Household Income Dynamics: A Four Country Story

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In this paper, we analyse the dynamics of household per capita incomes using longitudinal data from Indonesia, South Africa, Spain and Venezuela. We find that in all four countries reported initial income and job changes of the head are consistently the most important variables in accounting for income changes, overall and for initially poor households. We also find that changes in income are more important than changes in household size and that changes in labour earnings are more important than changes in other sources of household income.

Introduction

Who's getting ahead in economic terms, who's falling behind, and how? The rises and falls in income and consumption experienced by households are the most direct indicators available of who benefits how much from economic development. Yet studies of economic dynamics in developing countries remain scarce, largely because until very recently the comprehensive panel data surveys required to analyse income or consumption mobility in developing countries did not exist.[1] As a result, little is currently known about the factors and characteristics associated with the changes in economic well being experienced by most of the world's households.

This paper builds on a companion study [Fields et. al., 2002] which analysed patterns of household income change in Indonesia, South Africa, Spain, and Venezuela. That study showed that, in all four countries, households with the lowest reported base-year income experienced the largest absolute income gains. Results were robust to reasonably high levels of measurement error in two of the countries. We also showed that, in three of the four countries, households with the lowest predicted base-year income experienced gains at least as large as their wealthier counterparts. Thus we conclude that with one exception, the empirical importance of theories that predict income changes favourable to initially rich households, such as cumulative advantage, poverty traps, and skill biased technical change was no greater than structural or macroeconomic changes that favoured initially poor households.

The present paper builds on this earlier work by analyzing the primary factors associated with changes in household per capita income. First, we estimate the simple and multivariate correlates of these income changes, and use the results to assess the importance of household characteristics in accounting for income changes. Second, we ask if these correlates are equally important for initially poor households. Third, a household's per capita income can change because income changes, because the number of household members changes, or because both factors change. We therefore ask, how important are each of these in accounting for the per capita income change? Fourth, total household income change can be decomposed into percentages due to changes in labour income, capital income, remittance income, and other income sources. We quantify the relative importance of changes in these different sources of income in explaining income change.

To sum up, our main findings are these. First, in all four countries, initial income and job changes of the head are consistently the most important variables in accounting for household per capita income changes. Second, initial income and job changes of the head remain important variables in accounting for the household per capita changes of initially poor households. Third, changes in income are more important than changes in household size for the great majority of households. And fourth, changes in labour earnings are more important than changes in all other sources of household income combined.

. The Four Countries and Choice of Measures

A. Data

This research is a comparative study of four countries: Indonesia, South Africa, Spain, and Venezuela. These countries were chosen for analysis here because publicly accessible panel surveys were undertaken in each country during the mid 1990's. Other than that, these countries have little in common, differing in both base levels of economic development and the ongoing macroeconomic conditions during the mid 1990s. Together, the panel data sets present a unique chance to search for common underlying causes of change in household economic well being in economies that differ in terms of location, time period, and macroeconomic conditions. As the results will make clear, the similarities are numerous and, at times, surprising.

The Indonesian data come from the first and second rounds of the Indonesian Family Life Survey, a panel survey conducted jointly by the Rand Corporation and the Demographic Institute of the University of Indonesia. The survey interviewed households living in 321 communities in 13 of Indonesia's 27 provinces and is representative of 83% of the national population of roughly two hundred million. Approximately 7,200 households were interviewed in 1993, and ninety-four percent of these households were re-interviewed in 1997. This time period captures the final five years of an enduring trend of real GDP growth and relatively stable economic management that characterized much of the 30-year Soeharto regime. Real GDP grew at about 7% per year from 1993 to 1997, while inflation ran about 8% per year. The stunning collapse of the rupiah that led to massive economic dislocation and political chaos began in September 1997 and climaxed in January 1998. This survey was mostly conducted from August to November of 1997, largely before the adverse effects of the crisis were apparent.[2] The data are described in more detail in Frankenberg and Thomas [Frankenberg and Thomas, 2000].

The South African data come from the 964 African households in the KwaZulu-Natal Income Dynamics Study (KIDS) panel data set.[3] The 1993 South African Labour and Development Research Unit (SALDRU) national household survey provides information for the base period. A follow up 1998 survey was conducted in the KwaZulu-Natal region, which is home to roughly 20 percent of the South African population. The late-1993 survey took place just months before the historic 1994 elections and transition of political power to Nelson Mandela and the African National Congress. Thus, this research enables us to analyze which African households got ahead by how much in the first years after Apartheid. The country's macroeconomic performance in the time period was not stellar, with GDP averaging 2.7 % real growth per annum and with particularly low growth in 1998. In contrast, income growth rate among African households in the panel sample used in this work was 5.0 % per annum. The data are described in more detail in May et. al. [May et. al., 2000].

The data used for Spain come from the ECPF (Encuesta Continua de Presupuestos Familiares) or Spanish Household Panel Survey, from the years 1995 and 1996. It is a national quarterly rotating panel that follows households for a maximum of two years (after each quarter, 1/8 of the sample rotates). The target sample size each quarter rounds off to 3,200 households. A one-year panel of 1,233 households was constructed for this study, consisting of those households interviewed in the first quarter of 1996 and again in 1997 where at least one member remained the same. The income variable used corresponds to household real monetary income of the previous three months. The Spanish economy grew during this period, with real GDP expanding by 2.3% and the unemployment rate slightly diminishing from 22.9% to 22.2%.

The Venezuelan data come from the Sample Household Survey (Encuesta de Hogares por Muestreo) conducted by the Oficina Central de Estadística e Informática, Venezuela's government agency for the collection of statistics. It is a nationally representative survey whose rotation mechanism follows households for a maximum of six consecutive semesters. We matched households from the second semesters of 1997 and 1998 using a unique dwelling identification number and the condition that at least one member be the same in both periods. The resulting panel consists of a total of 7,521 households.

The Venezuelan economy experienced a sharp macroeconomic decline between 1997 and 1998 due to the decline of oil prices and a highly contentious electoral process. Output growth fell from 5.9% in 1997 to -0.7% in 1998. Inflation also declined but stayed high, going from 50% to 36%. Open unemployment grew from 10.7% to 11.3% and informal employment grew from 47.5% to 50.2%.

B. Choice of Measure

The authors are interested in analyzing household income dynamics because we believe understanding household income dynamics is fundamental to understanding the dynamics of household economic well-being. Some studies on economic dynamics in developing countries look at household consumption (Dercon and Krishnan (2000), Glewwe and Hall (1998) Grootaert, et al. (1997), Maluccio, Haddad, and May (2000)) while others use income (Gunning et al. (2000), Drèze, Lanjouw, and Stern (1992)). The use of consumption is often justified on the grounds that smoothing makes consumption a more accurate measure of longer-term welfare and that income, particularly self-employment income, is more difficult to measure. It is worth noting that analyses of data from India and China do not find that consumption is clearly superior to income as an indicator of longer-term economic well-being (Chaudhuri and Ravallion 1994, Naga and Burgess 2001). Still, there is little doubt that understanding income dynamics, per se, is of extreme relevance, and that is the primary goal of this article. In any event, in this study data considerations alone necessitate the use of income, as not all of our surveys contain measures of household consumption.[4]

Having decided on income as our measure of economic well-being, we next considered how to adjust for household size. The literature has come to no consensus on the proper way to take account of household economies of scale. Therefore, we chose to report the simplest and most popular household size adjustment, per capita income.

The next issue was the choice of dependent variable. We have chosen to conduct our analyses using two different dependent variables: first, change in per capita income measured in currency units, and second, change in log per capita income (real in both cases). Analyzing changes in currency units (denoted ΔPCI) is more traditional and measures absolute income gains. For comparison purposes, changes in log per capita income (Δlog PCI), which approximates percentage income gains, have also been analysed. The use of changes in logs is consistent with the widespread belief in concave utility functions -- that a fixed increase in per capita income leads to a greater increase in the economic welfare of a poor household than that of a rich household. To conserve space and avoid table duplication, the Δlog PCI results are highlighted in the text and displayed only when differences between the two approaches are particularly informative. In all cases, incomes are measured in inflation-adjusted terms.

Finally, measurement error can affect the results in many ways, for example, by leading to an apparent correlation between income change and initial income that is not representative of the relationship between true income change and true initial income. To address this issue, the study also presents analysis based on predicted initial income. The variables used to predict initial income include household location variables (urban/rural or regional breakouts), household head characteristics (gender, age, education), demographic characteristics of the household (number of children, family type), initial labour market outcomes (employment status of head) as well as an additional set variables specific to each country, which are listed in Table 2.

III. The Relationship Between Household Income Dynamics and Various Household Characteristics.

A. Results from Mobility Profiles

In determining what factors are important for determining the variation in income change, we begin by examining mobility profiles for our dependent variables of interest, ΔPCI and Δlog PCI. These profiles give the average income change, by category, for a variety of household characteristics. A mobility profile for ΔPCI, available from the authors upon request, shows that several variables are statistically significant determinants of household income change, where statistical significance for each variable is determined by rejecting the null hypothesis that average household income change was equal in each category. In the case of ΔPCI, the significant variables are reported starting income quintile (statistically significant in three countries), fitted starting income quintile (2), household location (2), gender of the head of the household (1), age of the household head (1), education of the head of the household (2), number of children (2), family type (2), employment status of the head of the household (3), change in the number of children (4), change in the gender of the head (1), change in family type (4), and change in employment status of the head (3). In the case of Δlog PCI, the numbers are only slightly different.

Statistical significance alone tells us nothing about the explanatory importance of these different factors in accounting for income changes. Accordingly, we turn to two other measures of the importance of different factors.

B. Gauging the Importance of Individual Factors Using Simple Regressions

One measure of explanatory power is the R^2 from a simple regression of income change on household characteristics. These R^2s for ΔPCI are presented in Table 1 in the first column for each country. We find that reported initial income is far and away the most important variable in explaining ΔPCI. However, this explanatory power is partially due to an unidentifiable mix of true changes and measurement error, and so predicted starting PCI is used as a proxy for true base year income. Making this substitution, we find predicted starting income remains a statistically significant variable in Indonesia and South Africa, but its importance is much diminished as compared with reported base year income.

After base year income, several other variables appear to be statistically significant in each country. Overall, the next most important variables are change in employment status and change in the number of children. Not surprisingly, the head getting a job or (where the information is available) getting a formal sector job is correlated with a higher household income change. Also, not surprisingly, an increase in the number of children in the household is associated with a fall in the household's per capita income. The change in employment status and change in number of children variables are generally of greater importance than predicted starting income but less important than reported starting income. What is also remarkable about these results is the *unimportance* of head's schooling and head's gender in the majority of cases. Innumerable studies have shown that these variables are consistently important in explaining income *levels*. Similar results are found for Δlog PCI as the dependent variable. With much discussion of the increasing premium for skills, one would expect the effect of the levels to be changing over time. Additionally, even in times without changing premiums for education, age-earnings profiles are often thought to have differing slopes by education level, so it is surprising to find that these variables are not only small but in fact statistically insignificant correlates of income *changes*.

C. Gauging the Importance of Individual Factors Using Multiple Regressions and Decompositions

The simple regressions presented above tell us the importance of different variables one at a time, but they cannot say how important one variable is in the presence of others. This issue can be addressed using multiple regressions. The causal structure underlying the econometric estimation is the following. Per capita income, whether measured in log units or in currency units and whether reported or predicted, is denoted here by Y, and its change by ΔY. Time-invariant characteristics Z determine time-varying characteristics in the base year, X_1. Together, Z and X_1 determine base year income Y_1 as well as time-varying characteristics in the next year, X_2. Together Z, X_1, Y_1, and X_2 determine final year income Y_2.

We estimate a descriptive model of income changes, which are derived as the difference of log income levels, based on a modified version of Duncan's (1983) model of the determinants of the natural logarithm of family income:

$$\ln(y_{it}) = X_{it}\beta_t + Z_i\gamma + \delta_i + \varepsilon_{it}, \qquad (1)$$

$$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \eta_{it}, \;\; E[\eta_{it}] = 0, \;\; Var[\eta_{it}] = \sigma_\eta^2 \qquad (2)$$

$$\delta_i = \lambda Z_i + \upsilon_i, \;\; E[\upsilon_i] = 0, \;\; Var[\upsilon_i] = \sigma_\upsilon^2 \qquad (3)$$

where X_{it} is a vector of time-variant family characteristics, Z_i is a vector of time-invariant family characteristics, δ_i stands for unobservable time-invariant family characteristics, and ε_{it} is a serially correlated error term.[5] Subtracting $\rho Y_{i,t-s}$ from both sides of equation (1), we get:

$$\ln(y_{i,t}) - \rho\ln(y_{i,t-1}) = X_{i,t}\beta_t - X_{i,t-1}\rho\beta_{t-1} + Z_i(\gamma_t - \rho\gamma_{t-1} + \lambda(1-\rho)) + \omega_{it}.$$

After adding ρY_{t-1} and $-Y_{t-1}$ to both sides and some rearranging, we get:

$$\ln(y_{i,t}) - \ln(y_{i,t-1}) = \Delta X_i\beta + X_{i,t-1}\tilde{\beta}_t + Z_i\tilde{\gamma}_t + (\rho-1)\ln(y_{i,t-1}) + \omega_{it}\;, \qquad (4)$$

where

$$\Delta X_i = (X_{i,t} - X_{i,t-1})$$

$$\tilde{\beta}_t = \beta_t - \rho\beta_{t-1}$$

$$\tilde{\gamma}_t = \gamma_t - \rho\gamma_{t-1} + \lambda(1-\rho)$$

$$\omega_{it} = (1-\rho)\upsilon_i + \eta_{it}.$$

Equation (4) is of the form $\Delta Y = f(X_1, \Delta X, Z, Y_1)$.

If there is measurement error, then what we observe is not true income Y_t but rather reported income Y_t^{rep}, which is related to true income Y_t by:

$$\ln(y_t^{rep}) = \ln(y_t) + \mu_t \tag{5}$$

$$E[\mu_t] = 0,\ Var[\mu_t] = \sigma^2_{\mu}.$$

Now, the model using reported change in income is:

$$\begin{aligned} &\ln(y_{i,t}^{rep}) - \ln(y_{i,t-s}^{rep}) = \Delta X_i \beta_t + X_{i,t-1}\widetilde{\beta}_t + Z_i \widetilde{\gamma}_t + (\rho - 1)\ln(y_{i,t-s}) + \xi_{it}, \\ &\xi_{it} = \omega_{it} + \mu_t - \mu_{t-s}. \end{aligned} \tag{6}$$

We do not observe true initial income, i.e., $Y_{i,t-1}$, but reported initial income. Therefore, when estimating equation (6) using reported initial income, measurement error in initial income induces both a spurious negative correlation and attenuation bias. Consequently, we also perform an IV estimation using an additional set of identifying instruments to predict true initial income:

$$\ln(y_{i,t-s}) = \beta_{t-1}X_{t-1} + \gamma_{t-1}Z + \kappa_{t-1}W_{t-1} + \zeta_{it}, \tag{7}$$

where W_{t-1} is a set of identifying variables, such as consumption expenditures and household or production assets.

Unfortunately, IV estimation does not get rid of all of the bias we would encounter using OLS. This finite sample bias of the IV estimator, relative to the bias of the OLS estimate, is approximately inversely proportional to the F statistic on the instruments in the first stage regression (Bound, Jaeger, and Baker, 1995). The relevant F statistics for the multivariate regressions are found in Table 2. These F statistics range from 5 to 43, implying little concern that finite sample bias of the IV will seriously affect our results, particularly outside Spain.

The IV estimates, however, may be upwardly biased and inconsistent estimates of the relationship between initial income and its change. This would occur if the component of initial income that is correlated with the instruments, conditional on the control variables, has a more positive relationship with income change than the component of true initial income that is orthogonal to the set of control variables and instruments. In particular, data limitations do not allow household expenditures to be used as identifying instruments in the prediction equation for Spain or Venezuela. In areas where financial constraints are present or households do not perfectly smooth consumption, these expenditures better reflect fluctuations in current income than the housing rental value or household durables used to predict income in Spain and Venezuela, respectively. This may partly explain the weaker results for predicted income in Spain and Venezuela. With these caveats in mind, we view reported and predicted income as alternative indicators of initial income, which give results that must be assessed with care, given their potential flaws.

The results of multivariate regressions using reported income and using an instrumental variables approach are presented in Tables 3a-d. In these regression tables, results are presented for each country and for each dependent variable (change in log PCI or change in PCI).

The first point of interest is to assess the impact of initial income, holding other variables constant. When reported income is used, those initially above or initially below their conditional mean appear to be regressing towards their conditional mean in all four countries, both for change in log PCI and for change in PCI. This is found by looking at the coefficients on reported initial income variable in each of the OLS regressions in Tables 3a-3d and observing that they are always significantly negative. On the other hand, when we instrument for initial income, the results are more mixed. Predicted initial income is often insignificant, but when it is significant, it is always negative. Thus, by both these measures, there is never a statistically significant case where those who start ahead of where they would be expected to be get further ahead.

Turning to other variables, the multiple regressions in Tables 3a-3d differ in important ways from the simple regression results. As an example of how these results differ, consider the effect of head's education. In the profiles and R-squared results from simple regressions, excluding Indonesia, schooling is either statistically insignificant or has an uncertain impact on earnings. However, analyzing regressions for each country, in which we gauge the ceteris paribus effect of schooling controlling for initial income as well as other characteristics, we find that the effect of schooling is often significantly positive. We know from earnings functions in these and other countries that schooling raises income levels. We thus have two offsetting effects of schooling on income mobility in these countries: 1. On the one hand, schooling raises base year income, and those with higher base year income have smaller income gains. 2. On the other hand, once base year income is controlled for, those with more schooling have more positive income gains. This may explain why schooling is statistically insignificant without controls but statistically significant (and positive) with controls.

In general, it is striking how few variables are found to be statistically significant in the multivariate analysis. Rather than trying to sum up this mass of regression coefficients, we shall gauge the importance of one group of variables in the presence of others by turning to decomposition analysis.

In all four countries, we decompose the observed inequality in per capita income changes across households. How much of the inequality in Δlog PCI or ΔPCI is attributable to factors such as initial income quintile, education, age, etc.? Building upon the regressions presented above, we may assign weights to these various factors in the following way [Fields and Yoo, 2000; Fields, forthcoming]. Let Y_i denote the i'th household's

Δlog PCI or ΔPCI. The equation determining Y (the regression corresponding to Tables 3a-d) can be written as follows:

$$Y_i = \sum_j a_j p_{ij} = a'P_i , \tag{8}$$

where

$$a = [\alpha \ \ \beta_1 \ \ \beta_2 \ \ \ldots \beta_j \ \ 1]'$$

and

$$P = [1 \ \ p_1 \ \ p_2 \ \ \ldots \ p_j \ \ \varepsilon]' .$$

Given the mobility function (8), let an inequality index I(Y) be defined on the vector of Y_i's: $Y \equiv (Y_1, \ldots, Y_N)$. Let $s_j(Y)$ denote the share of the inequality of Y that is attributable to the j'th explanatory factor and let $R^2(Y)$ be the fraction of inequality that is explained by all of the P's taken together. Then, the inequality of Y can be decomposed as

$$s_j(Y) = \text{cov}\ [a_j P_j, Y] / \sigma^2(Y) = \frac{a_j * \text{cov}[P_j, Y]}{\sigma^2(Y)}, \tag{9}$$

where

$$\sum_{j=1}^{J+2} s_j(Y) = 100\%, \tag{10}$$

$$\sum_{j=1}^{J+1} s_j(Y) = R^2(Y) . \tag{11}$$

The s_j's are the so-called `factor inequality weights.' The more positive these values are, the more that factor contributes to the inequality of the dependent variable (income change or log-income change). On the other hand, a negative weight means that the variable causes the dependent variable to be less unequally distributed than it otherwise would be. Another feature of this decomposition procedure is that it holds for any inequality index $I(Y_1, \ldots, Y_N)$ which is continuous and symmetric and for which $I(\mu, \mu, \ldots, \mu) = 0$. Virtually all inequality indices, such as the Gini coefficient and the Theil index, satisfy these properties.

The shares of different factors in accounting for the observed inequality in mobility experiences appear in the s_j columns of Table 1 for changes in currency units. In the middle column for each country, the decomposition is based on equations (9)-(11) using reported income, whereas in the right column, predicted income is used instead.

When changes in log-income are decomposed, the two variables besides initial income that show the biggest effects are change in head's employment status (all four countries) and change in number of children (Indonesia and South Africa).[1] Changes between single and multiple adult households and region of residence also have a measurable effect in South Africa. The remaining variables account for very little of the inequality of income changes. For all of these non-income variables, the factor inequality weights are very similar.

Table 1 reports the results of the decomposition for income changes in currency units, and reveals a more mixed picture. Initial PCI (reported) remains the single most important variable in South Africa and Venezuela. In those two countries, change in head's employment status is second in importance. In Spain, the role of those two variables is reversed. Indonesia, however, is different: measured in terms of s_j, reported initial PCI is of primary importance and change in head's employment status accounts for much less.

When we run this analysis using predicted income, rather than reported income, the importance of initial income falls tremendously. This reinforces the caution that there may be a fair amount of measurement error in our reported income measure. However, in South Africa, one of the two countries where per capita consumption is available as an instrument, our measure of initial income is still the largest or second largest explanatory variable, in terms of accounting for the variation in income change.

In sum, this multivariate analysis establishes the primary importance of initial economic position and change in household head's employment status in accounting for the observed inequality in income changes, suggesting that the labour market should be the principal focus of future mobility analysis, at least in these countries. In Indonesia and South Africa, change in the number of children appears important as well. These are the two countries in which the panel spans four years instead of one. The importance of this variable would be expected to increase in the other two countries as the time interval is enlarged and more demographic changes can take place within the households. Surprisingly, human capital characteristics of the household head such as education and age consistently account for little of the observed inequality in income change. Given these results, a priority for future research is to better understand the underlying causes of changes in employment and sector.

D. Assessing the Importance of Individual Factors for the Poor versus the Non-poor

Table 4 presents additional decomposition results for changes in PCI, after the data are separated on the basis of initial position. Country-specific poverty lines are drawn, and those reporting income below the line in the initial period are separated from those who report income above the poverty line.[6] The results show distinct differences in the extent to which covariates account for income change depending on initial poverty status. For example, looking at South African data in Table 4, demographic changes such as change in the number of children and change in family type seem to be much more important in accounting for changes among the initially non-poor than the initially poor. On the other hand, change in head's employment status accounts for

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These tables were omitted to conserve space, and are available from the authors upon request.

more of income change among the initially poor households. Results for changes in log PCI are only slightly different.

These differences between initially poor and initially non-poor households vary in a country-specific manner, and in some cases, they vary within a country depending on the choice of dependent variable. For example, in South Africa and Spain, there is strong evidence that the change in head's employment status can better account for changes in income among initially poor households as compared to initially non-poor households. In Indonesia, the evidence is mixed, varying by specification of dependent variable, and in Venezuela the situation is reversed and the difference across groups is of a smaller magnitude.

As we are particularly interested in income changes among initially poor households, we re-assess our previous conclusions looking exclusively at results for the initially poor households. Table 4 strongly reaffirms that focusing on the labour market is an important priority for understanding income changes among the initially poor. In all four countries, changes in the head's employment status is the most or second most powerful factor accounting for log income change among initially poor households, using either reported or predicted income specifications. This factor is similarly important in accounting for changes in currency terms for two of the four countries. Likewise, reported income is important in all countries and predicted income is important under PCI specifications for three of the four countries.

Most other conclusions from the previous section are robust to limiting analysis to a sample of the initially poor households. Demographic variables related to the number of children in the household are important predictors of income changes in South Africa and Spain but not in Indonesia or Venezuela. The education of the head continues to have little explanatory power, except in Venezuela where it is a powerful force explaining change in income measured in PCI terms.

Thus, increased understanding of employment transitions and labour market outcomes is a priority for more effective policies assisting today's poor.

IV. Decomposing the Sources of Change in Per Capita Income

We turn now from the characteristics of household per capita income changes to an analysis of household per capita income change itself. In this section, we answer two questions: first, how important is change in income versus change in household size, and second, changes in which type of household income are most important?

A. Gauging the Importance of Change in Income versus Change in Household Size

A basic accounting question is whether changes in household income or changes in household size drive the changes we observe in per capita household income. Change in log PCI can be easily decomposed into the portion due to change in the household log income and the portion due to change in the household size. We calculate the fraction of households for which the change in log-income accounts for at least half the total change in log PCI. These percentages -- 84% in Indonesia, 73% in South Africa, 96% for Spain, and 88% for Venezuela -- demonstrate that for the vast majority of households, change in the household income numerator account for the bulk of their per capita income changes.

B. Gauging the Relative Importance of Change in Different Income Sources

Next we seek to find which sources of income drive these income changes. Since our measure of per capita household income in a given year is a sum of various income components, change in per capita household income can be additively decomposed into the change in its component parts. We use two popular methods for assigning quantitative importance to various income components. The first was devised by Fei, Ranis, and Kuo [Fei et. al., 1978, 1979] and Pyatt, Chen, and Fei [Pyatt et.al., 1980] for work on Taiwan, and has since been used as well in studies of Pakistan [Ayub, 1977], Colombia [Fields, 1979], and the United States [Shorrocks, 1982b; Karoly and Burtless, 1995]. The inequality of total income is decomposed into components attributable to each factor component (e.g., labour income, capital income, land income). Fei, Ranis, and Kuo showed that the Gini coefficient of total income can be decomposed into a weighted sum of `pseudo-Ginis,' the weights being given by the corresponding factor shares:

$$G(Y) = \sum_k \phi_k \, G \ (Y_k), \tag{12}$$

where Y = total income, Y_k = income from the k'th factor component,

$\phi_k \equiv \sum_i Y_{ik} / \sum_k \sum_i Y_{ik}$ = the share of income from factor k in total income, and

$G\ (Y_k)$ is the `pseudo-Gini coefficient' of income from factor k.[7] Pyatt, Chen, and Fei showed that the pseudo-Gini coefficient (which they call the `concentration ratio') is in turn the product of the ordinary factor Gini $G(Y_k)$ and a `rank correlation ratio'

$$R_k = \frac{\mathrm{cov}(Y_k, \rho\ )}{\mathrm{cov}(Y_k, \rho_k)}$$

$$= \frac{\text{covariance between factor income amount and total income rank}}{\text{covariance between factor income amount and factor income rank}} \tag{13}$$

and therefore

$$G(Y) = \sum_k \phi_k \, G(Y_k) \, R_k \, . \tag{14}$$

Dividing (14) by G(Y), one obtains

$$100\% = \sum_k \phi_k \, G(Y_k) \, R_k / G(Y) \ \equiv \ \sum_k s_k, \tag{15}$$

the sum of the Fei-Ranis-Kuo-Pyatt-Chen relative factor inequality weights. These weights are used in the first decomposition exercise reported below.

The second method is the one developed by Shorrocks [Shorrocks, 1982], which was used to interpret the decomposition of inequality shares above. As above, the i'th recipient unit's total income Y_i is the sum of its

income from each of several factor components, e.g., labour income, capital income, transfer income, etc.:

$$Y_i = \sum_k Y_{ik}. \tag{16}$$

Shorrocks defines a `relative factor inequality weight' s_k to be the percentage of income inequality that is accounted for by the k'th factor -- for instance, how much of the inequality of total income is accounted for by the inequality in labour income, in capital income, in transfer income, etc.? He then shows that under a number of axioms on the decomposition itself, the relative factor inequality weights s_k are given by

$$s_k = \mathrm{cov}\,(Y_k, Y) / \sigma^2(Y) \tag{17}$$

such that

$$\sum_k s_k = 1 \tag{18}$$

for any inequality index $I(Y_1, \ldots, Y_N)$ which is continuous and symmetric and for which $I(\mu, \mu, \ldots, \mu) = 0$. Virtually all inequality indices satisfy these conditions, including the Gini coefficient, the Atkinson index, the generalized entropy family, the coefficient of variation, and various centile measures.

We then have two alternative source decomposition methods, the Fei-Ranis-Kuo-Pyatt-Chen method given by (12)-(15) and the Shorrocks method given by (16)-(18). The relative inequality weights given by the two methods (the S_k in equation (15) and the s_k in equation (17)) are not the same as each other, the difference being due to the different decomposition rules used by the different authors.

After replacing income with per capita income change in the above descriptions, these methods are immediately applicable to the question of which sources of changes in income are responsible for how much of the change in total income. The results of these factor inequality weights for the four countries are found in Table 5. The share of inequality accounted for by labour earnings ranges from more than 60% for Indonesia to nearly 90% in Venezuela. For these four countries, then, the message is strikingly clear: labour income change is the most important source of total household income change, accounting for more of the variation in income change than all other income sources combined[8].

V. Conclusions

This paper has examined change in per capita household income, in both logarithmic and monetary terms, in four very diverse economies -- Indonesia, South Africa, Spain, and Venezuela – and has asked four questions about changes in per capita household income in each. First, which household characteristics are most important in accounting for changes in household per capita income? Second, do the important household characteristics differ for the initially poor households as compared with other households? Third, which is more important: change in household income or change in household size? And fourth, how important is each income component (changes in labour earnings, changes in transfer income, changes in remittance income, etc.) in accounting for the change in total income?

Despite differences in types of data, years of observation, macroeconomic conditions, and income levels, consistent patterns emerged. First, of the variety of characteristics and events besides initial income that we considered, initial income and changes in the employment status of the household head appeared as the quantitatively most important variables in all four countries. In general, initial income was found to be related inversely to income change, i.e., with one exception, households with lower base year incomes enjoyed larger income gains, both in terms of log-changes and in absolute currency units. And not surprisingly, households whose heads gained employment or (where available) gained formal sector employment were the ones that exhibited the largest gains. Unexpectedly, other variables, such as education of the household head, had little impact in accounting for the changes in household per capita income. Second, these conclusions generally hold when we limit our analysis to initially poor households despite the fact that such analysis highlights important country specific differences between particular covariates' ability to account for income change among initially poor and initially non-poor households. Third, for the great majority of households in each country, the change in per capita income was primarily accounted for by their change in income and not by the change in number of household members. And fourth, changes in labour earnings are more important causes of change in household income than are changes in all other income sources combined.

These results establish several priorities for future work. First, the paramount role of changes in labour earnings demonstrates the centrality of labour market analysis in understanding economic mobility. This points to the importance of understanding earnings dynamics and employment transitions more fully. Second, what is surprising, at least to us, is that in all four countries, no important role emerged for the household head's education. We suspect that similar rates of income change are found because of offsetting effects, not because these countries' labour markets are indifferent to education, but this remains to be tested. And third, because the role of base year income is so different depending on whether reported base year income or estimated base year income is used, the results point to the need to take great care with the income variable itself. Presumably, administrative records and employers' records would provide better data on true income than household members' own statements. Unfortunately, while such matched employer-employee data sets are available for a number of other countries, they are not yet available for our four countries.[9] Until they are, researchers must remain sensitive to the possibility and implications of measurement error in income.

REFERENCES

Abowd, John M. and Francis Kramarz, 1999, `The Analysis of Labor Markets Using Matched Employer-Employee Data', Handbook of Labor Economics, ed. by O. Ashenfelter and D. Card, Vol 3, Chapter 26. Amsterdam: North Holland.

Ayub, Mahmood, 1977, Income Inequality in a Growth-Theoretic Context: The Case of Pakistan, Yale University.

Baulch, Bob and John Hoddinott, 2000, `Economic Mobility and Poverty Dynamics in Developing Countries,' Journal of Development Studies, Vol.36, No.6.

Belzil, Christian, 1997, `Job Creation and Destruction, Worker Reallocation and Wages', Concordia University Working Paper.

Bound, John, David Jaeger, and Regina Baker, 1995, 'Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak,' Journal of the American Statistical Association.

Cantó-Sánchez, Olga, 1995, `Income mobility in Spain: How much is there? Studies on the Spanish Economy, FEDEA.

Chaudhuri, Shubham and Martin Ravallion, 1994, "How Well do Static Indicators Identify the Chronically Poor?" Journal of Public Economics, Vol. 53, 367-394.

Dercon, Stefan and Pramila Krishnan, 2000, `Vulnerability, Seasonality and Poverty in Ethiopia,' Journal of Development Studies, Vol.36, No.6.

Drèze, Jean, Peter Lanjouw, and Nicholas Stern, 1992, `Economic Mobility and Agricultural Labour in Rural India: A Case Study', Indian Economic Review (Special Number). Vol.27.

Duncan, Greg J., "The Implications of Changing Family Composition for the Dynamic Analysis of Economic Cowell, eds., Panel Data on Incomes. London School of Economics, 1983.

Entorf, Horst and Francis Kramarz, 1997, `Does Unmeasured Ability Explain the Higher Wages of New Technology Workers?', European Economic Review. Vol. 41.

Fei, John C.H., Gustav Ranis, and Shirley W.Y. Kuo, 1978, `Growth and the Family Distribution of Income by Factor Components', Quarterly Journal of Economics.

Fei, John C.H., Gustav Ranis, and Shirley W.Y. Kuo, 1979, `Growth with Equity: the Taiwan Case', Oxford: Oxford University Press.

Fields, Gary S., 1979, `Income Inequality in Urban Colombia; A Decomposition Analysis', Review of Income and Wealth. Vol. .

Fields, Gary S., 2001, Distribution and Development: A New Look at the Developing World, Cambridge, MA: MIT Press and Russell Sage Foundation.

Fields, Gary S., forthcoming. "Accounting for Income Inequality and Its Change: A New Method, with Application to the Distribution of Earnings in the United States," Research in Labor Economics.

Fields, Gary S., Paul L. Cichello, Samuel Freije, Marta Menendez, and David Newhouse, 2002, `For Richer or for Poorer: Evidence from Indonesia, South Africa, Spain, and Venezuela', Journal of Economic Inequality, forthcoming.

Fields, Gary S. and Gyeongjoon Yoo, 2000, `Falling Labor Income Inequality in Korea's Economic Growth: Patterns and Underlying Causes', Review of Income and Wealth. Vol. 46. No.2.

Frankenberg, Elizabeth and Duncan Thomas, 2000, The Indonesia Family Life Survey (IFLS): Study Design and Results from Waves 1 and 2. DRU-2238/1-NIA/NICHD.

Glewwe, Paul and Gillette Hall, 1998, `Are Some Groups More Vulnerable to Macroeconomic Shocks Than Others?', Journal of Development Economics. Vol. 56.

Grootaert, Christiaan, Ravi Kanbur, and Gi Taik Oh, 1997, `The Dynamics of Welfare Gains and Losses: An African Case Study', Journal of Development Studies, Vol.31, No.4.

Gunning, Jan et al., 2000, `Revisiting Forever Gained: Income Dynamics in the Resettlement Areas of Zimbabwe, 1983-1996', Journal of Development Studies, Vol. 36, No. 6.

Hause, J.C., "The Covariance Structure of Earnings and the On-the-Job Training Hypothesis", Annals of Economic and Social Measurement, 1977.

Karoly, Lynn A. and Gary Burtless, 1995, `The Effects of Rising Earnings Inequality on the Distribution of US Income', Demography, Vol.32, No3.

Leonard, Jonathan S., and Marc Van Audenrode, 1995, `Persistence of Frima and Individual Wage Components', Paper presented at the 1996 AEA meetings.

Lillard, L.A. and R.J.Willis, "Dynamic Aspects of Earnings Mobility," Econometrica, 1978.

Maluccio, John, Lawrence Haddad, and Julian May, 2000, `Social Capital and Household Welfare in South Africa, 1993–98', Journal of Development Studies, Vol.36, No.6.

May, Julian, Michael Carter, Lawrence Haddad, and John Maluccio, 2000, "KwaZulu-Natal Income Dynamics Study (KIDS) 1993-98: A Longitudinal Household Data Set for South African Policy Analysis. " University of Natal - Durban, University of Wisconsin - Madison, and IFPRI.

Naga, R.A., and Robin Burgess, "Prediction and Determination of Household permanent Income", University of Lausanne DEEP Working Paper 9705, October, 2001.

Pyatt, Graham, Chau-Nan Chen, and John Fei, 1980, `The Distribution of Income by Factor Components', Quarterly Journal of Economics, Vol.95, No.3.

Shorrocks, Anthony F, 1982, “Inequality Decomposition by Factor Components’, Econometrica, Vol. 50.

Shorrocks, Anthony F, 1982b `The Impact of Income Components on the Distribution of Family Incomes,’ Quarterly Journal of Economics. Vol.98.

ENDNOTES

[1] For surveys of the available literature, see Baulch and Hoddinott [Baulch and Hoddinott, 2000] and Fields [Fields, 2001].

[2] There are two other reasons why the Indonesian results do not capture the economic crisis. First, income is reported for the previous year. Second, initial evidence shows that nominal wages stayed relatively constant during the start of the crisis. The government's inflation numbers jump in November and December, but that jump is still a small factor in the 1997 price index that was used to deflate incomes in this study.

[3] "African" is a racial term in sub-Saharan Africa, denoting persons who are pure black. In local parlance, those of mixed blood are denoted "coloreds." The 964 households come from the October 2001 re-release of the KIDS data set. In October, 2002, the authors learned that questions have been raised about the integrity of some of the responses in the existing version of the KwaZulu-Natal Income Dynamics Study. At this time, the extent of the flaws has not been determined, and the data set has not been amended. Accordingly, the reader is warned that all analyses using the KIDS data, including the results reported here, are subject to revision at a later time. Finally, if a 1993 household split into multiple households, only the first household interviewed in 1998 is used in constructing change in household income.

[4] The Spanish and Venezuelan data do not contain a consumption module. In addition, changes in the Indonesian non-food consumption module between 1993 and 1997 render consumption aggregates incomparable.

[5] Duncan credits Hause [1977] with originating this model, but it is very much like the model adopted by Lillard and Willis [1978] and all others doing variance components analysis. The difference is that Duncan uses family/needs income as dependent variable instead of head or individual earnings. We adopt most of Duncan's specification but include a time invariant observable vector Z. In addition, we model the unobservable family effect as a function of observable time invariant characteristics.

[6] Details on the specific poverty lines for each country available on request.

[7] The pseudo-Gini coefficient of a factor component is the Gini coefficient that is obtained if income recipients are arrayed in increasing order of total income rather than in increasing order of income from that factor.

[8] There are well known problems of under-reporting rents, dividends, interests and capital income in general. However, when other sources of income are reported (such as pensions, transfers, remittances, etc.) labor earnings are still the most important source of income change inequality.

[9] A few of the many examples are Belgium [Leonard and Van Audenrode, 1995], Denmark [Belzil, 1997], France [Entorf and Kramarz, 1997], and the US [Abowd and Kramarz, 1999].

Table 1: Relative Importance of Explanatory Variables for Change in PCI

	INDONESIA			*SOUTH AFRICA (KwaZulu-Natal)*			*SPAIN*			*VENEZUELA*		
	R^2	s_j	s_j	R^2	s_j	s_j	R^2	s_j	s_j	R^2	s_j	s_j
Reported initial PCI	0.052 *	9.3%		0.099 *	14.2%		0.025 *	3.8%		0.112 *	18.7%	
Predicted initial PCI	0.007 *		-0.4%	0.022 *		3.5%	0.000		0.1%	0.001		0.2%
Region	0.017 *	1.8%	1.3%	0.010	1.9%	1.4%	0.000	0.0%	0.0%	0.001 *	0.4%	0.2%
Initial number of children	0.000	-0.1%	0.0%	0.001	-0.5%	-0.4%	0.002	0.5%	0.1%	0.002 *	-0.3%	-0.1%
Head's gender	0.001	0.0%	0.0%	0.004	0.1%	0.1%	0.005 *	0.7%	0.7%	0.000	0.0%	0.0%
Initial family type	0.000	0.0%	0.0%	0.013 *	-2.0%	-1.5%	0.003	0.2%	0.4%	0.000 *	0.1%	0.1%
Head's age	0.004 *	0.4%	0.4%	0.003	0.4%	0.4%	0.011	0.7%	0.9%	0.001 *	0.1%	0.1%
Head's schooling	0.015 *	2.9%	1.5%	0.006	0.2%	0.2%	0.004	0.9%	0.4%	0.001 *	0.6%	0.3%
Head's employment status	0.020 *			0.027 *	-1.5%	-0.2%	0.004	-0.2%	0.0%	0.007 *	-0.1%	0.3%
Change in number of children	0.023 *	2.8%	2.8%	0.050 *	5.0%	4.9%	0.025 *	2.4%	2.4%	0.007 *	0.8%	0.7%
Change in head's gender	0.002 *	0.2%	0.2%	0.007	0.3%	0.3%	0.001	0.0%	0.0%	0.005 *	0.4%	0.5%
Change in family type	0.000	0.0%	0.0%	0.039 *	5.0%	4.8%	0.023 *	1.8%	2.1%	0.002 *	0.1%	0.1%
Change in head's employment status	0.026 *	1.9%	1.9%	0.087 *	8.1%	7.4%	0.033 *	4.3%	4.3%	0.027 *	2.5%	2.5%
Total explained		*19.2%*	*7.7%*		*31.0%*	*21.2%*		*14.9%*	*11.3%*		*23.3%*	*4.9%*
Unexplained		*80.8%*	*92.3%*		*69.0%*	*78.8%*		*85.0%*	*88.7%*		*76.7%*	*95.1%*
Total		*100%*	*100%*		*100%*	*100%*		*100%*	*100%*		*100%*	*100%*

R^2 values correspond to simple OLS regression of change in PCI on the corresponding variable. The s_j values represens the share of explanatory power of the corresponding variable in a multivariate regression that includes all other variables in the table, using the decomposition rule given by equations (9)-(11) in the text..
** denotes statistical significance at the 5% level*

Table 2: Prediction of Base Year Log Income: Identifying Instruments and First Stage F Statistics.

	INDONESIA	*SOUTH AFRICA (KwaZulu-Natal)*	*SPAIN*	*VENEZUELA*
R^2 from OLS regression on initial log PCI	0.450	0.599	0.145	0.088
F statistic on all variables	63.39	70.39	21.02	55.88
R^2 from OLS regression on initial PCI	0.414	0.660	0.329	0.354
F statistic on all variables	42.35	236.30	20.29	84.94
Set of identifying instruments (I)	{Household asset quintile, expenditure per capita quintile, floor and toilet type, number of household earners}	{Expenditure per capita, cluster average income per capita, presence of household durables}	{Housing rent value, detailed family type (with or without children, with one or two or more adults, other types)}	{Household durables (i.e. refrigerator, TV, stove, number of automobiles, etc.)}
F statistic on identifying instruments for log PCI	44.14	34.04	5.33	29.64
F statistic on identifying instruments for prediction of PCI	27.26	33.67	14.56	43.26

Table 3a: Regression of Change in Income for Indonesian Households, 1993-1997

	Log PCI		PCI	
	OLS on Z, X, Y, ΔX	**IV on Z, X, Y, ΔX**	**OLS on Z, X, Y, ΔX**	**IV on Z, X, Y, ΔX**
Number of observations	5370	5370	5370	5370
R-squared	0.4269	0.1161	0.1916	0.076
Constant	*		*	*
Initial Income- Reported	-0.661 *		-0.417 *	
	(0.02)		(0.04)	
Initial Income- IV approach		-0.372*		-0.076
		(0.04)		(0.05)
Region	*	*	*	*
Head's age			*	*
Head's school	*	*	*	*
Initial number of children	*	*	*	*
Head's gender				
Initial family type	*	*		
Change in number of children	*	*	*	*
Change in head's gender	*		*	
Change in number of adults	*			
Change in head's employment status	*	*	*	*

Z={Region, head's age, head's schooling}, X={number of children, head's gender, family type, head's employment}, Y={base year per capita income}, ΔX={change in number of children, change in head's sex, change in number of adults, change in head's employment}. Instruments for IV include assets, expenditure per capita quintile, type of floor and toilet facilities, number of household earners, and cluster average per capita income. Coefficients and standard errors (in brackets) are only shown for initial income variables.
** denotes statistical significance at the 5% level using an F-test on category variables*

Table 3b: Regression of Change in Income for South African Households in KwaZulu-Natal, 1993-1998

	Log PCI		**PCI**	
	OLS on Z, X, Y, ΔX	**IV on Z, X, Y, ΔX**	**OLS on Z, X, Y, ΔX**	**IV on Z, X, Y, ΔX**
Number of observations	818	818	818	818
Adjusted R-squared	.5187	.4967	.2891	.2760
Constant	*	*		
Initial Income- Reported	-0.796 *		-0.54 *	
	(0.043)		(0.07)	
Initial Income- IV approach		-0.583 *		-0.37 *
		(0.068)		(0.09)
Region	*	*	*	*
Head's age	*	*	*	
Head's school	*	*		*
Initial number of children	*	*	*	*
Head's gender	*			
Initial family type	*			
Head's employment status	*	*	*	
Change in number of children	*	*	*	*
Change in head's gender	*	*		
Change in family type	*	*	*	*
Change in head's employment status	*	*	*	*

Z={Region, head's age, head's schooling}, X={number of children, head's gender, family type, head's employment}, Y={base year per capita income}, ΔX={change in number of children, change in head's sex, change in number of adults, change in head's employment}. Instruments for IV include expenditure per capita, presence of household durables, and cluster average per capita income (excluding household). Coefficients and standard errors (in brackets) are only shown for initial income variables.
** denotes statistical significance at the 5% level using an F-test on category variables*

Table 3c: Regression of Change in Income for Spanish Households, 1995-1996

	Log PCI		PCI	
	OLS on Z, X, Y, ΔX	**IV on Z, X, Y, ΔX**	**OLS on Z, X, Y, ΔX**	**IV on Z, X, Y, ΔX**
Number of observations	1233	1233	1233	1233
Adjusted R-squared	0.3426	.	0.1253	0.1212
Constant				
Initial Income- Reported	-0.590 *	*	-0.1 *	
	(0.13)		(0.0)	
Initial Income- IV approach		0.094		0.0 *
		(0.29)		(0.0)
Region				
Head's age				
Head's school	*		*	
Initial number of children			*	
Head's gender		*	*	*
Initial family type				
Head's employment status	*	*	*	
Change in number of children		*	*	*
Change in head's gender				
Change in family type	*	*	*	*
Change in head's employment status	*	*	*	*

Z={Region, head's age, head's schooling}, X={number of children, head's gender, family type, head's employment}, Y={base year per capita income}, ΔX={change in number of children, change in head's sex, change in number of adults, change in head's employment}. Instruments for IV include housing rental value and more detailed family type breakouts. Coefficients and standard errors (in brackets) are only shown for initial income variables.

** denotes statistical significance at the 5% level using an F-test on category variables*

Table 3d: Regression of Change in Income for Venezuelan Households, 1996-1997

	Log PCI		PCI	
	OLS on Z, X, Y, ΔX	**IV on Z, X, Y, ΔX**	**OLS on Z, X, Y, ΔX**	**IV on Z, X, Y, ΔX**
Number of observations	7521	7521	7557	7557
Adjusted R-squared	0.2911	0.0203	0.2282	0.1100
Constant	*		*	
Initial Income- Reported	-0.603 *		-0.4 *	
	(0.026)		(0.0)	
Initial Income- IV approach		-0.011		-0.1
		(0.120)		(0.1)
Region	*		*	*
Head's age				
Head's school	*		*	
Initial number of children	*		*	
Head's gender				
Initial family type				
Head's employment status	*	*	*	*
Change in number of children	*		*	*
Change in head's gender	*	*	*	*
Change in family type				
Change in head's employment status	*	*	*	*

Z={Region, head's age, head's schooling}, X={number of children, head's gender, family type, head's employment}, Y={base year per capita income}, ΔX={change in number of children, change in head's sex, change in number of adults, change in head's employment}. Instruments for IV include household durables such as refrigerator, washing machine, air conditioning, TV set, gas or electric kitchen and automobiles. Coefficients and standard errors (in brackets) are only shown for initial income variables.

** denotes statistical significance at the 5% level using an F-test on category variables*

Table 4: Relative Importance of Explanatory Variables on Change in PCI, Initially Poor vs. Initially Non-Poor

	INDONESIA				***SOUTH AFRICA (KwaZulu-Natal)***				***SPAIN***				***VENEZUELA***			
	POOR		NON-POOR		POOR		NON-POOR		POOR		NON-POOR		POOR		NON-POOR	
	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j	s_j
Reported initial PCI	25.3		9.3		0.8		12.2		5.6		2.2		3.8		13.0	
Predicted initial PCI		1.9		-0.3		3.7		2.7		8.1		0.0		4.4		-0.2
Region	1.8	1.0	1.8	1.3	4.1	2.3	2.2	1.9	0.0	0.3	0.0	0.0	1.3	0.6	1.1	0.7
Initial number of children	-0.1	0.0	-0.1	0.0	3.1	1.7	-0.8	-0.5	9.5	5.5	0.7	0.4	2.9	1.1	-0.2	-0.1
Head's gender	0.1	0.1	0.0	0.0	0.1	0.0	0.1	0.1	2.4	3.1	0.6	0.6	0.0	0.0	0.0	0.0
Initial family type	0.1	0.1	0.0	0.0	-0.1	-0.1	-2.9	-2.2	-0.2	-0.4	0.2	0.4	0.0	0.0	0.2	0.3
Head's age	0.2	0.2	0.4	0.4	1.9	1.6	0.5	0.5	0.6	0.2	0.5	0.6	0.4	0.3	0.1	0.2
Head's schooling	1.9	0.3	3.0	1.6	0.1	0.2	0.3	0.4	1.9	2.0	1.4	0.8	7.0	4.0	1.0	0.4
Head's employment status					1.3	2.5	1.3	1.6	1.8	2.1	0.5	0.5	0.6	0.6	-0.1	0.3
Change in # of children	1.4	1.4	3.0	3.0	3.3	3.1	6.2	5.9	0.1	-0.1	2.6	2.6	0.6	0.6	1.1	1.2
Change in head's gender	0.0	0.0	0.2	0.2	0.4	0.4	0.0	0.0	1.6	1.9	0.0	-0.1	0.0	0.0	1.0	1.1
Change in family type	-0.1	-0.1	0.0	0.1	1.6	1.7	7.8	7.3	NA	NA	2.1	2.5	0.2	0.1	0.0	0.1
Change in head's employment status	0.5	0.7	2.1	2.0	17.3	17.3	1.3	3.3	6.7	6.1	4.1	4.2	1.6	1.7	3.9	3.9
Total explained	*31.0*	*5.6*	*19.7*	*8.3*	*33.8*	*34.4*	*30.6*	*21.2*	*30.0*	*29.0*	*15.0*	*12.5*	*18.4*	*13.4*	*21.2*	*7.9*
Unexplained	*69.0*	*94.4*	*80.3*	*91.7*	*66.2*	*65.6*	*69.4*	*78.8*	*70.0*	*71.0*	*85.0*	*87.5*	*81.6*	*86.6*	*78.8*	*82.1*
Total	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

s_j represents the share of explanatory power of the corresponding variable in a multivariate regression that includes all other variables in the table.

Table 5: Factor Weight Inequality Measures for Change in PCI
(1) Fei-Ranis-Pyatt-Kuo-Chen and (2) Shorrocks

INDONESIA			***SOUTH AFRICA (KwaZulu-Natal)***			***SPAIN***			***VENEZUELA***		
	(1)	**(2)**		**(1)**	**(2)**		**(1)**	**(2)**		**(1)**	**(2)**
Labor Earnings	61.4%	71.3%	Labor Earnings	82.7%	88.2%	Labor Earnings	79.5%	83.2%	Labor Earnings	89.8%	88.9%
Transfer Income	14.6%	9.8%	Rental	6.2%	4.4%	Capital Income	3.9%	3.5%	Private Transfers	3.1%	3.0%
Remittance Income	23.5%	16.2%	Remittance	3.0%	1.6%	Transfer Income	13.9%	11.1%	Social Security	3.2%	4.2%
Asset Income	0.5%	2.6%	Other Non- labor income	8.1%	5.8%	Other Non- labor Income	2.7%	2.1%	Other Non- labor Income	3.9%	3.9%

Note: All income sources are in per capita terms