average is a good representation of the quantile then this method works well, but if there is huge dispersion within the quantile then this could be problematic, and a finer division of quantiles is needed.

in poverty reduction by first computing the joint impact of a subset of variables, and then subtracting the marginal impact of each variable at a time. For instance, in step 2 in Table 1, they first compute the joint impact of inserting both the share of adults and the income per adult from the first period into the distribution of the second period. They then compute the impact of only changing the share of adults, and take the difference of these two simulations to approximate the marginal impact that changing the share of adults had on the distribution. However, in step 4, instead of computing the impact of income per adult on its own, they compute the impact of changing both the labor and non-labor income per adult. This is done because in principle, the sum of labor and non-labor income should be equivalent to changing total income per adult. However, the results of these two simulations are different. Moreover, the simulation of labor income is not done explicitly, but rather ends up being a "residual" in step 8, to ensure that the cumulative effect adds up to the total distributional change.

Table A1. Barros et al (2006) Methodology

1.	$\vartheta_0 = \Phi\left(F\left(\frac{n_A}{n}, \frac{n_o}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Initial poverty rate
2.	$\widehat{\vartheta_{a1}} = \Phi\left(F\left(\frac{\widehat{n_A}}{n}, \widehat{y_{PA}}\right)\right)$	Contribution of the interaction between share of adults and income per adult is $\widehat{\vartheta_{a1}} - \vartheta_0$
3.	$\widehat{\vartheta_{nA}} = \Phi\left(F\left(\frac{\widehat{n_A}}{n}, y_{PA}\right)\right)$	Contribution of share of household adults is $\widehat{\vartheta_{nA}} - \widehat{\vartheta_{a1}}$
4.	$\widehat{\vartheta_{a2}} = \Phi\left(F\left(\frac{n_A}{n}, \frac{n_o}{n_A}, \widehat{y^L_{PO}}, \widehat{y^{NL}_{PA}}\right)\right)$	Contribution of the interaction between labor and nonlabor income is $\widehat{\vartheta_{a2}} - \widehat{\vartheta_{nA}}$.
5.	$\widehat{\vartheta_{NL}} = \Phi\left(F\left(\frac{n_A}{n}, \frac{n_o}{n_A}, y^L_{PO}, \widehat{y^{NL}_{PA}}\right)\right)$	Contribution of non-labor income is $\widehat{\vartheta_{NL}} - \widehat{\vartheta_{a1}}$.
6.	$\widehat{\vartheta_{a3}} = \Phi\left(F\left(\frac{n_A}{n}, \frac{\widehat{n_o}}{n_A}, \widehat{y^L_{PO}}, y^{NL}_{PA}\right)\right)$	Contribution of the interaction between labor income and the share of occupied adults is $\widehat{\vartheta_{a3}} - \widehat{\vartheta_{NL}}$.
7.	$\widehat{\vartheta_{no}} = \Phi\left(F\left(\frac{n_A}{n}, \frac{\widehat{n_o}}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Contribution of the share of occupied adults is $\widehat{\vartheta_{no}} - \widehat{\vartheta_{a3}}$.
8.	$\vartheta_F = \Phi\left(F\left(\frac{n_A}{n}, \frac{n_o}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Final poverty rate, ϑ_F . The contribution of labor income, y^L_{PO}, is calculated as a residual: $\vartheta_f - \widehat{\vartheta_{a3}}$.

In contrast, we compute a cumulative counterfactual distribution by adding one variable at a time. The impact of changes in each variable and its interactions with all other variables is calculated as the difference between the cumulative counterfactuals (Table A2). In contrast to the Barros et al (2006) approach, this method does not separately identify the contribution of the interaction between variables on poverty reduction, since doing so is partial at best given that changing any variable can potentially affect all other variables. Moreover, the approach adopted in this paper has the advantage that it avoids attributing the residual to the last variable being considered and allows for a more straight-forward interpretation of the results. The order in which the cumulative effects are built up matter, as described below, so we adopt an ordering that follows a loose hierarchy, in which household demographic characteristics are defined first, followed by labor supply decisions, labor and then non-labor income. This ordering is consistent with the literature on transitions into and out of poverty[27], and is akin to a VAR structure in the macroeconometrics literature. Finally, as shown in step 2 in Table 2, this approach includes the contribution of changes in the consumption-to-income ratio as part of the decomposition, since the welfare measure is based on consumption rather than income.

Table A2. Proposed Methodology

1.	$\vartheta_0 = \Phi\left(F\left(\theta_h, \frac{n_A}{n}, \frac{n_o}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Initial poverty rate
2.	$\widehat{\vartheta_1} = \Phi\left(F\left(\widehat{\theta_h}, \frac{n_A}{n}, \frac{n_o}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Contribution of the consumption-to-income ratio is $\widehat{\vartheta_1} - \vartheta_0$
3.	$\widehat{\vartheta_2} = \Phi\left(F\left(\widehat{\theta_h}, \frac{\widehat{n_A}}{n}, \frac{n_o}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Contribution of share of household adults is $\widehat{\vartheta_2} - \widehat{\vartheta_1}$
4.	$\hat{\vartheta}_3 = \Phi\left(F\left(\widehat{\theta_h}, \frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Contribution of the share of occupied adults is $\widehat{\vartheta_3} - \widehat{\vartheta_2}$
5.	$\hat{\vartheta}_4 = \Phi\left(F\left(\widehat{\theta_h}, \frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, \widehat{y^L_{PO}}, y^{NL}_{PA}\right)\right)$	Contribution of labor income is $\widehat{\vartheta_4} - \widehat{\vartheta_3}$
6.	$\hat{\vartheta}_5 = \Phi\left(F\left(\widehat{\theta_h}, \frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, \widehat{y^L_{PO}}, \widehat{y^{NL}_{PA}}\right)\right)$	Contribution of non-labor income is $\vartheta_5 - \widehat{\vartheta_4}$
7.	$\vartheta_F = \Phi\left(F\left(\theta_h \frac{n_A}{n}, \frac{n_o}{n_A}, y^L_{PO}, y^{NL}_{PA}\right)\right)$	Final poverty rate. The unexplained portion $\vartheta_f - \widehat{\vartheta_5}$ is identified separately.

[27] See Bane and Ellwood (1986). For a recent review of that literature, see Jenkins (2011).

Annex 2. Decomposing the changes in poverty a la Bourguignon, Ferreira and Lustig (2005)

Given the model presented in equations (1) – (6), there are two important steps to get results for the decompositions. The first consists on defining the estimation strategy with the purpose of obtaining a set of parameters for the reduced-form model. The second is the decomposition based on the construction of approximated counterfactual distributions.

A. ESTIMATION STRATEGY

The reduced-form models established earlier require the estimation of different sets of parameters, ranging from the occupational choice model, the educational and economic sector conditional distributions, and (random) estimates of the residual terms. This subsection presents the estimation strategy which has been applied.

1- Occupational choice model: non-farm workers and farm workers

As described earlier, the allocation of individuals across occupations is represented through a multinomial logit model (McFadden 1974a, 1974b), specified as follows:

$$\mathrm{I}_{\mathrm{hi}}^{\mathrm{s}} = 1 \text{ if } \mathrm{Z}_{\mathrm{hi}}\Psi^{\mathrm{s}} + \mathrm{v}_{\mathrm{i}}^{\mathrm{s}} > Max\left(0, \mathrm{Z}_{\mathrm{hi}}\Psi^{\mathrm{j}} + \mathrm{v}_{\mathrm{i}}^{\mathrm{j}}\right), \mathrm{j} = 1, \dots, \mathrm{J}, \forall \mathrm{j} \neq \mathrm{s}$$
$$\mathrm{I}_{\mathrm{hi}}^{\mathrm{s}} = 0 \text{ for all } \mathrm{s} = 1, \dots, \mathrm{J} \text{ if } \mathrm{Z}_{\mathrm{hi}}\Psi^{\mathrm{s}} + \mathrm{v}_{\mathrm{i}}^{\mathrm{s}} \leq 0 \text{ for all } \mathrm{s} = 1, \dots, \mathrm{J}$$

where Z_{hi} is a vector of characteristics specific to individual i and household h, Ψ^{s} are vectors of coefficients, for the following activities j={salaried, daily worker, self-employed, not employed}, and $\mathrm{v}_{\mathrm{i}}^{\mathrm{s}}$ are random variables identically and independently distributed across individuals and activities according to the law of extreme values. Within a discrete utility-maximizing framework, $\mathrm{Z}_{\mathrm{hi}}\Psi^{\mathrm{s}} + \mathrm{v}_{\mathrm{i}}^{\mathrm{s}}$ is interpreted as the utility associated with activity s, with $\mathrm{v}_{\mathrm{i}}^{\mathrm{s}}$ being the unobserved utility determinants of activity s and the utility of inactivity being arbitrarily set to 0.

In order to calculate the utility of activity s and therefore allow for people to change occupations in the simulation exercise when either Z_{hi} or Ψ^{s} change, we must estimate the residual terms of the occupational choice model ($\mathrm{v}_{\mathrm{i}}^{\mathrm{s}}$), which are unobserved. They must be drawn from extreme value distributions in a way that is consistent with observed occupational choices. Train and Wilson (2008) define the distribution functions of the extreme value errors conditional on the chosen alternative. In particular, assume that the alternative zero is chosen ($j=0$) and denote $Z_{hi}\hat{\Psi}^{j} = V_{hi}^{j}$ for $j = 0 \dots, J$. Define $\hat{V}_{hi}^{0j} = V_{hi}^{0} - V_{hi}^{j}$ and $D_{hi}^{0} = \sum_{j=0}^{J} \exp(-\hat{V}_{hi}^{0j})$ where $P_{hi}^{0} = 1/D_{hi}^{0}$ is the logit choice probability. Then the cdf for the alternative chosen v_{hi}^{0} is:

$$F(v_{hi}^{0} \mid alternative\ 0\ is\ chosen) = \exp(-D_{hi}^{0}\exp(v_{hi}^{0}))$$

Calculating the inverse of this distribution:

$$\hat{v}^0_{hi} = \ln(D^0_{hi}) - \ln(-\ln(\mu)) \qquad \text{(a)}$$

where μ is a draw from a uniform distribution between 0 and 1. Error terms for other alternatives $(v^j_{hi} \ with \ j \neq 0)$ must be calculated conditioned on the error terms of the alternative chosen ($\hat{v}^0_{hi}$). The distribution for these errors is:

$$F(v^j_{hi} \mid alternative\ 0\ is\ chosen,\ j \geq 1) = \frac{\exp(-\exp(-v^j_{hi}))}{\exp(-\exp(-(\hat{V}^{0j}_{hi} + \hat{v}^0_{hi})))} \ for\ v^j_{hi} < (\hat{V}^{0j}_{hi} + v^0_{hi})$$

The inverse of this distribution is:

$$\hat{v}^j_{hi} = -\ln(-\ln(m(\hat{v}^0_{hi})\mu)),\ where\ m(\hat{v}^0_{hi}) = \exp(-\exp(-(\hat{V}^{0j}_{hi} + \hat{v}^0_{hi})) \qquad \text{(b)}$$

where μ is a draw from a uniform distribution between 0 and 1. We repeat this same method when an alternative other than zero is chosen and using expressions (a) and (b).

In the case of farm workers we estimate a model for the secondary occupation in order to capture the probability of diversifying or not into other nonfarm activities. We assume that the residuals are independently and identically distributed according to a logistic function, a logit model is the estimator of the diversification choice to having a secondary occupation or not, for all household heads self-employed in agriculture. The vector of characteristics includes individual and household variables such as age, gender, education level, region and areas among others. Random terms are drawn conditional on the choice that has been made at the initial point.

2- Earning equations: the non-farm and farm workers

Turning to the labor market determination of earnings, we separate the sample into two different groups depending on the kind of activities that these individuals perform: non-farm and farm workers. Individual earnings equations for the first group are estimated separately for household heads, spouses and other members if they are performing as daily workers, self-employed and salaried. The set of characteristics considered in the specification includes individual characteristics such as age, gender, education level, among others as well as characteristics of other members of the household. For instance, in the case of spouses and other members, characteristics of the household head i.e. his level of education; if she is employed or not; etc, were included in the specification. The second step corresponds to estimate the residual terms as random numbers normally distributed and their variances.

As mentioned before, farm net revenues are modeled at the household level and parameters are estimated using ordinary least squares. The vector of characteristics includes endowments such as land and irrigation, and individual and household characteristics of the household head, for instance, educational level, gender, civil status, and number of members involved in the farm activity among others. Random estimates of the residual terms are drawn from a standard normal distribution. Earnings from the secondary occupation are estimated only for farm workers as a function of their individual characteristics i.e. age, gender, education level and economic sector where they perform their secondary job as well as we add a random term distributed according to the normal standard distribution.

3- Other characteristics: educational structure and economic sectors for the main occupation

Since we do not have panel data, we do not observe the same individuals in both years. Hence, to find the contribution of changes in education and economic sector it is necessary to simulate the distribution of these characteristics in year *s* and apply these coefficients to the population in year *t*. We estimate conditional distributions of levels of education and economic sectors by occupation categories for each year based on individual age group, gender, region and area. Following Bourguignon, Ferreira and Leite (2008), this is done using multinomial models. These models are estimated separately for household heads, spouses and other members within the working age population.

4- Non-labor income and Consumption-income ratio

We estimate non-parametrically the conditional distribution of all non-labor incomes, both as a total as well as by their different components such as remittances, public transfers and other private transfers. For this purpose, we create cells of household heads with the same level of education, gender and region (urban-rural). Inside of each cell, we create quantiles of non-labor income, we will then ascribe the mean value of each non-labor income component in each quantile/cell in period s, to its counterpart in period t. A similar approach is employed for estimating the conditional distribution of the consumption-income ratio.

B. DECOMPOSITION APPROACH

After each of these reduced-form models has been estimated for two years *t* and *s* (early 2000 and late 2010) for each country (Bangladesh, Peru and Thailand), we decompose distributional changes by formulating the appropriate counterfactual distribution of income and consumption. We first estimate the following components of household income at time *t* and *s* as explained before as:

$$\log(y_h)^t = \sum_{i=1}^{n_h} I_{hi}^d\left(X_{hi}\Omega^d + \varepsilon_{hi}^d\right) + \sum_{i=1}^{n_h} I_{hi}^w\left(X_{hi}\Omega^w + \varepsilon_{hi}^w\right) + \sum_{i=1}^{n_h} I_{hi}^{se}\left(X_{hi}\Omega^{se} + \varepsilon_{hi}^{se}\right) + (W_h\Omega^F + \varepsilon_h^F) + \log(y_h^{NL}) \tag{7}$$

Which for simplicity we express as:

$$\log(y_h)^t = f(NF\left(\hat{\Omega}_{NF}^t, X_{hi}^t, H_{hi}^t, \hat{\varepsilon}_{hi}^t\right), O\left(\widehat{\Psi}^t, Z_{hi}^t, H_{hi}^t, \hat{v}_{hi}^t\right), F(\hat{\Omega}_F^t, W_h^t, H_h^t, \hat{\varepsilon}_h^t), y_h^{NL}|^t) \tag{8}$$

where

X_{hi}^t and Z_{hi}^t: are exogenous variables such as age, gender, region, and area that are used for the earnings and occupational choice models for the non-farm sector;

W_h^t: are exogenous variables such as age, gender, region, and area for net revenues for farm sector;

H_{hi}^t= $H(X_{hi}^t, \widehat{\Theta}_{hi}^t, \hat{\phi}_{hi}^t)$ are endogenous variables including education level ($X1_{hi}^t$) and economic sector choice ($X2_{hi}^t$) with $\widehat{\Theta 1}_{hi}^t$ and $\widehat{\Theta 2}_{hi}^t$ being the respective set of estimated parameters;

$NF(\cdot)$ = non-farm earning equations and $\hat{\Omega}_{NF}^t$ refers to the set of estimated parameters;

$O(\cdot)$ = occupation choice equations and $\widehat{\Psi}^t$ refers to the set of estimated parameters;

$F(\cdot)$ = net farm revenue equations and $\hat{\Omega}_F^t$ are the set of estimated parameters;

$\hat{\varepsilon}_{hi}^t, \hat{\varepsilon}_h^t, \hat{v}_{hi}^t, \hat{\phi}_{hi}^t$ = error terms for earning equations for non-farm and farm sector, occupational choice and endogenous variables: education structure and economic sector;

$y_h^{NL}|^t$ = non-labor income distribution.

We describe first the marginal decomposition technique which consists in changing one component of the distribution at a time, keeping everything else constant. Lastly, we briefly discuss the cumulative approach.

1. Changes in distribution due to changes in returns to endowments

We can simulate the counterfactual household income distribution by computing the earnings of every household at time *t* with the estimated returns to individual and household characteristics (Ω) computed for period *s*.[28]

$$\log(y_h)_\Omega^{t\to s} = f(NF(\widehat{\Omega}_{NF}^t, X_{hi}^t, H_{hi}^t, \hat{\varepsilon}_{hi}^t), O(\widehat{\Psi}^t, Z_{hi}^t, H_{hi}^t, \hat{v}_{hi}^t), F(\widehat{\Omega}_F^t, W_h^t, H_h^t, \hat{\varepsilon}_h^t), y_h^{NL}|^t) \qquad (9)$$

This simulation yields the earnings of each household in the sample if the returns to each observed characteristics had been those observed at time *s* rather than the actual returns observed at time *t*, keeping everything else constant.[29] The contribution to the overall change in the distribution assigned to a change in returns ($\Omega^{t\to s}$) between *t* and *s*, leaving everything else constant, can be obtained by comparing (8) with (9). However, in this paper we focus on comparing poverty indicators $P\{f(\cdot)\}$. Therefore, the effect of a change in returns on poverty change is:

$$\Delta P_\Omega^{t\to s} = P\{{y_h}^t\}_h - P\{(y_h)_\Omega^{t\to s}\}_h$$

The difference between this simulated distribution of household incomes $\{y_i\}_\Omega^{t\to s}$ and the actual distribution is equivalent to the *price effect* in the Oaxaca-Blinder calculation.

[28] The notation $t \to s$ refers to estimating earnings in period *t* using the returns to characteristics,Ω estimated at time *s*.

[29] The returns to the unobserved characteristics behind the residual term $\hat{\varepsilon}^t$ are assumed to be unchanged.

2. **Changes in distribution due to changes in unobservable factors**

To simulate the effect of changes in unobservable factors between *s* and *t*, we rescale the estimated residuals of the earning and net revenue equations for non-farm and farm workers of time *t* by the ratio of standard deviations at time *s* and *t*. This counterfactual is defined as:

$$\log(y_h)_{\varepsilon}^{t\to s} = f\left(NF\left(\hat{\Omega}_{NF}^{t}, X_{hi}^{t}, H_{hi}^{t}, \hat{\varepsilon}_{hi}^{t}\left(\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}}\right)\right), O\left(\hat{\Psi}^{t}, Z_{hi}^{t}, H_{hi}^{t}, \hat{v}_{hi}^{t}\right), F\left(\hat{\Omega}_{F}^{t}, W_{h}^{t}, H_{h}^{t}, \hat{\varepsilon}_{h}^{t}\left(\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}}\right)\right), y_{h}^{NL}|^{t}\right) \quad (10)$$

Again the contribution to the change in poverty assigned to a change in unobservable factors ($\varepsilon^{t\to s}$) between *t* and *s*, leaving everything else constant, can be obtained by comparing the actual distribution (8) with the counterfactual (10).

$$\Delta P_{\varepsilon}^{t\to s} = P\{{y_h}^{t}\}_h - P\{(y_h)_{\varepsilon}^{t\to s}\}_h$$

3. **Changes in distribution due to changes in occupation, education structure and economic sectors**

Whenever the coefficients of the occupational, educational or sectoral multinomial logit model of year *t* are replaced for those of year *s*, individuals may be reallocated into different occupations, education levels or economic sectors.[30] Labor income is imputed to account for these changes using the earnings equations as a linear projection with the relevant vector of parameters and the residuals drawn from a standard normal distribution.

For instance, the contribution to the change in poverty between *t* and *s* is calculated by first exchanging parameters $\hat{\Psi}^{t}$ for $\widehat{\Psi^{s}}$ in the occupational choice model, maintaining everything else constant, and then obtaining the following counterfactual distribution:

$$\log(y_h)_{\Psi}^{t\to s} = f\left(NF\left(\hat{\Omega}_{NF}^{t}, X_{hi}^{t}, H_{hi}^{t}, \hat{\varepsilon}_{hi}^{t}\right), O\left(\hat{\Psi}^{s}, Z_{hi}^{t}, H_{hi}^{t}, \hat{v}_{hi}^{t}\right), F\left(\hat{\Omega}_{F}^{t}, W_{h}^{t}, H_{h}^{t}, \hat{\varepsilon}_{h}^{t}\right), y_{h}^{NL}|^{t}\right) \quad (11)$$

This result can be compared to the actual distribution in (9). We calculate poverty indices for both distributions and take the difference between them to find the contribution to poverty reduction:

$$\Delta P_{\Psi}^{t\to s} = P\{{y_h}^{t}\}_h - P\{(y_h)_{\Psi}^{t\to s})\}_h$$

Note this example refers to the main occupation structure for individuals in the non-farm sector.

In the case of the education structure we change $\widehat{\Theta 1}_{hi}^{t}$ parameters with $\widehat{\Theta 1}_{hi}^{s}$ in the H function. However, since education has effects on occupation and earnings, it affects each of these functions (NF, *O* and *F*) and we obtain a counterfactual distribution such as:

[30] The estimated error terms for each reduced-from equation of occupation, education and economic sector, are kept constant in each decomposition exercise.

$log(y_h)_{\Theta 1}^{t\to s} =$

$$f\left(NF\left(\hat{\Omega}_{NF}^t, X_{hi}^t, H_{hi}^s(\widehat{\Theta 1}_{hi}^s), \hat{\varepsilon}_{hi}^t\right), O\left(\hat{\Psi}^s, Z_{hi}^t, H_{hi}^s(\hat{\Theta}1_{hi}^s), \hat{v}_{hi}^t\right), F(\hat{\Omega}_F^t, W_h^t, H_h^s(\widehat{\Theta 1}_h^s), \hat{\varepsilon}_h^t), y_h^{NL}|^t\right) \qquad (12)$$

Once again, the contribution of the change in education structure to the change in poverty between t and s can be estimated by the difference between poverty indices of actual (equation (9)) and counterfactual distribution (equation (12)):

$$\Delta P_{\Theta 1}^{t\to s} = P\{y_h{}^t\}_h - P\left\{(y_h)_{\Theta 1}^{t\to s}\right\}_h$$

For sector of work, we change $\widehat{\Theta 2}_{hi}^t$ parameters with $\widehat{\Theta 2}_{hi}^s$ in the H function. Since sector has effects only on earnings, if affects only the NF and F equations. We obtain the counterfactual distribution as follows:

$log(y_h)_{\Theta 2}^{t\to s} =$

$$f\left(NF\left(\hat{\Omega}_{NF}^t, X_{hi}^t, H_{hi}^s(\widehat{\Theta 2}_{hi}^s), \hat{\varepsilon}_{hi}^t\right), O\left(\hat{\Psi}^s, Z_{hi}^t, H_{hi}^t, \hat{v}_{hi}^t\right), F(\hat{\Omega}_F^t, W_h^t, H_h^s(\widehat{\Theta 2}_h^s), \hat{\varepsilon}_h^t), y_h^{NL}|^t\right) \qquad (13)$$

The difference between the distribution of this set of simulated incomes $\{y_i\}_{\Psi,\Theta}^{t\to s}$ and the actual set of incomes of period *t* is comparable to the *endowment effect* in the Oaxaca-Blinder decomposition.

4. Changes in distribution due to changes in demographics

The next decomposition consists of altering the joint distribution of exogenous household characteristics such as age, gender, region and area of each individual in the household. These variables do not depend on other exogenous variables in the model; the simulation is performed simply by recalibrating the population by the weights corresponding to the joint distribution of these attributes in the target year. Formally,

$$\log(y_h)_{X.Z,W}^{t\to s} = f\left(NF\left(\hat{\Omega}_{NF}^t, X_{hi}^s, H_{hi}^t, \hat{\varepsilon}_{hi}^t\right), O\left(\hat{\Psi}^t, Z_{hi}^s, H_{hi}^t, \hat{v}_{hi}^t\right), F(\hat{\Omega}_F^t, W_h^s, H_h^t, \hat{\varepsilon}_h^t), y_h^{NL}|^t\right) \qquad (14)$$

and the contribution to poverty change will be:

$$\Delta P_{X,Z,W}^{t\to s} = P\{y_h{}^t\}_h - P\left\{(y_h)_{X.Z,W}^{t\to s}\right\}_h$$

5. Changes in distribution due to changes in non-labor income & consumption-income ratio

The conditional distributions estimated in the previous step are used for the rank-preserving transformation of the observed distribution of non-labor income in each year. In particular, we created cells of household heads with the same level of education, gender and region (urban-rural). Inside of each cell, we created quantiles of non-labor income. We estimate the counterfactual distribution of non-labor income in year *t* by assigning the mean value of non-labor income of quantile q in cell c in year *s*, to the same quantile and cell in year *t*. In other words, we ranked the two distributions by per capita household non-labor income and if *q* was the rank of household with income $\mathrm{y_h^{NL}}$ at time *t*, we replace it with the non-labor income of the household with the same rank at time *s*. We apply the same decomposition methodology for the case of the consumption-income ratio.

For the non-labor income, the counterfactual distribution could be expressed formally as:

$$\log(y_h)_{y_h^{NL}}^{t\to s} = f\left(NF\left(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{t}, \hat{\varepsilon}_{hi}^{t}\right), O\left(\widehat{\Psi}^{t}, Z_{hi}^{s}, H_{hi}^{t}, \widehat{v}_{hi}^{t}\right), F\left(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{h}^{t}, \hat{\varepsilon}_{h}^{t}\right), y_h^{NL}|_{q}^{s}\right) \tag{15}$$

As before, we can compare with the actual distribution described in equation (9), calculate poverty indices and obtain the contribution of non-labor income to poverty change between years *t* and *s*:

$$\Delta P_{y_h^{NL}}^{t\to s} = P\{{y_h}^{t}\}_h - P\left\{(y_h)_{y_h^{NL}}^{t\to s}\right\}_h$$

It is important to note that all previous decompositions are also performed both considering *s* as the initial year and then considering *t* as base year. The average of these marginal effects decompositions is the final result reported in the analysis.[31]

The Cumulative decomposition technique

As mentioned before, there could be interaction effects between each of the marginal effects considered above. The cumulative decomposition technique allows us to account for these interactions by calculating each effect and successively and cumulating into counterfactuals that contain the cumulative effects of multiple changes. We attribute all of the additional contribution to poverty change to each specific factor being added. However, the magnitude of that contribution will depend on the path chosen for the decomposition.[32] We follow the Bourguignon, Ferreira and Leite (2008) approach by first calculating the effects of changes in the characteristics of the population, beginning with the exogenous variables such as age, gender, region and area ($X_{hi}^{s}, Z_{hi}^{s}, W_{h}^{s}$). Formally,

$$\begin{aligned}\Delta P^{t\to s} = {} & P\left\{f\left(NF\left(\widehat{\Omega}_{NF}^{t}, X_{hi}^{t}, H_{hi}^{t}, \hat{\varepsilon}_{hi}^{t}\right), O\left(\widehat{\Psi}^{t}, Z_{hi}^{t}, H_{hi}^{t}, \hat{v}_{hi}^{t}\right), F\left(\widehat{\Omega}_{F}^{t}, W_{h}^{t}, H_{h}^{t}, \hat{\varepsilon}_{h}^{t}\right), y_h^{NL}|_{q}^{t}\right)\right\}_h \\ & - P\left\{f\left(NF\left(\widehat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{t}, \hat{\varepsilon}_{hi}^{t}\right), O\left(\widehat{\Psi}^{t}, Z_{hi}^{s}, H_{hi}^{t}, \hat{v}_{hi}^{t}\right), F\left(\widehat{\Omega}_{F}^{t}, W_{h}^{s}, H_{h}^{t}, \hat{\varepsilon}_{h}^{t}\right), y_h^{NL}|_{q}^{t}\right)\right\}_h\end{aligned}$$

Second, keeping the demographic effects, we add the education structure change ($\widehat{\Theta 1}_{hi}^{s}$):

[31] Bear in mind that this does not solve all path-dependence problems. Shapley values are necessary to estimate in order to tackle this difficulty.
[32] Given the large number of factors, calculating Shapley values from *t* to *s* and vice versa is beyond the scope of this paper.

$$= P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{t}, \hat{\varepsilon}_{hi}^{t}\big), O\left(\hat{\Psi}^{t}, Z_{hi}^{s}, H_{hi}^{t}, \hat{\upsilon}_{hi}^{t}\right), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{h}^{t}, \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$
$$- P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{t}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$

Third, preserving the previous changes, we include the change in occupation structure ($\hat{\Psi}^{s}$):

$$= P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{t}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$
$$- P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\hat{\Theta}1_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\hat{\Theta}1_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$

Fourth, we add the change in the structure of economic sectors ($\widehat{\Theta 2}_{hi}^{s}$)::

$$= P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{t}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$
$$- P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{s}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}, \widehat{\Theta 2}_{hi}^{s}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$

Fifth, we include the returns to non-farm sector ($\hat{\Omega}_{NF}^{s}$):

$$= P\left\{f(NF\big(\hat{\Omega}_{NF}^{t}, X_{hi}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$
$$- P\left\{f(NF\big(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$

Then we change the returns to farm sector ($\hat{\Omega}_{F}^{s}$):

$$= P\left\{f(NF\big(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{t}, W_{h}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$
$$- P\left\{f(NF\big(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}(\widehat{\Theta 1}_{hi}^{s}), \hat{\upsilon}_{hi}^{t}\big), F(\hat{\Omega}_{F}^{s}, W_{h}^{s}, H_{hi}^{s}(\hat{\Theta}_{hi}^{s}), \hat{\varepsilon}_{h}^{t}), y_{h}^{NL}\big|_{q}^{t})\right\}_{h}$$

Next, we change residuals of earnings and net revenues equations:

$$= P\left\{f\left(NF\big(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{hi}^{t}\big), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}\big(\widehat{\Theta 1}_{hi}^{s}\big), \hat{\upsilon}_{hi}^{t}\big), F\big(\hat{\Omega}_{F}^{s}, W_{h}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{h}^{t}\big), y_{h}^{NL}\big|_{q}^{t}\right)\right\}_{h}$$
$$- P\left\{f\left(NF\left(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{hi}^{t}(\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}})\right), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}\big(\widehat{\Theta 1}_{hi}^{s}\big), \hat{\upsilon}_{hi}^{t}\big), F\left(\hat{\Omega}_{F}^{s}, W_{h}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{h}^{t}(\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}})\right), y_{h}^{NL}\big|_{q}^{t}\right)\right\}_{h}$$

Finally, we add the change in non-labor income components and the consumption ratio. The latter is not formally displayed in this example:

$$= P\left\{f\left(NF\left(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{hi}^{t}(\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}})\right), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}\big(\widehat{\Theta 1}_{hi}^{s}\big), \hat{\upsilon}_{hi}^{t}\big), F\left(\hat{\Omega}_{F}^{s}, W_{h}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{h}^{t}(\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}})\right), y_{h}^{NL}\big|_{q}^{t}\right)\right\}_{h}$$
$$- P\left\{f\left(NF\left(\hat{\Omega}_{NF}^{s}, X_{hi}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{hi}^{t}\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}}\right), O\big(\hat{\Psi}^{s}, Z_{hi}^{s}, H_{hi}^{s}\big(\widehat{\Theta 1}_{hi}^{s}\big), \hat{\upsilon}_{hi}^{t}\big), F\left(\hat{\Omega}_{F}^{s}, W_{h}^{s}, H_{hi}^{s}\big(\hat{\Theta}_{hi}^{s}\big), \hat{\varepsilon}_{h}^{t}\frac{\hat{\sigma}_{\varepsilon}^{s}}{\hat{\sigma}_{\varepsilon}^{t}}\right), y_{h}^{NL}\big|_{q}^{s}\right)\right\}_{h}$$

Again, this cumulative decomposition technique is also performed both considering *s* as the initial year and then considering *t* as the initial year. The average of these decomposition effects is the final result reported in the analysis.

Lastly, it is relevant to clarify that even we decompose these changes sequentially; it is still possible to have an unexplained portion, both because the sum of the average contributions does not necessarily lead to the total change in distribution and because there may be other factors that contributed to distributional changes that were not considered in the analysis. This residual term is relatively small, implying that either the factors not included are not extremely important or they tend to compensate for each other.

Appendix. Regression Results

Table A1. Bangladesh Multinomial Logit on Occupational Choice

Individuals between 15 and 64 years old

	Household Heads						Other Members					
	2000			2010			2000			2010		
	Daily workers	Self-employed	Salaried	Daily workers	Self-employed	Salaried	Daily workers	Self-employed	Salaried	Daily workers	Self-employed	Salaried
Primary & Lower secondary	-1.204***	-0.0182	0.614***	-1.082***	0.122	0.682***	-0.964***	-0.0334	0.259***	-0.802***	0.321***	0.240***
	(0.160)	(0.161)	(0.166)	(0.145)	(0.147)	(0.147)	(0.0977)	(0.117)	(0.0965)	(0.0739)	(0.0986)	(0.0704)
Higher secondary &	-2.408***	0.301	2.002***	-3.461***	-0.599***	1.227***	-2.894***	0.0292	1.227***	-2.253***	0.114	1.460***
Terciary	(0.368)	(0.294)	(0.287)	(0.267)	(0.203)	(0.194)	(0.358)	(0.197)	(0.155)	(0.264)	(0.171)	(0.111)
Age	0.0408	0.126**	0.114**	0.109**	0.281***	0.238***	0.180***	0.231***	0.190***	0.154***	0.336***	0.183***
	(0.0510)	(0.0544)	(0.0556)	(0.0423)	(0.0449)	(0.0440)	(0.0239)	(0.0311)	(0.0255)	(0.0207)	(0.0281)	(0.0194)
Age squared	0.00141**	.00228***	.00208***	-0.00211***	.00382***	.00360***	-0.00286***	.00345***	00308***	-0.00243***	.00459***	00303***
	(0.000572)	0.000611)	0.000627)	(0.000473)	(0.000504)	(0.000496)	(0.000345)	(0.000454)	0.000381)	(0.000296)	(0.000407)	0.000285)
Urban	-0.354**	0.421***	0.795***	-1.150***	-0.411***	-0.00785	-0.172	0.623***	0.781***	-0.134	0.358***	0.966***
	(0.160)	(0.161)	(0.162)	(0.134)	(0.135)	(0.133)	(0.108)	(0.112)	(0.0884)	(0.0826)	(0.0907)	(0.0617)
Barisal	0.0892	-0.0402	-0.313	0.101	-0.330	-0.310	0.219	-0.117	-0.284	0.0287	-0.406**	-0.677***
	(0.263)	(0.275)	(0.288)	(0.255)	(0.262)	(0.258)	(0.179)	(0.206)	(0.174)	(0.157)	(0.183)	(0.136)
Chittagong	-0.490***	-0.310*	-0.216	0.228	-0.525***	-0.264	0.107	-0.0791	0.0725	0.189*	-0.704***	-0.429***
	(0.179)	(0.184)	(0.186)	(0.161)	(0.168)	(0.161)	(0.119)	(0.136)	(0.103)	(0.100)	(0.124)	(0.0766)
Khulna	0.432*	0.273	0.0118	1.127***	0.352	0.128	0.504***	0.155	-0.540***	0.902***	0.219*	-0.506***
	(0.231)	(0.240)	(0.248)	(0.217)	(0.224)	(0.223)	(0.141)	(0.166)	(0.155)	(0.109)	(0.128)	(0.0996)
Rajsahi	1.735***	1.400***	0.834***	1.641***	1.141***	0.390**	1.508***	0.433***	-0.141	0.976***	0.0781	-0.748***
	(0.227)	(0.234)	(0.242)	(0.190)	(0.194)	(0.197)	(0.109)	(0.142)	(0.121)	(0.0901)	(0.108)	(0.0847)
Sylhet	0.541*	-0.0682	0.126	0.564**	0.467*	-0.0835	0.414**	0.0886	0.193	0.791***	0.0883	-0.629***
	(0.281)	(0.319)	(0.323)	(0.262)	(0.270)	(0.276)	(0.171)	(0.222)	(0.168)	(0.130)	(0.163)	(0.132)
Attends school	-3.549***	-3.393***	-2.742***	-0.263	-14.93	-1.508	-3.253***	-3.346***	-3.866***	-3.964***	-3.359***	-3.996***
	(0.753)	(0.866)	(0.724)	(1.439)	(565.3)	(1.281)	(0.281)	(0.287)	(0.228)	(0.251)	(0.239)	(0.151)
Remittances	-0.646***	-1.014***	-0.715***	-0.129	-0.00592	-0.178	-0.319**	-0.440***	-0.367***	-0.516***	-0.295**	-0.394***
	(0.172)	(0.178)	(0.181)	(0.214)	(0.215)	(0.218)	(0.127)	(0.139)	(0.125)	(0.110)	(0.123)	(0.106)
Female	-2.213***	-2.993***	-1.178***	-1.903***	-2.802***	-1.019***	-3.038***	-3.288***	-1.753***	-3.197***	-3.580***	-1.563***
	(0.409)	(0.489)	(0.444)	(0.376)	(0.444)	(0.379)	(0.161)	(0.269)	(0.136)	(0.146)	(0.256)	(0.0973)
Remitt x Female	-0.328	-0.985*	-1.450***	-1.534***	-1.583***	-2.358***	0.143	-0.0907	0.0784	0.0908	0.140	-0.352**
	(0.321)	(0.595)	(0.431)	(0.338)	(0.506)	(0.380)	(0.201)	(0.329)	(0.189)	(0.202)	(0.251)	(0.166)
Married	0.558	0.683*	0.593	1.295***	1.471***	1.235***	0.822***	1.240***	0.932***	0.817***	0.794***	0.639***
	(0.367)	(0.384)	(0.389)	(0.355)	(0.375)	(0.355)	(0.148)	(0.159)	(0.149)	(0.116)	(0.128)	(0.114)
Married x Female	-2.269***	-1.432**	-1.876***	-2.703***	-1.877***	-1.897***	-2.151***	-2.283***	-2.376***	-1.856***	-1.477***	-2.115***
	(0.496)	(0.651)	(0.569)	(0.467)	(0.590)	(0.464)	(0.202)	(0.309)	(0.189)	(0.176)	(0.276)	(0.138)
Employed Hd head							-0.413***	-0.412***	-0.331***	0.170	-0.0691	0.0817
							(0.121)	(0.135)	(0.112)	(0.123)	(0.135)	(0.0982)
Hd Head with primary							-0.952***	-0.244**	-0.379***	1.414***	0.171	0.213**
& Lower secondary							(0.104)	(0.115)	(0.0948)	(0.240)	(0.160)	(0.106)
Hd Head with Higher							-1.844***	-0.492**	-0.465***	0.630***	0.0284	-0.0465
secondary & Terciary							(0.314)	(0.204)	(0.156)	(0.244)	(0.156)	(0.100)
Other member employed	-0.521***	-0.385***	-0.513***	-0.395***	-0.492***	-0.363***						
	(0.0700)	(0.0717)	(0.0762)	(0.0730)	(0.0760)	(0.0736)						
Number of children	0.246***	0.267***	0.213***	0.114	0.0960	-0.115						
	(0.0484)	(0.0503)	(0.0521)	(0.0697)	(0.0713)	(0.0722)						
Constant	3.198***	0.0640	-0.443	1.710*	-3.336***	-2.206**	-1.512***	-3.638***	-2.838***	-3.080***	-5.940***	-2.808***
	(1.030)	(1.094)	(1.113)	(0.915)	(0.976)	(0.943)	(0.364)	(0.475)	(0.387)	(0.414)	(0.482)	(0.329)
Observations	4974	4974	4974	7862	7862	7862	14058	14058	14058	21715	21715	21715
Pseudo R2	0.233	0.233	0.233	0.259	0.259	0.259	0.362	0.362	0.362	0.359	0.359	0.359

Notes: (1) Self-employed in Non-agriculture

Dhaka is the base region

Non-Employed is the base category

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A2. Peru Multinomial Logit on Occupational Choice

	2004						2010					
	Head		Spouse		Other		Head		Spouse		Other	
	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed
At least High School					0.609***	0.416***					0.809***	0.527***
					(0.0476)	(0.0690)					(0.0510)	(0.0748)
Head or Spouse	0.395***	-0.0337	0.547***	0.0410	-0.323***	-0.572***	0.185*	-0.128	0.675***	0.119	-0.324***	-0.384***
with at least High	(0.0882)	(0.0881)	(0.0940)	(0.0685)	(0.0517)	(0.0730)	(0.102)	(0.103)	(0.0917)	(0.0763)	(0.0562)	(0.0787)
26 to 35 yrs old	0.737***	1.052***	0.709***	0.693***	0.777***	1.305***	0.401*	0.844***	0.439***	0.856***	0.863***	1.181***
	(0.187)	(0.205)	(0.165)	(0.125)	(0.0567)	(0.0774)	(0.233)	(0.257)	(0.161)	(0.154)	(0.0648)	(0.0866)
36 to 45 yrs old	0.673***	1.208***	0.859***	0.746***	0.564***	1.312***	0.286	0.894***	0.570***	0.946***	0.796***	1.425***
	(0.176)	(0.194)	(0.172)	(0.128)	(0.0941)	(0.113)	(0.224)	(0.246)	(0.165)	(0.154)	(0.0997)	(0.122)
46 to 55 yrs old	0.127	0.778***	0.192	0.179	0.372***	1.211***	-0.189	0.603**	0.296*	0.757***	0.316**	1.458***
	(0.179)	(0.196)	(0.190)	(0.139)	(0.144)	(0.167)	(0.229)	(0.250)	(0.177)	(0.162)	(0.154)	(0.163)
56 to 65 yrs old	-1.287***	-0.128	-0.479*	-0.200	-0.790***	0.455**	-1.307***	-0.204	-0.727***	0.260	-1.248***	0.911***
	(0.182)	(0.198)	(0.272)	(0.153)	(0.215)	(0.227)	(0.232)	(0.250)	(0.210)	(0.173)	(0.274)	(0.222)
At least one Family	0.0356	1.314***	-1.118***	0.689***	-0.261***	0.218**	-0.0482	1.003***	-0.844***	0.811***	-0.202***	0.221**
Worker	(0.239)	(0.208)	(0.234)	(0.0909)	(0.0633)	(0.0938)	(0.330)	(0.314)	(0.188)	(0.0940)	(0.0668)	(0.0984)
Farm Household	-0.315**	-0.900***	-0.829***	-0.480***	-0.317***	-0.568***	-0.162	-0.573***	-0.927***	-0.591***	-0.244***	-0.402***
	(0.150)	(0.170)	(0.134)	(0.103)	(0.0711)	(0.104)	(0.171)	(0.185)	(0.143)	(0.107)	(0.0771)	(0.116)
Female	-1.640***	-0.949***	-2.191***	-0.974***	-0.712***	-0.643***	-1.412***	-1.193***	-1.975***	-0.736***	-0.685***	-0.623***
	(0.129)	(0.127)	(0.231)	(0.245)	(0.0448)	(0.0630)	(0.152)	(0.155)	(0.224)	(0.234)	(0.0477)	(0.0661)
Attends School	-0.773***	-1.019***	0.995***	-0.00837	-1.110***	-0.803***	0.0414	-0.673**	0.714**	-0.461	-1.163***	-0.917***
	(0.206)	(0.252)	(0.298)	(0.340)	(0.0600)	(0.0840)	(0.275)	(0.301)	(0.279)	(0.350)	(0.0578)	(0.0842)
Married	-0.141	-0.0760			0.00307	0.267***	-0.185	-0.236			-0.109	0.138
	(0.128)	(0.128)			(0.0608)	(0.0833)	(0.155)	(0.158)			(0.0689)	(0.0866)
Head Employed			-0.00833	-0.431***	-0.0719	0.0156			0.203	-0.212*	-0.0477	0.117
			(0.155)	(0.106)	(0.0586)	(0.0775)			(0.163)	(0.125)	(0.0706)	(0.0889)
Spouse Employed					0.0886*	0.0435					0.0948*	0.0138
					(0.0496)	(0.0688)					(0.0513)	(0.0733)
Costa	-0.00486	0.0614	-0.153	0.307***	-0.0886	0.201**	-0.0765	0.121	0.0767	0.367***	-0.366***	-0.0823
	(0.103)	(0.103)	(0.107)	(0.0891)	(0.0586)	(0.0808)	(0.118)	(0.119)	(0.108)	(0.0990)	(0.0671)	(0.0904)
Sierra	-0.0484	0.0569	-0.150	0.340***	-0.418***	-0.0714	-0.0881	0.256**	-0.0680	0.289***	-0.477***	-0.275***
	(0.109)	(0.110)	(0.113)	(0.0921)	(0.0625)	(0.0861)	(0.125)	(0.127)	(0.112)	(0.100)	(0.0715)	(0.0944)
Selva	-0.190	0.105	-0.0935	0.200**	-0.388***	-0.0687	-0.0160	0.304**	0.0924	0.383***	-0.457***	-0.0230
	(0.128)	(0.125)	(0.120)	(0.101)	(0.0715)	(0.0987)	(0.141)	(0.143)	(0.117)	(0.105)	(0.0763)	(0.0987)
Rural	0.314***	-0.414***	-0.457***	-0.674***	-0.0716	-0.570***	-0.00734	-0.609***	-0.308**	-0.737***	-0.0120	-0.543***
	(0.113)	(0.121)	(0.129)	(0.0973)	(0.0716)	(0.103)	(0.148)	(0.152)	(0.139)	(0.106)	(0.0774)	(0.118)
Child <=5	0.0589	0.176*	-0.300***	-0.349***			-0.0138	-0.0140	-0.313***	-0.179***		
	(0.0971)	(0.102)	(0.0670)	(0.0496)			(0.0861)	(0.0898)	(0.0621)	(0.0418)		
Constant	1.349***	0.477**	0.594*	0.289	-0.0442	-1.454***	2.166***	1.253***	0.687**	-0.165	0.315***	-1.089***
	(0.204)	(0.220)	(0.329)	(0.291)	(0.0809)	(0.114)	(0.273)	(0.288)	(0.306)	(0.299)	(0.100)	(0.131)
Observations	10,087	10,087	12,004	12,004	21,720	21,720	8,312	8,312	9,327	9,327	16,824	16,824
Pseudo R-squared	0.0879	0.0879	0.0914	0.0914	0.118	0.118	0.0599	0.0599	0.0950	0.0950	0.136	0.136

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Own estimates based on Peru's ENAHO 2004 -2010.

Table A3. Thailand Multinomial Logit on Occupational Choice

	2000						2009					
	Head		Spouse		Others		Head		Spouse		Others	
	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed
6-11 yrs of Educ.					0.446***	0.535***					0.655***	0.581***
					(0.0872)	(0.136)					(0.0775)	(0.107)
>11 yrs of Educ.					0.618***	0.452***					1.336***	0.887***
					(0.0912)	(0.146)					(0.0796)	(0.114)
Head with 6-11 yrs of Educ.	0.122	0.0580	-0.153*	0.315**	-0.144	-0.128	0.194**	0.0547	0.0444	0.313***	-0.0690	-0.145
	(0.125)	(0.136)	(0.0902)	(0.124)	(0.0906)	(0.157)	(0.0819)	(0.0855)	(0.0716)	(0.0867)	(0.0624)	(0.120)
Head with >11 yrs of Educ.	0.795***	-0.265*	-0.418***	0.321**	0.158	-0.244	0.616***	-0.221**	0.0599	0.434***	-0.0296	-0.190
	(0.126)	(0.145)	(0.118)	(0.158)	(0.108)	(0.215)	(0.0842)	(0.0886)	(0.0839)	(0.103)	(0.0681)	(0.125)
Spouse with <6 yrs of Educ.	0.355**	0.602***			-0.254***	-0.305***	0.540***	0.581***			-0.258***	-0.169*
	(0.159)	(0.176)			(0.0679)	(0.113)	(0.120)	(0.123)			(0.0563)	(0.0914)
Spouse with 6-11 yrs of Educ.	0.886***	1.230***	0.245**	-0.0998	-0.357***	-0.727***	0.478***	0.807***	0.237***	0.0360	-0.390***	-0.307**
	(0.188)	(0.208)	(0.0985)	(0.127)	(0.123)	(0.229)	(0.126)	(0.132)	(0.0757)	(0.0867)	(0.0787)	(0.138)
Spouse with >11 yrs of Educ.	0.676***	1.009***	1.163***	-0.558***	-0.174	-0.226	0.598***	0.881***	0.842***	-0.200*	-0.422***	-0.358**
	(0.206)	(0.224)	(0.129)	(0.181)	(0.171)	(0.285)	(0.125)	(0.134)	(0.0879)	(0.113)	(0.0905)	(0.165)
26 to 35 yrs old	0.907***	1.914***	-0.0221	1.242***	0.601***	1.554***	1.159***	2.171***	0.157	0.743***	0.758***	1.352***
	(0.179)	(0.249)	(0.140)	(0.263)	(0.0702)	(0.134)	(0.156)	(0.227)	(0.114)	(0.245)	(0.0556)	(0.117)
36 to 45 yrs old	0.545***	1.925***	-0.350**	1.416***	0.490***	1.916***	0.619***	2.028***	-0.0610	1.234***	0.549***	1.760***
	(0.175)	(0.245)	(0.146)	(0.266)	(0.102)	(0.170)	(0.150)	(0.219)	(0.111)	(0.237)	(0.0663)	(0.123)
46 to 55 yrs old	-0.293	1.220***	-0.901***	1.216***	-0.0735	1.686***	-0.222	1.427***	-0.611***	1.070***	0.225**	1.778***
	(0.187)	(0.251)	(0.158)	(0.277)	(0.145)	(0.210)	(0.140)	(0.212)	(0.118)	(0.240)	(0.0972)	(0.147)
56 to 65 yrs old	-2.011***	-0.165	-2.003***	0.306	-2.428***	0.167	-1.934***	0.102	-1.705***	0.240	-1.330***	0.740***
	(0.184)	(0.249)	(0.187)	(0.292)	(0.225)	(0.297)	(0.147)	(0.214)	(0.138)	(0.249)	(0.143)	(0.184)
Female	-1.129***	-0.610***	-0.943***	-0.0673	-0.465***	-0.202**	-1.020***	-0.563***	-1.214***	-0.394***	-0.531***	-0.326***
	(0.112)	(0.124)	(0.146)	(0.184)	(0.0548)	(0.0949)	(0.0719)	(0.0734)	(0.0762)	(0.0953)	(0.0426)	(0.0709)
Central	-0.0208	0.0478	0.0450	0.0656	-0.426***	-0.187	0.278***	0.302***	0.109	0.248**	0.0418	0.0641
	(0.124)	(0.132)	(0.107)	(0.141)	(0.0941)	(0.166)	(0.0865)	(0.0923)	(0.0788)	(0.107)	(0.0639)	(0.112)
North	0.0424	0.108	0.374***	0.570***	-0.349***	0.269	-0.188**	0.295***	-0.403***	0.417***	-0.407***	0.110
	(0.130)	(0.140)	(0.114)	(0.147)	(0.103)	(0.171)	(0.0944)	(0.0983)	(0.0886)	(0.109)	(0.0735)	(0.121)
Northeast	-0.528***	-0.529***	-0.0345	0.234	-0.769***	-0.376**	-0.690***	-0.0869	-0.469***	0.255**	-0.649***	-0.0379
	(0.126)	(0.135)	(0.112)	(0.146)	(0.0968)	(0.176)	(0.0908)	(0.0954)	(0.0864)	(0.109)	(0.0693)	(0.119)
South	0.0260	0.239	-0.371***	0.382***	-0.898***	-0.175	0.172	0.420***	-0.230**	0.518***	-0.105	0.339**
	(0.145)	(0.154)	(0.119)	(0.148)	(0.104)	(0.182)	(0.108)	(0.114)	(0.0931)	(0.116)	(0.0801)	(0.136)
Urban	0.107	0.849***	-0.354***	-0.0933	-0.172***	0.0901	0.0459	0.728***	-0.277***	0.0603	-0.151***	0.144**
	(0.0755)	(0.0849)	(0.0677)	(0.0826)	(0.0538)	(0.0941)	(0.0569)	(0.0597)	(0.0498)	(0.0587)	(0.0420)	(0.0686)
Head Employed			0.607***	-0.236*	0.0274	-0.0914			0.599***	-0.217***	-0.220***	-0.406***
			(0.116)	(0.123)	(0.0641)	(0.103)			(0.0814)	(0.0837)	(0.0498)	(0.0784)
Spouse Employed					0.186**	0.261*					0.276***	0.146
					(0.0731)	(0.133)					(0.0566)	(0.105)
Married	-0.672***	-0.610***			0.104*	0.443***	-0.640***	-0.569***			0.190***	0.711***
	(0.139)	(0.157)			(0.0591)	(0.102)	(0.112)	(0.116)			(0.0470)	(0.0734)
Attends School	-2.993***	-2.684***	-0.723	0.521	-3.504***	-3.393***	-2.325***	-2.473***	-0.127	-2.850***	-3.016***	-3.195***
	(0.248)	(0.404)	(0.568)	(0.515)	(0.114)	(0.364)	(0.283)	(0.286)	(0.271)	(0.656)	(0.0823)	(0.254)
Number of children younger th	-0.364***	-0.171**	-0.520***	-0.400***			-0.350***	-0.286***	-0.575***	-0.386***		
	(0.0681)	(0.0708)	(0.0590)	(0.0706)			(0.0550)	(0.0562)	(0.0488)	(0.0574)		
Constant	1.999***	-0.891***	0.937***	-1.999***	0.814***	-2.579***	1.825***	-1.034***	1.009***	-1.653***	0.145	-2.818***
	(0.231)	(0.289)	(0.251)	(0.367)	(0.144)	(0.251)	(0.178)	(0.238)	(0.176)	(0.289)	(0.113)	(0.189)
Observations	15,221	15,221	11,386	11,386	19,603	19,603	25,341	25,341	19,176	19,176	31,564	31,564
Pseudo R-squared	0.162	0.162	0.0878	0.0878	0.268	0.268	0.145	0.145	0.106	0.106	0.262	0.262

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Sample includes individuals who are non-farmers in main occupation. The ommited occupational category includes family workers, unemployed and inactive individuals, i.e., individuals with zero earnings

Table A4. Bangladesh. Non-Farm Earnings

Individuals between 15 and 64 years old

	Household Heads						Other Members					
	2000			2010			2000			2010		
	Daily workers	Self-employed (1)	Salaried	Daily workers	Self-employed (1)	Salaried	Daily workers	Self-employed (1)	Salaried	Daily workers	Self-employed (1)	Salaried
Primary & Lower secondary	0.132***	0.370***	0.330***	0.0530***	0.312***	0.357***	0.133**	0.449***	0.459***	0.0492**	0.0246	0.292***
	(0.0392)	(0.0484)	(0.0499)	(0.0150)	(0.0387)	(0.0387)	(0.0554)	(0.0831)	(0.0674)	(0.0211)	(0.0676)	(0.0372)
Higher secondary &	0.420**	0.994***	0.796***	0.248***	0.632***	0.826***	0.114	0.975***	0.837***	0.466***	0.331***	0.954***
Terciary	(0.164)	(0.0810)	(0.0551)	(0.0654)	(0.0625)	(0.0420)	(0.270)	(0.124)	(0.0854)	(0.0992)	(0.107)	(0.0478)
Age	0.0510***	0.0591***	0.0529***	0.0224***	0.0411***	0.0916***	0.0514***	0.0693***	0.0478***	0.0384***	0.124***	.0693***
	(0.00989)	(0.0186)	(0.0161)	(0.00426)	(0.0149)	(0.0117)	(0.0131)	(0.0222)	(0.0178)	(0.00593)	(0.0167)	(0.00975)
Age squared	-0.000666***	-0.000664***	-0.000570***	-0.000267***	-0.000541***	-0.00107***	-0.000633***	-0.000774**	-0.000444	-0.000470***	-0.00170***	00846***
	(0.000119)	(0.000219)	(0.000191)	(5.09e-05)	(0.000172)	(0.000138)	(0.000203)	(0.000350)	(0.000282)	(9.17e-05)	(0.000246)	0.000153)
Female	-0.894***	-1.477***	-0.956***	-0.688***	-1.080***	-0.709***	-1.078***	-1.244***	-0.682***	-0.691***	-1.132***	-0.462***
	(0.0621)	(0.166)	(0.0849)	(0.0266)	(0.138)	(0.0609)	(0.0698)	(0.121)	(0.0656)	(0.0301)	(0.0841)	(0.0331)
Urban	0.0863*	0.234***	0.108**	-0.0217	0.264***	0.117***	-0.0135	0.0209	-0.147**	-0.104***	0.287***	-0.0407
	(0.0447)	(0.0495)	(0.0421)	(0.0164)	(0.0396)	(0.0315)	(0.0737)	(0.0803)	(0.0619)	(0.0276)	(0.0615)	(0.0316)
Barisal	0.0601	-0.193**	-0.0421	0.0120	-0.0592	-0.0989	0.216*	-0.0186	-0.228*	0.0885*	0.156	-0.0396
	(0.0641)	(0.0966)	(0.0880)	(0.0293)	(0.0857)	(0.0671)	(0.111)	(0.151)	(0.124)	(0.0502)	(0.127)	(0.0752)
Chittagong	-0.0891*	-0.0956	-0.0181	0.0488**	-0.152**	-0.0456	-0.200***	-0.123	-0.178**	0.101***	-0.149*	-0.0281
	(0.0461)	(0.0622)	(0.0521)	(0.0194)	(0.0597)	(0.0405)	(0.0756)	(0.101)	(0.0704)	(0.0321)	(0.0883)	(0.0388)
Khulna	0.103**	-0.108	-0.0193	-0.216***	-0.212***	-0.184***	-0.107	-0.0433	-0.215*	-0.204***	-0.297***	-0.237***
	(0.0478)	(0.0747)	(0.0677)	(0.0194)	(0.0621)	(0.0506)	(0.0855)	(0.121)	(0.117)	(0.0338)	(0.0907)	(0.0562)
Rajsahi	-0.182***	-0.242***	-0.195***	-0.179***	-0.314***	-0.112**	-0.227***	-0.396***	-0.295***	-0.103***	-0.00253	-0.0741
	(0.0364)	(0.0589)	(0.0610)	(0.0160)	(0.0466)	(0.0454)	(0.0665)	(0.103)	(0.0910)	(0.0281)	(0.0756)	(0.0481)
Sylhet	-0.0841	-0.183	-0.370***	-0.0994***	0.302***	-0.0124	-0.231**	-0.481***	-0.636***	0.0448	0.125	-0.0857
	(0.0604)	(0.131)	(0.111)	(0.0298)	(0.0846)	(0.0812)	(0.103)	(0.166)	(0.125)	(0.0389)	(0.112)	(0.0741)
Manufacturing	0.432***		0.446***	0.0674***		0.107	0.300***		0.463***	-0.169***		0.149*
	(0.0456)		(0.0780)	(0.0196)		(0.0699)	(0.0674)		(0.145)	(0.0274)		(0.0904)
Industry	0.178***	0.00876	0.433***	0.272***	-0.0833	0.250**	0.448***	-0.0366	0.440**	0.174***	0.700***	0.0853
	(0.0547)	(0.0962)	(0.121)	(0.0201)	(0.146)	(0.0969)	(0.0897)	(0.148)	(0.221)	(0.0296)	(0.171)	(0.126)
Services	0.429***	-0.0220	0.403***	0.111***	-0.0844*	0.0882	0.469***	0.0881	0.297**	0.0930***	0.195***	-0.0847
	(0.0379)	(0.0472)	(0.0740)	(0.0156)	(0.0475)	(0.0670)	(0.0692)	(0.0777)	(0.144)	(0.0276)	(0.0707)	(0.0905)
Public job			0.178***			0.320***			0.555***			0.437***
			(0.0452)			(0.0393)			(0.0921)			(0.0522)
Constant	6.395***	6.636***	6.256***	7.190***	7.164***	5.698***	6.270***	6.379***	6.198***	6.974***	5.456***	6.227***
	(0.198)	(0.386)	(0.334)	(0.0872)	(0.317)	(0.248)	(0.192)	(0.334)	(0.285)	(0.0892)	(0.273)	(0.163)
Observations	2092	1269	1134	3390	2007	1820	1153	673	1104	1857	973	1984
R-squared	0.216	0.240	0.401	0.289	0.183	0.373	0.307	0.317	0.285	0.383	0.343	0.348
Adj R-squared	0.211	0.232	0.393	0.286	0.177	0.368	0.299	0.304	0.275	0.379	0.334	0.343

Notes: (1) Self-employed in Non-agriculture

Dhaka is the base region

Illiterate and Incomplete primary education is the base for education levels

Agriculture is base sector for Daily and Salaried while Manufacturing is base sector for Self-employed in Non-Agriculture

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5. Peru. Non-Farm Earnings

	2004						2010					
	Head		Spouse		Other		Head		Spouse		Other	
	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed	Salaried Job	Self-employed
Primary Education	0.132***		0.296***		0.0984**		0.148***		0.220***		0.142***	
	(0.0383)		(0.0637)		(0.0417)		(0.0367)		(0.0623)		(0.0457)	
Secondary Education	0.350***		0.558***		0.238***		0.271***		0.519***		0.278***	
	(0.0382)		(0.0663)		(0.0415)		(0.0359)		(0.0633)		(0.0451)	
College Education	0.837***		0.937***		0.570***		0.627***		0.825***		0.578***	
	(0.0404)		(0.0727)		(0.0452)		(0.0381)		(0.0662)		(0.0477)	
26 to 35 yrs old	0.243***	0.314***	0.280***	0.291***	0.321***	0.389***	0.169***	0.305***	0.249***	0.457***	0.283***	0.556***
	(0.0441)	(0.0842)	(0.0875)	(0.0955)	(0.0206)	(0.0486)	(0.0422)	(0.0946)	(0.0754)	(0.110)	(0.0198)	(0.0539)
36 to 45 yrs old	0.358***	0.428***	0.318***	0.372***	0.313***	0.482***	0.192***	0.390***	0.254***	0.591***	0.285***	0.705***
	(0.0436)	(0.0818)	(0.0876)	(0.0946)	(0.0307)	(0.0634)	(0.0413)	(0.0922)	(0.0731)	(0.108)	(0.0289)	(0.0691)
46 to 55 yrs old	0.405***	0.277***	0.357***	0.329***	0.396***	0.339***	0.167***	0.253***	0.241***	0.554***	0.251***	0.545***
	(0.0446)	(0.0824)	(0.0922)	(0.0983)	(0.0484)	(0.0935)	(0.0419)	(0.0919)	(0.0759)	(0.110)	(0.0462)	(0.0899)
56 to 65 yrs old	0.305***	0.0801	0.541***	0.128	0.548***	0.220	0.0896**	-0.00376	0.405***	0.418***	0.223**	0.711***
	(0.0504)	(0.0845)	(0.107)	(0.106)	(0.0968)	(0.156)	(0.0456)	(0.0940)	(0.0907)	(0.116)	(0.0994)	(0.133)
Female	-0.427***	-0.582***			-0.166***	-0.601***	-0.435***	-0.781***			-0.236***	-0.859***
	(0.0287)	(0.0338)			(0.0182)	(0.0416)	(0.0235)	(0.0337)			(0.0172)	(0.0461)
Informal	-0.373***	-0.554***	-0.539***	-0.568***	-0.336***	-0.538***	-0.383***	-0.596***	-0.731***	-0.829***	-0.373***	-0.580***
	(0.0248)	(0.0323)	(0.0504)	(0.0592)	(0.0194)	(0.0505)	(0.0229)	(0.0317)	(0.0425)	(0.0554)	(0.0187)	(0.0545)
Manufacturing	0.0471		0.327***		0.299***		-0.00185		0.497***		0.153***	
	(0.0383)		(0.0924)		(0.0347)		(0.0371)		(0.0856)		(0.0339)	
Services	-0.0832***	-0.00266	0.402***	0.855***	0.266***	0.478***	0.0911***	0.113***	0.599***	0.723***	0.209***	0.534***
	(0.0322)	(0.0396)	(0.0770)	(0.0569)	(0.0297)	(0.0648)	(0.0312)	(0.0414)	(0.0708)	(0.0575)	(0.0287)	(0.0713)
Public Sector	-0.188***		0.352***		0.337***		-0.0215		0.460***		0.287***	
	(0.0357)		(0.0804)		(0.0387)		(0.0351)		(0.0736)		(0.0368)	
Costa	-0.360***	-0.491***	-0.392***	-0.575***	-0.459***	-0.682***	-0.233***	-0.234***	-0.347***	-0.176***	-0.255***	-0.298***
	(0.0257)	(0.0345)	(0.0502)	(0.0526)	(0.0222)	(0.0501)	(0.0231)	(0.0353)	(0.0457)	(0.0543)	(0.0219)	(0.0563)
Sierra	-0.342***	-0.632***	-0.570***	-0.563***	-0.599***	-0.730***	-0.233***	-0.212***	-0.486***	-0.305***	-0.370***	-0.386***
	(0.0283)	(0.0393)	(0.0537)	(0.0553)	(0.0257)	(0.0612)	(0.0254)	(0.0391)	(0.0494)	(0.0581)	(0.0241)	(0.0676)
Selva	-0.452***	-0.521***	-0.409***	-0.490***	-0.442***	-0.645***	-0.209***	-0.201***	-0.444***	-0.0545	-0.230***	-0.232***
	(0.0381)	(0.0501)	(0.0667)	(0.0686)	(0.0339)	(0.0784)	(0.0347)	(0.0512)	(0.0638)	(0.0703)	(0.0315)	(0.0787)
Rural	-0.186***	-0.200***	-0.104	-0.496***	-0.0519*	-0.524***	-0.208***	-0.196***	-0.196***	-0.513***	-0.112***	-0.348***
	(0.0339)	(0.0595)	(0.0675)	(0.0540)	(0.0289)	(0.0722)	(0.0318)	(0.0575)	(0.0629)	(0.0573)	(0.0259)	(0.0739)
Has two jobs	0.243***	0.229***	0.324***	0.539***	0.316***	0.448***	0.0652***	0.190***	0.163***	0.403***	0.111***	0.361***
	(0.0284)	(0.0435)	(0.0575)	(0.0601)	(0.0317)	(0.0700)	(0.0228)	(0.0387)	(0.0454)	(0.0543)	(0.0262)	(0.0637)
Head or Spouse with		0.201***		0.156***		-0.241***		0.0844***		0.103**		-0.266***
at least High School		(0.0312)		(0.0432)		(0.0457)		(0.0327)		(0.0466)		(0.0477)
At least one Family		0.307***		0.160***		-0.00777		0.246***		0.283***		-0.00123
Worker		(0.0525)		(0.0535)		(0.0601)		(0.0554)		(0.0552)		(0.0652)
At least High School						0.178***						0.410***
						(0.0482)						(0.0540)
Constant	6.248***	6.709***	5.268***	5.133***	5.813***	5.949***	6.495***	6.764***	5.462***	5.114***	5.992***	5.530***
	(0.0605)	(0.0954)	(0.115)	(0.127)	(0.0484)	(0.0978)	(0.0592)	(0.107)	(0.105)	(0.137)	(0.0506)	(0.109)
Observations	4,758	3,651	1,665	3,022	6,374	2,375	5,483	4,250	2,326	3,586	7,963	2,817
R-squared	0.370	0.300	0.444	0.264	0.414	0.380	0.271	0.265	0.437	0.198	0.300	0.327
Sigma	0.650	0.846	0.761	1.049	0.722	1.025	0.649	0.921	0.801	1.206	0.764	1.162

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Own estimates based on Peru's ENAHO 2004 -2010.

Table A6. Thailand. Non-Farm Earnings

	2000						2009					
	Head		Spouse		Others		Head		Spouse		Others	
	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed	Wage worker	Self-Employed
6-11 yrs of Educ.	0.372***		0.281***		0.328***	0.238***	0.428***		0.376***		0.369***	0.130*
	(0.0242)		(0.0366)		(0.0324)	(0.0793)	(0.0176)		(0.0243)		(0.0264)	(0.0716)
>11 yrs of Educ.	0.943***		1.105***		0.801***	0.447***	1.090***		1.058***		0.888***	0.377***
	(0.0260)		(0.0417)		(0.0352)	(0.0870)	(0.0180)		(0.0261)		(0.0269)	(0.0733)
Head with 6-11 yrs of Educ.		0.189***		0.159***		0.0444		0.211***		0.196***		0.0745
		(0.0389)		(0.0562)		(0.0989)		(0.0306)		(0.0459)		(0.0654)
Head with >11 yrs of Educ.		0.548***		0.314***		0.294**		0.510***		0.324***		0.0691
		(0.0498)		(0.0740)		(0.119)		(0.0355)		(0.0530)		(0.0767)
Spouse with <6 yrs of Educ.		0.115**				0.118**		0.178***				-0.00374
		(0.0478)				(0.0595)		(0.0357)				(0.0460)
Spouse with 6-11 yrs of Educ.		0.280***		0.0253		0.236		0.270***		0.155***		-0.113
		(0.0522)		(0.0639)		(0.159)		(0.0352)		(0.0488)		(0.0900)
Spouse with >11 yrs of Educ.		0.469***		0.454***		0.0732		0.346***		0.268***		-0.0628
		(0.0636)		(0.0957)		(0.167)		(0.0384)		(0.0612)		(0.107)
26 to 35 yrs old	0.312***	0.148	0.213***	-0.0781	0.347***	0.522***	0.259***	0.202**	0.209***	1.188***	0.392***	0.367***
	(0.0331)	(0.107)	(0.0455)	(0.169)	(0.0212)	(0.0777)	(0.0258)	(0.102)	(0.0361)	(0.146)	(0.0144)	(0.0671)
36 to 45 yrs old	0.541***	0.285***	0.338***	0.211	0.506***	0.765***	0.457***	0.308***	0.361***	1.334***	0.573***	0.591***
	(0.0342)	(0.107)	(0.0503)	(0.170)	(0.0326)	(0.0909)	(0.0252)	(0.0992)	(0.0358)	(0.140)	(0.0181)	(0.0692)
46 to 55 yrs old	0.601***	0.438***	0.442***	0.207	0.627***	0.694***	0.657***	0.242**	0.577***	1.369***	0.701***	0.508***
	(0.0372)	(0.109)	(0.0579)	(0.175)	(0.0587)	(0.127)	(0.0266)	(0.1000)	(0.0391)	(0.144)	(0.0292)	(0.0885)
56 to 65 yrs old	0.397***	0.0758	0.139*	0.0415	0.352***	-0.111	0.542***	-0.00831	0.487***	1.172***	0.639***	0.185
	(0.0439)	(0.113)	(0.0745)	(0.183)	(0.132)	(0.190)	(0.0311)	(0.102)	(0.0490)	(0.150)	(0.0597)	(0.126)
Female	-0.292***	-0.265***	-0.242***	-0.275**	-0.0580***	-0.0616	-0.241***	-0.253***	-0.244***	-0.282***	-0.0644***	-0.167***
	(0.0195)	(0.0446)	(0.0447)	(0.111)	(0.0193)	(0.0572)	(0.0130)	(0.0287)	(0.0207)	(0.0541)	(0.0124)	(0.0417)
Manufacturing	1.058***	-0.0413	1.046***	-0.662***	1.051***	-0.354***	0.641***	0.0127	0.614***	-0.614***	0.482***	-0.315***
	(0.0261)	(0.0406)	(0.0361)	(0.0567)	(0.0292)	(0.0707)	(0.0214)	(0.0299)	(0.0295)	(0.0456)	(0.0249)	(0.0533)
Central	0.129***	0.117***	0.129***	-0.0255	0.104***	-0.0665	0.0143	0.00470	0.0638**	0.0862	-0.0619***	-0.175**
	(0.0257)	(0.0439)	(0.0417)	(0.0849)	(0.0321)	(0.0985)	(0.0183)	(0.0353)	(0.0281)	(0.0660)	(0.0210)	(0.0765)
North	-0.241***	-0.217***	-0.319***	-0.335***	-0.353***	-0.0840	-0.170***	-0.0656	-0.270***	-0.167**	-0.298***	-0.410***
	(0.0308)	(0.0519)	(0.0482)	(0.0845)	(0.0367)	(0.105)	(0.0232)	(0.0405)	(0.0339)	(0.0692)	(0.0247)	(0.0814)
Northeast	-0.355***	-0.285***	-0.359***	-0.354***	-0.440***	-0.406***	-0.271***	-0.0607	-0.292***	-0.0887	-0.356***	-0.316***
	(0.0295)	(0.0491)	(0.0471)	(0.0844)	(0.0353)	(0.103)	(0.0217)	(0.0373)	(0.0319)	(0.0673)	(0.0227)	(0.0773)
South	0.0438	0.0453	-0.0215	-0.0192	-0.0747*	0.141	0.0217	0.0749*	0.0600*	0.0718	-0.203***	-0.0335
	(0.0325)	(0.0538)	(0.0518)	(0.0892)	(0.0407)	(0.116)	(0.0228)	(0.0415)	(0.0341)	(0.0711)	(0.0251)	(0.0853)
Urban	0.0191	0.216***	0.00627	-0.0147	-0.0698***	0.0265	0.123***	0.276***	0.103***	0.229***	0.114***	0.196***
	(0.0210)	(0.0343)	(0.0324)	(0.0537)	(0.0249)	(0.0659)	(0.0140)	(0.0255)	(0.0205)	(0.0399)	(0.0151)	(0.0488)
Services	1.153***		1.144***		1.004***		0.640***		0.652***		0.518***	
	(0.0285)		(0.0401)		(0.0318)		(0.0223)		(0.0308)		(0.0257)	
Public Sector	1.486***		1.453***		1.184***		0.983***		1.121***		0.777***	
	(0.0303)		(0.0477)		(0.0382)		(0.0243)		(0.0356)		(0.0292)	
Constant	7.301***	8.683***	7.324***	9.005***	7.249***	8.204***	7.625***	8.756***	7.641***	7.618***	7.619***	8.663***
	(0.0458)	(0.122)	(0.0813)	(0.220)	(0.0498)	(0.143)	(0.0369)	(0.109)	(0.0562)	(0.166)	(0.0392)	(0.121)
Observations	8,251	4,216	4,138	1,929	7,755	1,350	13,016	7,564	7,216	3,421	13,185	2,587
R-squared	0.579	0.173	0.585	0.158	0.398	0.130	0.486	0.158	0.476	0.156	0.357	0.111
Sigma	0.729	0.962	0.763	0.977	0.821	1.008	0.669	0.935	0.702	0.978	0.688	1.001

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A7. Bangladesh. Farm Earnings

	2000	2010
Primary & Lower secondary	0.132**	0.0331
	(0.0633)	(0.0489)
Higher secondary & Terciary	0.295**	-0.00290
	(0.147)	(0.119)
Age	0.142***	0.0795***
	(0.0214)	(0.0172)
Age squared	-0.00175***	-0.000843***
	(0.000245)	(0.000190)
Female	-2.243***	-0.926***
	(0.123)	(0.0605)
Urban	0.197	-0.161**
	(0.123)	(0.0816)
Barisal	-0.285**	0.270***
	(0.123)	(0.0920)
Chittagong	-0.240**	0.164**
	(0.0977)	(0.0680)
Khulna	0.405***	0.204***
	(0.0955)	(0.0751)
Rajsahi	0.0125	0.303***
	(0.0763)	(0.0629)
Sylhet	0.0104	0.253**
	(0.126)	(0.108)
Low land	-0.107	0.743***
	(0.0986)	(0.0666)
High land	0.457***	1.333***
	(0.111)	(0.0786)
Irrigation	0.458***	0.408***
	(0.0941)	(0.0707)
Number of members	0.525***	0.429***
	(0.0507)	(0.0525)
Constant	4.007***	4.780***
	(0.462)	(0.381)
Observations	1678	2956
R-squared	0.340	0.323
Adj R-squared	0.334	0.320

Notes: Sample: Self-employed in Agriculture
Dhaka is the base region
Illiterate and Incomplete primary education is the base for educa
No-land is the base category

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A8. Peru. Farm Earnings

	2004	2010
Head or Spouse with at least High School	0.133***	0.128***
	(0.0296)	(0.0273)
26 to 35 yrs old	0.267***	0.231***
	(0.0610)	(0.0736)
36 to 45 yrs old	0.412***	0.333***
	(0.0598)	(0.0722)
46 to 55 yrs old	0.473***	0.272***
	(0.0600)	(0.0724)
56 to 65 yrs old	0.373***	0.214***
	(0.0607)	(0.0736)
Female	-0.420***	-0.385***
	(0.0349)	(0.0318)
Head Farmer	0.421***	0.304***
	(0.0409)	(0.0351)
More than 1 farmer in HH	0.688***	0.513***
	(0.0571)	(0.0453)
Land size 0.5 to 2 ha	-0.0127	0.437***
	(0.0377)	(0.0281)
Land size 2 to 5 ha	0.288***	0.799***
	(0.0443)	(0.0348)
Land size >5 ha	0.604***	1.055***
	(0.0468)	(0.0371)
Share of Adults >50%	0.0476*	0.0206
	(0.0254)	(0.0251)
Improved Irrigation System	0.130***	0.177***
	(0.0340)	(0.0249)
Owns land	-0.218***	0.0647**
	(0.0336)	(0.0252)
Sierra	-0.151***	0.00957
	(0.0336)	(0.0326)
Selva	0.0414	-0.0303
	(0.0404)	(0.0422)
Rural	0.0757**	0.0935***
	(0.0302)	(0.0303)
Constant	4.249***	4.182***
	(0.0784)	(0.0845)
Observations	6,870	7,117
R-squared	0.123	0.238
Sigma	0.922	0.894

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: Own estimates based on Peru's ENAHO 2004 -2010.

Table A9. Thailand. Farm Earnings

	Farm Profits	
	2000	2009
Head with 6-11 yrs of Educ.	0.0660	0.0472
	(0.0554)	(0.0387)
Head with >11 yrs of Educ.	0.260**	0.0813
	(0.105)	(0.0565)
Spouse with <6 yrs of Educ.	0.206***	0.343***
	(0.0740)	(0.0429)
Spouse with 6-11 yrs of Educ.	0.290***	0.422***
	(0.0888)	(0.0497)
Spouse with >11 yrs of Educ.	0.773***	0.630***
	(0.154)	(0.0724)
26 to 35 yrs old	0.183	0.371**
	(0.167)	(0.170)
36 to 45 yrs old	0.434***	0.575***
	(0.167)	(0.165)
46 to 55 yrs old	0.465***	0.613***
	(0.169)	(0.167)
56 to 65 yrs old	0.558***	0.513***
	(0.170)	(0.168)
Female	-0.313***	-0.157***
	(0.0759)	(0.0388)
North	-0.699***	-0.411***
	(0.0616)	(0.0443)
Northeast	-0.958***	-1.002***
	(0.0564)	(0.0413)
South	-0.0330	0.282***
	(0.0672)	(0.0508)
Urban	-0.289***	-0.210***
	(0.0692)	(0.0485)
HH owns land	0.152	0.167***
	(0.103)	(0.0585)
Share of members older than 18	-0.162*	-0.0814
	(0.0946)	(0.0686)
Constant	7.691***	7.759***
	(0.206)	(0.177)
Observations	5,801	10,118
R-squared	0.107	0.141
Sigma	1.392	1.349

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1