Changes in Welfare with a Heterogeneous Workforce: The Case of Peru

Adrian Robles
Marcos Robles

Changes in Welfare with a Heterogeneous Workforce: The Case of Peru

Adrian Robles
Marcos Robles

March 2016

http://www.iadb.org

Adrian Robles (adrianrbls@gmail.com), Marcos Robles (marcosr@iadb.org)

Changes in Welfare with a Heterogeneous Workforce: The Case of Peru[*]

Adrian Robles
Johns Hopkins University
Washington, DC

Marcos Robles
Inter-American Development Bank
Washington, DC

February 2015

Abstract

This paper argues that the assumption of a homogeneous workforce, which is implicitly invoked in the decomposition analysis of changes in welfare indicators, hides the role that schooling and its returns may have on the understanding of these changes. Using Peruvian cross-sectional data for a period of ten years (2004–2013) and counterfactual simulations, this paper finds that the main factor contributing to poverty reduction has been individuals' changes in labor earnings, and the role of these changes has been less important in reducing income inequality. The main driving force of reduced income inequality has been the fall in returns to education, which at the same time has been one of the important factors to constraining the period's remarkable progress in poverty reduction and expansion of the middle class.

Key words: Poverty; middle class; inequality; decomposition; labor; Peru.
JEL classification: C83, E24, D63, I24, I32.

---

1. Introduction

The period from 2003 to 2013 was one of Latin America's most notable in terms of economic progress. Both the sustained economic growth (the GDP per capita grew at an average annual rate of 5.2 percent)[1] and the substantial fall in income inequality (the Gini coefficient for per capita income decreased from 0.56 to 0.49; IDB, 2015) implied significant increases in purchasing power—both in absolute and relative terms—at the bottom of the income distribution, with considerable upward mobility along this distribution. The percentage of people with income below USD 4.00 a day decreased by 20 percentage points, from 43 percent to 23 percent; extreme poverty (people with income below USD 2.50 a day) was cut in half, from 26 percent to 11 percent; and the size of the middle class (people with income between USD 10.00 and USD 50.00 a day) increased from 21 percent to 33 percent. In this period, Peru—with 31 million inhabitants, the fifth-most populous country in Latin America, after Brazil, Mexico, Colombia, and Argentina—showed some of the most significant changes. Compared to the Latin American (18 countries) average, the annual per capita product of Peru grew faster than a 36 percent pace, and its Gini coefficient decreased nearly 3 additional percentage points between 2003 and 2013. Also, the headcount poverty ratio, at the USD 4-a-day line, fell 16 percent faster than the regional average, and the middle class grew 50 percent faster. Peru also showed greater resilience to shocks of the recent global financial crisis (Grosh, Bussolo and Freije, 2014). (The changes observed in Peru are described in detail in the Stylized Facts section.)

The region's dramatic changes have been detailed in a number of recent studies, which have also provided plausible explanations of how the changes came about and described the challenges to maintain and deepen the progress achieved (Gasparini and Lustig, 2011; Ferreira et al., 2012; Levy and Schady, 2013; Lustig, Lopez-Calva and Ortiz-Juarez, 2013). Several studies have focused more closely on the factors that have contributed to changes in poverty and inequality based on a non-parametric decomposition approach (Azevedo, Inchauste and Sanfelice, 2013; Azevedo, Davalos et al., 2013; Inchauste et al. 2014; Freije 2014). We follow this approach, but we concentrate exclusively on Peru and, in doing so, we use decomposition techniques enriched in terms of analytical scope and empirical application. Specifically, this paper aims to quantify the contribution of the forces behind the changes in Peru's welfare indicators based on counterfactual simulations.

---

[1] Gross Domestic Product in USD based on 2011 purchasing power parity (IMF, 2014).

The methods for counterfactual decompositions developed by Ravallion and Huppi (1991), Datt and Ravallion (1992), and Kolenikov and Shorrocks (2005) explain variations in poverty based on changes in aggregated components that have limited usefulness to define specific policies that fight against it. Unlike these works, the methods proposed more recently (Barros et al., 2006, 2007, and 2010; Azevedo, Inchauste, Olivieri et al., 2013; Azevedo, Nguyen et al., 2012) generate entire counterfactual distributions, allowing us to quantify the contribution of changes in a greater number of factors to the observed distributional change in poverty and inequality. On this basis, we explicitly consider the educational dimension in the income identity equation. By using an indicator of human capital stock, utilized extensively in the literature on economic growth for aggregate production functions, the assumption that all units of the labor force are homogeneous and possess equal capacities is relaxed.

Using data gathered from the National Household Survey of Peru (ENAHO, for its Spanish acronym) collected over 10 years, our results show that while the changes in labor income are one of the main factors contributing to poverty reduction in recent years, their role—in contrast to previous estimates—is less important to inequality reduction if the analysis takes into account that the working-age population's human capital is not homogeneous. Instead, the main driving force of the reduction in poverty was the fall in returns to education. Both unequalizing and equalizing effects of this fall occurred, i.e., returns were larger for higher levels of education and the fall was smaller for higher levels of education (convexities in returns increased), but returns were also proportionately higher for graduates of each education level, particularly among those with the lowest levels (sheepskin effects in the returns[2]). At the same time, the fall in returns to education was one of the most important factors that limited the achievement of more effective progress in reducing poverty and increasing the size of the middle class.

This paper provides three key contributions to the existing literature and sheds some light from a policy perspective. Firstly, an indicator of human capital stock for the working age population, associated with schooling and its returns, is incorporated into the income identity equation. This allows for a more appropriate identification of the forces behind the movements of population groups over the income distribution and improves the depth in the decomposition analysis. Secondly, consistent with the values of international lines, we define multiples of the national

---

[2] Larger returns to diploma years (or complete level years) than to other years of education, indicating that individuals with more schooling tend to earn more not because (or, at least, not solely because) schooling makes them more productive, but rather because it certifies them as more productive (Hungerford and Solon, 1987).

poverty lines that may be appropriate in the case studies at country level to define and analyze poor, vulnerable, middle class, and rich groups in the population. The lines thus defined consider the geographical price differences within countries, an aspect that is treated poorly in cross-country studies using international lines. Thirdly, we provide detailed evidence on Peruvian population movements along the income distribution over the last decade and contributions of monetary and non-monetary income components on changes in poverty, inequality, and the middle class. The revision of the Peruvian experience can provide lessons to other countries in the region, given the tremendous distributive changes over the last decade.

This paper is organized in five sections. After the introduction, the second section describes three methodological aspects: the procedure used to include the educational dimension in the income identity equation, the strategy used to estimate returns to education by identifying convexities and sheepskin effects, and the decomposition method based on counterfactual simulations. The third section shows the characteristics of data sources and the values of the poverty lines used. The fourth section reports distributional changes observed in Peru and the changes of more immediate determinants that have contributed to the recent increase in household income. Decomposition results and final remarks are presented in the last two sections.

2. Empirical Methodology

2.1 Income Identity

In order to decompose the observed changes in monetary welfare indicators (poverty, middle class, or inequality), the household per capita income (Y_{pc}) is disaggregated by monetary and non-monetary components as follows:

(1)
$$Y_{pc} = \frac{Y}{n} = \frac{Y^L + Y^{NL}}{n} = \frac{n_a}{n} * h * \left(\frac{n_o}{n_a} * n_h * \frac{Y^L}{n_o * h * n_h} + \frac{Y^{NL}}{n_a * h} \right)$$

where n is the number of household members, Y^L is the household's labor income (sum of each occupied adult member's labor income), Y^{NL} is the household's non-labor income (sum of each adult member's non-labor income), n_a is the number of adults in the household, n_o represents the number of occupied adults, n_h the number of hours worked, $h = e^{\emptyset(s)}$ is the adults' stock of

human capital defined as a function of the years of education completed (s) (following Mankiw, Romer and Weil, 1992; Hall and Jones, 1999; Bils and Klenow, 2000), and $(n_a * h)$ and $(n_o * h)$ are the units of adult and employed human capital, respectively.

The function $\emptyset(s)$ reflects the efficiency of an individual with s years of education regarding the efficiency of an individual with no schooling, $\emptyset(0) = 0$. For example, if an individual has completed tertiary education (16 years of schooling) and the average return per year of education is 0.08, the person's stock of human capital (h) in this formulation is 3.6 ($= e^{0.08*16}$) times the stock of a worker with 0 years of education. The derivative of $\emptyset(s)$ is the return to schooling (r) estimated in a Mincerian wage regression: an additional year of schooling raises a worker's efficiency proportionally by $\emptyset'(s)$. The next section discusses the suggestion that $\emptyset(s)$ can be approximated by a piecewise linear function if returns are estimated for each education level. Note that if $\emptyset(0) = 0$ is always true, i.e., h = 1 for all individuals, the per capita income equation to be decomposed will therefore be the same as the one used so far, i.e. assuming an undifferentiated workforce.

2.2 Returns to Education

Given the evidence of convexities and sheepskin effects in estimating returns to education in Peru (Yamada, 2007; Yamada and Castro, 2010), we use a specification of labor income equation that allows obtaining the return to an additional year of schooling at each education level:

(2)
$$lnW = \alpha + \sum_i \sum_j r_{ij} s_{ij} + \gamma_1 X + \gamma_2 X2 + \gamma_3 Z + \mu$$

where *lnW* is the natural logarithm of real hourly labor income; r_{ij} are the returns to an *i* = incomplete or complete additional year of education for *j* = primary, secondary, tertiary, and postgraduate, and s_{ij} are years of education completed;[3] *X* is the potential experience measures as the age minus years of completed schooling and six years (the mandatory starting age for school), and *X2* is its squared divided by 100; *Z* is a vector of controls that includes

---

[3] For the graduate level, returns are estimated without discriminating between incomplete and complete.

dummies for sex, urban-rural residence area, and parent education (at least incomplete secondary and otherwise);[4] and μ is the error term in the regression.[5]

Equation (2) was estimated using the Heckman sample selection correction procedure due to the presence of sample selection bias in this type of specification (non-random selection to be in or out of the sample associated with people's decisions to work or not work). The procedure corrects this problem in two stages. First a probit model for the probability of working is estimated in order to predict the employment probability for each individual, and then a labor-income ordinary least squares model is estimated by incorporating a transformation of predicted individual probabilities as an additional explanatory variable. The selection model considers marital status (married/cohabiting and otherwise), the number of children in the home aged 0–11 years (both variables strongly affect the chances of labor participation, but not our outcome), and, implicitly, the individual's salary income via the inclusion of its predictors (age, years of education, urban-rural, and sex).

After estimating returns to education, the function $\emptyset(s)$ can be approximated by a piecewise linear function breaking years of education (s) in splines and taking into account the education levels of individuals:

$$(3) \quad \emptyset(s) = \begin{cases} r_{ip}^t * (s - 0), & 0 \leq s \leq 5 \\ r_{ip}^t * 5 + r_{cp}^t * (s - 5), & s = 6 \\ r_{ip}^t * 5 + r_{cp}^t * 1 + r_{is}^t * (s - 6), & 7 \leq s \leq 10 \\ r_{ip}^t * 5 + r_{cp}^t * 1 + r_{is}^t * 4 + r_{cs}^t * (s - 10), & s = 11 \\ r_{ip}^t * 5 + r_{cp}^t * 1 + r_{is}^t * 4 + r_{cs}^t * 1 + r_{it}^t * (s - 11), & 12 \leq s \leq 15 \\ r_{ip}^t * 5 + r_{cp}^t * 1 + r_{is}^t * 4 + r_{cs}^t * 1 + r_{it}^t * 4 + r_{ct}^t * (s - 15), & s = 16 \\ r_{ip}^t * 5 + r_{cp}^t * 1 + r_{is}^t * 4 + r_{cs}^t * 1 + r_{it}^t * 4 + r_{ct}^t * 1 + r_{po}^t * (s - 16), & s \geq 17 \end{cases}$$

where r_{ij}^t are the returns to an additional year of education for the level ij (as detailed above) in each period t.[6] If $\bar{r} = \emptyset(s)/s$ is the average return to education, equation (1) can be rewritten as:

---

[4] Given that demand for education is endogenous to ability (individuals with greater learning ability are more likely to consume greater amounts of education), the variable "parent education" is included to reduce the effect of this endogeneity on estimating returns.
[5] A specification based on dummies for education levels produces the same results if estimated coefficients are then divided by the average years of education at each level.
[6] The approximation proposed is an extension of the function $\emptyset(s)$ from the simplest formulation of the earnings equation, when the schooling variable is not broken into splines, $\emptyset(s)$ = r*s, as described by Hall and Jones (1999).

(4)
$$Y_{pc} = \frac{n_a}{n} * (e^s)^{\bar{r}} * \left(\frac{n_o}{n_a} * n_h * \frac{Y^L}{n_o * h * n_h} + \frac{Y^{NL}}{n_a * h} \right)$$

This is the equation we use to decompose the observed change in poverty, the middle class, and inequality. Note that in this specification, although labor and non-labor income are estimated at the household level (aggregating income from its members), the heterogeneity of human capital is not altered because the decomposition is estimated at individual level and, therefore, the adults' stock of human capital does not need to be aggregated because $(e^s)^{\bar{r}} = e^{\emptyset(s)} = h$.

2.3 Decomposition Method

The decomposition of observed changes in welfare measures into contributions of each component (and of its interactions with all other components) in two points in time ($t = 0, 1$) can be estimated in a straightforward manner. According to Barros et al. (2006) and Azevedo, Inchauste, Olivieri, et al. (2013), counterfactual distributions of the welfare aggregate for t_1 can be constructed by replacing the observed values of components in t_0. Thus, poverty, middle-class, or inequality rates could be computed for each cumulative counterfactual distribution, i.e. measures that would have prevailed in absence of the change in that component. For example, if p_j is the contribution of the component j on change in the Gini (G), this contribution and its interactions with all other components can be calculated as the difference between the observed Gini in t_1 and its estimated cumulative counterfactual for t_1 by substituting the observed value of the component j (c_j) in t_0 to the observed distribution in t_1:

(5)
$$p_j = G(f(c_1^{t1}, ..., c_j^{t1}, ..., c_n^{t1})) - G(f(c_1^{t1}, ..., c_j^{t0}, ..., c_n^{t1}))$$

where *f(.)* is a cumulative density function of household income per capita, which depends on each of its components. However, this procedure has two problems. Shorrocks (1982 and 2013) argues that this kind of decompositions (by factor components) does not guarantee that the final sum of all contributions is equal to the total change, in our example in G from t_0 to t_1, because the sum depends on the order in which the component cumulative effects are calculated. An additional problem is the way to assign to households the value c_j from the period t_0 to the period t_1 in the context of cross-sectional data.

Following the example of the Gini, for the first problem, Shorrocks (1982 and 2013) shows that marginal effects of the sequential elimination of each component contributing to the change in Gini, considering all the possible sequences, and assigning to each component the average of its marginal contributions, produces an exact additive decomposition of the Gini into n contributions. This means that if the exercise is done starting from the left and then from the right, the averages are the result of n! elimination sequences, where n! is the factorial of the number of income components. Formally, this is the equivalent to the Shapley value allocation method in game theory, and is therefore referred to as the Shapley decomposition (Sastre and Trannoy, 2002).

We follow Azevedo, Nguyen, et al. (2012) to address the second problem. They propose to match individuals or households based on their observed income rank in each period, i.e., assuming a distributional dynamic in which each individual keeps his or her rank across the periods. Thus, the entire trajectory of the observed income distribution and its components are tracked by assigning the average value of each component for each percentile in t_0 to each individual or household in the same percentile in t_1.

It should be noted that this kind of decomposition has some analytical limitations: It does not identify causal effects; counterfactuals are generated by modifying one income component at a time keeping everything else constant; and the decomposition procedure does not ensure aggregation consistency.[7] Despite these limitations, the procedure provides relevant empirical evidence on the immediate determinants behind the distributional changes.

3. Data Characteristics

In order to estimate the contributions of monetary and non-monetary per capita household income components (equation 4) in reducing poverty and inequality, we use the 2004–2013 rounds of the ENAHO, conducted by the National Institute of Statistics and Informatics (INEI for its acronym in Spanish). The survey's data is collected annually from a sample of about 90,000 people in 22,000 households in urban and rural areas of all regions. It provides detailed information on demographics, employment, education, housing, and income and expenditure of households and their members. Although the labor and non-labor income as well as

---

[7] I.e., results may be different depending on the level of disaggregation of a component, for example if non-labor income is expressed in two or four variables (Shorrocks, 2013). We show below (Table 4) that the disaggregation generates minimal differences in the results.

employment characteristics data are collected from the members aged 14 and over, non-monetary income components (adults, employed, schooling, and returns) used for the decomposition were constructed in terms of the population aged 18 and over. Since the decomposition is estimated at the individual level, we avoid data loss by estimating household income per adult member or member employed, i.e., after aggregating income of all household members.

We also take advantage of the detailed information offered in the ENAHO to use more comprehensive measures of labor and non-labor income than those from harmonized databases used for cross-country analysis. The ENAHO includes labor income from primary and secondary activity, in cash and in-kind (including those used for self-consumption),[8] and the non-labor income includes the following subgroups: property income, imputed rent of the owned or occupied home, public transfers (including transfers from social program and living allowance), private transfers (including domestic and overseas remittances), and other income. The sum of all these components corresponds to the concept of total net household income, i.e., excluding deductions for taxes, retirement pension, and others. Our measure of economic welfare is then obtained dividing this income by the household's size. We do not use any adjustment by economies of scale and equivalence scales because in Peru there is no standard procedure for this measurement. However, below we use the scale of a Latin America country in order to check the robustness of our decomposition results.

The values of the monetary income components were expressed at 2013 prices using the National Consumer Price Index, which is constructed monthly by the INEI based on the price indexes of the country's most important cities. In addition, we use national poverty lines to decompose the observed changes in poverty, which are a set of 83 lines corresponding to the same number of subregions, a combination of consumption baskets for seven geographic domains, and median prices in the cities (3 or 4 lines for each of 25 regions). In other words, we use a variable that takes 83 different values corresponding to the same number of subregions where the Peruvian population lives. The value of these lines is equal to the cost of a basic basket of food and non-food items and, and on average, very close to the value of a poverty line

---

[8] The self-consumption measure is calculated using the survey question: "At how much do you estimate the value of the goods used for consumption that are produced by the household or are purchased to sell?"

of $5.0 per capita a day at 2005 purchasing power parity (PPP) for the period analyzed. With this line we measure what is known as "moderate poverty."[9]

In this paper we propose using multiples of the national moderate poverty line in order to measure the size of other population groups. Given that the national poverty line is close on average to USD 5 per capita a day at 2005 purchasing power parity (Table 1), the resultant values (USD 10 and 50) are similar to those used in comparative studies between countries based on suggestions from Lopez-Calva and Ortiz-Juarez (2011). These authors use an empirical methodology to analyze the middle class based on the notion of vulnerability to poverty. They found that USD 10 a day, associated with a low (0.10) probability of falling into poverty, depicts the beginning of the middle class (lower threshold). Also, they established the upper threshold at USD 50 a day, an income amount that it is observed in the upper tail of the income distribution of the countries studied. Based on these thresholds, we define three groups that, in turn, reflect different probabilities of falling into poverty. Thus, the *vulnerable* are defined as those who live in households with per capita income between one and two times the national poverty line, the *middle class* are those with income between 2 and 10 times the national poverty line,[10] and the *rich* are those with income more than 10 times the national poverty line.

4. Distributional Changes of Household Income Sources

Peru experienced enormous distributional changes in recent years, much broader than the average changes experienced in Latin America, as described above. Based on income measures, national poverty lines, and data from the ENAHOs, the moderate poverty rate declined from 54 percent in 2004 to 24 percent in 2013, the size of middle class was multiplied by 2.4 over the same period (from 16 to 39 percent), becoming the largest group of the four considered in the analysis since 2012 (Figure 1), and the income inequality (Gini coefficient) decreased 6.6 percentage points (from 0.513 to 0.447).[11] The economic growth that accompanied this process was also substantial. The GDP and per capita GDP accumulated 80

---

[9] To calculate the share of extreme and moderate poverty, countries generally use the "cost of basic needs" approach to drawing consumption-based poverty lines. According to the World Bank's handbook on poverty (Haughton and Khandker 2009), first the cost of acquiring enough food for adequate nutrition is estimated (extreme poverty line) and then the cost of other essentials such as clothing and shelter are added (moderate poverty line).

[10] In addition to income, other definitions of the middle class have been considered in the literature. Atkinson and Brandolini (2013) consider, for example, roles of property and wealth, and labor market status. They analyze the interrelationships of these different notions and assess the extent of overlapping in the resultant classifications.

[11] If per capita income is expressed at 2013 prices of the Lima Metropolitan Area using the values of the poverty line (as proxies for regional deflators), the Gini coefficient falls 5.1 percentage points.

and 62 percent of real growth, respectively, during the same period (BCRP, 2014), despite negative effects in 2008 and 2009 from the global economic crisis.

The growth-inequality decomposition introduced by Datt and Ravallion (1992) quantifies the relative contributions of economic growth and redistribution to changes in poverty. We follow Azevedo, Castaneda, and Sanfelice (2012), who implemented the Shapley value of this decomposition and extended it to changes in the middle class. The results show that 70 percent of the reduction in poverty and 75 percent of the increase in the size of the middle class is due to the increase in per capita household income (Table 2). This evidence also shows that, with respect to growth, the size of the middle class is more sensitive than the incidence of poverty. Our estimates indicate that on average, for each point of per capita GDP growth, poverty fell by 1.6 percent, while the size of the middle class grew by 1.9 percent between 2004 and 2013. In addition, disaggregated data from the ENAHOs shows that regions with low initial levels of income inequality (Gini coefficient lower than 0.45 in 2004) are associated with higher poverty reductions. These regions experienced falls of 11.4 percent a year between 2004 and 2013 versus 8.6 percent in regions with higher initial inequality (Gini above 0.45). This coincides with the cross-country literature that argues that the higher initial inequality in a country, the higher the growth rate required for a given amount of poverty reduction (World Bank, 2005; Fosu, 2009).

These growth and redistribution components of changes in a welfare indicator are the results of several monetary and non-monetary forces that determine population movements along different segments of income distribution. Before quantifying the contribution of each of these forces on changes in indicators of poverty, the middle class, and inequality, we describe some associations between the annual growth of some of these forces with annual growth in per capita income between 2004 and 2013 by income deciles. Our purpose is to observe how such forces might have influenced in distributive changes. Figure 2 summarizes this dynamic for per capita income and each of its components defined in equation (4). Monetary components include labor income and non-labor income (public transfers, private transfers, property income, imputed rent, and other income) and non-monetary components at the adult level: number, schooling, and returns to education of adults, and number, and hours worked of adult employed.

Among the monetary components, a couple of facts stand out owing to their clearly defined trends and relatively high increases. Pro-poor growth in per capita income was associated with a shrinking of the labor earnings gap between poor and non-poor workers. Although the increase in earnings was shared by all population groups, the annual growth of this variable was almost three times higher among the poorest deciles than among the richest deciles. As the labor earnings are calculated per hour worked and per unit of the adults' stock of human capital (defined as a function of the years of education completed),[12] it can be deduced that closing the earning gaps was partly associated with changes in the type of employment—according to the ENAHOs, formal employment increased 4 percentage points for the poorest 40 percent of the population between 2004 and 2013—than with the increase in working hours or number of jobs (see corresponding panels in Figure 2).

The equalizing influence of government transfers is also remarkable—two-thirds of growth in this source was concentrated in the four poorest deciles. This trend began to be more pronounced in 2007 when the conditional cash transfers program (*Juntos*) significantly increased its coverage, and again with the implementation of *Pension 65*, *Beca 18,* and *Bono Gas*, all with well-established pro-poor targeting strategies. It should be noted that this change also meant the poorest deciles were more dependent on government transfers (10 percentage points of total household income, from 7 percent to 17 percent) and less dependent on labor earnings (6 points, from 65 percent to 59 percent) between 2004 and 2013. The increase in private transfers (remittances, child support, alimony, and so on), income from property (interest, rents, profits), and imputed income from owner-occupied housing were generally more favorable for vulnerable and middle class groups.[13]

Among the non-monetary components, changes in returns to education should show important influences on movements along different segments of the income distribution because of the magnitude and heterogeneity of changes across the adult population (third panel of Figure 2). The average return per additional year of education fell at an annual rate of 6.7 percent between 2004 and 2013, and the rate was higher among the poorest population (7.9 percent in the poorest decile versus 5.7 in the richest decile). In addition, as has been shown in several studies with disaggregated estimates (e.g., Castro and Yamada, 2012), Table 3 shows that the returns were not only greater for higher levels of education (i.e., there were convexities in

---

[12] Figure 3 shows the values of this stock in 2004 and 2013 by years of education.
[13] Note that the population classification based on the national poverty lines described above identifies the poor in percentiles 0–24 and the middle class in percentiles 59–98 in 2013 (0–54 and 83–99 in 2004, respectively).

returns or increasing marginal returns), but they also fell less for individuals with higher levels of education. For example, the returns for each additional incomplete primary year decreased three times more than complete tertiary: 8.8 versus 2.8 percent per year between 2004 and 2013. But as well as changes in returns showing unequalizing effects on per capita income growth, they also showed equalizing effects for those that complete levels of education (lower part of Table 3). The returns per additional year of education were proportionately higher for those who completed the last year of each education level (sheepskin effects[14]), particularly for those who completed only the lowest levels, as discussed in Figure 4.

Also, the second and fourth panels of Figure 2 consistently show that the fall in returns is associated with an increase in the labor supply, which is somewhat more marked among the lowest deciles. According to information from ENAHOs, this would happen for size of the working-age population (adults) and their levels of schooling. The years of education completed in adults increased by 1.3 percent annually between 2004 and 2013 (2 percent in the poorest decile versus 0.7 in the richest), and the numbers of adults rose on average by 2.4 percent annually in the last nine years (2.8 percent in the poorest decile versus 1.9 in the richest). These increases are, in turn, associated with what is known as the demographic bonus or demographic window[15] that the country and most of Latin America is currently experiencing, which tends to benefit the lowest deciles or poorest members of the population. Below we show that this situation of educational expansion and heterogeneous falling returns (and their influences on income inequality) is also associated with the phenomenon labeled by Bourguignon et al. (2005) as the "paradox of progress."

5. Decomposition Results

The four panels of Table 4 summarize the estimates on decomposing changes in poverty, size of the middle class, and income distribution (Gini coefficient) between 2004 and 2013. The first panel shows the changes in each indicator (described in detail in the previous section), and the following three panels show sequentially disaggregated decompositions. The most

---

[14] In other words, workers are not rewarded for the contributions of schooling that improve productivity, but rather for obtaining the certificate that comes with completing the level of schooling.
[15] Defined as a period in which the proportion of the working-age population is particularly prominent. More precisely, it occurs when the population under 15 years of age falls below 30 percent of the total population and the proportion of population 65 years and older is still below 15 percent of the total (UN, 2004). According to CELADE-CEPAL (2013), Peru started one such period in 2010 and will finish it in 2043. The working-age population per dependent person increased from 1.59 at the beginning of the 2000s to 1.87 in 2014 (16 percent) and will reach its highest figure (2.03) in 2030. As such, the window of opportunity or bonus means, for example, a lower spending in children aged 0–14 between 1990 and 2015 (when the size of this group of the population decreased from 38 percent to 28 percent) and the possibility to use this saving in education for the secondary-age population.

disaggregated panel includes 11 income components, six monetary and five non-monetary (second panel).[16] The following decomposition compresses the four non-labor income components (third panel), and the last one excludes education, return, and hour components (fourth panel). In all cases, the estimates include measures of incidence, income gap and squared income gap. We focus on the incidence measures.

The second panel suggests that the most important contributor to poverty reduction and the rise of the middle class was growth in labor earnings (per hour worked of one unit of human capital stock). This factor explained almost 60 percent of movements observed in both population groups between 2004 and 2013.[17] Although the increase in labor earnings was also important to reducing income inequality, it was not the main driving force. The fall in returns to education played this role. The third part of the Gini coefficient reduction was due to this fall, which is in line with the findings of several authors that assign a relevant role to changes in returns to education (Lopez-Calva and Lustig, 2010; Gasparini and Lustig, 2011; Azevedo, Davalos et al., 2013). Unlike those other papers, our evidence on the role of returns to education in the reduction of inequality was obtained by introducing indicators of the adults' stock of human capital in the equation of household income (compare the results of the panels 2 and 4 of Table 4). The fall in returns to education was also an important factor that explained the changes in poverty incidence and size of the middle class. It was the second driving force after labor earnings, although in both cases the decline in returns to education restricted progress toward a situation with less poverty (in 21 percent) and more middle class (in 26 percent).

The positive influence of the fall in returns to education on income inequality—unlike the negative impact on poverty reduction and rise of the middle class associated with changes in labor supply—would be largely connected with the differentiated increase in sheepskin effects in the returns at all education levels during the period analyzed. Table 3 shows that the last grade of schooling in each level is disproportionately rewarded in terms of higher hourly labor earnings, i.e., returns higher associated with graduation from primary school, secondary school, and university (as has been detected several times in the literature, e.g., Hungerford and Solon 1987; Schady 2003), and, interestingly, they changed favorably for the first two levels of education. The ratio between returns to complete and incomplete primary education and the ratio between complete and incomplete secondary education substantially increased 3.5 and

---

[16] Observed values in this panel are the average of 39.9 million (11!) possible sequences.
[17] If an indicator declines over period, a negative sign denotes contribution to the decline, while a positive sign indicates the opposite effect.

2.8 percent per year between 2004 and 2013, respectively, while the ratio for tertiary education decreased 1.2 percent per year. This implied income redistributions within all groups (poor, vulnerable, middle class) that primarily benefited the workforce with lower levels of education. It should be noted that the volume of graduates at all levels was equivalent to 35 percent of the labor force in 2013, a group that since 2004 grew almost three times more than non-graduates. Consequently, the unequalizing effect of the convexities in the returns to education (i.e., increasing returns with the levels of education) would have been more than exceeded by the equalizing effect of the observed changes in sheepskin effects (i.e., important increases of returns for graduates of primary and secondary). This does not mean that the paradox of progress (a situation, as cited above, where an equalizing increase in schooling generates an initial unequalizing change in the income distribution due to the convexities of returns) has been overcome—that will only occur when the dispersion of years of schooling becomes smaller and smaller (Lustig et al., 2013).

Changes in returns to education, as noted above, were associated with an increased supply of educated workers happened by increasing the proportion of the working-age population (given de demographic transition) and investments made in previous decades to improve the coverage of education. The decomposition results in Table 4 indicate that a greater share of working-age adults was as important as changes in labor earnings (around 18 percent) to understand the fall of the Gini coefficient. This factor explained similar percentages of poverty reduction and increases in the size of the middle class. The second panel also suggests that a larger proportion of this workforce was able to participate in the labor market with extended workdays. The increase of hours worked contributed to a 12 and 15 percent in poverty reduction and rise of the middle class, respectively—almost double the contribution from increased employment.

Moreover, despite the substantial change of government transfers in favor of the poorest members of the population, these transfers had a relatively small role in explaining declines in poverty and income inequality. Their impact only accounted for 6 and 15 percent of reduction in poverty and the Gini coefficient, respectively. According to data from the 2013 ENAHO, despite public transfers representing about a quarter of net income for poor people who receive such transfers, 69 percent beneficiaries were not poor and 7 percent of the extreme poor did not receive them. The same source shows that even the conditional cash transfer program (*Juntos*), the best targeted of all existing programs, has room to improve its distributional impact: 29 percent of beneficiaries are not poor and 56 percent of the extreme poor do not receive

transfers. The room for improving the impact of public transfers is much broader if we consider that *Juntos* is only a small part of the budget for transfers.

The contrast between the second to fourth panels confirms that the understanding of the fall in income inequality is more complex than poverty reduction and the rise of the middle class. The contribution of forces to changes in the Gini coefficient is less clear. In general, it can be noted in both panels that despite the decomposition methodology used does not ensure the principle of aggregation consistency (Shorrocks, 2013), the findings on the main factors that led to changes in the size of poverty and middle class in the last decade are not altered. It may also be noted that contributions of labor income, the size of the working-age population and the employment rate, and interactions of each with all other components remain almost unchanged in the three panels. We can also see that the effects of changes in non-labor income may have reduced interactions with all other components. The sum of effects of these subcomponents for incomes represented in the second panel is similar to the aggregate of such incomes in the third panel. The numbers are significantly different when the same comparisons are made for the Gini coefficient.

Finally, in order to observe in detail the importance of the factors associated with changes in the economic status of a larger number of groups, Figure 5 shows the decomposition of changes in per capita income by decile between 2004 and 2013. For this purpose, we use the same equation (4) utilized to decompose poverty, middle class, and inequality. In general, the trends are observed more clearly in Table 4. Note the important role of labor earnings and returns to education in reducing income (second panel), the equalizing effects of public transfers (third panel), the share of working-age population in the household, and the hours worked by adults (first panel).

The robustness of the results described above is observed when the information in the first two panels of Tables 4 and 5 are compared. Table 5 was built considering equivalence scales. Among the scales for Mexico, Jamaica, and Argentina, the only Latin American countries that have this instrument for measuring poverty levels, we use Mexico's[18] because its GDP per capita is most similar to Peru's. Despite the significant changes in the incidence of poverty and the middle class due to the application of equivalence scales (panel 1 in both tables), the contributions of forces behind the changes in both indicators are practically the same.

---

[18] The weights range between 0.7 and 1, according to the age of individuals (CONEVAL, 2014).

6. Summary and Final Remarks

Peru experienced significant distributional changes from 2004 to 2013. Poverty incidence was reduced to less than half (from 54 to 24 percent), the size of the middle class more than doubled (from 16 to 39 percent)—it has been the predominant group since 2012—and the income inequality figure fell by almost 7 percentage points. With a series of counterfactual simulations, we identified and quantified the contribution of the more immediate determinants of these changes. We modified the assumption of a homogenous working-age population and introduce additional dimensions to the income identity equation. This allowed a more accurate identification of the forces behind the changes in welfare indicators and a more comprehensive analysis of decomposition.

We found that the favorable performance of the labor market, mainly from labor earnings, accounts for slightly above three-quarters of the percentage rise in both poverty reduction and the rise of the middle class. We also found that a greater number of factors (compared to other economic mobility indicators used in this paper) affect the reduction of income inequality, revealing a more complex understanding of its changes over time and how to fight against it. The labor earnings increase was not the main factor in reducing the Gini coefficient, as it was for changes in the poverty rate and the size of the middle class. The earnings increase explained only about half of what the decline in returns to education added to the lowered Gini coefficient. We also found that the fall of returns, at the same time, was one of the important factors constraining the most effective period of progress in reducing poverty and increasing mobility into the middle class. Finally, we saw how differences in the demographic trajectories inside the country are associated with what is known as the demographic bonus or demographic window, which played a key role in understanding the distributional changes observed.

Learning about the causes of these changes can be very useful for the design of future interventions. Emphasis should be placed on the factors that led to falling poverty and inequality and rising numbers of the middle class, particularly to enhance their effects to increase their role in the generation of expected changes. The decomposition analysis used in the paper has provided evidence on the efficacy of such factors. Given the demographic transition that the country is experiencing (similar to most countries in the region), investments that aim to close schooling gaps can allow the working-age population—particularly young people from poor

areas—to continue expanding their opportunities for improved labor-market participation, through employment and higher wages. Additionally, improvements in levels of learning, particularly among the lowest deciles of the population, will allow the distributional effects of returns to education promote both an upward mobility and a more equitable income distribution. The literature has showed that returns to education are sensitive to improvements in learning (Card and Krueger, 1990; Hanushek and Wossmann, 2007). Finally, although social programs introduced since the mid-2000s have had substantial consequences on the welfare of the poor, an important proportion of government transfers benefits households that are not necessarily at the bottom of the income distribution. Consequently, there is significant room for improving the targeting of these programs to reduce poverty and inequality.

References

Atkinson, A.B., and A. Brandolini. 2013. "On the Identification of the Middle Class." In: J.C. Gornick, and M. Jäntti, editors. *Income Inequality: Economic Disparities and The Middle Class in Affluent Countries.* Social Inequality Series. Redwood City, CA, United States: Stanford University Press.

Azevedo, J.P., A. Castaneda and V. Sanfelice. 2012. "DRDECOMP: Stata Module to Estimate Shapley Value of Growth and Distribution Components of Changes in Poverty Indicators." *Statistical Software Components* S457563 (Boston, MA: Department of Economics, Boston College).

Azevedo, J.P., Davalos, M. E., Diaz-Bonilla, C. et al. 2013. "Fifteen Years of Inequality in Latin America: How Have Labor Markets Helped?" World Bank Policy Research Working Paper No. 6384. Washington, DC, United States: World Bank.

Azevedo, J.P., G. Inchauste and V. Sanfelice. 2013. "Decomposing the Recent Inequality Decline in Latin America." World Bank Policy Research Working Paper No. 6715. Washington, DC, United States: World Bank.

Azevedo, J.P., Inchauste, G., Olivieri, S. et al. 2013. "Is Labor Income Responsible for Poverty Reduction? A Decomposition Approach." World Bank Policy Research Working Paper No. 6414. Washington, DC, United States: World Bank.

Azevedo, J.P., M.C. Nguyen and V. Sanfelice. 2012. "Shapley Decomposition by Components of a Welfare Aggregate." Washington, DC, United States. Mimeo.

Barros, Ricardo Paes de, Carvalho, Mirela de, Samuel Franco and Rosane Mendoca. 2006. "Uma Análise das Principais Causas da Queda Recente na Desigualdade de Renda Brasileira." *Revista Econômica* 8(1): 117–147.

Barros, Ricardo Paes de, Carvalho, Mirela de, Samuel Franco and Rosane Mendoca. 2007. "Determinantes Imediatos da Queda da Desigualdade de Renda Brasileira." Texto para Discussão No. 1253. Rio de Janeiro, Brazil: IPEA.
Available at: http://repositorio.ipea.gov.br/bitstream/11058/2161/1/TD_1253.pdf.

Barros, Ricardo Paes de, Carvalho, Mirela de, Samuel Franco and Rosane Mendoca. 2010. "Determinantes da Queda na Desigualdade de Renda no Brasil." Texto para Discussão, No. 1460. Rio de Janeiro, Brazil: Instituto de Pesquisa Econômica Aplicada.
Available at: www.econstor.eu/dspace/bitstream/10419/91343/1/617127948.pdf.

BCRP (Banco Central de Reserva de Peru). 2014. *Annual Economic Statistics.* Available at: www.bcrp.gob.pe/statistics.html.

Bils, Mark, and Peter J. Klenow. 2000. "Does Schooling Cause Growth?" *American Economic Review* 90(5): 1160–1183. Available at: http://klenow.com/BKHK.pdf.

Bourguignon, F., F.H. Ferreira and N. Lustig, editors. 2005. *The Microeconomics of Income Distribution Dynamics in East Asia and Latin America.* Washington, DC, United States: World Bank.

Card, D., and A. Krueger. 1990. *Does School Quality Matter? Returns to Education and the Characteristics of Public Schools in the United States.* Working Paper No. 3358. Cambridge, MA, United States: National Bureau of Economic Research.

Castro, J.F., and G. Yamada. 2012. "Convexification and Deconvexification of the Peruvian Wage Profile: A Tale of Declining Education Quality." Documento de Discusión DD/12/02. Lima, Peru: Centro de Investigación de la Universidad del Pacífico.

CELADE (Centro Latinoamericano y Caribeño de Demografía)-CEPAL (Comisión Económica para América Latina). 2013. "*Estimaciones y Proyecciones de Población a Largo Plazo 1950–2100.*" Revisión 2013.
Available at: http://www.cepal.org/celade/proyecciones/basedatos_BD.htm.

CONEVAL (Consejo Nacional de Evaluación de la Política de Desarrollo Social). 2014. *Methodology for Multidimensional Poverty Measurement in Mexico.* Second Edition. City, Mexico: CONEVAL.

Datt, G., and M. Ravallion. 1992. "Growth and Redistribution Components of Changes in Poverty Measures: A Decomposition with Applications to Brazil and India in the 1980s." *Journal of Development Economics* 38: 275–295.

Ferreira, F.H., Messina, J., Rigolini, J. et al. 2012. *Economic Mobility and the Rise of the Latin American Middle Class*. Washington, DC, United States: World Bank.

Fosu, A.K. 2009. "Inequality and the Impact of Growth on Poverty: Comparative Evidence for sub-Saharan Africa." *Journal of Development Studies* 45(5): 726–745.

Freije, S. 2014. "Changes in Poverty and Inequality in Latin America during the Great Recession." In Grosh, M., M. Bussolo and S. Freije, editors. 2014. *Understanding the Poverty Impact of the Global Financial Crisis in Latin America and the Caribbean*. Washington, DC, United States: World Bank.

Gasparini, L. and N. Lustig. 2011. "The Rise and Fall of Income Inequality in Latin America." In J.A. Ocampo, and J. Ros (eds), *The Oxford Handbook of Latin American Economics*, 691–714. Oxford: Oxford University Press.

Grosh, M., M. Bussolo and S. Freije, editors. 2014. *Understanding the Poverty Impact of the Global Financial Crisis in Latin America and the Caribbean*. Washington, DC, United States: World Bank.

Hall, Robert E., and Charles I. Jones. 1999. "Why Do Some Countries Produce So Much More Output per Worker Than Others?" *Quarterly Journal of Economics* 114(1): 83–116.

Hanushek, Erik, and Ludger Wossmann. 2007. "The Role of Education Quality in Economic Growth." World Bank Policy Research Working Paper No. 4122. Washington, DC, United States: World Bank.

Haughton, J., and S. Khandker. 2009. *Handbook on Poverty + Inequality*. World Bank Training Series. Washington, DC, United States: World Bank.

Hungerford, Thomas, and Gary Solon. 1987. "Sheepskin Effects in the Returns to Education." *Review of Economics and Statistics* 69:175–77.

Inchauste, G., Azevedo, J.P., Essama-Nssah, B., et al. 2014. *Understanding Changes in Poverty*. Washington, DC, United States: World Bank.

Instituto Nacional de Estadistica e Informatica. 2015. "Nationa Household Survey – 2004-2013 Original Databases." Available at: http://iinei.inei.gob.pe/microdatos.

Inter-American Development Bank. 2015. *Sociometro-BID*. Database. Available at: www.iadb.org/en/research-and-data//poverty,7526.html.

International Monetary Fund. 2014. "World Economic Outlook Database, October 2014." Available at: www.imf.org/external/ns/cs.aspx?id=28.

Kolenikov, S., and A. Shorrocks. 2005. "A Decomposition Analysis of Regional Poverty in Russia." *Review of Development Economics* 9(1): 25–46.

Levy, S., and N. Schady. 2013. "Latin America's Social Policy Challenge: Education, Social Insurance, Redistribution." *The Journal of Economic Perspectives 27*(2): 193–218.

Lopez-Calva, L.F., and N. Lustig, editors. 2010. *Declining Inequality in Latin America: A Decade of Progress?* Washington, DC, United States: Brookings Institution Press.

Lopez-Calva, Luis F., and Eduardo Ortiz-Juarez. 2011. "A Vulnerability Approach to the Definition of the Middle Class." Policy Research Working Paper No. 5902. Washington, DC, United States: World Bank.

Lustig, N., L.F. Lopez-Calva and E. Ortiz-Juarez. 2013. "Deconstructing the Decline in Inequality in Latin America" World Bank Policy Research Working Paper No. 6552. Washington, DC, United States: World Bank.

Mankiw N.G., D. Romer and D.N. Weil. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107:407–437.

Ravallion, M., and M. Huppi. 1991. "Measuring Changes in Poverty: A Methodological Case Study of Indonesia during an Adjustment Period." *The World Bank Economic Review* 5(5): 57–82.

Sastre, Mercedes, and Alain Trannoy. 2002. "Shapley Inequality Decomposition by Factor Components: Some Methodological Issues." *Journal of Economics* 77(Issue 1 Supplement): 51–89.

Schady, N. 2003. "Convexity and Sheepskin Effects in the Human Capital Earnings Function: Recent Evidence for Filipino Men." *Oxford Bulletin of Economics and Statistics* 65(2): 171–196, 205.

Shorrocks, Anthony. 1982. "Inequality Decomposition by Factor Components." *Econometrica* 50(1): 193–211. Available at: www.jstor.org/stable/1912537.

Shorrocks, Anthony F. 2013. "Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value." *The Journal of Economic Inequality* 11(1): 99–126.

United Nations. 2004. "World Population to 2300." New York, NY, United States: Population Division, Economic and Social Affairs, United Nations. Available at: www.un.org/esa/population/publications/longrange2/WorldPop2300final.pdf.

Yamada, Gustavo. 2007. "Retornos a la Educación Superior en el Mercado Laboral: ¿Vale la Pena el Esfuerzo?" Documento de Trabajo No. 78. Lima, Peru: Centro de Investigación de la Universidad del Pacífico.

Yamada, Gustavo and Juan Castro. 2010. "Educación Superior e Ingresos Laborales: Estimaciones Paramétricas y No Paramétricas de la Rentabilidad por Niveles y Carreras en el Perú." Documento de Discusión No. DD/10/06. Lima: Centro de Investigación de la Universidad del Pacífico.

World Bank. 2005. *World Development Report 2006: Equity and Development.* Washington, DC, United States: World Bank.

Figure 1: Percentage of Poor, Vulnerable, Middle-Class, and Rich People, 2004–2013
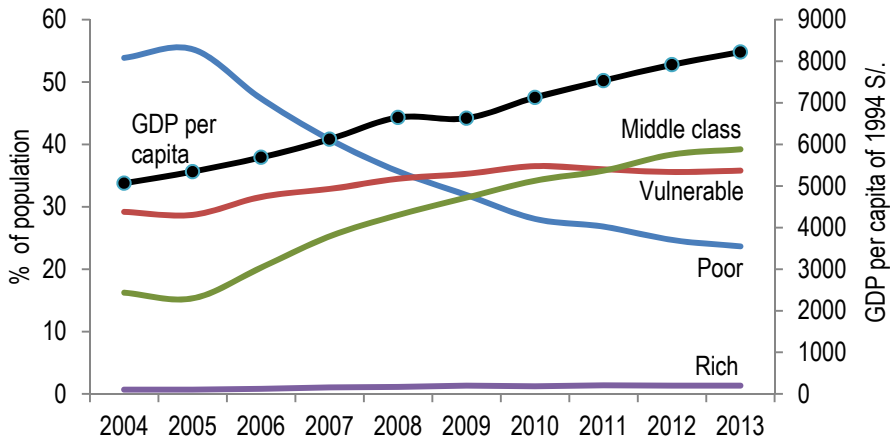
Source: Authors' calculation based on data from the INEI and the BCRP.
Note: The *poor* are those living in households with per capita income below the national poverty line, the *vulnerable* with per capita income between 1 and 2 times the poverty line, the *middle class* with per capita income between 2 and 10 times the poverty line, and the *rich* with per capita income above 10 times the poverty line.

Figure 2: Annual Change in Per Capita Income and Its Components by Deciles (%), 2004–2013
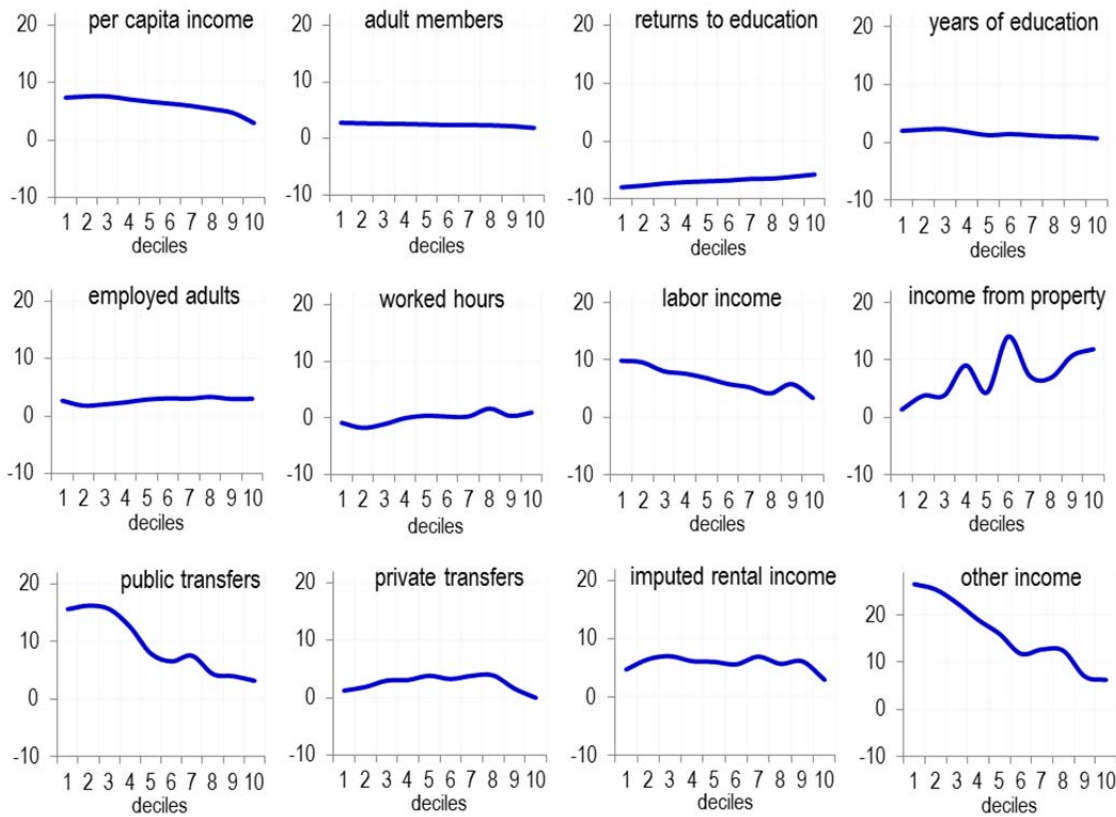
Source: Authors' calculation based on data from the 2004–2013 ENAHOs.

Figure 3: Human Capital Stock of Adult Population [h = exp(φ(s))], 2004 and 2013

Source: Authors' calculation based on data from the 2004–2013 ENAHOs.
Note: After estimating returns to education, the function $\emptyset(s)$ is approximated by a piecewise linear function breaking years of education in splines and taking into account the education levels of individuals (see equation [3]).

Figure 4: Sheepskin Effects in Returns to Education

Note: Sheepskin effects: ratio between returns to complete/incomplete level
Source: Authors' calculation based on data from the 2004–2013 ENAHOs.

Figure 5: Decomposition of Observed Changes in Per Capita Income by Deciles (%), 2004–2013

Source: Authors' calculation based on data from the 2004–2013 ENAHOs.

Table 1: Per Capita Poverty Lines, 2004–2013

Year	2005 PPP*	2005 CPI**	National (S/. per month)	$ a day (2005 PPP)		
				1	2	10
2004	1.653	0.984	237.9	5.7	11.4	57.0
2005	1.653	1.000	235.9	5.6	11.1	55.7
2006	1.653	1.020	235.1	5.4	10.9	54.4
2007	1.653	1.038	238.2	5.4	10.8	54.1
2008	1.653	1.098	250.3	5.4	10.8	53.8
2009	1.653	1.130	251.6	5.3	10.5	52.5
2010	1.653	1.148	259.9	5.3	10.7	53.4
2011	1.653	1.186	272.3	5.4	10.8	54.1
2012	1.653	1.230	283.9	5.4	10.9	54.5
2013	1.653	1.264	292.2	5.5	10.9	54.5

Source: Authors' calculation based on data from the INEI and the World Bank.
* 2005 PPP conversion factor, private consumption (local currency unit [LCU] per international $).
** National Consumer Price Index.

Table 2: Shapley Value of Growth and Distribution Components of Changes in Poverty and Middle Class, 2004–2013

	Percentage points			%		
	FGT0	FGT1	FGT2	FGT0	FGT1	FGT2
Poverty						
Growth	-21.04	-10.15	-5.99	70	67	65
Distribution	-9.18	-5.11	-3.21	30	34	35
Total change	-30.22	-15.25	-9.20	100	100	100
Middle-class size						
Growth	17.30	10.73	7.15	75	73	72
Distribution	5.69	3.92	2.77	25	27	28
Total change	22.98	14.65	9.91	100	100	100

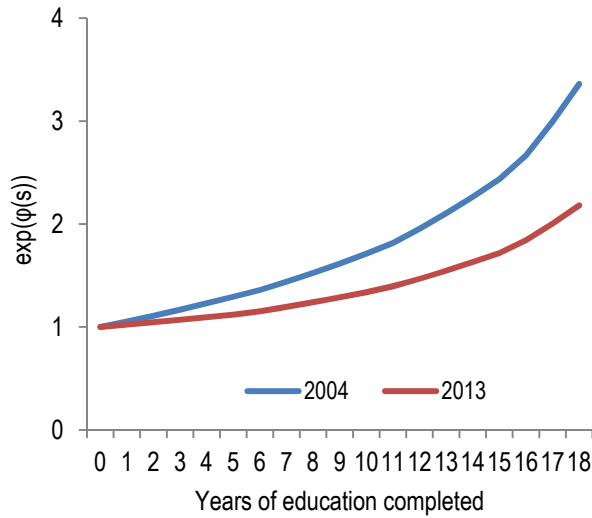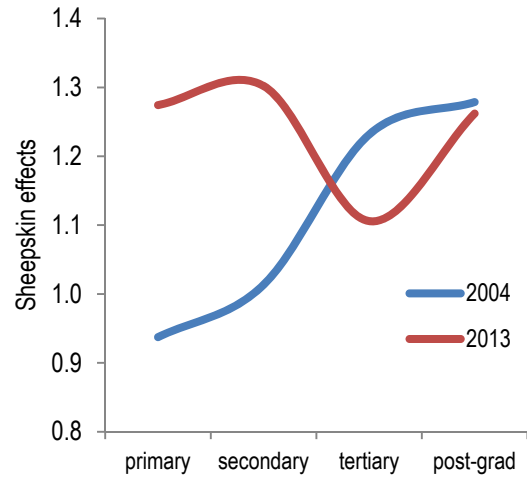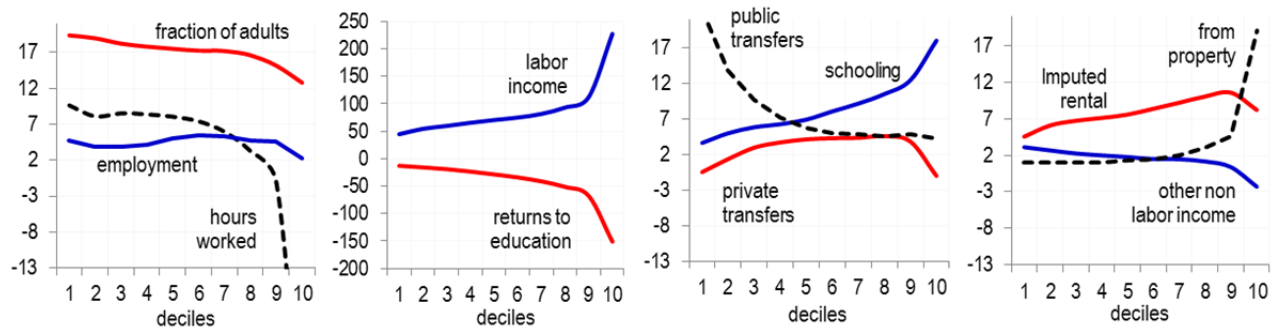Source: Authors' calculation based on data from the 2004–2013 ENAHOs.
Notes: The poor are those living in households with per capita income below the national poverty line, and the middle class with per capita income between 2 and 10 times the poverty line; FGT0 = poverty headcount, FGT1 = poverty gap, FGT2 = poverty gap squared.

Table 3: Returns to Education, 2004–2013

	Heckman estimation										Annual growth 2004–13
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	
Incomplete primary	0.052	0.055	0.067	0.036	0.057	0.036	0.027	0.025	0.025	0.023	-8.8
Complete primary	0.048	0.057	0.064	0.040	0.047	0.042	0.028	0.031	0.035	0.029	-5.6
Incomplete secondary	0.058	0.061	0.062	0.050	0.055	0.045	0.037	0.037	0.041	0.037	-4.7
Complete secondary	0.059	0.061	0.063	0.051	0.057	0.046	0.041	0.041	0.043	0.041	-3.8
Incomplete tertiary	0.073	0.071	0.076	0.066	0.068	0.059	0.054	0.052	0.054	0.052	-3.7
Complete tertiary	0.090	0.089	0.094	0.086	0.088	0.079	0.069	0.069	0.071	0.070	-2.8
Post-graduate	0.116	0.110	0.115	0.098	0.101	0.096	0.084	0.085	0.085	0.085	-3.4
Sheepskin effects: Complete/incomplete level											
Primary	0.94	1.02	0.96	1.13	0.82	1.17	1.04	1.23	1.39	1.27	3.5
Secondary	1.01	1.01	1.02	1.03	1.04	1.04	1.10	1.11	1.18	1.30	2.8
Tertiary	1.23	1.26	1.23	1.30	1.30	1.33	1.28	1.33	1.04	1.11	-1.2

Source: Authors' calculation based on data from the 2004–2013 ENAHOs.
Note: Returns correspond to an additional year of schooling at each education level based on estimating the natural logarithm of real hourly labor income model (equation [2]).

Table 4: Decomposition of Observed Changes in Poverty, the Middle Class, and Inequality, 2004–2013

	Poor			Middle class			Gini
	FGT0 (%)	FGT1 (%)	FGT2 (%)	FGT0 (%)	FGT1 (%)	FGT2 (%)	coeff. (%)
2004	53.9	23.1	12.9	16.2	10.7	7.5	51.3
2013	23.7	7.9	3.7	39.2	25.4	17.4	44.7
Total change (percentage points)	-30.2	-15.3	-9.2	23.0	14.7	9.9	-6.6
Disaggregated decomposition							
Adult population	18.8	19.2	19.1	16.2	16.6	16.9	18.2
Years of education	6.3	4.7	3.9	9.7	9.2	8.8	-3.0
Returns to education	-21.0	-21.1	-21.8	-25.5	-21.3	-19.2	33.3
Employed adults	6.0	2.7	0.3	6.9	7.1	7.2	-1.5
Hours worked	11.6	5.5	1.2	14.6	15.9	16.5	7.6
Labor income	58.0	62.7	66.1	57.3	52.8	50.5	18.2
Income from property	1.2	1.1	1.1	1.9	1.4	1.2	-7.6
Public transfers*	6.1	11.8	16.6	5.0	4.7	4.6	15.2
Private transfers*	4.2	3.0	1.6	4.5	4.5	4.6	6.1
Imputed rental income**	6.9	7.9	8.5	7.5	7.1	6.8	7.6
Other non-labor income	1.8	2.6	3.2	1.9	2.0	2.0	6.1
Total change	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Decomposition with aggregate non-labor income							
Adult population	18.9	19.5	19.5	16.3	16.8	17.1	21.2
Years of education	6.5	5.0	4.2	9.9	9.3	9.0	-1.5
Returns to education	-20.8	-20.9	-21.5	-25.1	-20.8	-18.6	36.4
Employed adults	6.0	2.6	0.2	7.1	7.3	7.5	0.0
Hours worked	11.6	5.3	0.6	14.9	16.3	17.0	9.1
Labor income	58.1	63.2	67.0	57.4	52.9	50.6	22.7
Non-labor income	19.7	25.3	29.9	19.5	18.2	17.5	13.6
Total change	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Decomposition with aggregate non-labor income; without education, returns, and hours							
Adult population	20.7	20.5	19.9	17.7	18.9	19.6	27.3
Employed adults	6.7	2.5	-0.1	8.0	8.6	9.0	3.0
Labor income	57.1	58.6	59.6	58.1	56.4	55.5	51.5
Non-labor income	15.6	18.4	20.6	16.2	16.1	15.9	19.7
Total change	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: Authors' calculation based on data from the 2004–2013 ENAHOs.
Notes: The poor are those living in households with per capita income below the national poverty line, and the middle class with per capita income between 2 and 10 times the poverty line; FGT0 = incidence, FGT1 = income gap regarding poverty line, FGT2 = FGT1 squared.
* cash and in-kind.
** from owner-occupied housing.

**Table 5: Decomposition of Observed Changes in Poverty, the Middle Class,
and Inequality Using Equivalence Scales, 2004–2013**

	Poor			Middle class			Gini
	FGT0 (%)	FGT1 (%)	FGT2 (%)	FGT0 (%)	FGT1 (%)	FGT2 (%)	coeff. (%)
% of population in 2004	46.8	18.7	10.1	19.8	13.1	9.1	50.4
% of population in 2013	18.8	5.9	2.7	45.7	29.3	19.9	43.8
Total change (percentage points)	-28.0	-12.8	-7.3	25.8	16.3	10.9	-6.6
Adult population	16.7	17.6	17.7	14.0	14.8	15.3	18.4
Years of education	6.0	4.4	3.6	9.0	8.3	7.9	-4.2
Returns to education	-21.7	-22.7	-23.8	-22.8	-18.9	-16.8	28.4
Employed adults	5.9	1.9	-0.8	7.9	8.3	8.6	-2.6
Hours worked	11.1	4.0	-1.0	16.3	17.2	17.6	8.8
Labor income	60.0	65.6	69.4	55.2	50.9	48.8	20.1
Income from property	1.3	1.2	1.2	1.9	1.4	1.1	-5.2
Public transfers*	7.5	14.4	20.0	5.1	4.9	4.7	15.9
Private transfers*	3.9	2.3	0.6	4.3	4.3	4.2	5.4
Imputed rental income**	7.3	8.5	9.4	7.3	6.8	6.5	8.8
Other non-labor income	2.1	3.0	3.7	2.0	2.0	2.0	6.1
Total change	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: Authors' calculation based on data from the 2004–2013 ENAHOs.
Notes: Equivalence scales are those from Mexico with a range between 0.7 and 1 according to the
age of individuals. The poor are those living in households with per capita income below the national
poverty line, and the middle class with per capita income between 2 and 10 times the poverty line;
FGT0 = incidence, FGT1 = income gap regarding poverty line, FGT2 = FGT1 squared.
* cash and in-kind.
** from owner-occupied housing.