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More educated, less mobile?

Diverging trends in income and educational mobility in Chile and Peru

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Abstract

We analyse intergenerational persistence in income and education in Chile and Peru for birth cohorts of the early 1950s to 1990. Both countries have seen a structural expansion of education over this period and decreasing income inequality in recent decades. We impute non-observed parental income from repeated cross-sections and estimate persistence in the range of 0.63 to 0.67 in Peru and 0.66 to 0.76 in Chile for household heads of the birth cohorts 1977–90. The analysis of educational mobility covers household heads of birth cohorts from 1953 to 1990 and relies on retrospective information. We observe an increase in absolute mobility for younger generations, which we relate to the structural expansion of education that created room at the top. In relative terms, mobility patterns remain more stable – parental education is still a strong predictor of children's educational achievement. The relationship is non-linear in both countries: persistence among very poorly and highly educated groups is strong, while individuals with parents of average education levels are more mobile. Upward mobility is stronger in Peru than in Chile: the chances to move from no formal education to higher education across one generation are 46% of the average in Peru compared to 20% in Chile. The chances of persisting in the top across generations are also slightly higher in Peru, with a factor of three times the average compared to 2.76 in Chile.

Keywords

Intergeneration mobility, income mobility, educational mobility, inequality of opportunity

JEL Codes

I24, I26, J62, O15

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1. **Introduction**

Intergenerational mobility measures the degree to which individuals' socioeconomic outcomes can be explained by the status of their parents when these individuals were children. A more mobile society is one where an individual's outcomes are less dependent on the socioeconomic status of her parents. Low social mobility is a concern from an equity perspective because it may be indicative of unequal opportunities, as well as from an efficiency perspective if it prevents children from disadvantaged backgrounds realising their full economic potential in later life. There is, however, no consensus on what level of intergenerational persistence may be considered appropriate, as there will always be some transmission between parents and children as a result of heritable traits.

Education and income, or earnings, are the two indicators of welfare that economists and sociologists use most to analyse intergenerational mobility;[1] in fact, they often use them interchangeably. In the US, estimates of the intergenerational elasticity (IGE) of earnings have evolved from measures of around 0.2 (Behrman and Taubman, 1985) to 0.4 (Solon, 1992) and more recently 0.45 (Chetty et al., 2014). The few studies that investigate IGE in income or earnings for Latin America suggest that it is much higher than in the US. In Brazil, for example, Guimarães Ferreira and Veloso (2006) estimate that persistence in the wages of male full-time workers may be as high as 0.67, while Torche (2015b) finds a similar association for men in Mexico but a lower one for women. More evidence exists for educational mobility in Latin America and confirms the hypothesis that social mobility is lower in this region than elsewhere. In a comparison of 42 countries that includes seven from the region, Hertz et al. (2008) find that Latin America displays the highest intergenerational correlations, lying around 0.6 and thus well above the global level of about 0.4 for the past 50 years. Most studies assume a linear functional form to describe intergenerational mobility.

This paper investigates intergenerational mobility in Chile and Peru and thus compares the relative importance of parental background for an individual's own achievements in later life. Latin America is a region that displays extremely high levels of cross-sectional income inequality. According to Galor and Zeira (1993), high inequality lowers the prospects for social mobility and thus inhibits growth, because families at the low end of the distribution face constraints on investing in human capital. In a cross-country comparison, Corak (2013) provides descriptive evidence for a positive relationship between current levels of income inequality and intergenerational elasticity in earnings, an association often described as the 'Great Gatsby Curve'. Contrary to the trends observed in many Western economies, income inequality has fallen in both countries since the turn of the century – by almost 5 Gini points in Chile and 9 in Peru (see Table A1 in the annex). This trend has in large part been driven by pro-poor growth and decreasing returns to skills (Torche, 2014). At the same time, the education sector has

[1] Sociologists also look at mobility between occupational groups and social class. However, this goes beyond the scope of our paper.

seen a structural expansion over the past few decades, which has caused a rise in average education levels in Chile and Peru.

Although there are comparative cross-country studies on the intergenerational correlation in educational attainment that include Chile and Peru , to our knowledge there are only two studies for Chile that analyse the IGE of income (Celhay et al, 2010; Nunez and Miranda, 2007) and none for Peru. Celhay et al (2010) observed individuals when they were living with their parents in 1996 and again 10 years later, when some of them had become household heads. Based on these pairs, they estimated income elasticities of 0.51 for sons and lower for daughters. Nunez and Miranda (2007) used a two-sample approach and estimated income elasticities of 0.57–0.73. The key problem that explains the relative scarcity of empirical studies on earnings or income mobility is the absence of longer-term panel data. To overcome this limitation, we impute parental earnings in a two-stage procedure that allows us to combine information from two different surveys. In the analysis of educational mobility, we go beyond the conventional analysis of linear estimators to look at the strength of persistence at different points of the distribution. As argued by Becker et al (2015), there are good reasons to believe that the strength of persistence varies along the income distribution. A less restrictive functional form is particularly acute in the analysis of educational mobility because of the categorical nature of the outcome variable. In other words, the advantage of an extra year of parental education might vary between parents who attained only incomplete primary, as opposed to a parent who is only one year short of finishing secondary schooling.

The structure of the paper is as follows. The subsection below gives a brief overview of socioeconomic developments in the two countries over recent decades, which any reader who is familiar with the institutional context may skip. Section 2 outlines our research question and discusses the theoretical framework. Section 3 introduces the mobility measures that our analysis applies before Section 4 describes the data and variables of interest. Section 5 provides estimates for intergenerational income mobility of the cohorts born between 1977 and 1990. Section 6 then turns to the analysis of educational mobility for the cohorts born between the early 1950s and 1990s, based on retrospective information of parental education from cross-sectional data. The final section discusses the results.

1.1. Trends in education and economic policy in Chile and Peru

Latin American countries provide an interesting setting for our study: the region has experienced decreasing returns to skills and educational attainment explains a smaller share of the variation in income than is typically the case in high-income countries. We provide a detailed analysis of mobility patterns in Chile and Peru, a comparison that is insightful because both countries have undertaken similar reforms in education and both build on a similar economic growth model. Peru, which has seen a stronger decline in income inequality and higher growth than Chile over the past two decades but remains much poorer overall, has followed Chile’s example of opening the education sector to private investment but at a later point in time than its neighbour.

Chile and Peru have followed a similar path of economic development in recent decades. They opened their economies to international trade during the 1980s and 1990s, respectively, starting cycles of expansive growth. The 1980s were marked by the debt crisis that affected both countries strongly. The economic policy that followed was characterised by liberalisation and privatisation. In Chile, despite recession and high unemployment in the early 1980s, the economy started to recover and saw continuous growth rates that stood in contrast to the rest of the region. Nonetheless, the social consequences of structural adjustment policies were severe: large cuts in public and social services coincided with rising unemployment and falling wages during the 1980s, while the education sector became more stratified (Ffrench-Davis, 2002). Poverty rates of around 45% (CEDLAS and World Bank, 2017) in the late 1980s stood in contrast to growth performance. The 1990s saw a slow rise in social spending, domestic tax revenues and the legitimisation of labour unions (Escobar and LeBert, 2003). Representative household data have only been available since the late 1980s but suggest that inequality as measured by the Gini index remained fairly stable at between 0.55 and 0.57 from 1987 until the turn of the century (CEDLAS and World Bank, 2017).

The education sector was strongly affected by privatisation efforts that began in 1973. By 1981, government support for public schools had been largely cut. School financing operated via a voucher scheme, whereby school fees differed between institutions. This sparked a massive increase in enrolment in private voucher schools and an increase in for-profit educational institutions (McEwan, 2001). The university reform of the 1960s, which aimed to establish autonomy and widen access, was halted and higher education became increasingly expensive, which eventually led to a student debt crisis in the 1990s. Compulsory and free education up to secondary level was only established via a constitutional reform in 2003, and educational reform remains one of the most fiercely debated issues in contemporary Chilean politics.

Developments in Peru up to the turn of the century were led by a similar spirit, yet placed in a different context. Peru’s high geographic and ethnic diversity also determines socioeconomic inequalities in many ways. Coastal regions are more densely populated, and benefit from access to the sea and more developed infrastructure. The remote mountain and jungle regions have a much higher indigenous population, and high levels of informality and subsistence agriculture. Peru was severely affected by the crisis of the early 1980s, which offset a prolonged recession that left the economy in a dismal state by the end of the decade. Despite large increases in foreign direct investment and the country’s further integration into the global economy during the 1990s, poverty rates were high and severe malnourishment in rural regions was a consequence not only of fighting terrorists but also of the lack of social progress. Poverty stood at almost 50% (CEDLAS and World Bank, 2017) in 2000.

Average years of schooling were below four years up to 1970 and characterised by large regional inequalities.[2] Although the 1973 Constitution provided for compulsory education for six years (elementary level) and expanded this to nine years in 1979, schooling rates fell below that in many regions. The 1993 constitutional reform included an increase in compulsory schooling up to secondary level (an additional five years) and introduced three years of pre-school education. The educational infrastructure for this gradually expanded during the 1990s, albeit continuous criticism about declining quality in education grew (Balarin, 2008). In 1996, a new education law completely opened the sector to private investment at all levels, dismantled state regulation and granted preferential tax and tariff treatment to private education institutions. The following decade saw a rapid increase in private institutions at all levels, from pre-school to university. Between 1998 and 2013, the share of students enrolled in private institutions from pre-school to secondary level more than doubled in urban areas but saw a much smaller increase and overall share in rural areas (Alarcón and Martínez, 2015).

Both economies are strongly dependent on natural resource exploitation and have seen high growth rates during the time of high commodity prices that coincided with a sharp increase in inequality at the end of the 20th century (Williamson, 2010). From the early 2000s, growing public discontent with what was referred to as the 'social debt' of the previous decades (Barrientos, 2014) led to a stronger focus on poverty reduction and an expansion of social protection in both countries. Particularly in Peru, the boom in the commodity sector facilitated pro-poor growth driven by an expanding services sector and high consumer spending starting in the early years of this century (Bank, 2016). Since 2000, expansive cycles have been more stable in Chile; however, Peru has shown higher growth rates on average (see Graph A1 in the annex). The drop in inequality and poverty since the early 2000s was more pronounced in Peru than in Chile, although Peru remains much poorer overall (see annex Table A3).

2. **Mobility of what?**

The classic model of intergenerational mobility (Becker and Tomes, 1979; Becker and Tomes, 1986) explains persistence as resulting from investments that families make into the human capital of their children and from inherited traits. Further, the returns to skills in the labour market may differ between generations. Solon (2004) provides a theoretical framework where increasing labour market inequality has a negative effect on intergenerational elasticities, because higher returns provide incentives to invest in human capital formation. Becker et al. (2015) expand this model to explain why

[2] Table A1 (annex) compares educational achievement between the two countries: mean years of schooling are higher in Chile (11.2 years versus 9.6), while the cleavages between the poorest and richest quintiles are much larger in Peru.

societies with higher inequality may display lower mobility, and how changes in the returns to human capital over time affect mobility.

According to Becker et al. (2015), societies where human capital is more unequally distributed feature lower rates of intergenerational mobility. In this model, persistence of economic status depends on the initial position in the income distribution. The root cause of low rates of social mobility lies in the differential productivity of parental investments. Returns to investment in children increase in parental human capital, since well-educated parents are more likely to raise their children in an environment that acts as a complement to their investments. Such complementarities between parental human capital and their investments in children shape a convex human capital production function, which affects intergenerational mobility differently along the income distribution and leads to higher persistence among well-to-do families. At the other end, credit constraints reduce mobility in the lower part of the income distribution. In sum, their model predicts low mobility at both ends of the income distribution, alongside a more mobile middle class.

Studies investigating the non-linearities in the transmission process described by Becker et al. (2015) are scarce even for countries with rich data availability. Jäntti et al. (2006) study non-linearities in a comparative analysis of six countries and find that mobility patterns in the middle of the earnings distribution are similar but mobility at the tails of the distribution is much lower in the US compared with the UK and Scandinavian countries. Bratsberg et al. (2007) find that IGE in earnings is almost linear in the UK and the US but has a convex shape in Denmark, Finland and Norway, which they attribute to a strong and equitable public education system in these countries. Correlation in log earnings in the Nordic countries is almost flat in the lower part of the parental earnings distribution and rises in the middle and upper part. For the US, Chetty et al (2014) find a linear relationship in percentile ranks with an elasticity parameter of 0.34. Corak and Heisz (1999) find earnings and income elasticities in Canada to be around 0.2 on average, but weaker at the lower end of the distribution than at the top. They describe the pattern of intergenerational mobility as an inverted V-shape.

2.1. Returns to skills and mobility

Such non-linear relationships between child and parental human capital help to explain why countries with higher inequality – and thus more mass in the tails of the distribution – display lower income mobility. This is not necessarily true for other dimensions of social mobility. According to Becker et al. (2015), changes in inequality that result from changes in returns to human capital across generations have different effects on earnings mobility from those on human capital mobility. Increases in returns to skills should have no or relatively small effects on human capital persistence, because they leave unaffected the extent to which children benefit from parental education. Persistence in earnings, in contrast, depends on returns to skills because of a convex relationship: holding returns fixed in the parental generation while increasing them for the next generation implies an increase in the coefficient of parental earnings. This holds for the short term (one generation) but looks different in the long term precisely because of the convexity assumption.

Becker et al (2015) illustrate their theory with reference to the recent increase in inequality and returns to skills in the US. As described above, trends in Chile and Peru have been rather different. Both countries experienced highly volatile economic development in the two decades up to the turn of the century, which was accompanied by high levels of inequality, poverty and high returns to skills. The high returns to education that characterised Latin American countries during the 1990s were depleted in Chile and Peru mainly as a result of increased coverage in secondary and higher education (Torche, 2014) and a growth pattern that relied on commodity exports more than on innovation and productivity gains (which would increase the demand for skilled labour). Although this lowering of the skill premium contributed to declining inequality during the past two decades, the implications for social mobility are ambiguous. The rise in schooling levels should increase educational mobility when comparing how much better- or worse-educated children are than their parents (in years of schooling). It should not necessarily influence relative mobility, which compares how good a predictor parental education is for the child's position in the education distribution of her generation. Declining returns to skills since the early 2000s should leave unaffected the persistence in educational mobility (because returns to parental education stay fixed) but would, according to Becker et al (2015), lead to an increase in income mobility in the short term that we observe. In both countries, the role of private education has increased and may affect mobility in a way that is masked when looking at educational persistence in terms of years of schooling as a rather noisy measure of skills.

In sum, and for the sake of simplification, economic theory suggests three dynamics that we aim to test in the following sections.

1) The welfare of current generations is positively associated with the welfare of their parents. This holds for income and education as distinct measures of welfare.
2) The correlation in socioeconomic status declines for younger cohorts as a result of decreasing income inequality, which particularly benefited the lower deciles, where poverty declined significantly.
3) Patterns of persistence are not linear across the distribution but instead more pronounced at the ends.

3. Measuring mobility

In a broad sense, mobility refers to changes in status over time. When changes are compared between consecutive dynasties (parents and their children), we refer to intergenerational mobility. These changes can be measured in terms of levels or ranks: Jantti and Jenkins (2013, p. 7) distinguish between income changes that alter an individual's position relative to others in society as opposed to "equiproportionate income growth or equal absolute additions to income for everyone [which] raise incomes but there is immobility in the positional sense".

In this sense, absolute mobility compares levels of earnings or occupational status across generations over time and is informative, as people often compare their own living standards with that of their parents (Chetty et al., 2017). Transition matrices, for instance, show the share of individuals that remain in the same income bracket as their parents compared to those who move upwards or downwards. They thus capture both structural changes that affect average levels, such as economic growth, demographic changes, economic policy or immigration, and changes in the individual's relative position in society. Relative mobility shows the level of 'social fluidity' or 'social openness' as Torche (2015a) calls it.[3] It is often measured by odds ratios that compare the odds of two individuals with different origins reaching the same social class or level of outcome. For instance, we can compare the chances that someone from a highly educated family reaches the top of the distribution relative to the chances of someone from a family with a low level of education.

3.1. Summary measures of mobility

Conceptual issues aside, a further basic question that economists discuss surprisingly little is the underlying functional form assumption. Sociologists commonly use transition matrices, which compare the odds of mobility across different starting positions. While transition matrices give a comprehensive (descriptive) overview of mobility patterns at different points of the distribution, most economic studies compare more parsimonious measures. The two most common summary measures of intergenerational persistence are the regression and the correlation coefficient (Blanden, 2013). These are based on a linear regression of the child's outcomes in adulthood on parental outcomes:

$$w_{ci} = \alpha_1 + \beta_1 w_{pi} + \beta_2 X_{ci} + \varepsilon_{1i} \qquad (1)$$

where w represents a socioeconomic indicator of welfare, the subscripts c and p indicate the child's and parents' generation respectively, β_1 is the intergenerational regression coefficient and X is a vector of control variables including age and gender. When welfare is measured by income or earnings, these are generally log-transformed because of their right-skewed distributions: here, the intergenerational elasticity β_1 may be interpreted as the percentage change in children's income associated with a percentage change in parental income (log-log estimation). Measuring this association as a percentage change captures absolute mobility: a coefficient of 0.5 would tell us

[3] JANTTI, M. & JENKINS, S. P. 2013. Income Mobility. Available: https://ssrn.com/abstract=2363217. use the term 'exchange mobility' for relative mobility and refer to 'absolute mobility' as the cumulative changes arising from structural and relative mobility. For the sake of simplicity, we use only the concepts absolute and relative mobility for the remainder of the section.

that children's incomes would on average differ by 50% if their parents' incomes differed by 100%. A linear specification of the same formula is often applied in the analysis of educational mobility, although – as we will discuss below – this has drawbacks, and alternative specifications may be more suitable for outcomes that are measured as discrete or categorical variables.

While straightforward in its interpretation, the explanatory power of the regression coefficient can be weaker when marginal distributions change between generations. In other words, it needs a relatively stronger coefficient to predict income differences when the spread of the income distribution widens. To net out any differences in the variance of outcomes between periods that may be caused for example by changes in inequality, the correlation coefficient adjusts by the ratio of standard deviations after partialling out the effect of X_{ci} on w_{pi}: [4]

$$\varphi = Corr_{w_{ci}w_{pi}} = \widehat{\beta_1}\left(\frac{SD_{w_p}}{SD_{w_c}}\right) \tag{2}$$

where φ can be thought of as a positional persistence measure between generations (respectively $1-\varphi$ as the mobility measure). This measures mobility as changes in standard deviations of the child's income associated with marginal changes in the standard deviation of parental income (Björklund and Jäntti, 2011). We hence interpret φ as a relative measure of mobility.

3. 2 Measuring education as an ordered response

These summary measures have been criticised on various accounts precisely for their linearity assumption (Torche, 2015a); (Durlauf et al., 2017); (Bratsberg et al., 2007). To allow for a more flexible functional form, we apply an ordered probit model to estimate educational persistence. An ordered probit can be applied when the response variable has a natural ordering but the values are not an accurate measure of spacing between them. This model can be derived from a latent variable specification, where we treat skills as a latent variable s^* that is determined by $s^* = \beta x + \varepsilon$ and where we assume the error ε (conditional on x) to be i.i.d. with a standard normal distribution (Wooldridge, 2002). We only observe s_i, which takes the value of one of four ordered completed schooling levels (none, primary, secondary and higher). The cut-offs C for k number of schooling levels are defined as: $C_{k-1} < C_k$ and $s_i^* = k$ if and only if $C_{k-1} < s_i \leq C_k$. In our case, we want to measure the probability of child c reaching any of the four schooling levels s conditional on parental schooling s_p, age and gender:

[4] Given that we are only interested in estimating β_1 but assume that X_{ci} and w_{pi} are correlated, we want to clear β_1 from any variation that may arise from not holding X_{ci} constant. We hence partial out the effects of X_{ci} by first estimating the residuals from a regression of w_{pi} on X_{ci} (and a constant) to then use the variation of this residual in our estimation of $\widehat{\beta_1}$.

$$s^*_{ci} = \delta s_{pi} + \vartheta X'_{ci} + \varepsilon_{ci} \tag{3}$$

We specify parental education as binary variables for each of the four completed education levels and treat these as exogenous.[5] This allows us to estimate the conditional probability of educational achievement along different levels of parental education.

4. Data

Our study will draw upon the household surveys CASEN (Caracterización Socioeconómica Nacional) from Chile and ENAHO (Encuesta Nacional de Hogares) from Peru. We use the waves of 2015 and 1997 from ENAHO and 2013 and 1996 from CASEN).[6] Both are cross-sectional household surveys that contain longitudinal subsamples only in the form of semi-rotating three- to five-year panels. It is hence not possible to link parents and children over a longer time period. Both use a multistage stratified sampling design, such that ENAHO is representative at the province level and CASEN at the municipal *comuna* level. The surveys hold a rich set of information on demographics, income sources of all household members aged 14 and above, consumption and expenditure, as well as receipt of government transfers. They also collect retrospective information on the highest level and years of education reached by both parents of the household head (CASEN since 2006 and ENAHO since 2001), as well as the region of birth. CASEN additionally holds information on whether the child lived with both parents up to age 15, while both surveys lack information about parental occupation or income. CASEN has been conducted every three years since 1985, and every two years since 2009. ENAHO has been carried out yearly since 1996.

While the analysis of educational mobility looks at household heads in the age range of 25 to 60 years, for the analysis of income persistence we restrict our sample of adult children observed in 2013 and 2015 to household heads aged 25 to 36 years for two reasons. First, at this age individuals should have completed education and entered the labour market.[7] Second, we want to observe their parental generation at a time when

[5] Ideally, we would like to apply a bivariate ordered probit that treats both parental and child education as latent variables and estimates their joint densities, assuming a non-zero error-term correlation. Such a model allows us to treat one of the latent variables – in our case parental skills – as an endogenous regressor in the second data generating process (Sajaia, 2008). We would then jointly measure $s^*_{pi} = \delta_p X'_{pi} + \varepsilon_{pi}$ and $s^*_{ci} = \rho s^*_{pi} + \delta_c X'_{ci} + \varepsilon_{ci}$ where $Corr \varepsilon_{pi} \varepsilon_{ci} \neq 0$. We can only identify the parameters of this system by imposing an exclusion restriction on X'_{pi} and X'_{ci}. Given that we rely on retrospective data and do not observe the age (or other observables) of parents, $X'_{pi} = X'_{ci}$ and that our system is not identified, we hence resort to a standard ordered probit estimation.

[6] The latest CASEN wave where income can be compared with previous years is 2013. In earlier waves incomes were corrected in order to match the national accounts. The most recent wave (2015) has departed from this practice.

[7] Secondary school ends after 11 years of total schooling in Peru and 12 years in Chile, while a typical University degree takes 4-6 years depending on the career chosen. There is no mandatory military service in either country.

these children were of schooling age (defined here as the regular schooling age of 6–18 years) and have to rely on survey waves from 1996 and 1997. While there is a large literature that examines the age at which investment into children reaps the largest returns (Heckman, 2007), we choose this age range since parental income is one of the main determining factors for school enrolment in the presence of credit constraints. The restriction to household heads is mandated by data constraints: retrospective parental information is only recorded for heads of the household in Peru.

We measure two types of income concepts: individual net market income and adult equivalent disposable household income. Our definition of net market income includes labour income from dependent and independent work (cash and in-kind) net of direct taxes and social security contributions, income from self-production, private pensions and capital income (land or property rent, interest, dividends). Disposable income additionally includes public and private cash transfers, and imputed rents of owner-occupied housing. Income is adjusted to 2013 real prices and expressed in terms of purchasing power parity to allow cross-country comparison. We use the equivalence scale applied by the National Statistics Office Chile.[8]

We measure education in years as deviation from the mean by cohort and gender,[9] and in four levels (no formal education, completed primary, completed secondary, completed tertiary). Tertiary education includes university education and technical or vocational training. We truncate years of education at 18 years for those who have completed university. Parents' educational achievement comes from retrospective information provided by household heads. Since the Peruvian survey only reports nine levels of education, we need to transform these into years. We do so by assigning regular years of schooling to completed levels and testing two different approaches for incomplete levels: (1) assigning the median value between the reported levels; and (2) assigning random values. Results are not sensitive to the specification used. We count the parent with the highest education among the two. Some 23% of the sample in Chile and 12% in Peru lack information on parental education. To test whether dropping these observations introduces a selection bias, we compare the restricted sample with information on parental education against the sample without. In a regression of education on a dummy that indicates whether an observation has information on parental education, age, gender and birth region, the dummy is not significant at conventional levels in Peru, although there is a slight downward bias in Chile. Regressing income on the same variables shows that the dummy is not significant at the 95% level in both countries (see annex Table A3).

[8] The equivalence scale used by the National Statistics Office Chile is $N^{0.7}$, with N referring to the number of household members.
[9] Parental education is measured in years as deviation of the mean by cohort of the child, since age of the parents is not available in the adult (child) survey.

5. **Mobility in income**

Recalling equation (1), we now want to measure economic advantage in terms of income:

$$y_{ci} = \alpha_2 + \gamma y_{pi} + \theta X'_{ci} + \varepsilon_{2i} \qquad (4)$$

Where y is log income of the adult child and parent, respectively, X is a vector of controls including age and gender, α_2 is a constant that captures average income in the children's generation, and ε_2 is an i.i.d error. We interpret the parameter γ as the elasticity of child's income with respect to parental income: a coefficient of 0 would indicate that parental income does not constitute an unequal starting position, while $\gamma = 1$ would represent a completely immobile society where parents' relative income shares are reproduced in their offspring's generation.

We can measure γ consistently if we observe y_p and y_c without error in a random sample of parent–child pairs, where $E(\varepsilon_2|y_p, X'_c) = 0$. Even in a setting with rich panel data where parents and their adult children are observed jointly, this bears challenges. The two most obvious ones are measurement error and omitted variable bias. Measurement error arises when we observe current income rather than permanent or long-term income (Blanden, 2013). In the presence of lifecycle bias in income, this measurement error varies along the distribution. The resulting bias will depend upon the age at which both parents and adult children are observed: if we observe young children and old parents, the downward bias will probably be stronger.[10] Haider and Solon (2006) show for the US that income should be observed roughly between the ages of the early 30s to mid-40s to obtain measures that are relatively close to permanent incomes. Omitted variable bias is an obvious concern if we believe that the child's income in adult life is determined by other factors that are correlated with parental income – such as parental education or networks –not controlled for in equation (4).

Previous studies have addressed these sources of endogeneity and lack of panel data through the two-sample instrumental variable (TSIV) estimator. This estimator uses an instrument for parental earnings and combines information from two surveys – the main one containing information on the child's income and a supplemental one that holds data on the parental generation. It was formally developed by Angrist and Krueger (1992) and more recently extended by Inoue and Solon (2010) and Pacini and Windmeijer (2016) to account for differences in the distributions of the instruments that may arise from heterogeneous samples, referred to as Two-Samples-Two-Stages Least Squares (TS2SLS). Only a few studies applying this methodology can identify

[10] This holds if we assume that individuals with high permanent incomes start with a low income that rises steeply in comparison to individuals with low permanent incomes. In this case, we would underestimate income elasticities among higher earning individuals.

actual parents in the supplemental dataset,[11] while the majority predict some average value of 'synthetic fathers' in an older survey of working men of the parental generation. The approach has been used to estimate earning elasticities between fathers and sons *inter alia* by Björklund and Jäntti (1997) for Sweden and the US, Nicoletti and Ermisch (2008) for the UK and Dunn (2007) for Brazil. These studies adopt a similar strategy in their choice of instruments: they predict a father's earnings from his father's education (Dunn, 2007) in combination with information on the father's occupation (Björklund and Jäntti, 1997) and age (Nicoletti and Ermisch, 2008). Since there are compelling reasons to question the exogeneity of the father's education in the structural equation, this estimator is biased and inconsistent. Nicoletti and Ermisch (2008) show that, under the plausible assumption of a positive correlation between parental education and the error term, the estimator will be biased upwards to the degree that parental education influences children's earnings independently.

Given that retrospective data on parental characteristics are even sparser in our surveys, TS2SLS is not a valid approach in our setting.[12] Instead, our strategy is to impute unobserved parental income as a function of educational attainment and regional characteristics. We draw upon previous CASEN and ENAHO survey waves to observe earnings in the parental generation, an approach also known as cold-deck imputation. We thus provide estimates of the strength of intergenerational correlation in income between successive generations of children born between 1977 and 1990 and their parents. Even though we cannot claim causal inference, comparing the strength of correlation in education and income will give insights into where barriers to mobility are higher, or if the two dimensions are indeed close substitutes. If, for example, the correlation across generations is significantly stronger in income than in educational attainment, this may point towards labour markets where returns to factors associated with parental income are relatively stronger than returns to years of education.[13] Conversely, if there is a strong association in educational attainment but higher mobility in income, a more rigorous analysis of growth patterns and structural economic changes may provide explanations. Comparing these dynamics across two neighbouring countries can shed additional light on mobility dynamics.

5. 1 Predicting parental income

As proposed by Haider and Solon (2006), we limit the age range within the sample of adult children. We choose a minimum age of 25 because, by this age, individuals should have completed education and entered the labour market. The maximum age of

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[11] To our knowledge, Björklund and Jäntti (1997) is the only study that estimates IGE in income using a TSIV method based on actual father–son pairs.

[12] The choice of potential instruments is limited to parental education and regional characteristics. Place of residence during childhood fails the exclusion restriction since there is large heterogeneity in both countries in regional educational infrastructure, which would in turn affect the dependent variable independently through its effect on a child's educational attainment.

[13] Such parental income factors may be manifold and include parental networks, segregated educational systems where costly private education reaps higher returns than public education, or even nepotism.

36 years is a result of the availability of parental cross-sections. Although this age range is younger than that proposed by Haider and Solon (2006), it is in line with the range chosen in other studies.[14] Our offspring sample thus contains household heads of the birth cohorts 1977–90 observed in 2013 (CASEN) and 2015 (ENAHO). At the time we observed the parental generation in 1996 (CASEN) and 1997 (ENAHO), these individuals were aged between 7 and 18 years. We restrict our sample of the parental generation to household heads aged 25–45 years who report having children born between 1977 and 1990. Unfortunately, CASEN and ENAHO do not report retrospective information on parental age or occupation. Confining the parental sample to this age group allows us to minimise lifecycle bias as described above, however.[15]

We predict parental income by an OLS log earnings equation in the first step:

$$y_p = \alpha_3 + \sum_{i=1}^{k} p_j \, \beta_j + \varepsilon_3 \tag{5}$$

where y_p is log income observed in the supplementary dataset, the constant α_3 represents average income in the parental generation, p stands for the group of predictors that are specified as binary variables for each of the four completed education levels and the 15 (Chile) and eight (Peru) regions in the two countries , and β_j is the slope coefficient for each of the k predictors. Thus, we obtain expected income $\hat{y}_p = p \, \hat{\beta}_x$, where $\hat{\beta}_x$ is the estimated coefficient vector. Our measure of parental income is hence an average of current income over cells defined by education and region. This is analogous to the use of cohort values described by Deaton (1985) to avoid errors-in-variables bias in repeated cross-sections and thus helps us to address measurement error in the explanatory variable. It relies on the assumption that transitory fluctuations are random.

In the next step, we carry these predictions over to our main equation and regress the log of child income on $\hat{y}_p$ and a vector X of observable characteristics that include age and gender:

$$y_{ci} = \alpha + \gamma \hat{y}_{pi} + \theta_2 \, X'_{ci} + \varepsilon_{2i} \tag{6}$$

To account for the uncertainty that arises from generating the regressor $\hat{y}_p$, we derive robust standard errors as a function of the variances and covariances of the estimators in (5) and their linear projection in our main dataset (Pacini and Windmeijer, 2016).

[14] Compare in particular three studies for the US: Solon (1992), Zimmerman (1992) and Mazumder (2005), as well as Corak and Heisz (1999) and Dunn (2007).

[15] The parental age range 25–45 years in 1996 (Chile) and 1997 (Peru) is based on a plausible reproductive age. While we thus exclude very young and very old parents, which may cause a bias if parental age is correlated with children's circumstances, we argue that this age range allows us to better control for lifecycle effects on earnings, which are plausibly larger.

5.2 Intergenerational Income mobility

As described above, we analyse income as our variable of interest, in contrast to many other studies that look at earnings. In the two countries under analysis, a considerable share of the population makes a living from self-employment, in the informal sector or through subsistence activities, which we include in our income concept, but which would not be fully reflected in an earnings concept. Our analysis compares net market income of the parent and child with an alternative specification using adult equivalent disposable income. Persistence in disposable income is naturally subject to different dynamics: it includes redistribution through the tax and transfer system and a needs-based adjustment for household composition. Elasticities of disposable income are hence not indicative of opportunities, but they provide an indication of the correlation in living standards across generations.[16]

The results from the first stage prediction of parental income are reported in Table A4 in the annex. Table 1 reports the results from the estimation of intergenerational elasticities that we obtain from regressing the child's observed income on imputed parental income. In both countries, the correlation coefficient γ is higher for disposable than for market income, but only in Chile is the difference between the two statistically significant. Simple statistical tests suggest that this is a result of family size and patterns of assortative mating.[17] In Chile, we estimate a γ coefficient for market income of 0.66 and of 0.76 for disposable income. Confidence intervals range from 0.61 to 0.70 for persistence in market income and 0.72 to 0.81 in disposable income. These figures are in line with previous estimates for Chile of between 0.57 and 0.73, derived from TSIV estimation (Nunez and Miranda, 2007)[18]. Female-headed households have significantly lower incomes in both countries but controlling for the sex of the household head does not affect the elasticity parameter. In Peru, we estimate an elasticity of 0.63 for market income, with the slightly higher 0.67 for disposable income (confidence intervals range from 0.56 to 0.71 for the former and 0.61 to 0.73 for the latter estimate). The difference is not statistically significant; the same applies to the change associated with controlling for the gender of the household head.

[16] In this sense, such a measure may, for example, show weaker persistence if there has been an expansion of the welfare state that redistributes towards the lower end of the distribution.
[17] The analysis is based on adult equivalent disposable income. Family size decreases with income, and educational attainment among spouses is highly correlated.
[18] Nunez and Miranda (2007) use TSIV estimation in a descriptive analysis of income elasticities, where they predict a father's earnings using years of schooling and potential experience (defined as the difference between age and years of schooling minus 6) in an older survey of the parental generation.

Table 1: Estimates of Intergenerational income elasticities for cohorts born between 1977 and 1990

	CHILE				PERU			
	γ (log market income)		*γ (log disp. income)*		*γ (log market income)*		*γ (log disp. income)*	
Log Y_p	0.656***	0.656***	0.761***	0.761***	0.630***	0.668***	0.671***	0.660***
	(0.0246)	(0.0238)	(0.0231)	(0.0232)	(0.0384)	(0.0392)	(0.0298)	(0.0298)
Female (=1)		-0.232***		-0.230***		-0.266***		-0.0858***
		(0.0226)		(0.0211)		(0.0342)		(0.0312)
Constant	2.769***	2.926***	2.238***	2.336***	2.917***	2.717***	2.685***	2.767***
	(0.137)	(0.132)	(0.117)	(0.116)	(0.185)	(0.188)	(0.127)	(0.125)
Observations	6,691	6,691	6,905	6,905	4,369	4,369	4,623	4,623
R-squared	0.131	0.203	0.178	0.200	0.106	0.136	0.174	0.174

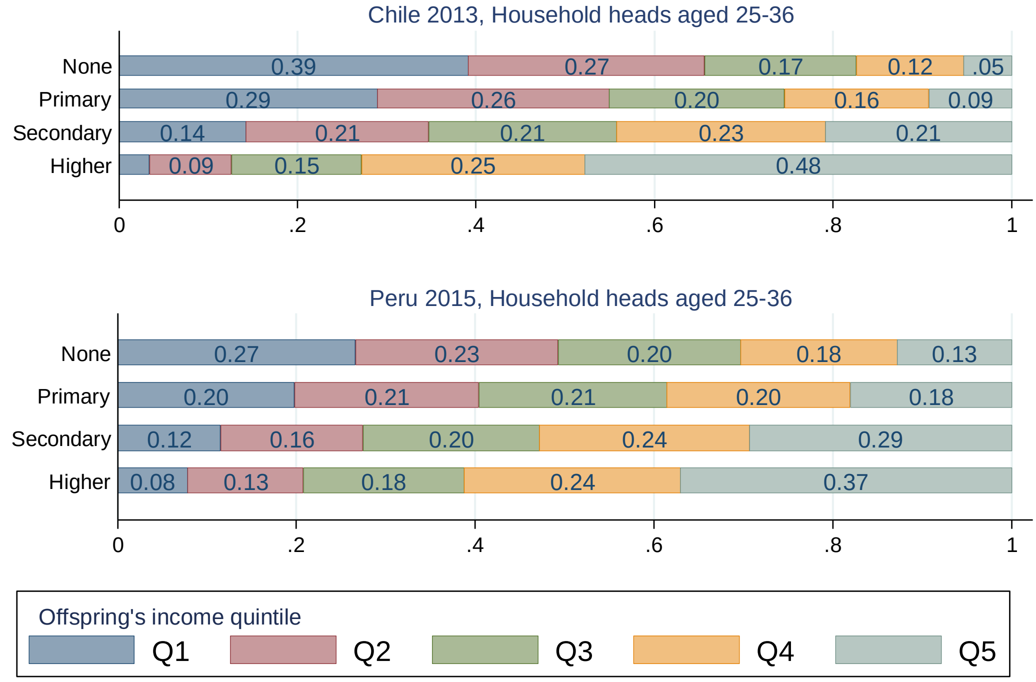
*Notes: Robust standard errors in parentheses; the robust variance estimator for $ß_{ts}$ is obtained by incorporating robust variance estimators for estimated $ß_{yp}$ from the first stage and for the vector of its linear projections in our main dataset. *** p<0.01, ** p<0.05, * p<0.1*

In quantitative terms, this would mean that same-aged children of parents whose income differed by 10% would earn incomes in adult life that differed by 6.6% on average in Chile and by 6.3% in Peru. These measures are by themselves not indicative of unequal opportunities, since persistence may be driven by differential efforts or preferences that persist over generations.

Persistence is slightly lower in Peru, where inequality has seen a greater decline, and recent growth patterns have increased demand for low-skilled workers. Since the earliest household data on income for the parental generation are from the 1990s, we cannot test whether income mobility has changed over time and whether Peru started at a similar level of mobility to Chile's in previous generations. Testing for differential coefficients along the distribution of offspring's income is also complicated by our reliance on imputed average income values for parents. We hence resort to comparing offspring's relative income position across parental education levels.

Graph 1 plots the probability of being in one of five income quintiles conditional on parental education. For Chile, being born to parents without any formal education raises the probability of belonging to the bottom quintile to almost twice the average, while the probability of being in the top quintile is only a quarter the average. Persistence at the top is even stronger: having highly educated parents raises the chances of being in the top quintile to 2.4 times the average but lowers the chances of landing in the lowest quintile to around 15% of the average. The association is weakest for children of parents with secondary education. In Peru, the association between income and parental education is lower than in Chile. At the bottom, the probability of being in the lowest quintile is about 35% higher than the average for children of parents without formal education, while their probability of being in the top is still 65% of the average. For those with highly educated parents, the chances of being in the bottom quintile are 40% of the average and of being in the top quintile almost twice the average. In both countries, there is hardly any association with income at the median parental education level, which is primary in Peru and secondary in Chile. The association between parental education and adult equivalent disposable income (see graph A2 in the annex) is more pronounced than with individual market income.

Graph 1: Offspring's income quintile conditional on parental education



The matrix shows the offspring's probability of reaching each quintile of individual market income

Overall, we find evidence for a stronger association between parental education and adult child income for children of parents with very high or very low education. Nonetheless, this correlation appears less strong than we might have expected from our analysis of income persistence. This is not surprising, since we assume that parental education primarily affects one’s offspring’s educational attainment. Further, we ignore income variation within education levels, which may also be correlated across generations. To analyse non-linear patterns in more detail, the next section will examine patterns of mobility and persistence in educational achievement across generations.

6. **Mobility in education**

Although we assume that a linear specification is biased as a result of functional form misspecification, we report results for the two summary measures introduced above in order to compare our estimates with those of previous studies. In this sense, the summary measures serve to illustrate trends in mobility over time and across countries rather than as an interpretation of the strength of the coefficient itself. We estimate measures of β_1 in a linear OLS regression as specified in equation (1) and scale for changes in the marginal distributions over time to estimate φ from equation (2). Both are measures of persistence: a higher measure implies a stronger association between the outcomes of successive generations.

Table 2 reports the estimates of educational mobility for household heads of the birth cohorts 1953–90 in both countries, where attainment is measured in years of education. We estimate a β_1 of 0.43 in Chile and 0.49 in Peru, and a φ of 0.54 in Chile and 0.45 in Peru. On average, absolute mobility as measured by β_1 is hence higher in Chile, while relative mobility appears higher in Peru. Marginal changes in the distribution play a role in both countries but affect our measures differently. In Peru, the fact that φ is lower than β_1 indicates that the dispersion in education has increased in the children's generation relative to that of their parents. It thus needs a larger β_1 – larger absolute differences – to explain the same level of correlation. In Chile, on the other hand, β_1 is smaller than φ and indicates the opposite: the dispersion of educational attainment has decreased in the children's generation compared to that of the parents. Levels centre more closely around the mean. A marginal change in parental education may hence explain less variation in children's education when measured in levels as compared to standard deviations. Adjusting for marginal changes in the distribution thus leads to higher measures of persistence in Chile and lower ones in Peru.

Table 2: Summary measures of intergenerational persistence in years of education

	Chile			Peru		
	β_1	β_1	φ	β_1	β_1	φ
Parental education	0.454***	0.431***	0.542***	0.516***	0.492***	0.459***
	(0.00674)	(0.00696)	(0.00696)	(0.00858)	(0.00876)	(0.00876)
Controls: age, gender	No	Yes	Yes	No	Yes	Yes
Constant	8.023***	-0.000849		6.645***	0.456***	
	(0.0686)	(0.0308)		(0.0642)	(0.0408)	
Observations	29,618	29,618	29,618	19,022	19,022	19,022
R-squared	0.325	0.293		0.228	0.210	

*Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.*

Compared to Hertz et al. (2008), our measures of persistence are lower than those found for Peru and Chile, but still much higher than the levels in other regions. The authors estimate a regression coefficient of 0.64 for Chile and 0.88 for Peru, and a correlation coefficient of 0.60 for Chile and 0.66 for Peru. Their estimates for other world regions are significantly smaller (correlation coefficients of around 0.4). We explain this difference by the fact that their study is based on older cohorts and smaller sample sizes.[19] As we will see below, our estimates suggest trends of increasing mobility that explain why our younger sample experiences higher mobility.

Graph 2 disaggregates these summary measures by birth cohorts in order to examine the trend over time. The first thing that becomes apparent is that trends over time differ between the two countries. In Chile, the regression coefficient suggests higher mobility than the correlation coefficient, and a continuous decrease in persistence across cohorts. The correlation coefficient is larger throughout and shows a decrease in mobility for the cohorts born between 1966 until 1980, after which it starts increasing again. The distance between the two widens because of this increase. Given that the correlation coefficient adjusts for changes in the margins of the distribution, such a pattern shows that the variability of years of education is smaller for children relative to that of their parents. This can be explained by the rise in years of education over time, which had a large effect at the bottom of the distribution: the share of people with no

[19] Hertz et al (2008) base their analysis for Chile on individuals born between 1930 and 1979 and observed in 1998–99; and, for Peru, on individuals born between 1916 and 1965 and observed in 1985.

formal education has decreased considerably over time, reducing mass in the bottom tail of the distribution. Nonetheless, these absolute changes do not translate into positional changes. There is a diverging trend for the birth cohorts 1961–80 that were of school age between the early 1970s and early 1990s: the regression coefficient moves very little, while the correlation coefficient increases. This suggests that the spread in the distribution of these cohorts' years of schooling decreased relative to that of their parents, while the average association between their years remained fairly constant. In the early 1960s and until the military coup of 1973, access to higher education was promoted in Chile and led to a spread in parental years of education. Although the children of these parents benefited from increased schooling infrastructure, the privatisation of education starting in the mid-1970s meant that it became harder to attain the higher levels for successive generations of students. Positional mobility increased again for the birth cohorts 1981 onwards, which were in secondary school from the mid-1990s onwards, when public education expenditure slowly started to rise again. We will investigate mobility patterns at the tails of the distribution further below to see whether the structural expansion of education altered children's chances of upward mobility conditional on parental education.

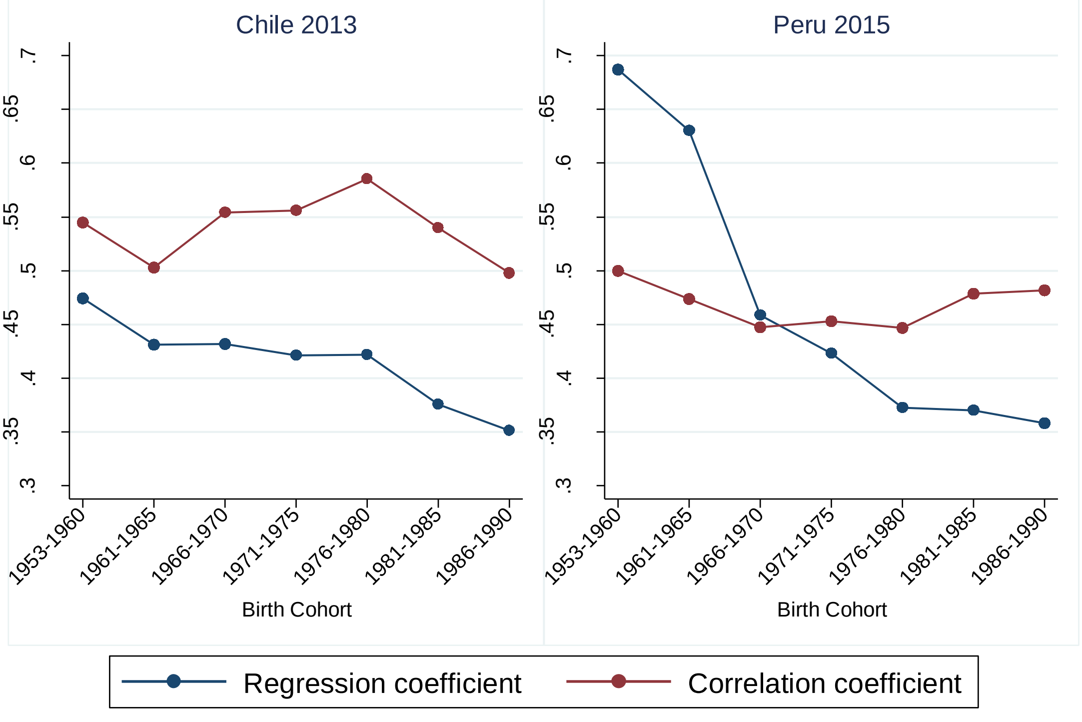
Peru, in turn, has seen a large increase in absolute mobility over time that is not reflected in relative mobility. The regression coefficient stands at almost 0.7 for the older cohorts and falls to 0.36 for the youngest cohorts in our sample. It has thus reached the same average mobility levels as Chile in absolute terms. Peru had very low schooling levels until the 1970s, so the expansion of educational infrastructure even at the primary level had a strong impact upon rising absolute mobility. Whereas low average education allowed for little absolute mobility in older cohorts, the expansion of schooling infrastructure beyond urbanised regions in the 1970s soon induced high increases in mobility. As Table A4 shows, more than 55% of parents in our sample had no formal schooling;[20] this share declined to less than 13% in the offspring generation. Scaling for these large changes in the marginal distribution suggests a far less dynamic scenario. The correlation coefficient decreases by around 5 percentage points from an initial 0.5 for the first cohorts in our sample, but then stays flat and sees a moderate increase again for the youngest cohorts, which were of school age during the 1980s. This period in Peru was marked by political terrorism, which affected the poorest regions in the highlands most strongly. At the same time, the economy declined and public services were virtually non-existent in remote rural regions. The regression coefficient is higher than the correlation coefficient until we reach the cohorts of 1966–70 and then falls below it. Hence, at this point, the spread in children's marginal education distribution starts to surpass that of their parents. This is doubtless a result of the initial increase in education from very low average levels among the oldest cohorts. The next generations then see a decreasing dispersion around a higher mean than that of their parents. There is still room for absolute

[20] This coarseness of the education variable is in fact another reason why we introduce non-linear estimation below.

mobility, since even the cohorts of the 1970s and 1980s saw only a gradual enforcement of compliance with compulsory primary education.

In summary, we can conclude from Graph 2 that relative and absolute measures can paint quite a different picture, a distinction that merits particular attention in countries that have seen significant changes in mean education levels. There has been a large increase in absolute mobility that was particularly strong in Peru. This is consistent with the average rise in years of education in both countries resulting from structural expansion and creating much room at the top. The changes over age cohorts in relative persistence are more modest, indicating that distributional patterns have shown a considerable degree of stability. Parents' educational achievement continues to be a fairly strong predictor of the child's position in the education distribution of their generation. Relative mobility has seen an increase in Chile for younger cohorts in parallel with increasing absolute mobility, which may be indicative of education levels rising equitably across the distribution. We do not see this trend in Peru. We know that Peru has implemented similar reforms to Chile in the past few decades but with a time lag. From these average measures it is, however, difficult to speculate about whether we are seeing different windows of the same larger trend in each country, or whether the two countries are following different trends altogether.

Graph 2: Educational persistence by birth cohorts



6.1. Non-linearities in the mobility process

Summary measures can provide a description of average degrees of correlation across the whole population but it seems implausible that the strength of such correlation would be the same for all educational backgrounds. To provide a more detailed picture of mobility processes across different levels of parental education, we report the results from an ordered probit estimation. This answers the question of how likely it is for children to move across the education distribution holding parental education fixed. It is thus not affected by the large changes in the margins that occurred between the two generations. We specify education as a categorical variable with four possible outcomes and regress these on binary variables for the same educational outcomes in the parental generation, controlling for age and gender.

Table A5 (annex) reports the estimation results of the ordered probit model: as expected, the coefficients are significant and the threshold estimators differ from each other statistically. Table 3 reports the marginal effects of parental education on the child's educational attainment. In both countries, the probability of reaching primary or less decreases steadily at all levels of parental education compared with the baseline of no formal education. The effect is stronger in Chile, where the conditional probability of having no education decreases by 14.5 percentage points when parental education increases from none to primary, and by 23.7 percentage points when it increases to higher education. At the primary level, the likelihood decreases by 9.4 percentage points when parental education increases to primary and by 35.3 percentage points when it increases to a higher level. In Peru, the effects are somewhat smaller but follow the same trends. These trends reverse for individuals who have completed secondary or higher education. The chances of finishing secondary school increase with parental education up to secondary level in both countries but falls again with higher education. Only the chances of reaching higher education increase at all levels of parental education, and this increase is particularly strong at the top: having highly educated parents increases such chances by 69.1 percentage points in Chile and by 52.7 percentage points in Peru against the baseline. This is consistent with the small changes in φ that we observed in the previous section.

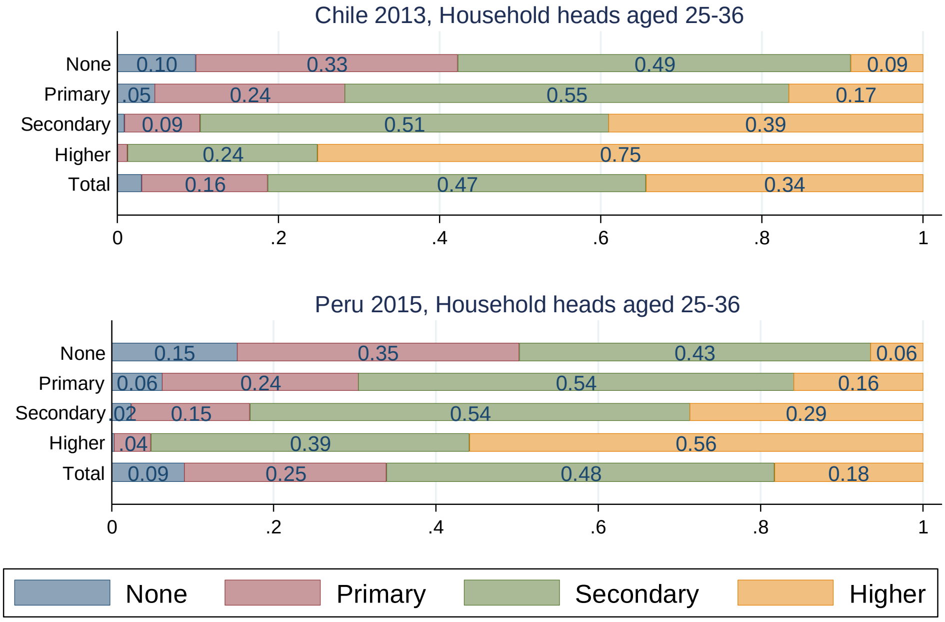
Table 3: Marginal effects of parental education on adult child's educational attainment –
results from an ordered probit estimation (evaluated at sample means)

	Chile				**Peru**			
	None	**Primary**	**Secondary**	**Higher**	**None**	**Primary**	**Secondary**	**Higher**
Parental education								
Primary	-0.145	-0.094	0.128	0.111	-0.126	-0.114	0.089	0.151
	(0.0046)	(0.0027)	(0.0042)	(0.0030)	(0.0037)	(0.0042)	(0.0028)	(0.0054)
Secondary	-0.215	-0.238	0.125	0.328	-0.163	-0.192	0.074	0.281
	(0.00456)	(0.0040)	(0.0044)	(0.0051)	(0.0035)	(0.0052)	(0.0036)	(0.0082)
Higher	-0.237	-0.353	-0.100	0.691	-0.188	-0.288	-0.051	0.527
	(0.0047)	(0.0039)	(0.0069)	(0.0074)	(0.0035)	(0.0052)	(0.0089)	(0.0129)

Note: Standard errors in parentheses.

These numbers suggest that persistence is strong at the bottom and the top. Graph A3 (annex) is a graphical representation of Table 3 and shows that the conditional probability of having no formal education decreases from around 22% in Chile and 20% in Peru to zero when we move from having parents with no educational qualification to a post-secondary one. In Chile, the conditional probability of achieving only primary education also decreases to almost zero when parents have higher education; in Peru it is below 10%. Conversely, the graph also shows that there is upward mobility: the chances of reaching higher education for those whose parents had only primary schooling or below lies between 5% and 18% in Chile and between 10 and 22% in Peru. In Peru, parental background is not a strong predictor for individuals who have completed secondary (mandatory secondary schooling was introduced in 1993 in Peru, although compliance is not enforced). Graphs A4 and A5 (annex) depict how these marginal effects of parental education differ by birth cohorts. Whereas the differences are small and not always significant in Peru, persistence at the bottom seems to have decreased for younger cohorts in Chile and increased at the top.

Graph 3: Offspring education conditional on parental education



The matrix shows the probability of child c reaching one of 4 education levels conditional upon parental education.

The transition matrix in Graph 3 depicts how conditional probabilities vary across parental background for household heads aged 25–36 years, the same group for which we analysed income mobility above. The last bar of each graph describes the marginal probability – or overall shares – of each level in the respective country, and year of observation. In the case of zero transmission of educational advantage from parent to child, we would expect the chances of reaching post-secondary training to be the same for someone with parents of no education as for her peer whose parents hold a university degree. In the other extreme case of perfect transmission, we would expect children to remain in exactly the same rank in the education distribution as their parents, which in absolute terms may translate to a higher level thanks to the rise in average years of education.[21] Table A4 (annex) reports the empirical distribution of education in both generations observed in our sample. It shows the rise in average education levels between the two generations: while almost half of the parents of our sample in Peru had no formal education, the average adult child observed in 2015 reached secondary education. In Chile, the average level of education is primary among parents and secondary among the children's generation.

As the above analysis suggests, the conditional distributions are very different from the marginal distributions in both countries. To compare the degree of persistence across educational categories, we calculate persistence factors defined as the ratio between the conditional distribution in each cell and its marginal distribution in the child's

[21] We do not consider dynamic effects in our analysis, which would account for the fact that the counterfactual scenarios of zero or perfect transmission from parents to children imply a different marginal distribution of education among the child's generation than we observe empirically.

generation: $P(E_c|E_p)/P(E_c)$, where P stands for the probability of educational attainment of the child c and parent p. The closer to one the persistence factor, the less persistence we observe. Table 4 reports the results. In Peru, the probability of having no formal education, given that one's parents also had, none is two-thirds higher for the younger sample aged 25–36 than the average, while the chances of reaching post-secondary education are half the average. Persistence at the upper end is three times the average. The picture is equally pronounced in Chile: persistence at the low end of educational achievement is more than three times the average, and more than double at the upper end of the matrix. Hence, in both countries, persistence is highest at the lower and upper ends, while we observe more mobility in the middle. The fact that these factors have changed at both ends across cohorts suggests that stronger persistence at the top and bottom is not just a result of ceiling and floor effects (see Torche, 2015a). In Chile persistence at the bottom has increased from 2.58 to 3.14 for the younger group compared with the full sample; in Peru this increase was from a factor of 1.49 to 1.7. At the top, persistence has stayed roughly the same in Peru but decreased from 2.76 to 2.19 in Chile. The chances for upward mobility from the lowest educational class to the highest – a measure of directional mobility that Corak (2017) calls 'Rags to Riches' – are larger in Peru than in Chile. In the pooled sample, the chances in Peru are around 46% of the average while they are only 20% in Chile (top right corner in each table). For the younger age groups, the difference between countries is smaller.

In both countries, persistence at the lower end has decreased for younger cohorts (slightly in Peru and markedly in Chile), and increased at the upper end (markedly in Peru and slightly in Chile). Graph A6 (annex) compares diagonal persistence factors for the oldest and youngest two cohorts in our sample (figures for other cohorts available upon request) and visualises the strength of top persistence compared to the weak persistence in the middle. Obviously, whether perfect mobility is an appropriate benchmark remains a much-debated issue, since transmission from parents to children may happen for various reasons. Nonetheless, the fact that the simple correlation between parental and offspring education is so strong underlines the importance that opportunities might play.

Table 4: Persistence factor in education by country and age groups

Parental education		None	Primary	Secondary	Higher	None	Primary	Secondary	Higher
		Chile: Age group 25–60				**Chile: Age group 25–36**			
	None	**2.58**	1.63	0.80	**0.20**	**3.14**	2.09	1.04	**0.26**
	Primary	0.99	**1.22**	1.15	0.60	1.51	**1.51**	1.17	0.49
	Secondary	0.23	0.58	**1.14**	1.43	0.29	0.61	**1.08**	1.14
	Higher	0.01	0.09	0.54	**2.76**	0.01	0.08	0.50	**2.19**
		Peru: Age group 25–60				**Peru: Age group 25–36**			
	None	**1.49**	1.29	0.92	**0.46**	**1.70**	1.41	0.90	**0.35**
	Primary	0.53	**0.86**	1.15	1.20	0.68	**0.98**	1.12	0.87
	Secondary	0.25	0.58	**1.11**	1.80	0.27	0.60	**1.13**	1.58
	Higher	0.05	0.22	0.80	**3.00**	0.04	0.18	0.82	**3.07**

Note: Persistence factors are calculated as the ratio between the child's conditional expectation of educational attainment and its marginal expectation.

6.2. Absolute versus relative mobility

Scholars and policy makers remain divided as to whether more importance should be attached to relative or absolute mobility (Jantti and Jenkins, 2013). Those that focus on absolute mobility emphasise that increasing the pie means everyone will have a larger share than previously. Others argue that maintaining distributional patterns across generations is evidence of unequal opportunities and inequality traps (see; Durlauf et al, 2017). The above analysis of conditional expectations focuses on relative mobility and neglects the decreasing share of people with low education in both countries. In other words, although bottom persistence has increased in both countries, overall there are far fewer persons with low education currently than there were in previous generations. Similarly, while top privilege remains very strong, more people overall attain a higher education and contribute to upward mobility at other points of the distribution. The sharply falling β_1 measure in Graph 2 vividly illustrates this point.

Table 5: Joint probabilities of educational achievement between parents and children, household heads aged 25–60.

			Children				
			None	Primary	Secondary	Higher	Total
Parents	Chile	None	**5.2**	8.0	6.2	1.3	20.7
		Primary	3.8	**11.9**	18.3	6.8	40.7
		Secondary	0.7	3.0	**12.4**	10.2	26.4
		Higher	0.1	0.3	2.4	**9.4**	12.2
		Total	9.7	23.2	39.3	27.8	100.0
		N	29630				
	Peru	None	**11.4**	19.1	18.6	6.4	55.5
		Primary	1.2	**5.8**	10.9	5.4	23.3
		Secondary	0.3	1.6	**7.8**	4.7	14.4
		Higher	0.0	0.3	2.3	**4.1**	6.7
		Total	12.9	26.9	39.6	20.6	100.0
		N	19023				

To put the different dimensions of mobility into perspective, Table 5 reports the joint probabilities of the possible $edu_p\ x\ edu_c$ combinations. It shows that the underlying education distributions in both countries are quite different. Bottom persistence seems to be a lesser concern in terms of scale than upper class persistence in Chile: the probabilities of both parent and child having no formal education is 5.2% as opposed to 9.4% for both having higher education. Upward mobility in turn is very small. The odds of having a higher education and parents without any formal education are only 1.2 (compared to 6.4 in Peru). The increase in education levels has been much smaller in Chile than in Peru. Peru has almost caught up with Chile in terms of average education levels in recent decades. The very large share of parents with no formal education in Peru clearly drives the comparably high probability of bottom persistence there. Almost the entire share of individuals from the children's generation who have no formal education also had parents without education. Upper persistence seems less a phenomenon than upward mobility, but this is probably driven by a tripling of the population share that has achieved higher education among the children's generation. Moving down the education ladder is a rare phenomenon in both countries: having parents with higher education while reaching only primary or lower scarcely happens (despite more than a quarter of the children's generation reaching only primary or less). Of course, downward mobility is not a desirable trend or a sign of widening opportunities, but rather serves to underline the differences in odds.

6.3. Comparing mobility in income and education

Comparing these patterns of persistence in education with those of income is inherently difficult for various reasons, chiefly because we cannot observe income mobility over a span of generations long enough to detect trends. Thanks to the same data limitations, we cannot depart from a linear analysis of income mobility and compare patterns across the distribution. Nonetheless, several observations can be made. First, educational persistence has decreased substantially in absolute terms and more moderately in relative terms. Summary measures of the correlation in educational attainment of around 0.5 for the younger cohorts in both countries are still higher than those estimated in high income countries such as the UK and US (correlations in the range of 0.35 and 0.46, respectively, according to (Blanden, 2013), or Italy (0.47 according to Checchi, 2009). Nonetheless, this difference seems to be less strong than the comparative analysis for older cohorts by Hertz et al (2008) suggested. While our estimates of income persistence do not allow comparison of younger with older cohorts, they suggest that correlation in income is at least on a similar scale to that in education. Even for young cohorts that have experienced educational expansion and economic growth benefiting the lower deciles, income elasticities are still high at around 0.66 in market income. These correlations may be biased upwards because of the imputation of parental income that relies on parental education. Blanden (2013) suggests scaling down estimates that are derived from two-sample estimation approaches by a factor of 0.75 to make them comparable to OLS estimates that do not rely on instrumental variable or imputation techniques. While this scaling factor may seem somewhat arbitrary, even allowing for it leads to significantly higher persistence measures in Peru and Chile than those other studies have found for high income countries – in the range of 0.24 for Canada, Sweden and Germany to around 0.37 in the UK (scaled). (For a comparative review of these studies, see (Blanden, 2013).) The association between a child's income quintile and parental education suggests that a non-linear pattern may also be present in income mobility in Chile and Peru (to the degree that parental education determines parental income).

7. Discussion

This paper has analysed two dimensions of intergenerational mobility, namely education and income, in Chile and Peru using measures that capture both relative and absolute mobility. Whereas absolute mobility serves to compare living standards between generations, relative mobility is often associated with equality of opportunity. Previous studies have argued that educational mobility is a good proxy for income mobility since education constitutes a major determinant of income (Blanden, 2013). The fact that the distribution of educational achievement experienced rather different trends than did the distribution of incomes over the past two decades in both countries calls into question whether this is a valid assumption for Chile and Peru. Comparing these two countries is insightful because they have experienced similar education policy reforms and relied on a growth strategy in recent decades which, in combination with educational expansion, favoured a decrease in the skills premium. Peru has experienced stronger growth and higher reductions in inequality in the past few decades than has Chile but is still poorer and has lower schooling levels, leaving more scope for upward mobility in times of growth.

We tested three hypotheses that we derived from economic theory. We found support for the first one that parental welfare is positively associated with that of their children as adults. Given the challenges in data availability inherent in measuring persistence in an intergenerational framework, we adopted a combination of strategies. We analysed intergenerational income elasticities in a first step. Because of the absence of long-term panel data, we do not observe actual parent–child pairs and instead adopt a two-sample imputation strategy that combines information from repeated cross-sections. We limited the analysis to household heads aged 25–36 observed in 2013 (Chile) and 2015 (Peru) and linked these to older cross-sections of the late 1990s representing the parental generation. Our results suggest that income mobility is low when compared to countries in other regions (for an overview of IGE estimates for different countries see Blanden (2013)). We estimate income elasticity coefficients of between 0.63 and 0.67 in Peru and 0.66 and 0.76 in Chile. These estimates are consistent with previous studies for the region. Slightly higher mobility in Peru than in Chile is consistent with trends of decreasing inequality since the early 2000s and economic growth that has benefited the lower deciles disproportionately. These trends were stronger in Peru than in Chile. As a result of data limitations, we cannot test for a convex relationship in income mobility but instead assume a relationship that is linear in logs.

The plausible assumption that educational achievement stays constant in adulthood allows for a more detailed analysis of educational mobility. Our analysis of educational mobility covers household heads aged between 25 and 60 years, who correspond to the birth cohorts 1953–90. Such analysis is possible with cross-sectional data, since household surveys contain retrospective information on parental education. We find that absolute mobility has increased strongly over time in both countries, but much more so in Peru. Peru had very low average schooling levels during the 1970s and 1980s, leaving much room at the top. This is one reason why upward mobility – the probability of children from low-educated families reaching higher education levels than their parents – is stronger in Peru than in Chile. Chile also experienced a structural education expansion but started at higher average years of schooling than Peru. Nonetheless, parental background remains a strong predictor of relative educational achievement in both countries: scaling mobility measures for changes in the marginal distribution shows that there is less dynamism across cohorts than absolute mobility signals. The fact that persistence at the tails of the education distribution is much stronger than in the middle is indicative of this finding. In both countries, self-reproducing educational elites seem to exist alongside persisting low achievement across generations, which may be indicative of a poverty trap. Individuals with parents of average education in turn experience relatively high mobility in both countries.

Hence, our findings offer support for the third hypothesis that persistence is non-linear across the distribution, with some (albeit ambiguous) support for the second hypothesis that welfare persistence should decrease for younger cohorts. The ambiguity arises from the diverging trends in absolute and relative mobility: our analysis has shown that it is important to distinguish between the two concepts, even more so in countries that have experienced a structural expansion of education or large changes in inequality over time. Looking only at measures of absolute mobility suggests a much more optimistic outlook for trends in both countries. It is equally important to look beyond summary measures and examine whether the strength of persistence differs along the distribution. While summary indicators are a convenient way of comparing measures between countries or over time, they hide important dimensions of heterogeneity that result from non-linearities in the transmission process. Although intuitively compelling, non-linear approaches still see much less application in the literature than do linear models.

The limitations of our analysis suggest scope for further research. In particular, the links between intergenerational mobility in income and education merit a deeper analysis. The intuitive hypothesis that both experience the same trend does not follow from theory. As Becker et al. (2015) outline, a crucial factor in the equation are changes in returns to human capital that may affect income persistence while holding skills persistence constant. Our discussion of institutional reforms in Chile and Peru further suggests that educational achievement is only a noisy measure of human capital, which disregards changes in quality and the degree of segmentation spurred by the privatisation of education, for example. Such an analysis of the interdependencies between education and income necessitates a modelling of the underlying causal mechanisms that drive persistence. Since the different dimensions of advantage probably influence mobility simultaneously, analysing a single outcome dimension inherently fails to address endogeneity. In this sense, our analysis does not aim to identify the underlying structural factors of mobility and persistence but rather provides a detailed analysis of intergenerational correlation patterns that causal analysis can build upon.

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Annex

Table A1: Average years of education in Chile and Peru from 1996 to 2014 by equivalised income quintiles, adults aged 25 to 65

Chile				Peru			
Year	**Q1**	**Mean**	**Q5**	**Year**	**Q1**	**Mean**	**Q5**
1996	6.9	10	12.7	1997	3.2	7.3	10.7
2006	8.2	10	13.3	2005	4.5	8.7	12.2
2013	9.1	11	14	2014	5.6	9.6	12.7

Source: CEDLAS and World Bank, 2017.

Table A2: Descriptive statistics for Chile and Peru from 1995 to 2015

	Chile			Peru		
	1996	**2006**	**2015***	**1995***	**2005**	**2015**
Mean income (pc, 2010 US$)	8,534	11,313	14,547	3,140	3,831	5,935
Mean income (pc, 2010 $PPP)	12,203	16,783	20,946	6,099	7,440	11,527
Gini coefficient	55.3%	52.2%	50.9%	53.2%	48.9%	43.9%
Poverty rate	23.2%	13.7%	11.7%	47.5%	48.7%	22.7%
Total population (000s)	14,596	16,332	17,819	24,039	27,610	31,377

*Note: * Gini coefficient reported for 2013 (Chile) and 1997 (Peru).*

Source: OECD, ECLAC, SEDLAC, National Institute for Statistics and Informatics (INEI) Peru.

Table A3: Testing sample selectivity

	Chile		Peru	
	(1)	(2)	(1)	(2)
	Education level	Log market income	Education level	Log market income
Restricted	-0.32***	-0.03	0.02	0.10*
R. st. errors	(0.03)	(0.02)	(0.02)	(0.04)
N	34309	7612	21765	5188
R-sq	0.113	0.36	0.085	0.271

Notes: Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001.

The dummy 'Restricted' equals 1 for observations that miss information on parental education. The samples in columns 1 include household heads aged 25–60, those in columns 2 household heads aged 25–36.

Table A4: The distribution of educational attainment across generations (%)

	Highest completed education level			
	None	Primary	Secondary	Higher
Chile				
Whole sample (N: 29630)				
Adult children	9.74	23.22	39.28	27.76
Parents	20.72	40.75	26.37	12.17
Age group 25–36 (N: 7288)				
Adult children	3.11	15.6	47.03	34.26
Parents	11.72	34.96	34.90	18.41
Peru				
Whole sample (N: 19023)				
Adult children	12.9	26.9	39.6	20.6
Parents	55.5	23.3	14.4	6.7
Age group 25–36 (N: 4630)				
Adult children	9.13	24.6	48.09	18.18
Parents	44.24	24.76	21.65	9.35

Notes: The samples are drawn from CASEN (2013) and ENAHO. 'Children' refers to the educational level of household heads aged 25–60 years, while 'Parents' refers to the educational level of parents that these same household heads report retrospectively.

Table A5: Ordered probit estimation of adult child's education level

	Chile	Peru
Parental education		
Primary	0.614***	0.626***
	(0.0171)	(0.0195)
Secondary	1.287***	0.997***
	(0.0197)	(0.0242)
Higher	2.254***	1.624***
	(0.0277)	(0.0359)
Cohort	0.0672***	-0.0123***
	(0.00364)	(0.00431)
Female (=1)	0.0286**	-0.0772***
	(0.0136)	(0.0179)
Constant cut1	-0.483***	-0.927***
	(0.0184)	(0.0198)
Constant cut2	0.532***	0.0377**
	(0.0185)	(0.0191)
Constant cut3	1.807***	1.252***
	(0.0202)	(0.0204)
Observations	29,630	19,023

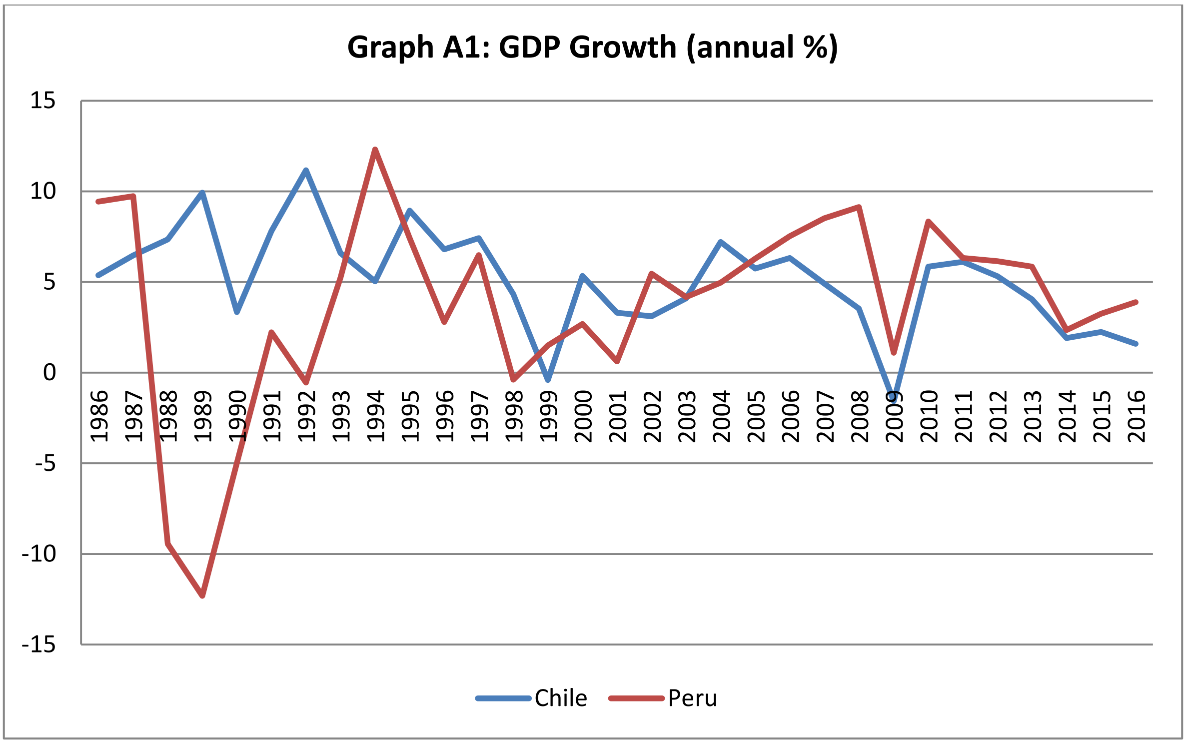
Notes: Standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1.*

Table A7: Predicting Parental Income, CASEN (1996) and ENAHO (1997)

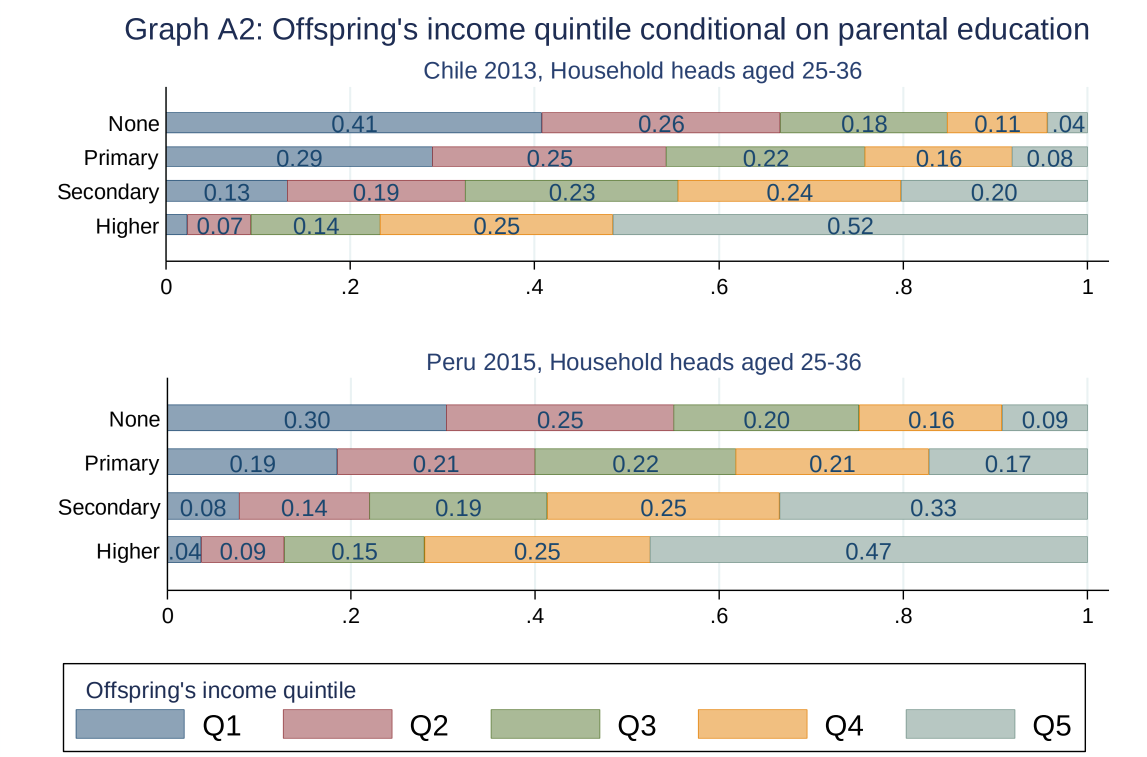
	Chile			Peru	
	log y-mkt	log y-disp		log y-mkt	log y-disp
Primary	0.268***	0.234***	Primary	0.435***	0.385***
	(0.0327)	(0.0322)		(0.0864)	(0.0578)
Secondary	0.681***	0.637***	Secondary	0.891***	0.873***
	(0.0366)	(0.0355)		(0.100)	(0.0625)
Higher	1.574***	1.597***	Higher	1.385***	1.528***
	(0.0570)	(0.0501)		(0.111)	(0.0713)
Regional dummies					
Tarapacá	-0.0468	-0.102	Northern	-0.254***	-0.450***
	(0.0937)	(0.102)	Coast	(0.0948)	(0.0786)
Antofagasta	0.192**	0.0273	Central	-0.180*	-0.250***
	(0.0761)	(0.0738)	Coast	(0.105)	(0.0735)
Atacama	0.0786	-0.132	Southern	-0.138	-0.266***
	(0.0939)	(0.0862)	Coast	(0.0975)	(0.0968)
Coquimbo	-0.288***	-0.339***	Northern	-0.766***	-0.978***
	(0.0497)	(0.0483)	Highland	(0.122)	(0.0909)
Valparaíso	-0.223***	-0.246***	Central	-0.601***	-0.813***
	(0.0427)	(0.0413)	Highland	(0.0966)	(0.0710)
Libertador	-0.282***	-0.295***	Southern	-0.349***	-0.600***
G.B. O'H.	(0.0479)	(0.0410)	Highland	(0.0891)	(0.0692)
Maule	-0.401***	-0.420***	Jungle	-0.295***	-0.563***
	(0.0416)	(0.0391)		(0.0868)	(0.0685)
Bío Bío	-0.362***	-0.431***			
	(0.0457)	(0.0429)			
La Araucanía	-0.437***	-0.419***			
	(0.0492)	(0.0469)			
Los Lagos	-0.373***	-0.323***			
	(0.0643)	(0.0565)			
Aysen	-0.0943	-0.0462			
	(0.0723)	(0.0585)			
Magallanes y	0.0762	0.157			
Antártica	(0.118)	(0.102)			
Los Ríos	-0.428***	-0.541***			
	(0.0623)	(0.0621)			
Arica y	-0.412***	-0.400***			
Parinacota	(0.117)	(0.0923)			
Constant	6.339***	5.695***		6.616***	6.090***
	(0.0354)	(0.0339)		(0.131)	(0.0740)
Observation:	8,802	9,010		2,199	2,290
R-squared	0.340	0.370		0.289	0.415

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
The variables Primary, Secondary and Higher are specified as binary variables for completed education levels. The regional dummies exclude the metropolitan regions of Santiago and Lima as base categories.

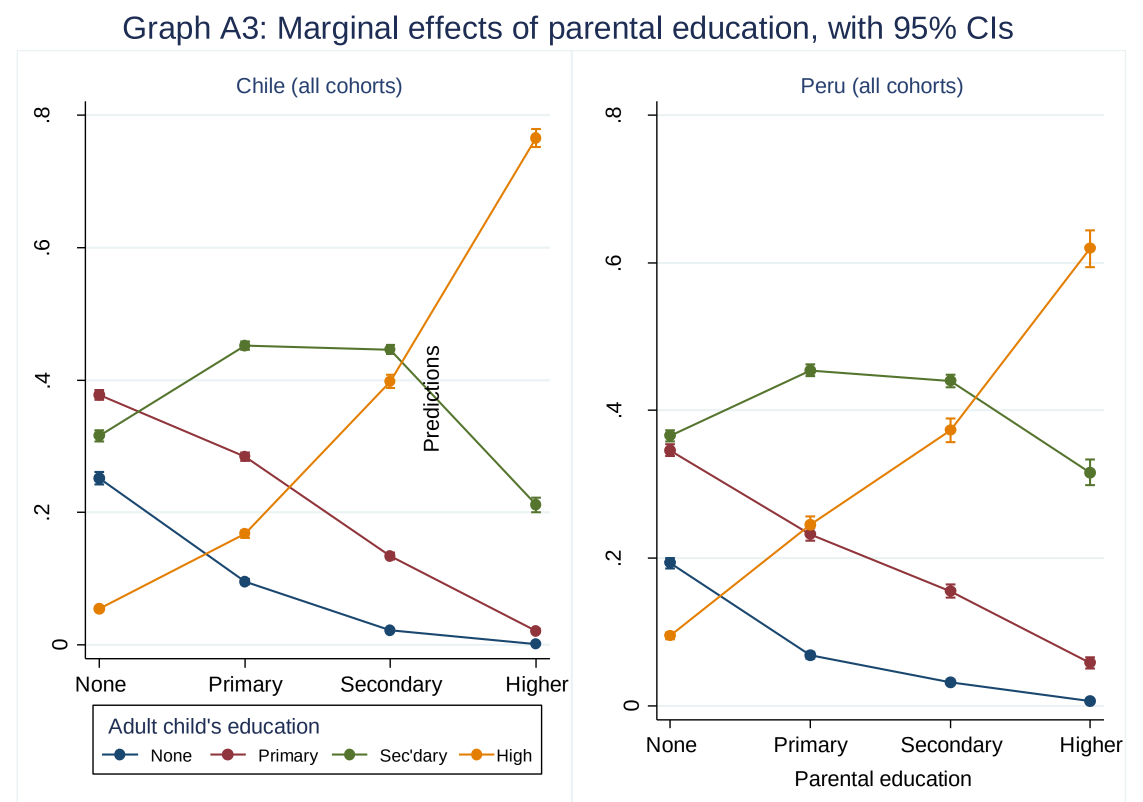


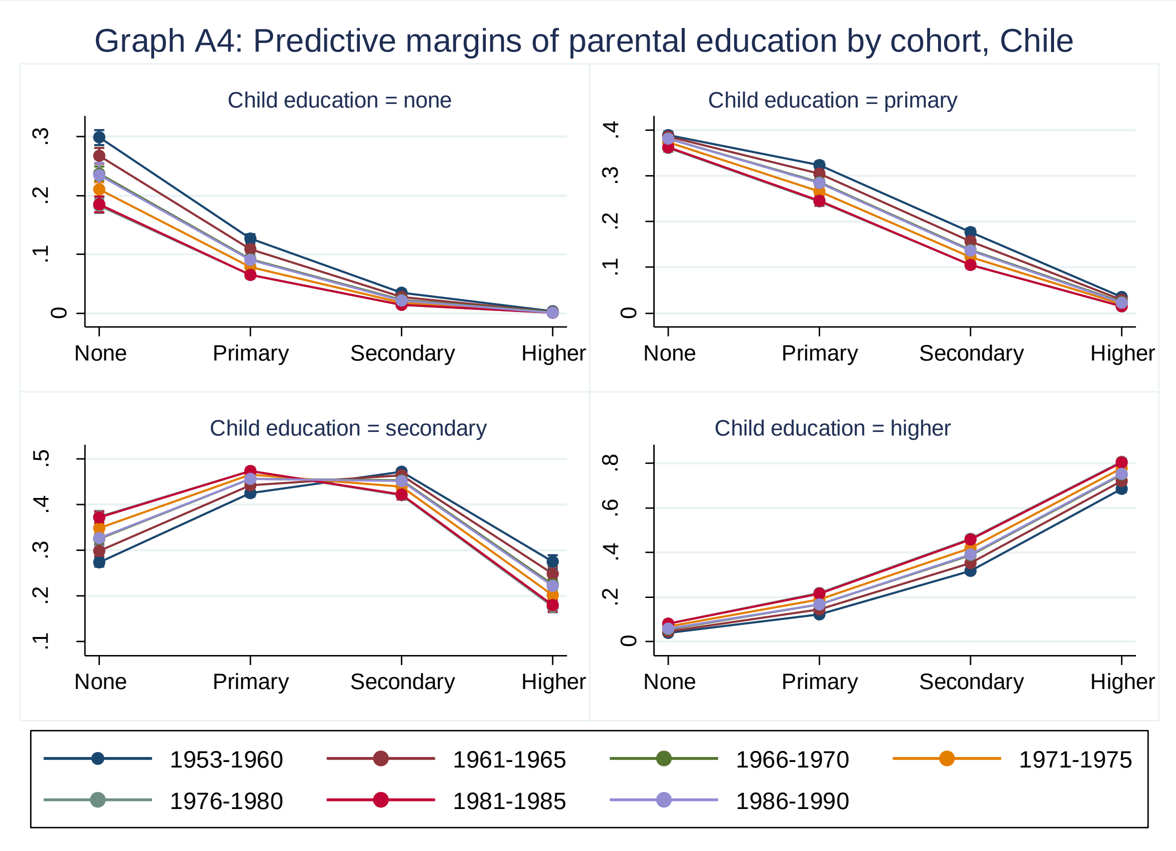
Notes: Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars.

Source: World Bank.

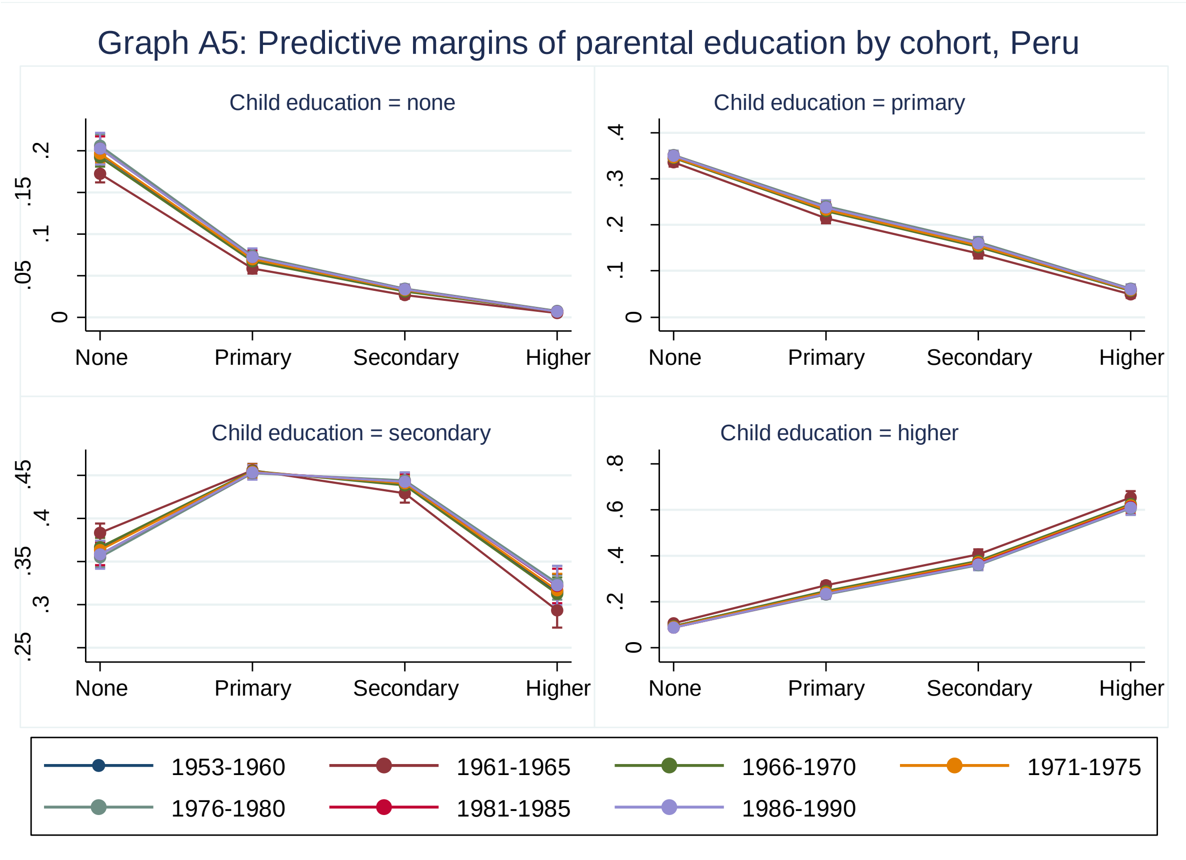


The matrix shows the offspring's probability of reaching each quintile of adult equivalend disposable income

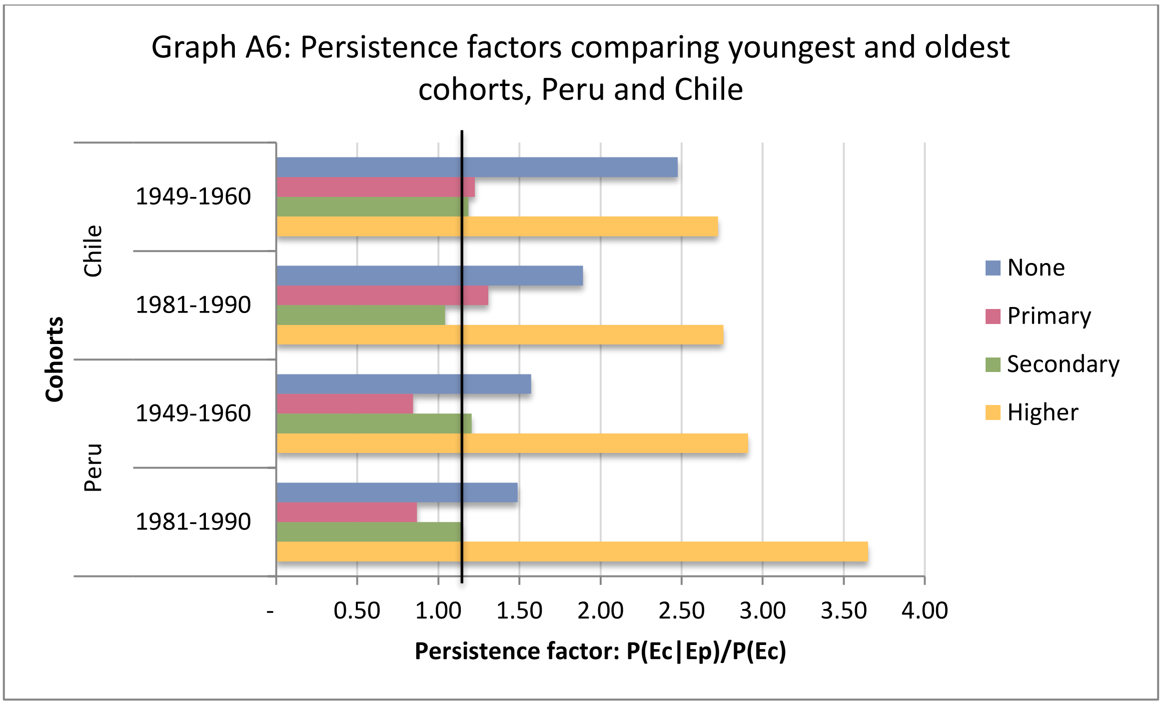




Graph A4: Predictive margins of parental education by cohort, Chile
Child education = none
Child education = primary
Child education = secondary
Child education = higher
None
Primary
Secondary
Higher
1953-1960
1961-1965
1966-1970
1971-1975
1976-1980
1981-1985
1986-1990



Graph A5: Predictive margins of parental education by cohort, Peru
Child education = none
Child education = primary
Child education = secondary
Child education = higher
None
Primary
Secondary
Higher
1953-1960
1961-1965
1966-1970
1971-1975
1976-1980
1981-1985
1986-1990


Graph A6: Persistence factors comparing youngest and oldest cohorts, Peru and Chile
Cohorts
Chile
1949-1960
1981-1990
Peru
1949-1960
1981-1990
-
0.50
1.00
1.50
2.00
2.50
3.00
3.50
4.00
Persistence factor: P(Ec|Ep)/P(Ec)
None
Primary
Secondary
Higher

9.