Guide to employment, low pay and poverty analysis

I. BACKGROUND

1.1. Why this guide?

There is broad agreement that economic growth is essential for sustained poverty reduction; growth provides the basis for increases in labor earnings and the poor depend far more on labor earnings than on other forms of income. However, as explained in the guide Performing Labor Market Diagnostics for Developing Countries, labor exchange in developing countries differs from conditions in more developed countries. For example, most of the population already works, especially the poor who have no option but to use their labor to get an income, and access to a job is consequently a less useful welfare indicator than in more developed countries. As a result, higher growth and poverty reduction are generally not associated with higher employment rates in developing countries, precisely because there are no idle labor resources to draw on. Instead, higher growth is generally linked to higher labor productivity and changing employment structures. An approach to disentangle the way in which growth spills over into labor markets is explained in an accompanying guide, Guide to Growth, Employment and Productivity Analysis.

However, while growth may be a necessary long term condition for poverty reduction, it is not sufficient. The patterns and distribution of growth also matters, and economy-wide labor productivity increases need not result in increased earnings for the low paid workers. First, output growth does not automatically translate into higher labor earnings, if instead labor productivity gains are captured in enterprise profits or government taxes. But second, even where average earnings increase, the sectoral and other specificities of the growth pattern may signify very unequal earnings growth among different types of workers, whether to the benefit or detriment of the poor. Moreover, there is a risk of path dependent persistence, so that somebody who falls into low pay is more likely than others to stay there. Avoiding low pay traps ex ante, and unlocking them ex-post, is also important for the policy agenda.

A low paid person might see increasing earnings through (i) access to more hours of work, which potentially comes at a mental and physical cost if they are already at full employment or have non-market work (e.g. child care) responsibilities (ii) higher earnings on the job (iii) moving to a different category of jobs that are better paid or offers more hours of work – assuming that he/she has the characteristics which allow him to take on such a jobs. Finding out which is the most efficient option or combination of options are important from a policy perspective. If, for example, earnings increase largely is the result of within-sector increases, policy makers may want to concentrate on how to support low productivity sectors in which the poor typically work. If earnings increase is due to shifts in occupations and sectors, policy needs to focus both on how to encourage labor demand in better paying sectors and how to help the poor access those sectors.

Against this background, the present guide maps out an approach to understanding better the links between earnings mobility for the low paid and poverty reduction. While the Diagnostics guide provides an overview of the labor market status of the poor (and the poverty status of workers), this guide addresses the dynamic perspective. All definitions of terms and notations are provided in the guide entitled Introduction to Employment Lab Guides, which also provides the context of these guides in the World Bank's overall work on shared growth and employment. The Guide thus focuses on methods that address the following issues:

Earnings mobility versus low pay persistence

- What are the main determinants of earnings?
- What are the main determinants of earnings growth – are they different from those determining earnings levels?
- What are the respective roles of mobility across sectors vs. earnings growth within sectors?
- Do low pay traps exist and who is most vulnerable to fall into them?

Earnings and poverty at the household level

- Linking poverty with earnings, what is the role of earnings growth and sectoral shifts for poverty alleviation at the household level?

The specific issue of labor market segmentation – when specific institutional features divide the labor market into different segments and the poor normally are prevented from accessing the higher paying segments – is treated in the Guide to Labor Market Segmentation.

1.2. Data requirements

The data needed for this analysis includes consumption, to measure poverty (if not available, income measures will have to be used), information on earnings and non-labor income at the household level, and individual worker characteristics (age, gender, education, etc.). The work on earnings mobility and low pay traps requires panel data to follow individual outcomes over time. For other types of dynamic analysis, cross section data for at least two points in time will be necessary.

II. EARNINGS MOBILITY AND POVERTY

2.1. Pro-poor or anti-poor earnings growth patterns

Table 1 provides an overview of the growth in median earnings by poverty status and consumption quintile. It is clear that increases in the earnings of a median worker can differ significantly from the increases that the poor obtain. However, where median earnings growth has been high, poverty reduction has been significant (Albania, Vietnam), even without a pro-poor pattern, and conversely, low but pro-poor earnings growth can also be consistent with poverty reduction, as in Bangladesh.[1]

Table 1: High and pro-poor earnings growth associated with poverty reduction

	Albania	Bangladesh	Madagascar	Rwanda	Vietnam
Growth in median earnings (average percentage per year)					
All	15.8	1.3	11.0	1.7	10.1
By poverty status					
Poor	9.8	0.8	11.9	3.6	5.9
Non-poor	12.8	-1.5	-4.0	1.7	8.6
By quintiles[1]					
Poorest	11.9	4.0	17.7	11.2	6.5
Second	12.5	0.4	14.1	2.9	8.9
Third	17.8	-0.4	9.0	0.8	10.4
Fourth	11.3	-0.9	0.8	1.2	12.5
Richest	14.1	-0.8	-6.5	2.8	15.8
Memorandum items					
GDP per capita (% growth per year)	5.3	3.7	-1.5	4.0	6.5
Poverty headcount index (% change per year)	-2.2	-1.6	-0.3	-0.6	-4.1

Source: World Bank (2008a, 2008b), Cichello and Sienaert (2009), Ranzani (2009). Additional Albania data estimates from the World Bank online Labor Market Micro-level Data Base. 1. Consumption/expenditure. Years covered: Albania 2002-2005, Bangladesh 2000-2005, Madagascar 2001-2005, Rwanda 2000-2006, Vietnam 1993-1998.

2.2. Determinants of Earnings and Earnings growth

This section describes Mincer type earnings functions drawing on Rijkers (2010). The analysis is context specific and adapted to the specific issues and data availability in Ghana and Tanzania, and should be seen as a guide to the overall approach and the kind of issues that can arise and need to be dealt with when looking at the determinants of earnings. A more general overview is available in Ehrenberg and Smith (2003).

[1] Note: information on median earnings by poverty status and consumption quintile form part of the automatic output from ADePT. For more information, see Introduction to the Employment Lab Guides at www.worldbank.org/employment.

Determinants of earnings

Framework

The baseline semi-logarithmic model of earnings is as follows:

(1) $$y_{it} = \alpha_0 + \alpha_1 X_{1it} + a_2 X_{2i} + u_i + \varepsilon_{it}$$

where:

- y_{it} is the natural logarithm of net monthly income
- X_{1it} is a vector of time-variant determinants of earnings (including common time trends, e.g. changes in firm size, tenure, hours worked and occupational category)
- X_{2i} is a vector of time-invariant determinants of earnings (including education, gender and height as a proxy for physical strenght)
- u_i is a time-invariant individual-specific determinant of earnings
- ε_{it} is a time-varying error term.

OLS estimates of equation (1) will be unbiased and consistent if both time-variant and time-invariant determinants of earnings are uncorrelated with the time-invariant (OLSA1) and time-variant (OLSA2) components of the residual:

(OLS A1): $$E[X_{1it}\varepsilon_{it}] = E[X_{2i}\varepsilon_{it}] = 0$$

(OLS A2): $$E[X_{1it}u_i] = \mathrm{E}[X_{2i}u_i] = 0$$

Tackling the endogeneity of schooling

Assumption OLS A1 may potentially be violated by the potential endogeneity of education. This is the case if educational attainment is correlated with ability and ability affects earnings, yet is unobserved to the researcher. In such a scenario, OLS estimates of equation (1) will be biased. To correct for this potential bias, the preferred approach is to control for ability *directly* by including a proxy of ability among the regressors. However, such measures are likely to be unavailable to the majority of researchers. The second option is a control function (CF) approach, where the residual of a model of educational attainment is used in a second step as a regressor in the earnings equation.

The idea behind the CF approach is to model the dependence between the unobserved error terms in such a way that the endogeneity bias disappears. As an example, the model of educational attainment, $E_{i,}$ can include (i) distance to primary school at to secondary school at relevant ages as exclusion restrictions, Z_i, that is, assuming they are correlated with education and do not have a direct impact on earnings (i.e., once education is controlled for, they do not have any additional impact on earnings(ii) the individual's age and (iii) gender. The estimable equation thus becomes:

(2) $$E_{it} = \varphi_0 + \varphi_1 X_{1it} + \varphi_2 X_{2i} + \varphi_3 Z_i + \eta_{it}$$

Predicted residuals from the first-stage regression are then used as controls for unobserved factors affecting both earnings and education in an earnings specification that is equal to equation (1) in all other respects.

(3) $$y_{it} = \alpha_0 + \alpha_1 X_{1it} + a_2 X_{2i} + \hat{\eta}_{it} + u_i + \varepsilon_{it}$$

where:

$$\hat{\eta}_{it} = E_{it} - (\hat{\varphi}_0 + \hat{\varphi}_1 X_{1it} + \hat{\varphi}_2 X_{2i} + \hat{\varphi}_3 Z_i)$$

As shown by Wooldridge (2007), under the rather stringent assumptions that:

$$E(\varepsilon_{it} | X_{1it}, X_{2i}, Z_i, E_{it}) = E(\varepsilon_{it} | X_{1it}, X_{2i}, Z_i, \eta_{it}) = E(\varepsilon_{it} | \eta_{it}) = \rho\, \eta_{it}$$

estimates of α_0, α_1 and a_2 will now be unbiased. Note that the first equality holds because E_{it} and η_{it} are one-to-one functions of each other. The second equality would hold if $(\varepsilon_{it}, \eta_{it})$ was independent of (X_{1it}, X_{2i}, Z_i) and if we are willing to assume linearity in the conditional expectation $E(\varepsilon_{it} | \eta_{it})$. Both these conditions are non-trivial, but generate an estimator that is more efficient than standard IV in non-linear models.

Controlling for unobserved fixed effects

The second of the identification assumptions will be violated if there is correlation between fixed effects u_i and observable determinants of earnings, X_{1it} and X_{2i}.

$$E[X_{1it} u_i] \neq 0;\ E[X_{2i} u_i] \neq 0$$

Two alternative assumptions are possible. First, to assume that the time-variant determinant of earnings is uncorrelated with time-variant unobservables *at any other point in time*.

(WG A1): $$E[X_{1is} \varepsilon_{it}] = 0 \ \ \forall\, s, t$$

A Within Group Estimator can then be used, which is effectively equivalent to OLS on the following transformed model:

(4) $$\tilde{y}_{it} = \alpha_1 \tilde{X}_{1it} + \tilde{\varepsilon}_{it}$$

where $\tilde{y}_{it} = y_{it} - \frac{1}{T}\sum_1^T y_{it}$, $\tilde{X}_{1it} = X_{1it} - \frac{1}{T}\sum_1^T X_{1it}$ and $\tilde{\varepsilon}_{it} = \varepsilon_{it} - \frac{1}{T}\sum_1^T \varepsilon_{it}$. It should be noted that in small samples $\tilde{\varepsilon}_{it}$ is negatively correlated with $\tilde{X}_{1it}$ by construction, leading to the Nickell-bias (Nickell, 1983)— which is typically in the opposite direction of the bias in the OLS estimator

A second and less restrictive assumption is that the time-variant determinants of earnings are uncorrelated with time-variant unobservables only in the same and in the previous period.

(FD A1): $$E[X_{1it}\varepsilon_{it-1}] = E[X_{1it-1}\varepsilon_{it}] = 0$$

This second variant will justify the estimation of the following model in first differences, using OLS regressions.

(5) $$\Delta y_{it} = \alpha_1 \Delta X_{1it} + \Delta\varepsilon_{it}$$

Since first differences are not available for the first sample wave, this leads to a reduction in sample size, and, consequently, less precise estimates. Table 2 summarizes results from Ghana and Tanzania using OLS, CF, and OLS with direct measurements of ability (here: cognitive skills). They suggest that:

- **Earnings rise with age and experience, but age-earnings profiles are *concave* and eventually the increase becomes a decrease**.
- **Earnings tend to rise with firm size;** both wage employees and the self-employed earn more in larger firms.
- **Men tend to earn more than women**, even after controlling for their educational attainment and other observable characteristics as well as their occupational choice.
- **Returns to education are *convex*, meaning that the earnings increase associated with an additional year of education rises with the level of education.** The results of the control function approach *(*columns 2 and 5) suggest the impact of ability bias is minimal. The estimated returns to education are also robust to including proxies for people's unobserved skills (columns 3 and 6).

Table 2**: Earnings functions on Ghana and Tanzania**

	Ghana			**Tanzania**		
Dependent Variable: Log of monthly earnings	**OLS**	**CF - education**	**OLS with ability**	**OLS**	**CF – education**	**OLS with ability**
	coef	**coef**	**coef**	**coef**	**coef**	**coef**
Dummy for male	0.240***	0.163	0.203***	0.334***	0.318***	0.329***
Years of age	0.075***	0.061***	0.078***	0.044***	0.037**	0.042***
(age^2)/100	-0.089***	-0.069**	-0.093***	-0.045**	-0.032	-0.041**
Height (cm)	0.005	0.005	0.006	0.004	0.003	0.003
Years in formal educ	-0.040**	0.008	-0.037**	-0.056***	0.007	-0.053***
(educ^2)/100	0.004***	0.004***	0.004***	0.007***	0.007***	0.007***
Currently an apprentice	-0.786***	-0.785***	-0.749***			
An apprentice in the past	-0.039	-0.041	-0.031	0.023	0.018	0.021
Ln(hours)	0.223***	0.225***	0.217***	0.073	0.079	0.077
Tenure - self-reported	0.013***	0.013***	0.013***	0.006	0.006	0.006
Ln(employees)	0.296***	0.296***	0.289***	0.484***	0.487***	0.471***
Ln(firmsize)	0.171***	0.171***	0.160***	0.137***	0.136***	0.132***
Private wage	-0.256***	-0.257***	-0.252***	-0.056	-0.055	-0.049
Civil servant	0.566***	0.564***	0.503***	0.474***	0.474***	0.450***
Pub enterprise	-0.161	-0.158	-0.175	0.269**	0.270**	0.247**
Residual education		-0.047			-0.064	
Residual apprenticeship						
Avg perc. math score			0.004***			0.003**
City and year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.158*	-1.296**	-1.308**	8.586***	8.395***	8.471***
Number of observations	2,610	2,610	2,610	1,328	1,328	1,328
R2	0.310	0.310	0.316	0.304	0.305	0.308
Adjusted R2	0.304	0.304	0.310	0.293	0.293	0.297

Note: *** p<0.01, ** p<0.05, * p<0.1. Source: Adapted from Rijkers (2010). Standard errors not reported here.

Determinants of earnings growth

Earnings growth over time may be modeled as a function of changes in the time-variant explanatory variables that determine earnings levels, and of (the level of) the time-invariant characteristics such as education, gender and height[2]. However, there may be a rationale for including the time-invariant variables as explanatory variables to examine whether they affect the *growth rate* in earnings, in other words, whether or not these variables have an additional impact on the rate of earnings *growth* over and above their impact on changes in earnings through their impact on *levels*.

The base is a general growth model:

(1) $$y_{it} = \alpha_0 + \lambda y_{i,t-1} + \alpha_1 X_{1it} + a_2 X_{2i} + \alpha_3 X_{2i} \cdot time + u_i + \rho_i \cdot time + \varepsilon_{it}$$

Which allows both both time-varying X_{1it} and time-invariant X_{2i} observables to have an impact on earnings. The crucial difference with the model in levels presented earlier is an explicit treatment of income dynamics by including income in the previous period among the explanatory variables. Moreover, by allowing time-invariant observables X_{2i} to have a different impact on earning levels at different points in time (hence the interaction term $\alpha_3 X_{2i} \cdot time$), one can test whether personal and job characteristics impact *earnings growth*.

As pointed out by Deaton (1997, p110), in short panels it is very difficult to distinguish between persistence in earnings due to unobserved individual heterogeneity (as captured in u_i and ρ_i) and persistence due to the effect of the lagged dependent variables, as captured by λ. Differencing equation (1) will enable one to get rid of the fixed effect u_i, yet also induces serial correlation in the error term, which will yield a downward bias in OLS estimates of λ. This observation is a key concern in the large literature on earnings convergence, which typically finds strong evidence for high persistence and regression to the mean. To circumvent the identification problems that introduction of the lagged dependent variable would entail, it is necessary to make an admittedly very restrictive assumption that changes in earnings are fully persistent, i.e., that $\lambda = 0$. The model thus becomes:

(2) $$y_{it} = \alpha_0 + \alpha_1 X_{1it} + a_2 X_{2i} + \alpha_3 X_{2i} \cdot time + u_i + \rho_i \cdot time + \varepsilon_{it}$$

Differencing yields the model:

(3) $$\Delta y_{it} = \alpha_1 \Delta X_{1it} + \alpha_3 X_{2it-1} + \rho_i + \Delta\varepsilon_{it}$$

Equation (3) allows for identification of the effect of time-invariant factors on growth, while controlling for the changes in time-variant determinants of earnings levels. Moreover, when

[2] Height and education need to be constructed to be time-invariant.

modeling growth from period *t-1* to *t*, it is possible to include time-variant factors measured at time *t-1* among the time-invariant characteristics in X_{2i}. This approach, explained in Quinn and Teal (2008), is motivated by the observation that time-variant characteristics measured at *t-1* that are predetermined are effectively time-invariant with respect to growth between *t-1* and *t,* and can therefore be included among the time-invariant regressors.

The above model can be estimated with OLS under the assumption that the error term is uncorrelated with the explanatory variables, e.g. if (OLS A1): $E[X_{1is}\varepsilon_{ij}] = 0 \;\forall s, t$ ε {t, t-1} and $E[X_{1is}\rho_i] = \mathrm{E}[X_{2i}\rho_i] = 0 \;\forall s, t$ ε {t, t-1} (OLS A2). As with static earnings regressions, the fixed effect ρ_i can be tackled by using fixed effects and first-differences estimators. For Ghana and Tanzania (not presented here, but discussed in Rijkers, 2010), the estimation of (3) yields very little insight, as R2 are very low and few if any variables are significant predictor of earnings growth.

Role of sector shifts vs. within sector increases in earnings

The poor are overrepresented in low paying sectors and low paying occupations (see the accompanying guide on Creating Labor Market Diagnostics in Developing Countries). Shifting them into better paying sectors would thus result in better earnings, assuming that such flows do not result in full earnings convergence with their former sector. It can therefore be useful to see to what extent the employment structure changes over time, and what this may mean for the low paid in particular. Unlike previous sections, this information does not require panel data. However, it is important to recall that without panel data it is not possible to know whether the employment status shifts for the poor, or whether the poverty status shifts between workers.

As seen in the case of Albania, total median earnings increased significantly – by 52 percent, or 15 percent per year -because of a combination of (i) increases in the number of hours worked (ii) increases in median hourly earnings in all sectors (iii) net job creation in higher paying sectors (non-agriculture, waged) and net job destruction in low paying sectors (unpaid agricultural household workers).

Table 3: Sources of earnings increases: Albania

	Change in Earnings (Percentage, 2002-2005)		Change in shares of employment (Percentage points, 2002-2005)
	Total	Hourly	
TOTAL ALL SECTORS	52	26	0
Non-agriculture, total			9
Waged	14	10	4
Self-employed	42	40	2
Unpaid	45	23	3
Agriculture, total			-9
Waged	10	49	2
Self-employed	49	22	1
Unpaid	36	15	-12

Source: Estimates based on Labor-Market Micro-level Database.

Low pay persistence

Some groups may be more vulnerable to ending up in low paid jobs, even if they start out with a higher paid job; they may also experience more significant difficulties in escaping low paid sectors and occupations if they start off there. If low paid jobs are transitory, then temporary support schemes may be the most adequate policy response. But if they are permanent and self-reinforcing, more significant policy reforms may be needed. Finding out if there are low pay traps and who is susceptible to such traps is therefore important from a policy perspective.

Panel data can be used to establish a pay transition matrix over time (much like an employment matrix showing flows in and out of employment and activity). Such a matrix is displayed in Table 4. As seen, there is significant raw low pay persistence in Ghana and Tanzania. The probability of being low paid is several times higher for those who were low paid in the previous period compared to those who were not low paid. The table also confirms significantly higher persistence in low pay for women and for youth and that these groups are particularly vulnerable to falling into low pay.

Table 4 Pay transition matrix, period t to t+1, Ghana and Tanzania

		PERIOD T+1					
		Ghana			*Tanzania*		
		Not low paid	Low paid	Total	Not low paid	Low paid	Total
PERIOD T	***All***						
	Not low paid	87	13	100	85	15	100
	Low paid	45	55	100	46	54	100
	Total	73	27	100	70	30	100
	Women						
	Not low paid	82	18	100	76	24	100
	Low paid	42	58	100	35	65	100
	Total	65	35	100	56	44	100
	Youth						
	Not low paid	83	17	100	84	16	100
	Low paid	39	61	100	42	58	100
	Total	63	37	100	63	37	100

Source: Rijkers (2010). Low pay is defined as revenue below 1.25$ per day per individual (not calculated in household per capita terms and thus a conservative measure).

III. EMPLOYMENT AND POVERTY AT THE HOUSEHOLD LEVEL

Sections II and III above have shown that earnings mobility often differs significantly for different groups, and that returns to characteristics often differ between otherwise identical workers. What does household level analysis tell us of the relationship between earnings mobility and poverty?

3.1. The role of earnings for poor households' income growth

The labor income profile is best described at the household level. In the spirit of the macro level decomposition described in the Introduction to Growth and Employment guide, Kakwani, Neri, and Son (2006) propose a simple characterization of household labor supply and income by noting that the average labor income of household *j* can be written as:

$$\frac{I_j^L}{N_j} = \frac{I_j^L}{H_j}\frac{H_j}{E_j}\frac{E_j}{L_j}\frac{L_j}{A_j}\frac{A_j}{N_j}$$

where I_j^L is the total labor income of household *j*; H_j is the total hours worked by working-age members of household, *j*; E_j is the total number of employed in the household; L_j is the number of participants in the labor market; and A_j is the number of working-age members. In this way $\varpi = I^L/H$ corresponds to average earnings per hour worked, $h = H/E$ corresponds to average hours worked, E/L is the employment rate, $l = L/A$ is the participation rate, and $a = A/N$ is the ratio of working-age members to total household members, or the dependency rate. For simplicity, let the above equation be rewritten as:

$$\iota_j^L = \varpi_j h_j (1-u_j) l_j a_j$$

where $(1 - u_j)$ corresponds to the employment rate of household *j*, which can be rewritten as 1 minus the household's unemployment rate u_j.

$$\ln(\iota_j^L) = \ln(\varpi_j) + \ln(h_j) + \ln(1-u_j) + \ln(l_j) + \ln(a_j)$$

In many contexts there is an important fraction of child laborers and elderly workers, and calculating earnings per hour worked by the employed of working age is overestimating real household productivity. In these cases, it might be better to abstract from the structure of the household according to working age (A_j) and calculate dependency rates as the number of participating individuals over the total of working household members (A_j/L_j). Then E_j should be defined as the number of working individuals irrespective of whether they are of working age or not and define hours worked, H_j, as total hours worked for all employed individuals irrespective of age.

By averaging each of the components of the household's per capita labor income over subgroups of population, we can obtain a full profile of labor market characteristics. For example, the equations can be used to describe the average labor market characteristics of each quintile. Let Ω denote the subset of households belonging to a particular quintile. It is possible to compare deciles by average dependency rates, $\frac{1}{N_\Omega}\sum_{j\in\Omega} a_j$, average participation rates, $\frac{1}{N_\Omega}\sum_{j\in\Omega} l_j$, average hours worked, $\frac{1}{N_\Omega}\sum_{j\in\Omega} h_j$, incidence of unemployment, $\frac{1}{N_\Omega}\sum_{j\in\Omega} u_j$, and earnings per hour worked $\frac{1}{N_\Omega}\sum_{j\in\Omega} \varpi_j$.

This relationship can be used to disentangle how the changes in components contribute to changes in total labor income. The average per capita labor income of the subset Ω of households (whether poor or nonpoor households, or households falling within an income range or with particular demographic characteristics), will then be:

$$\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln \iota_j^L = \frac{1}{N_\Omega}\left(\sum_{j\in\Omega}\ln\varpi_j + \sum_{j\in\Omega}\ln h_j + \sum_{j\in\Omega}\ln(1-u_j) + \sum_{j\in\Omega}\ln l_j + \sum_{j\in\Omega}\ln a_j\right)$$

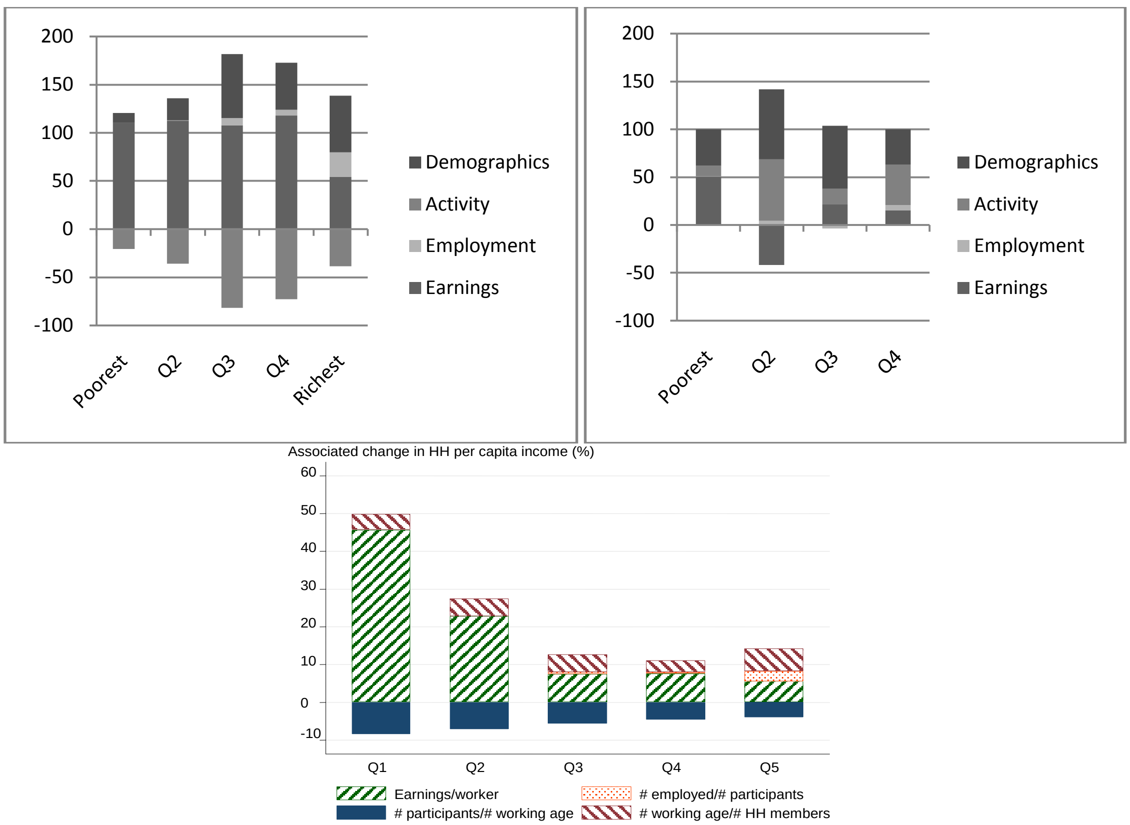
The relationship can then be explored to decompose the change in the average per capita household labor income of group Ω into changes in its different components: changes in average log earnings per hour worked, changes in average of log hours worked, changes in average log unemployment rates, and so forth. In particular:

$$\Delta\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln \iota_j^L = \Delta\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln\varpi_j + \Delta\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln h_j + \Delta\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln(1-u_j) + \Delta\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln l_j + \Delta\frac{1}{N_\Omega}\sum_{j\in\Omega}\ln a_j$$

Average earnings per hour can also be decomposed into earnings per hour from self-employment (π_j) and earnings per hour from wage employment (w_j): ${\varpi_j}^L = h_j^w w_j + h_j^\pi \pi_j$, with h_j^w corresponding to the share of wage employment in total hours worked and h_j^π corresponding to the share of self-employment. In this case, however, log-linearization is no longer possible, and Shapley decompositions would have to be performed.

Performing this exercise for Madagascar shows how earnings are more strongly associated with income per capita increases than other components, especially for the poorer quintiles (Figure 1). The effect of activity is negative, as labor force participation rates have fallen in households, although this effect is smaller for the poorest quintiles, while the effect of employment is negligible. The case of Nicaragua is different. Earnings have contributed positively to income growth for the very poorest, but negatively, or less, to income growth in the second and third quintiles. The demographic effect – smaller share of household dependents, generally children - is positive and important for these quintiles as well. In the case of Rwanda, the role of earnings has been the most important by far, especially for the two poorest quintiles. Demographic changes have also been favorable while, as expected, the reduction in participation rates has had a negative contribution. Because poor households already have high participation and employment rates, the by far most important source of income growth is in earnings.

Figure 1: Contribution of earnings in Madagascar (left), Nicaragua (right), Rwanda (below) by consumption quintile.



Source: World Bank 2008b, 2008c, and Cichello and Sienaert (2009)

3.2. Sectoral contributions to poverty reduction

The importance of sector shifts in increasing earnings can also be linked to poverty changes. Ravallion and Huppi (1991) provide a decomposition of the contribution of sectoral shifts to earnings and poverty. By applying an additively separable poverty measure, P, to two distributions of household consumption over time (years 1 and 2), the analysis can break down the difference in national poverty for this period into three general components:

$P^2 - P^1 =$	
$\sum_{s=1}^{3}(P_s^2 - P_s^1)n_s^1 +$	**Intrasectoral effect**: Change in poverty arising from within-sector poverty changes
$\sum_{s=1}^{3}(n_s^2 - n_s^1)P_s^1 +$	**Intersectoral effects**: Change in poverty arising from population shifts
$\sum_{s=1}^{3}(P_s^2 - P_s^1)(n_s^2 - n_s^1)$	**Interaction effects:** Interaction between sectoral employment/earning shifts

Where P_s^t is the poverty measured in sector s (here limited to three: Primary, Secondary, and Tertiary) at time t, and n_s^t is the population share of sector s at time t. The first component, the intrasectoral effects, shows how changes in poverty within each sector contribute to the aggregate change in poverty. The second component is the contribution of changes in the distribution of the population across the sectors. The final component, the residual, can be interpreted as a measure of the correlation between the population shifts and change in poverty within the sectors.

Because the decomposition is performed at the household level, households must be assigned to a sector. How this is done is a somewhat arbitrary choice. For example, households can be assigned to a sector if more than half of total household labor income was derived from workers who work in that sector and households which cannot be categorized in this way should then be excluded from the analysis. For agriculturally dependent rural areas, this may not be a problem. For urban areas, with a mix of secondary and tertiary activities and even some farming, the approach may be more limiting.

Table 5 presents the result of the decomposition along economic sectors for Rwanda and Madagascar, which provide quite contrasting examples. In Rwanda, the population shifts – especially the important shift out of agriculture – accounts for most of the poverty reduction in terms of proportion of poor (the headcount index) and the poverty gap. Earnings actually fell in sectors which accommodated the inflow of presumably poorer and perhaps less skilled workers from agriculture. However, even with falling earnings, these sectors still offered considerably better earnings opportunities than farming - so average earnings increased, and poverty fell. In fact, there was a relatively important increase in the poverty headcount index in the tertiary sector, but less so in the poverty gap, indicating that the sector generally offered better earnings, also for the poor.

In Madagascar, the story is different. Earnings increased in agriculture, sufficiently so to compensate for the fact that workers left non-agricultural sectors where income opportunities normally are higher. This effect was particularly strong in making the poor “less poor”, i.e. lowering the poverty gap. In the cases of Bangladesh and Albania (not shown here), increases in earnings within sectors – in Albania across the board, in Bangladesh especially in agriculture and services - played a much more important role than a restructuring of the labor market by sector for reducing poverty.

Table 5: Contribution to poverty reduction: the role of economic sectors.

	Rwanda		Madagascar	
	Poverty headcount	Poverty gap	Poverty headcount	Poverty gap
Within sectors	**-0.4**	**-0.9**	**-4.1**	**-9.6**
Primary	-2.9	-2.0	-6.8	-10.5
Secondary	0.5	0.3	-0.4	-0.3
Tertiary	2.0	0.8	3.1	1.2
Between sectors total	**-5.5**	**-2.6**	**5.0**	**2.9**
Primary	-8.5	-3.6	7.0	3.7
Secondary	1.7	0.6	-1.5	-0.6
Tertiary	1.3	0.4	-0.5	-0.2
Residual	**2.2**	**1.2**	**-1.8**	**-1.4**
Total	-3.7	-2.3	-1.0	-5.2

Source: World Bank (2008b), Cichello and Sienaert (2009)

3.3. Vulnerability to changes in non-labor income sources may be important

Finally, while the focus of the analysis is labor earnings, it is also important to consider how changes in non-labor sources of income might impact poverty: these may be highly relevant for countries with a high share of migrants sending remittances home, or more developed countries where government social safety nets may fill a more important role for households. In order to estimate this vulnerability, one can estimate two poverty levels for different groups: first, the poverty level of the households in that group based on total income (note -not consumption) and second, the poverty level of the households based on total income less remittances and public transfers, and compared the two.

In the case of Madagascar, public transfers and remittances do reduce poverty in this way. Without international remittances and public transfers, another 1.7 percent of the population would have been poor; the poverty gap would also have increased by 2 percent. However, the effect must be considered limited in view of the very high poverty levels. Moreover, the role of public transfers is very limited: (i) their contribution is much smaller than that of international remittances (ii) it fell between 2001 and 2005, meaning that international remittances increased in importance and (iii) public transfers do not at all lower the poverty gap in 2005 (and the role of international remittances diminished). The role of labor income remains crucial.

Table 6: The impact of non-labor transfers on poverty, Madagascar

	2001	2005
Headcount poverty, based on income		
Total income	69.5	69.2
Total income, less remittances and public transfers	71.2	70.9
Difference	1.7	1.7
Total income, less public transfers	69.9	69.4
Difference	0.4	0.2
Poverty gap, based on income		
Total income	28	36
Total income, less remittances and public transfers	30	38
Difference	2.0	2.0
Total income, less public transfers	29	36
Difference	1.0	0.0

Source: World Bank (2008b)

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