For Richer or For Poorer?
Evidence from Indonesia, South Africa, Spain, and Venezuela

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Abstract

We analyze household income dynamics using longitudinal data from Indonesia, South Africa (KwaZulu-Natal), Spain and Venezuela. In all four countries, households with the lowest reported base-year income experienced the largest absolute income gains. This result is robust to reasonable amounts of measurement error in two of the countries. 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, with one exception, the empirical importance of cumulative advantage, poverty traps, and skill-biased technical change was no greater than structural or macroeconomic changes that favored initially poor households in these four countries.

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The fate of the world's poor in today's increasingly globalized world is a hotly-contested issue. Opponents of free trade argue that unfettered access to foreign capital, technology, and goods primarily benefits a well-connected and highly skilled elite, to the exclusion of the poor, voiceless majority. The anti-globalization crowd has literally thrown stones at those who assert that free trade and highly integrated markets are in the economic interest of the poor. In this paper, we use panel data from four countries to ask how initially poor households fared economically relative to their wealthier counterparts during the 1990's. The more that economic growth benefited initially wealthy households to the exclusion of the initially poor, the greater the justification for policies that redistribute income to the poor, even at the expense of economic growth.

A large literature uses cross-sectional regressions to analyze the determinants of economic growth at the country level (Levine and Renelt, 1992; Barro and Sala-i-Martin, 1997; Benhabib and Spiegel, 2000). However, these papers analyze the determinants of aggregate income rather than examining changes in the economic condition of households.

When looking at changes in households' incomes within countries, analysts typically consider changes in the anonymous income distribution from comparable cross sectional surveys or censuses. These studies compare one set of poor households in the base year to another set of poor households in the final year, but can say nothing about the income

changes of initially poor or rich households. To see how those with different initial positions in the income distribution have fared, longitudinal data are required.

This work uses new panel data to analyze household income dynamics in four very different economies - Indonesia, South Africa, Spain, and Venezuela - during the 1990's. We address two main questions: First, what is the relationship between households' reported base year income and their subsequent income change? Did households that reported a high level of income in the base year experience greater or lesser income gains, on average, than initially low-income households? Second, what is the relationship between households' longer-term economic position in the base year and their subsequent income changes? Did households with high predicted income, based on their asset holdings, education levels, and other household characteristics, enjoy disproportionately large income gains?

The remainder of this paper is laid out in five sections. Section II reviews theoretical foundations, the four panel surveys and the macroeconomic conditions they captured, and a number of methodological choices. Section III presents a detailed analysis of the relationship between base-year economic position and subsequent income change. Section IV examines how that relationship is influenced by the extent and properties of measurement error in income. Section V briefly examines relative mobility. Finally, Section VI summarizes the main conclusions, caveats, and directions for further research.

II. Theory and Methods

A. Theoretical Foundations

Various theories offer guidance on the forces influencing household income dynamics. One theory is cumulative advantage, which posits that households with higher predicted income in the base year experience the highest or most positive income changes. Wealthier households' ownership of physical and human capital, access to social and political connections, and greater ability to borrow and save, could all contribute to cumulative advantage (Merton, 1968; Boudon, 1973; Huber, 1998). Complementing cumulative advantage is the notion of poverty traps: that households lacking a minimum level of human, physical, and social assets are consigned to a life in poverty. These processes generate what Nobel-Laureate James Meade (1976, p. 155) called "self-reinforcing influences which help to sustain the good fortune of the fortunate and the bad fortune of the unfortunate."

A third factor that may contribute to cumulative advantage and poverty traps is labor market twist. This idea holds that in an increasingly globalized and technology-dependent world, the demand for skills is outpacing the available supply, bidding up the earnings of skilled workers while lowering those of the unskilled. (Gottschalk, 1997; Johnson, 1997; Topel, 1997; Fortin and Lemieux, 1997; Friedman, 2000). Skill-biased technical change would act to propel households with the highest human and physical capital endowments ahead the most -- that is, a pattern where the households with the highest predicted income experience the largest gains.

An opposing set of theories posits that economic changes in these four countries would have favored the initially disadvantaged households, those endowed with relatively low levels of human and physical capital. The traditional Heckscher-Ohlin framework predicts that increased international trade raises the returns to relatively abundant factors of production. In Indonesia, South Africa, and Venezuela, this theory would predict that a period of increased trade would benefit households with relatively low levels of human and physical capital.[6]

In addition to increased international trade, in two of the four countries studied, political and macroeconomic events may have favored initially poorer households. In South Africa, the end of Apartheid coincided with a change in the informal sector that brought increased employment and earnings to prime working-aged black South Africans (Cichello, Fields, Leibbrandt, 2001). In Venezuela, the burden of a recession caused largely by a fall in oil prices and political instability may have fallen disproportionately on middle-class and richer households. In these two countries in particular, political and macroeconomic conditions may have favored households with lower expected income.

The theories of cumulative advantage, the effects of international trade, and macroeconomic and political conditions discussed so far bear on the relationship between a household's longer-run economic position and its subsequent income changes. However, two additional sets of theories apply to the relationship between a household's actual base year income and subsequent income changes. Transitory income shocks may

[6] See Wood [1997] for a critique of the traditional Heckscher-Ohlin model, particularly as applied to middle-income countries.

persist and build on themselves, since income windfalls or shortfalls can lead to the accumulation or loss of physical, financial, or social capital. In particular, in models in which household income is subject to at least one or more unstable equilibria, income shocks can lead a household on a path towards a new steady state income level. These multiple-equilibrium models are consistent with the notion of a poverty trap based on income: that households whose incomes fall below a certain level are trapped in poverty. (Nelson, 1956; Galbraith, 1979; Schultz, 1980; Dasgupta and Ray, 1986; Banerjee and Newman, 1993.)

In contrast with theories predicting that income shocks persist, the permanent income hypothesis assumes that transitory income shocks are serially independent, which on average leads household incomes to regress to their expected level the following period (Friedman, 1957). A weaker version of the permanent income hypothesis allows for a partial correlation between successive transitory income shocks, which leads household incomes to gradually regress towards their mean. In either case, this theory implies that households with low reported incomes in the initial year are more likely to have experienced a negative transitory shock in the initial year, and their subsequent recovery therefore appears as a relatively large income gain. Thus, if transitory income shocks are less persistent than changes in longer-term income, transitory income shocks will contribute to a more *negative* relationship between reported base year income and income change.

Finally, measurement error is a serious concern when dealing with estimates of income drawn from household surveys, particularly in developing countries, where income from self-employment is notoriously difficult to measure. Measurement error in base year income typically produces a spurious negative association between reported base year income and measured income change. Therefore, measurement error may also be an important factor contributing to a negative relationship between reported initial income and income change. The influence of measurement error on our results is discussed in detail below.

B. Data and Macroeconomic Conditions in the Four Countries

This research is a comparative study of four countries: Indonesia, South Africa, Spain, and Venezuela. Publicly accessible panel surveys were undertaken in each country during the mid 1990s. Other than that, these countries have little in common, differing in both their base levels of economic development and their ongoing macroeconomic conditions. Together, the panel data sets present a unique chance to identify common patterns in the dynamics of household income across surveys that differ in terms of location, time period, and macroeconomic conditions.

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 first round of the survey interviewed approximately 7,200 households in 1993. These households lived in 320 communities, spanning 13 provinces, and were representative of 83% of the national population of

roughly two hundred million. Ninety-four percent of these households were re-interviewed in 1997. This time period covers the final five years of an enduring trend of real GDP growth and stable economic management that characterized most of the 30-year Soeharto regime. Real GDP grew at about 7% per year from 1993 to 1997, raising per capita GDP from approximately $920 to $1130. Meanwhile, prices held steady, rising 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. The second round of the IFLS was mostly conducted from August to November of 1997, largely before the adverse effects of the crisis were apparent.[7] The data are described in more detail in 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.[8] 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 initial survey took place just months before the historic 1994 elections and transition of political

[7] 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.

[8] "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

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 (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, as Real GDP expanding by 2.3%, per capita GDP increased from roughly $14,950 to $15,300, and the unemployment rate slightly diminished 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

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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.

government agency for the collection of statistics. Since 1997, it has been conducted in urban areas only; the urban population in Venezuela is 80.3% of the total. Households are followed 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 fall of oil prices and a highly contentious electoral process. Output growth fell from 5.9% in 1997 to -0.7% in 1998, and per capita income fell from about $3610 to $3510. Inflation declined but remained 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%.

C. Methodological Choices

Our analysis of household income dynamics in the four countries rests on a number of methodological choices. The first was the unit of analysis. As a practical matter, our surveys contain substantial numbers of individuals who moved into and out of households. In general, our surveys did not track household members who moved, and thus their economic outcomes are unobserved. Therefore, we have chosen in this study to present a relatively accurate snapshot of the demographic and economic changes of households rather than an incomplete and biased picture of the changes experienced by individuals.

Our next fundamental decision was to investigate income dynamics rather than consumption dynamics. 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. However, 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). More importantly, in this study data considerations alone necessitate the use of income, as not all of our surveys contain measures of household consumption.[9]

Next, we had to decide 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 method, the per capita adjustment.

The final 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

[9] 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.

measures absolute income gains. For comparison purposes, results are also reported using changes in log per capita income (Δlog PCI), which approximates percentage income gains. Using changes in logs is consistent with the widespread belief in concave utility functions -- that a given increase in per capita income leads to a greater increase in the economic welfare of a poor household than that of a rich household. In all cases, incomes are measured in inflation-adjusted terms.

III. Empirical Results.

A. Trends in Inequality

Some analysts believe that patterns of income dynamics are apparent from changes in cross-sectional income inequality but, as we shall show, this is *not* the case in our four countries. We begin by documenting the changes in the cross-sectional inequality among households that appear in both years of our panel surveys. In addition, in Spain and Venezuela, nationally representative samples can be used to calculate income inequality. Table 1 presents the Gini coefficient of inequality in the base and final years, for household income in both log per capita and per capita terms.[10] Inequality showed little change or decreased in Indonesia and Venezuela, while inequality showed little change or increased in Spain and South Africa.

Occasionally, rising income inequality is misinterpreted as evidence that economic conditions have worsened for the poor in an absolute sense. A more common error is to interpret rising income inequality as suggesting that, on average, the initially rich

[10] In Table 1, we classify inequality as showing little change if the change in Gini coefficients was less than 0.01.

experienced more favorable income changes than the initially poor. Rising inequality indicates that the dispersion of income has widened, but contains no information on the movement of specific households within that distribution. If sufficient numbers of poor and rich households swap positions, the initially poor will gain more on average than the initially rich, even as the distribution of income grows more unequal. To investigate whether pro-poor income changes occurred in countries with rising cross-sectional income inequality, we now turn to analyzing changes in household income, measured directly.

B. Univariate Regressions

Do initially poorer households get ahead more or less than initially richer households? A number of previous studies have attempted to answer this question by estimating the extent to which household economic well-being converges towards the grand mean or diverges away from it. In these studies, the measure of economic position is household per capita expenditure, individual earnings, or its logarithm. The extent of convergence or divergence can be measured by regressing change in economic position (which we denote here by Y_2-Y_1) on base year economic position (Y_1) with no other variables present. A slope less than zero has been found in studies of the United Kingdom (Creedy and Hart, 1979; Thatcher, 1971), the United States (Moffitt and Gottschalk, 1995), and Côte d'Ivoire (Grootaert et al., 1997), indicating convergence in these cases.[11] Convergence does not appear everywhere, however. In France, incomes were found to have converged

[11] Many of these studies report the coefficient from a regression of final year income on initial year income, from which we subtract one to obtain the coefficient on income change. Also,

between 1963 and 1966 but incomes neither converged nor diverged between 1966 and 1970 (Hart, 1976). In the United States, convergence was found for 1970-1975 and 1975-1980, neither convergence nor divergence was found between 1980 and 1985, and incomes diverged from 1985 and1990 and from 1990 to 1995 (Fields, forthcoming). Taken at face value (i.e., without considering the possibility of measurement error), these studies show that household incomes in these countries sometimes converge towards the grand mean, sometimes diverge away from it, and sometimes do neither.

Turning now to our four countries, the coefficients for regressions of this type are presented in the top half of Table 2. The first row demonstrates that households with lower reported incomes, measured in monetary terms, experienced more favorable income changes. The second row demonstrates an even stronger negative relationship between reported log income per capita and log income change in all four countries.

The bottom two rows report results using predicted initial income as a measure of longer-term economic position in the initial period. Initial income is predicted using household composition, educational and occupational status, physical assets, and local characteristics.[12] Table 2 shows mixed results when changes are measured in currency units. A statistically significant negative relationship is found between predicted incomes

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Moffitt and Gottschalk provided variance and covariance terms for log earnings in various years from which the coefficient was calculated.

[12] The set of variables used to predict income is listed in Table 4. Table 4 also provides evidence of the strong predictive power of these covariates. However, the resulting predictions cannot capture all sources of a household's expected or permanent income. If initial permanent income omitted from the prediction has a systematically different effect on income change predicted income, estimates of the relationship between permanent income and income change will be biased accordingly.

and income change in Venezuela. However, the relationship between predicted income and income change in monetary units is insignificant in South Africa and Spain, and households with higher predicted incomes experienced significantly more favorable income changes in Indonesia. When measured in log units, however, in all four countries households with lower predicted log-income experienced the largest income gains.

Overall, these results show a pronounced *negative* relationship between reported income and subsequent income change, and a negative relationship between predicted log income and income change. In only one case, Indonesia, is the relationship between predicted income and income change statistically significant and positive. So far, in these four countries, there is remarkably little evidence supporting the theory of cumulative advantage, which predicted that those households that started in the most favorable economic positions experienced the most favorable income changes.

It is possible that allowing for non-linearity in the relationship between initial income and income change would cause a different pattern of income dynamics to emerge. The next subsections address these concerns, presenting profile analysis based on quintiles of initial economic well-being and non-parametric regressions in turn.

C. Profile of Changes in PCI

Tables 3.a and 3b relate changes in household per capita and log per capita income, respectively, to the quintiles of reported and predicted base year income. [13] In addition,

[13] Predicted initial income quintiles are the quintiles of households' predicted income.

households' longer-term economic positions in the base year are also gauged using the quintile of consumption, total value of assets, and housing rent when available. Quintiles are used to allow for the possibility of non-linear relationships. The upper portion of Table 3.a shows the relationship between the quintile of initial reported income and average income change. In Spain and Venezuela, the relationship is monotonically negative, and it is nearly so in South Africa. In Indonesia, though, income changes were essentially the same in the first four quintiles, but significantly lower for the richest quintile. Overall, the relationship between the quintile of reported initial income and average income change is statistically significant and negative, meaning that households that reported lower initial income experienced larger average gains.

On the other hand, the measures of longer-term economic position shown in Table 3.a indicate a variety of patterns. In South Africa, we continue to find that those who started in the richest predicted income or consumption quintile got ahead the *least*. In Indonesia, on the other hand, the longer-term indicators (predicted income quintile, consumption quintile, asset quintile) all show the opposite pattern: those who got ahead the most in currency units were the ones who started *ahead*. In Spain and in Venezuela, these other indicators exhibit no statistically significant pattern. Thus, there is no clear cross-country pattern for the changes in currency units: we find divergence in Indonesia, convergence in South Africa, and no statistically significant pattern in Spain and Venezuela.

D. Profile of Changes in Log PCI

Two further checks were performed to test the robustness of the conclusion of unconditional convergence. First, the analysis was redone taking as the dependent variable the change in per capita income measured in log units (Δlog PCI). These results appear in Table 3.b. In all four countries, the relationship between the quintile of reported income and log income change is strongly negative; those who reported higher base year incomes got ahead the least in percentage terms. Meanwhile, in Indonesia and South Africa, the relationships between all measures of longer-term measures of well-being and log income change are negative and statistically significant. There is *no evidence* in any of the four countries that those who started with a higher level of income, consumption, or assets experienced *greater* percentage income gains than others.

E. Non-Parametric Regressions

Non-parametric regressions give a more detailed view of the relationship between base year economic position and household income mobility. The plots in Figures 1.a-d are obtained by using a running line smoother, which locally estimates slopes between each point taking into account the nearest neighboring points.[14] Analytic confidence intervals bracket the smoothed plot. Figures 1.a. and 1.b show the smoothed relationship between change in per capita income change and both initial reported income and initial predicted income. Figures 1.c and 1.d plot the smoothed relationships between log income change

[14] The number of neighbors to include is determined point by point by an algorithm that uses cross-validation techniques to minimize mean squared error. Running line estimators are similar to Cleveland's (1979) Lowess estimator; the difference is the lack of weighting kernel. For South Africa and Indonesia, graphs constructed using Lowess differed little.

and both the log of reported income and predicted log income. Quintile boundaries are marked by vertical lines.

These non-parametric regressions generally confirm what we found in the profile analysis above, namely:

1. The relationship between ΔPCI and reported initial PCI is markedly *negative* in Spain and Venezuela, generally negative and nearly monotonic in South Africa, and negative only within the bottom and top quintiles in the case of Indonesia.
2. Relating ΔPCI to predicted PCI, the non-parametric analysis reveals a negative relationship in the top three quintiles in Venezuela and South Africa, hints at a positive relationship in Spain, and provides further evidence that the top quintile experienced relatively large gains in Indonesia.
3. The relationship between Δlog PCI and reported initial log PCI is markedly *negative* in all four countries.
4. The relationship between Δlog PCI and predicted log PCI is negative in South Africa and Indonesia, while confidence bands reveal that there is no clear statistically valid relationship in Venezuela and Spain.

IV. Robustness to Measurement Error

So far, we have reported results relating income change to reported and predicted base year income, which are approximations to actual income and longer-term income respectively. Unfortunately, household incomes are notoriously difficult to measure.. This section discusses how measurement error in our income data influences the results

reported above. How robust are the generally negative relationships between base year reported and predicted income and income change to the existence of measurement error?

A. Measurement Error in Reported Income

To analyze the effect of measurement error on the relationship between base year reported income and income change, the income reported by household i in year t is written as the sum of unobserved true income Y_{it} * and a measurement error component μ_{it}:

$$Y_{it} = Y_{it}^{*} + \mu_{it} . \qquad (1)$$

Measurement error may be correlated with true income. A negative correlation arises if wealthier households are reluctant to report their full incomes, perhaps out of fear that the survey will be used for tax purposes, or if shame or embarrassment leads some poorer households to overstate their incomes. Following Bound et al (1994), measurement error in the initial period is taken to be a linear function of true income in the initial period, plus a white-noise disturbance term, u_1. Letting $\overline{Y}_1$ * equal average true income in the initial period, and δ_1 represent the correlation between true base year income and measurement error, measurement error in base year reported income is written as:

$$\mu_{i1} = \delta_1 \left(Y_{i1}^{*} - \overline{Y}_1^{*} \right) + u_{i1} . \qquad (2)$$

In the second period, measurement error may not only be correlated with true income in that period but also with measurement error in the first period. Serial correlation in measurement error μ_{it} occurs if particular households systematically under or over-report their income; the serial correlation parameter is labeled ρ. Therefore, we assume that measurement error in the final period is correlated both with true income in the final

period and the idiosyncratic portion of the previous period's measurement error in the following way:

$$\mu_{i2} = \delta_2\left(Y_{i2}* - \overline{Y}_2*\right) + \rho u_{i1} + u_{i2}. \tag{3}$$

The relationship between households' income in the initial period and their subsequent income change, when income is measured without error, is the coefficient from a regression of true income change on true initial income. This coefficient measures the extent of convergence or divergence in true incomes, measured without error, and can be expressed as:

$$\gamma* = \frac{Cov\left[Y_2* - Y_1*, Y_1*\right]}{Var\left[Y_1*\right]}. \tag{4}$$

The OLS estimate from a regression of reported income change on reported base year income, reported in Table 2, is expressed as:

$$\hat{\gamma} = \frac{Cov\left[Y_2 - Y_1, Y_1\right]}{Var\left[Y_1\right]}. \tag{5}$$

Substituting equations (1) through (4) into equation (5), as shown in appendix A, gives:

$$\hat{\gamma} = \gamma* \frac{Var\left[Y_1*\right]}{Var\left[Y_1\right]}\left(1+\delta_1\right)\left(1+\delta_2\right) - \frac{Var\left[u_1\right]\left(1-\rho\right)}{Var\left[Y_1\right]} + \frac{Var\left[Y_1*\right]}{Var\left[Y_1\right]}\left(1+\delta_1\right)\left(\delta_2 - \delta_1\right). \tag{6}$$

Signing the components of bias requires two additional assumptions. First, a particular household's propensity to misreport income is assumed to decline or remain constant over time, such that $\rho \leq 1$. Second, measurement error is assumed partially correlated with true income, such that $\delta_t > -1$. Both of these assumptions are consistent with validation studies using U.S. data, as discussed further below.

Under these assumptions, the second term of equation (6) shows that measurement error in initial income contributes to an apparent negative correlation between base-year income and subsequent income change. This negative correlation occurs because the mismeasured estimate of initial income is also used to calculate income change. This bias, however, is lessened if measurement error exhibits serial correlation in measurement error. The first term of equation (6) captures the standard attenuation bias caused by the stochastic independent variable. This attenuation bias is exacerbated if measurement error is negatively correlated with true income in each period. If the true relationship between initial income and income change is negative, so that true incomes converged towards the grand mean, then this attenuation bias counteracts the effects of the second term by raising the value of the estimated coefficient towards zero. Finally, the third term will be relatively small, unless the strength of the correlation between measurement error and true income changed considerably between periods.

The variance of reported income in the first period, which appears in the denominator of equation (6), is itself a function of the covariance between measurement error and true base year income. Substituting for the variance of reported income Y_1, as described in Appendix A, leads to the following expression:

$$\frac{Var[u_1]}{Var[Y_1 *]} = \frac{\gamma * f(\delta_1, \delta_2) + g(\delta_1, \delta_2) - \hat{\gamma}(1+\delta_1)^2}{1 - \rho + \hat{\gamma}}. \tag{7}$$

Equation (7) gives the variance of stochastic measurement error, relative to the variance of true income, given the observed coefficient on reported income $\hat{\gamma}$ and a particular

value of the unknown coefficient on true income, γ^*. Setting γ^* equal to zero gives the minimum amount of measurement error required to overturn the negative relationship between initial income and income change. Table 5a reports this minimum threshold, which is calculated for combinations of three different values of the ρ and δ parameters (δ_1 and δ_2 are assumed to be equal). In South Africa and Venezuela, for divergence to have taken place, the variance of measurement error would need to be at least 34 to 78 percent of the variance of true incomes, depending on the correlation between measurement error and both true income and past measurement error. In Indonesia, measurement error with variance that ranges from 20 to 40 percent of true income could be entirely responsible for the observed estimates of convergence. Finally, in the Spanish data, if the variance of stochastic measurement error is over 10 percent of the variance of true income, higher-income households got ahead more.

The nature and extent of measurement error in our data on household income cannot be determined without a valid observation on true household income. As a rough basis for comparison, two validation studies of U.S. earnings data compared the Current Population Survey and the Panel Study of Income Dynamics to Social Security or firm records (Krueger and Bound, 1991, Bound et al 1994). These two studies found the following three regularities: First, the ratio of the variance of measurement error to true variance in true log annual earnings, $\frac{Var[u_t]}{Var[Y_t^*]}$, ranged from 7 to 25 percent. Second, measurement error was negatively correlated with true log earnings and this correlation, which we call δ_t, was between -0.15 and -0.03. Finally, measurement error exhibited

serial correlation, ρ, that ranged from 0.10 to 0.15. The level of measurement error in annual earnings data in the CPS or PSID is liable to be an imprecise approximation of measurement error in our data, which applies to the income of households, from outside the U.S., expressed in levels rather than logs. Nonetheless, a level of stochastic measurement error equal to ten percent of true income in our counties seems a credible lower bound. Thus, given the sensitivity of the Spanish results to measurement error, it is quite likely that higher income households in Spain experienced larger average income gains than lower income households did. Meanwhile, in the Indonesian data, a moderately high amount of measurement error would imply that high-income households got ahead more. In South Africa and Venezuela, however, we are more confident that measurement error is not so high as to overturn the conclusion that low-income households experienced the largest gains.

B. Measurement Error in Predicted Income

In the model above, measurement error in reported incomes is correlated with household characteristics that determine income, and is therefore present in predicted income. Predicted income is thus an imperfect indicator of true longer-term income, a latent variable defined as income predicted using true initial income, measured without error, as the dependent variable. In addition, true longer-term income is likely to be correlated with non-classical measurement error in reported income. For both of these reasons, the presence of non-classical measurement error, both in predicted base year income and in reported incomes, influences the estimated relationship between longer-term income and income change.

Appendix A describes a model in which the extent of the bias in this relationship primarily depends on two factors: the correlation between measurement error and true longer-term income, and the relationship between true initial income and income change. Table 5b presents the coefficient from a hypothetical regression of true income change on true longer-term income, for a range of negative correlations between measurement error and true longer-term income. In all simulations, Indonesian households with higher predicted income experienced the highest income gains, while in Spain, predicted income is essentially unrelated to income change. Meanwhile, in South Africa and Venezuela, households with the lowest longer-term income experienced the largest income gains. Therefore, we conclude that the qualitative relationships between predicted income and income change are unaffected by a sizeable amount of measurement error.

C. Summary

In Spain and Indonesia, the negative relationship between reported income and income change is not robust to measurement error. Simulations of the effect of measurement error, under reasonable values of parameters, indicate that in Spain, initial income and income change are positively related if the variance of measurement error is one tenth of the variance of true income. In the Indonesian data, if the variance of a stochastic measurement error component in income equals 20 to 40 percent of the variance of true income, the relationship between true initial income and true income change is positive. Finally, in South Africa and Venezuela, a positive relationship requires that the variance of measurement error equal 34 to 78 percent of the variance of true income . We

therefore conclude that true income probably did not converge in Spain, may not have converged in Indonesia, and likely converged in South Africa and Venezuela. Measurement error in income may also affect the relationship between predicted income and income change. In this case, however, the effect of measurement error is relatively minor, and the main conclusions are robust.

V. Relative Mobility

All of the analysis thus far has been in terms of changes in real currency units or their logarithms. In this section, we supplement the absolute mobility analysis with a look at relative mobility. Relative mobility is gauged by assessing which decile or centile of the per capita income distribution the household was in in the base year and in the final year.

It is customary in mobility studies to present a decile transition matrix; these appear for our four countries in Table 6. In all of them, the largest entries are in the (10, 10) cell, followed by the (1, 1) cell. That is, the richest and the poorest households are the ones that are most likely to stay in the same income decile. The greatest positional movement is found in the middle income deciles. This is a standard pattern throughout the world (Atkinson, Bourguignon, and Morrisson, 1992; Fields, 2001).

In addition, we have also calculated the mean number of centiles changed for households in each of the ten base-year income quintiles. As shown in Table 7, in all four countries, the relationship is clearly an inverse one. That is, on average, those households who started in the lowest positions moved up while those who started in the highest positions

moved down. Of course, 10% of the households must always be in each income decile, so whenever some household moves up in the relative distribution, some other household must move down. Moreover, households in the lowest income deciles have little or no room to move downward, and likewise those in the top deciles have little or no room to move upward. For these reasons, the negative relationship between initial income decile and mean centile change could hardly have come out otherwise.

By contrast, the absolute mobility changes calculated above *could* have come out otherwise but for the most part did not. For this reason, we give much more weight to the earlier results than to the relative mobility findings of this section.

VI. Conclusions

For many people, judgments regarding economic changes in the 1990's depend critically on the extent to which initially poor households improved their economic well-being relative to their richer counterparts. This paper examined change in per capita household income, in both logarithmic and monetary terms, in four very diverse economies: Indonesia, South Africa (KwaZulu-Natal), Spain, and Venezuela. Despite differences in types of data, years of observation, macroeconomic conditions, and income levels, strong patterns emerged.

The first question was whether households that reported higher base year incomes gained more or less than households that reported low base year incomes. In other words, did reported incomes converge towards or diverge away from the grand mean? Overall, both linear and non-linear techniques show that in all four countries, households that reported

the lowest base year incomes enjoyed the most favorable income changes. The pattern of convergence in reported income was even stronger when incomes were measured in log terms. We therefore draw a qualified conclusion: before taking account of measurement error, in all four countries, the combined effects of economic and political changes favoring poor households, recovery from transitory income shocks, and measurement error in income outweighed the combined effects of cumulative advantage and poverty traps.

To what extent is the conclusion that reported incomes converged driven by measurement error in income? Without a validation study, measurement error in initial incomes cannot be distinguished from legitimate transitory income shocks, meaning that any assessment of the relationship between transitory income shocks and income change necessarily includes the effect of measurement error as well. If measurement error in household income in our four countries is as large as prevailing estimates for earnings data on U.S. males, our results suggest the following. In Spain, true incomes did not converge towards the grand mean. In Indonesia, under reasonable assumptions regarding the properties and extent of measurement error, it is difficult to tell whether true incomes converged. However, in South Africa and Venezuela, the conclusion of income convergence is quite robust to measurement error.

The second question addressed in this study was whether households with higher permanent or longer-term income experienced higher income gains than households with lower permanent income. Longer-term income was approximated by predicting

household income, based on the household's demographic characteristics, ownership of physical assets, and the age, education, and occupation of the head. In three of the four countries, households with lower predicted income experienced income gains at least as large as households with higher predicted income. The one exception was Indonesia, where households with low predicted income had above-average percentage gains in income but below-average gains in income measured in currency units. These results are robust with respect to reasonable amounts of measurement error in income. Unless measurement error is in fact larger than we have reason to believe it is, the results suggest that in South Africa, Spain, and Venezuela, the total effects of cumulative advantage based on wealth or connections, asset-based poverty traps, and labor market twist were more than offset by structural economic changes that favored poorer households.

Looking ahead, we see several priorities for future work. Are the relatively large income gains of the initially poor permanent or temporary? Panel data with at least three observations would be needed to quantify the extent to which transient income fluctuations account for the largely progressive pattern of income changes that we observe. In addition, further work could document how the relationship between initial income and subsequent income change varies according to households' observed characteristics. Finally, we would like to know how the characteristics of countries and their economies influence the extent to which income changes favor poor households. Longitudinal data from additional countries would be required to answer this important question convincingly, and we hope that the methods developed in this study will be

applied to other economies. Establishing the stylized facts on income dynamics in a wide range of countries and time periods still lies ahead.

Appendix A: Bias due to measurement error

Equations (1)-(5) define the model of measurement error. From those definitions (i subscripts omitted for convenience), it follows that:

(A.1) $\Delta Y = Y_2 * (1+\delta_2) + (\rho - 1)u_1 + u_2 - Y_1 * (1+\delta_1)$,

where $\Delta Y = (Y_2 - Y_1)$. The following equation relates final year true income to initial year true income:

(A.2) $Y_2 * = (\gamma * + 1)Y_1 * + \varepsilon$,

where ε is a classical error term. From (A.1) and (A.2), it follows that:

(A.3) $Cov[\Delta Y, (1+\delta_1)Y_1 *] = (1+\delta_1)(1+\delta_2)(\gamma * + 1)Var[Y_1 *] - (1+\delta_1)^2 Var[Y_1 *]$,

and:

(A.4) $Cov[\Delta Y, u_1] = (\rho - 1)Var[u_1]$.

Therefore:

(A.5) $Cov[\Delta Y_1, Y_1] = Var[Y_1 *]\gamma * (1+\delta_1)(1+\delta_2) + Var[Y_1 *](1+\delta_1)(\delta_2 - \delta_1) + (\rho - 1)Var[u_1]$,

from which equation (6) in the text follows directly. Next, rewrite (5) as:

(A.6) $Cov[\Delta Y, Y_1] = Var[Y_1]\hat{\gamma}$,

and use equation (2) to obtain

(A.7) $Var[Y_1] = Var[Y_1 *](1+\delta_1)^2 + Var[u_1]$.

Substituting (A.7) into (A.6), using (A.5), and rearranging, yields:

(A.8) $Var[u_1](\hat{\gamma} + 1 - \rho) = Var[Y_1 *](\gamma * f(\delta_1, \delta_2) + g(\delta_1, \delta_2) - \hat{\gamma}(1+\delta_1)^2)$,

where $f(\delta_1, \delta_2) = (1+\delta_1)(1+\delta_2)$,

and $g(\delta_1, \delta_2) = (1+\delta_1)(\delta_2 - \delta_1)$.

Equation (7) in the text follows directly.

Non-classical measurement error is correlated to household characteristics used to predict income, and will therefore be present in predicted income. To account for this possibility, we define a latent variable $\hat{Y}_1 *$ as predicted income in the absence of measurement error, which we call a household's true longer-term income. Let δ_3 represent the correlation between true longer-term income and the measurement error component of predicted income. u_3 represents additional noise in the prediction due to the stochastic component of measurement error u_1. Predicted income is modeled as a linear function of true longer-term income plus a disturbance term:

(A.9) $\hat{Y}_1 = (1+\delta_3)\hat{Y}_1 * + u_3$.

True predicted income is assumed to be an unbiased estimate of a household's actual income.

(A.10) $Y_1 * = \hat{Y}_1 * + u_4$.

The coefficient of interest is the relationship between true predicted income and true income change, defined as:

(A.11) $\gamma_2 * = \dfrac{Cov\left[\Delta Y *, \hat{Y}_1 *\right]}{Var\left[\hat{Y}_1 *\right]}$

Table 2 reports the coefficient from a regression of observed income change on predicted income:

(A.12) $\hat{\gamma}_2 = \dfrac{Cov\left[\Delta Y, \hat{Y}_1\right]}{Var\left[\hat{Y}_1\right]}$,

which can be rewritten:

(A.13) $Var\left[\hat{Y}_1\right]\hat{\gamma}_2 = Var\left[\hat{Y}_1 *\right](1+\delta_3)\left[\gamma_2 * + h(\delta, \gamma *)\right]$, where

$$h(\delta, \gamma *) = \delta_2 \gamma * + \delta_2 - \delta_1 .$$

Taking the variance of equation (A.9) gives

(A.14) $Var\left[\hat{Y}_1\right] = (1+\delta_3)^2 Var\left[\hat{Y}_1 *\right] + Var\left[u_3\right]$.

Substituting (A.14) into (A.13), after rearranging, yields:

(A.15) $\gamma_2 * = \hat{\gamma}_2 \left((\delta_3 + 1) + \dfrac{Var\left[u_3\right]}{Var\left[\hat{Y}_1 *\right](\delta_3 + 1)} \right) - h(\delta, \gamma *)$.

For the purposes of simulation, we assume that $\delta_1=\delta_2=\delta_3$, that Var[$u_3$] is negligible, and that the estimated coefficients using reported base year income, $\hat{\gamma}$, is equal to $\gamma *$. Equation (A.15), under these assumptions, provides the coefficients $\gamma_2 *$ that appear in Table 5b.

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Table 1.a Cross-Sectional Evidence on Change in Inequality: Gini Coefficients for Household Log Per Capita Income

	INDONESIA		*SOUTH AFRICA*		*SPAIN*		*VENEZUELA*	
	1993	**1997**	**1993**	**1998**	**1995**	**1996**	**1997**	**1998**
Panel Households Only	.207	.170	.119	.120	.337	.339	.048	.049
Nationally Representative Sample	*	*	*	*	.311	.328	.051	.049
Conclusion	Decreased inequality		Little Change		Increased inequality		Little change	

Table 1.b Cross-sectional changes in Inequality: Gini Coefficients for Household Per Capita Income

	INDONESIA		*SOUTH AFRICA*		*SPAIN*		*VENEZUELA*	
	1993	**1997**	**1993**	**1998**	**1995**	**1996**	**1997**	**1998**
Panel Households Only	.559	.555	.515	.543	.319	.321	.458	.459
Nationally Representative Sample	*	*	*	*	.320	.317	.487	.473
Conclusion	Decreased Inequality		Increased inequality		Little change		Decrease	

* Representative samples for Indonesia and South Africa are not available in the final year.

Table 2: Coefficients from a Regression of Income Change on Base Year Income

DEPENDENT VARIABLE	*BASE YEAR INCOME*	*INDONESIA*		*SOUTH AFRICA*		*SPAIN*		*VENEZUELA*	
Change in PCI	Reported income	-0.23*	Pro-Poor	-0.35*	Pro-Poor	-0.07*	Pro-Poor	-0.35*	Pro-Poor
Change in log PCI	Reported log income	-0.53*	Pro-Poor	-0.56*	Pro-Poor	-0.52*	Pro-Poor	-0.64*	Pro-Poor
Change in PCI	Predicted income	0.14*	Pro-Rich	-0.13	Insignificant	0.01	Insignificant	-0.37*	Pro-Poor
Change in log PCI	Predicted log income	-0.27*	Pro-poor	-0.32*	Pro-Poor	-0.13*	Pro-Poor	-0.21*	Pro-Poor
Source: Authors' calculations									

** denotes statistical significance at the 5% level*

Table 3a: Mobility Profiles by Initial Position: Mean Changes in PCI

INDONESIA			*SOUTH AFRICA*			*SPAIN*			*VENEZUELA*		
	Mean	**Std. Dev.**		**Mean**	**Std. Dev.**		**Mean**	**Std. Dev.**		**Mean**	**Std. Dev.**
Total population	17.8	1.3	***Total population***	46.5	13.7	***Total population***	9.2	48.4	***Total population***	2.2	0.9
By reported initial income quintile *			By reported initial income quintile *			By reported initial income quintile *			By reported initial income quintile *		
Poorest Quintile	26.8	1.7	Poorest Quintile	140.9	23.0	Poorest Quintile	21.0	2.4	Poorest Quintile	20.7	1.2
2nd quintile	22.6	1.8	2nd quintile	73.6	15.8	2nd quintile	11.5	2.4	2nd quintile	13.4	1.0
3rd quintile	21.9	1.8	3rd quintile	85.3	21.3	3rd quintile	9.9	2.8	3rd quintile	8.2	1.3
4th quintile	18.1	2.2	4th quintile	33.8	26.3	4th quintile	7.1	3.5	4th quintile	-0.5	1.5
Richest quintile	-0.2	4.0	Richest quintile	-101.7	38.0	Richest quintile	-2.6	4.1	Richest quintile	-31.8	2.9
By fitted initial Income quintile *			By fitted initial Income quintile			By fitted initial income quintile			By fitted initial income quintile		
Poorest Quintile	14.2	1.0	Poorest Quintile	32.0	10.1	Poorest Quintile	6.0	2.5	Poorest Quintile	4.5	1.0
2nd quintile	15.3	1.8	2nd quintile	82.0	27.9	2nd quintile	9.1	2.3	2nd quintile	4.0	1.1
3rd quintile	15.2	2.0	3rd quintile	65.6	20.7	3rd quintile	11.8	3.1	3rd quintile	3.1	1.3
4th quintile	19.0	2.8	4th quintile	41.4	24.9	4th quintile	9.2	3.2	4th quintile	0.1	1.7
Richest quintile	29.3	4.3	Richest quintile	11.7	35.3	Richest quintile	11.1	3.6	Richest quintile	0.2	2.8
By initial Consumption quintile *			By initial Consumption quintile *			By initial Consumption quintile					
Poorest Quintile	10.4	1.2	Poorest Quintile	66.7	15.3	Poorest Quintile	9.2	2.7			
2nd quintile	17.3	1.6	2nd quintile	40.7	15.2	2nd quintile	2.3	2.4			
3rd quintile	17.2	1.9	3rd quintile	74.0	21.3	3rd quintile	10.2	3.1			
4th quintile	21.2	2.3	4th quintile	90.9	28.3	4th quintile	12.2	3.8			
Richest quintile	26.1	4.3	Richest quintile	-34.1	30.5	Richest quintile	13.5	4.2			
By initial Asset quintile *						By initial Housing rent quintile					
Poorest Quintile	18.6	1.7				Poorest Quintile	7.4	2.6			
2nd quintile	12.6	1.7				2nd quintile	8.8	2.6			
3rd quintile	12.2	1.9				3rd quintile	9.0	2.7			
4th quintile	18.8	2.5				4th quintile	6.4	3.4			
Richest quintile	29.3	3.4				Richest quintile	15.5	4.0			

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

Table 3b: Mobility Profiles by Initial Position: Mean Changes in Log PCI

INDONESIA			*SOUTH AFRICA*			*SPAIN*			*VENEZUELA*		
	Mean	**Std. Dev.**		**Mean**	**Std. Dev.**		**Mean**	**Std. Dev.**		**Mean**	**Std. Dev.**
Total population	0.38	0.02	***Total population***	0.15	0.05	***Total population***	0.076	1.05	***Total population***	-0.043	0.036
By reported initial income quintile *			By reported initial income quintile *			By reported initial income quintile *			By reported initial income quintile *		
Poorest Quintile	1.53	0.08	Poorest Quintile	1.10	0.14	Poorest Quintile	0.27	0.17	Poorest Quintile	1.150	0.118
2nd quintile	0.43	0.05	2nd quintile	0.23	0.08	2nd quintile	0.06	0.02	2nd quintile	-0.150	0.060
3rd quintile	0.17	0.04	3rd quintile	0.08	0.09	3rd quintile	-0.01	0.05	3rd quintile	-0.461	0.075
4th quintile	-0.02	0.04	4th quintile	-0.19	0.10	4th quintile	0.00	0.02	4th quintile	-0.335	0.049
Richest quintile	-0.22	0.03	Richest quintile	-0.46	0.07	Richest quintile	-0.02	0.01	Richest quintile	-0.408	0.027
By fitted initial income quintile *			By fitted initial Income quintile *			By fitted initial income quintile			By fitted initial income quintile		
Poorest Quintile	0.75	0.06	Poorest Quintile	0.51	0.13	Poorest Quintile	0.04	0.08	Poorest Quintile	0.065	0.075
2nd quintile	0.38	0.04	2nd quintile	0.23	0.09	2nd quintile	0.05	0.07	2nd quintile	-0.188	0.090
3rd quintile	0.27	0.04	3rd quintile	0.18	0.09	3rd quintile	0.01	0.08	3rd quintile	-0.021	0.078
4th quintile	0.20	0.04	4th quintile	0.02	0.10	4th quintile	0.06	0.03	4th quintile	-0.030	0.059
Richest quintile	0.16	0.03	Richest quintile	-0.18	0.07	Richest quintile	0.14	0.09	Richest quintile	-0.041	0.065
By initial Consumption quintile *			By initial Consumption quintile *			By initial Consumption quintile					
Poorest Quintile	0.49	0.05	Poorest Quintile	0.47	0.11	Poorest Quintile	0.06	0.16			
2nd quintile	0.47	0.05	2nd quintile	0.20	0.10	2nd quintile	0.02	0.04			
3rd quintile	0.37	0.05	3rd quintile	0.20	0.10	3rd quintile	0.06	0.02			
4th quintile	0.29	0.04	4th quintile	0.14	0.10	4th quintile	0.04	0.04			
Richest quintile	0.22	0.05	Richest quintile	-0.23	0.07	Richest quintile	0.14	0.06			
By initial Asset quintile *						By initial Housing rent quintile					
Poorest Quintile	0.53	0.05				Poorest Quintile	0.06	0.09			
2nd quintile	0.40	0.05				2nd quintile	0.07	0.02			
3rd quintile	0.30	0.05				3rd quintile	-0.01	0.07			
4th quintile	0.37	0.04				4th quintile	0.05	0.03			
Richest quintile	0.28	0.04				Richest quintile	0.14	0.10			

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

Table 4: Prediction of Base Year Per Capital Income and log Per Capita Income

	INDONESIA	*SOUTH AFRICA*	*SPAIN*	*VENEZUELA*
Common Prediction Variables	Region, head's age, head's schooling, number of children, head's gender, family type, head's employment			
Additional Prediction Variables	{Value of Assets, type of floor and toilet facilities, number of household earners, cluster-average income 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.)}
R^2 from OLS regression on initial PCI	0.364	0.483	0.329	0.354
F statistic on all variables	29.36	27.95	20.29	84.94
R^2 from OLS regression on initial log PCI	0.396	0.510	0.145	0.337
F statistic on all variables	50.37	25.60	21.02	78.75

Table 5a: Ratio of measurement error variance to true income variance implying zero correlation between true initial income and true income change.

Correlation with true income δ_1, δ_2.	Serial Correlation ρ	*INDONESIA*	*SOUTH AFRICA*	*SPAIN*	*VENEZUELA*
0	0	0.30	0.54	0.08	0.54
0	0.1	0.34	0.64	0.08	0.64
0	0.2	0.40	0.78	0.10	0.78
-0.1	0	0.24	0.44	0.05	0.44
-0.1	0.1	0.28	0.52	0.06	0.52
-0.1	0.2	0.33	0.63	0.06	0.63
-0.2	0	0.19	0.34	0.01	0.34
-0.2	0.1	0.22	0.41	0.01	0.41
-0.2	0.2	0.26	0.50	0.01	0.50

Table 5b: Coefficient from hypothetical regression of true income change on permanent income, by measurement error parameters.

Correlation with true income δ_1, δ_2, δ_3.	*INDONESIA*	*SOUTH AFRICA*	*SPAIN*	*VENEZUELA*
0	0.14	-0.13	0.01	-0.37
-0.05	0.12	-0.14	0.01	-0.37
-0.1	0.10	-0.15	0.00	-0.37
-0.15	0.08	-0.16	-0.00	-0.37
-0.2	0.07	-0.17	-0.01	-0.37
-0.25	0.05	-0.19	-0.00	-0.37

Table 6: Decile transition matrices.

Indonesia: Per Capita Income Transition Matrix
(Percent of sample in 1997 log PCI decile, conditional on 1993 log PCI decile)

1993 \ 1997	1	2	3	4	5	6	7	8	9	10
Lowest decile	**27.0**	19.8	14.7	13.4	7.6	7.3	3.6	2.9	3.0	0.8
2nd decile	22.4	**22.6**	17.0	10.3	7.1	8.0	5.8	4.3	1.6	0.9
3rd decile	16.3	15.8	**16.4**	16.7	10.7	8.4	8.2	4.3	2.0	1.3
4th decile	13.9	10.6	14.3	**15.3**	13.8	10.2	10.3	6.2	4.1	1.3
5th decile	8.4	9.8	13.7	14.2	**14.3**	14.5	9.9	8.5	3.7	3.2
6th decile	8.5	7.2	7.9	11.6	15.9	**13.4**	13.8	9.4	7.6	4.7
7th decile	5.7	9.6	7.1	8.2	10.7	12.1	**17.3**	14.0	10.2	5.3
8th decile	5.0	4.5	6.6	6.1	8.5	13.3	13.0	**14.9**	16.9	11.2
9th decile	2.5	3.4	3.8	4.1	8.6	7.1	9.0	17.9	**21.6**	22.1
Highest decile	2.5	0.6	2.5	1.4	3.8	3.9	6.4	12.8	23.4	**42.6**

South Africa: Per Capita Income Transition Matrix
(Percent of sample in 1998 log PCI decile, conditional on 1993 log PCI decile)

1993 \ 1998	1	2	3	4	5	6	7	8	9	10
Lowest decile	**20.7**	19.5	17.1	12.2	8.6	7.3	8.5	1.2	4.9	0
2nd decile	14.7	**23.2**	17.1	8.5	15.8	4.9	8.5	3.7	0	3.7
3rd decile	13.4	11	**14.6**	9.8	12.2	11	7.3	9.7	8.5	2.4
4th decile	11	8.5	18.3	**13.4**	11	9.8	12.2	9.7	2.4	3.7
5th decile	12.1	9.6	10.9	18.1	**12**	8.4	9.6	9.6	7.2	2.4
6th decile	7.3	4.9	3.7	18.3	4.9	**22**	15.8	11	7.3	4.9
7th decile	9.8	6.1	4.9	9.8	9.8	11	**13.4**	14.6	12.2	8.5
8th decile	5	6.2	6.2	3.7	11.1	11.1	11.1	**13.6**	19.8	12.4
9th decile	4.9	6.1	3.7	4.9	7.3	7.3	8.5	14.6	**19.5**	23.2
Highest decile	2.4	4.9	3.7	1.2	7.3	7.3	4.9	12.2	18.3	**37.8**

Table 6: Decile transition matrices (cont.).

Spain: Per Capita Income Transition Matrix (Percent of sample in 1996 log PCI decile, conditional on 1995 log PCI decile)										
1995 \ 1996	1	2	3	4	5	6	7	8	9	10
Lowest decile	**60.5**	19.6	8.8	3.4	0.0	4.3	1.5	0.7	0.6	0.6
2nd decile	25.2	**42.9**	9.9	10.5	3.6	3.1	1.5	1.0	1.3	1.1
3rd decile	4.0	19.4	**39.9**	15.7	13.4	1.2	5.3	1.2	0.0	0.0
4th decile	5.2	12.0	24.9	**33.2**	9.9	4.5	6.1	1.9	1.8	0.6
5th decile	1.5	2.9	7.6	28.0	**30.7**	12.9	6.1	5.9	2.4	2.0
6th decile	2.3	0.9	4.3	3.9	27.6	**34.7**	10.0	10.5	5.1	0.7
7th decile	2.0	1.0	1.1	6.3	7.6	26.4	**35.2**	11.6	7.3	1.6
8th decile	1.0	0.9	0.0	2.2	5.0	7.2	20.3	**39.4**	18.0	6.1
9th decile	0.0	0.0	0.0	0.2	0.0	4.3	9.3	27.5	**42.3**	16.5
Highest decile	0.0	0.0	0.0	0.0	0.4	0.7	1.2	2.5	23.9	**71.4**

Venezuela: Per Capita Income Transition Matrix (Percent of sample in 1998 log PCI decile, conditional on 1997 log PCI decile)										
1997 \ 1998	1	2	3	4	5	6	7	8	9	10
Lowest decile	**34.2**	14.0	12.6	8.4	8.9	7.1	6.9	4.2	3.3	0.5
2nd decile	19.3	**22.7**	16.6	13.7	7.6	6.9	4.9	4.7	2.3	1.3
3rd decile	12.4	14.4	**17.3**	18.0	11.3	9.0	8.8	3.1	3.8	2.1
4th decile	8.2	12.6	15.1	**15.8**	16.3	10.4	7.6	6.2	5.1	2.8
5th decile	6.3	9.0	11.4	16.6	**13.9**	13.4	12.3	7.7	5.7	3.9
6th decile	5.6	7.2	7.3	10.5	14.1	**16.6**	12.4	12.7	9.4	4.2
7th decile	4.3	5.1	8.8	6.2	11.8	11.4	**14.4**	17.4	14.7	6.0
8th decile	4.9	3.9	5.1	6.3	7.8	11.9	14.3	**18.7**	15.8	11.5
9th decile	2.4	3.8	2.6	4.3	5.9	9.5	13.5	14.9	**22.8**	20.2
Highest decile	1.3	2.2	2.5	3.1	2.7	4.8	7.2	9.6	18.2	**48.3**

Table 7: Average centile change, by initial income decile.

By Initial Income Decile	*INDONESIA*		*SOUTH AFRICA*		*SPAIN*		*VENEZUELA*	
	Mean Centile Change	**Std. Dev.**	**Mean Centile Change**	**Std. Dev.**	**Mean Centile Change**	**Std. Dev.**	**Mean Centile Change**	**Std. Dev.**
Lowest decile	+22.9	1.8	+30.6	3.5	+9.8	1.7	+20.4	1.1
2nd decile	+15.2	1.1	+20.7	3.8	+5.0	1.5	+17.2	1.1
3rd decile	+9.3	1.4	+9.7	2.8	+4.3	1.3	+10.9	0.9
4th decile	+1.6	1.1	+6.8	3.0	0.0	1.5	+4.3	1.0
5th decile	+0.4	1.3	+0.2	3.6	0.6	1.5	-0.3	1.0
6th decile	-7.8	1.4	-3.6	3.3	-2.1	1.5	-4.5	1.1
7th decile	-12.8	1.2	-14.8	3.5	-5.0	1.5	-9.7	1.2
8th decile	-14.4	1.5	-14.4	3.2	-5.0	1.3	-13.7	1.0
9th decile	-15.1	1.3	-18.3	3.1	-4.4	0.9	-16.7	1.1
Highest decile	-15.2	1.1	-17.3	3.0	-3.2	0.7	-13.7	1.0

Figure 1.a: Non-parametric regression for change in PCI on initial PCI
(extreme outlier data not shown, vertical lines indicate quintiles)

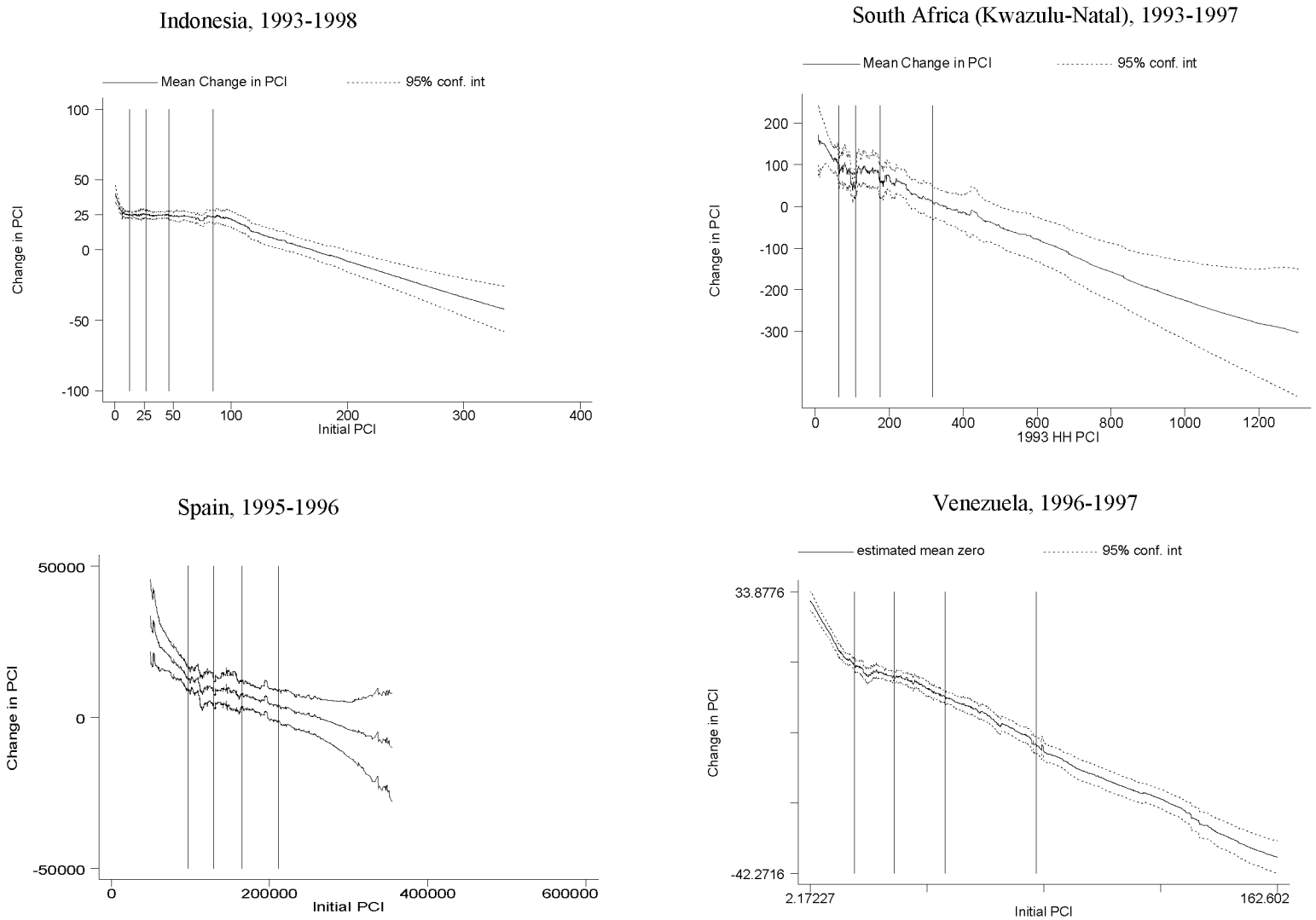
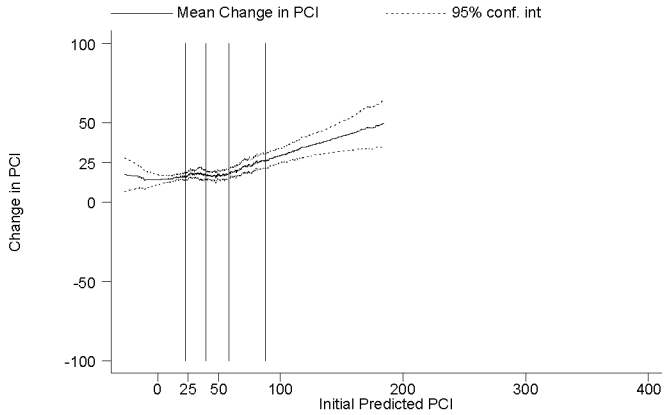
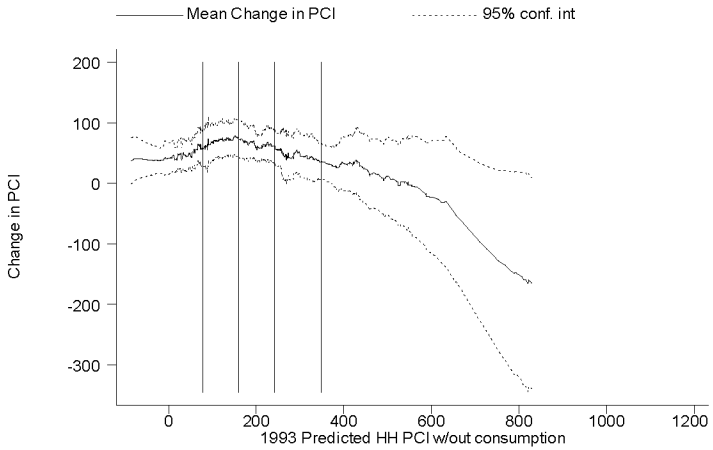


Figure 1.b: Non-parametric regression for change in PCI on predicted initial PCI
(extreme outlier data not shown, vertical lines indicate quintiles)

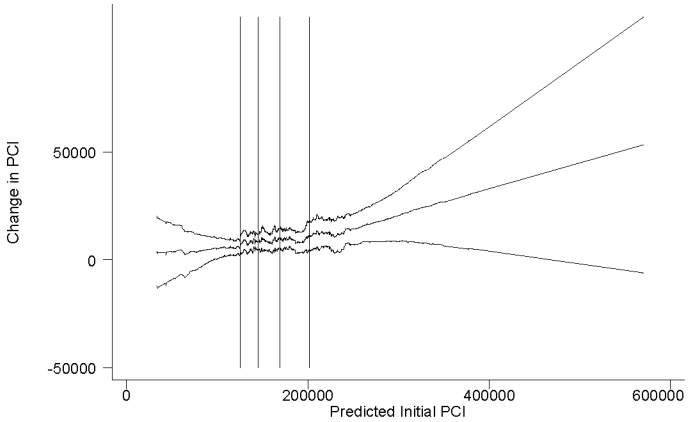
Indonesia, 1993-1998



South Africa (KwaZulu-Natal), 1993-1997



Spain, 1995-1996



Venezuela, 1996-1997

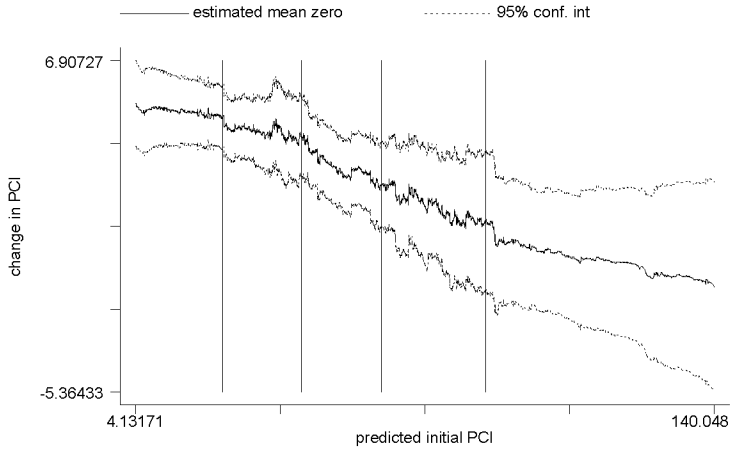
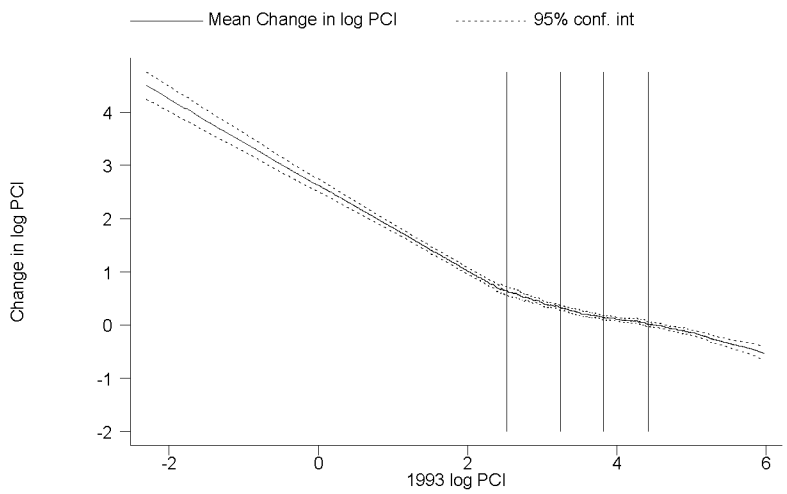
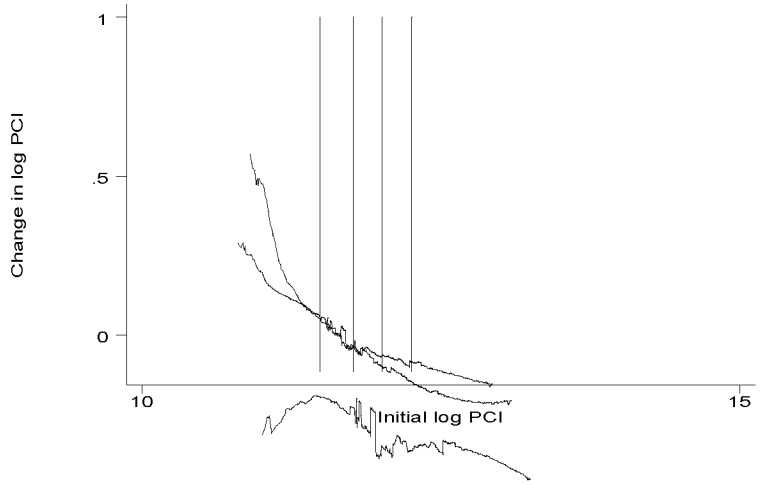


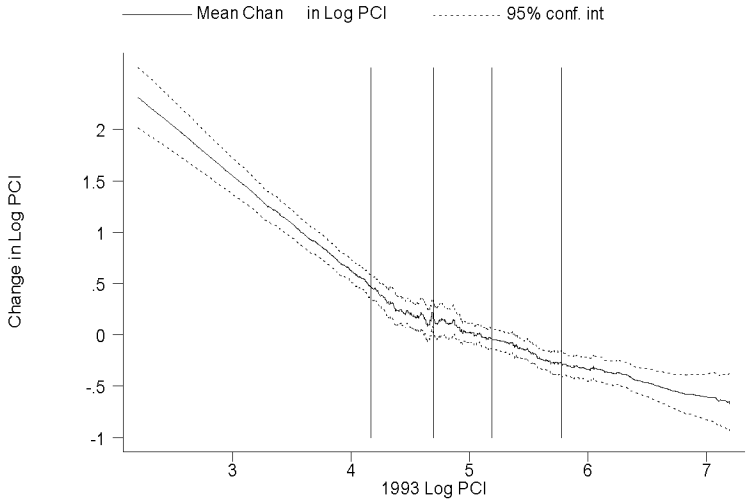
Figure 1.c: Non-parametric regression of change in log PCI on initial log PCI
(extreme outlier data not shown, vertical lines indicate quintiles)

Indonesia, 1993-1998





South Africa (KwaZulu-Natal), 1993-1997



Venezuela, 1996-1997

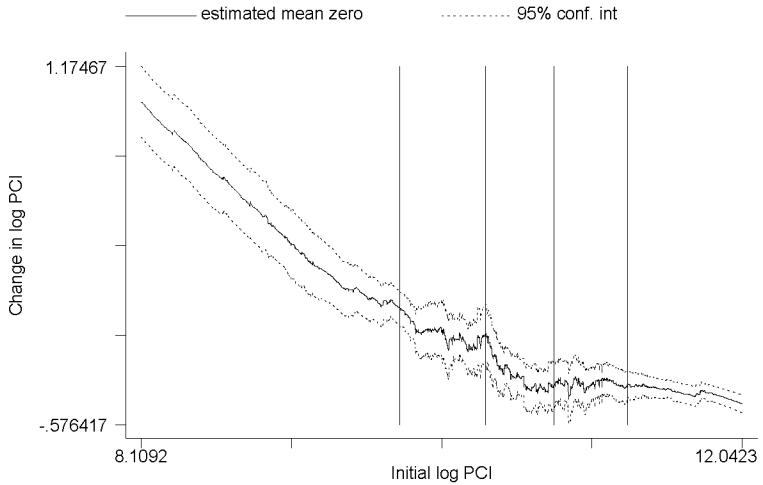
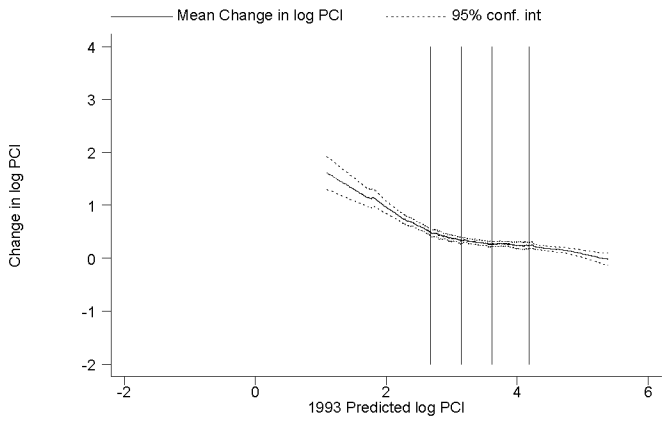
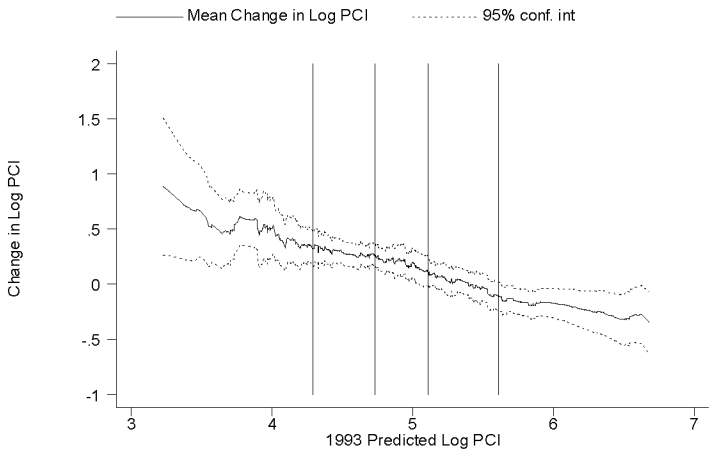


Figure 1.d: Non-parametric regression for change in log PCI on predicted log PCI
(extreme outlier data not shown, vertical lines indicate quintiles)

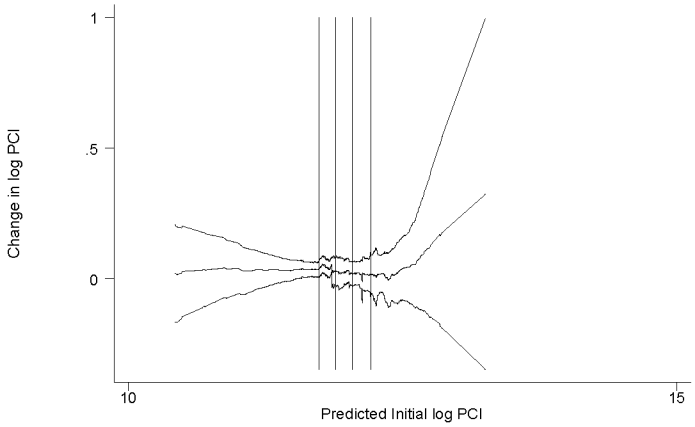
Indonesia, 1993-1998



South Africa (Kwazulu-Natal), 1993-1997



Spain, 1995-1996



Venezuela, 1996-1997