The Dynamics of Earnings in Chile[1]

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Abstract

This paper provides an empirical analysis of individual earnings using data from the *Encuesta Suplementaria de Ingresos*. We find that the predictable component of income is hump-shaped over the life-cycle, and that there are strong education effects. The unpredictable component of income can be described by a very persistent permanent shock and a transitory shock. Our estimates are built from a panel of cohorts, so we use US data from the PSID to provide a magnitude for the underestimation of the estimated variances. Surprisingly, we find that the variance of the permanent shock is almost 4 times smaller in Chile than in the US, a result, perhaps, of the relative rigidity of the Chilean labor market.

JEL classification: D12 (Consumer economics: empirical analysis), D89 (Information and uncertainty), H54 (National government expenditures and welfare programs).

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Introduction

Uncertainty is a key dimension of individual decision making. Under incomplete markets there are contingencies for which individuals cannot insure. Uncertainty thus influences the life-cycle evolution of consumption and savings, labor supply and asset allocation, and education and occupation choices. Uncertainty and risk also determine income and consumption inequality. Ex-ante identical individuals will have different lifetime paths of consumption ex-post, as some individuals are lucky and get good draws of income, employment and health, whereas others get bad shocks and end up with lower levels of consumption over the life-cycle. Income mobility and the persistence of income inequality and poverty depend upon the dynamics of earnings, health outcomes, investment opportunities, and more generally, earnings capacity.

In this paper we measure the earnings uncertainty faced by individuals. Most of the existing empirical literature focuses on the dynamics of income and wages using data from developed countries (Abowd and Card, 1989; Pischke, 1995; Meghir and Pistaferri, 2003). Our data draw from a survey of Chilean households -- the *Encuesta Suplementaria de Ingresos* (ESI) carried out by the *Instituto Nacional de Estadísticas* (INE). Whether consumers in an emerging economy face levels of uncertainty similar to those in developed economies is an empirical matter that is addressed in this paper. However, the welfare consequences of uncertainty may be much larger. On the one hand, individuals have fewer opportunities to share risks through the marketplace when markets are less developed. On the other hand, the public welfare system is much smaller in developing countries, providing fewer opportunities to offset negative shocks.

Our modelling structure allows us to distinguish between a predictable and an unpredictable component of income. Furthermore, we decompose the unpredictable part into permanent and transitory shocks to income. Specifically, we model the unexplained portion of individual earnings as the sum of a permanent and a (persistent) transitory disturbance. We also allow for time varying variances of permanent and transitory perturbances, and evaluate whether they correlate with the business cycle. Since the ESI dataset is a repeated cross-section, we construct synthetic panels to perform our estimations. Our synthetic panels contain annual observations from 1990-2000, on 5-year birth cohorts.

Using data on men between the ages of 25 and 60, our results indicate that the age profile of labor income has the typical hump-shape, and that there are very large educational effects. At age 50, a college educated individual expects to earn 2.5 times the earnings of a person who attained up to high school, and 3.8 times the earnings of an individual who only completed 8 years of schooling. We also find that married men earn more than their single and divorced counterparts, and that household size has a negative impact on earnings.

Our decomposition of the unexplained portion of income yields very persistent but low variance permanent shocks, and a neglegible variance of the transitory shock. These low variances may be an artifact of our synthetic panel technique, as averaging reduces the observed variability. We investigate this hypothesis by comparing our results to those obtained using US data from the Panel Study of Income Dynamics. We find that if we replicate our cohort estimation procedure with US data, we find a similar process for the dynamics of income. However, we find a significantly higher variance of earnings in the US than in Chile. We interpret this as evidence of the relative rigidity of the Chilean labor market (vis a vis the US labor market). We also find that averaging within cohorts reduces the estimated variance by one order of magnitude. Extrapolating the US results to Chilean data, we find that the variance of the permanent shock at the individual level is about 0.021. We cannot provide an estimate of the variance of the transitory shock, as our benchmark estimates all turn out non significant.

If markets are complete, individuals can perfectly share their good and bad fortunes. If so, then the measurement of individual uncertainty becomes irrelevant. However, there exists vast evidence showing that in practice many important events are not insured and that markets do not fully pool risks (Attanasio and Davis (1996), Dynarski and Gruber (1996)). A number of mechanisms help individuals insulate their consumption from income shocks (changes in their labor supply, spousal income, public and private transfers, and through the progressivity of the income tax). In this paper we ask whether government transfers allow consumers to partly offset persistent shifts in earnings capacity. To answer this question we reestimate our basic model using labor income plus the receipts from public welfare programs as our measure of individual earnings. We find that the inclusion of government transfers hardly affects the estimated process of income, although there is a negative effect of earned income on the likelihood that any given individual receives a transfer.

The paper also provides a number of applications. Specifically, we analyze income inequality and earnings mobility simulating the life-cycle income profiles of an individual that faces the process we have estimated. Since income is estimated to be highly persistent, our simulations show that we should expect to observe little mobility of individuals across the distribution of income. In particular, our results show that an individual who starts-off at the lowest quintile of the earnings distribution will stay in that same quintile for a year with a 0.77-0.84 chance. Furthermore, the likelihood that the same individual will be again in the lowest quintile ten years ahead ranges between 0.40 and 0.58. A similar pattern is found at the top of the distribution. That is, we find that the Chilean distribution of income is highly persistent because the underlying earnings process is also highly persistent. Finally, we find that a large portion of income inequality can be explained by the underlying variability of the earnings process.

The paper is organized as follows. In the next section we describe the data and compare the ESI to the CASEN, the *Encuesta de Caracterización Socioeconómica Nacional* the most widely used survey for the analysis of Chilean household behavior. In Section 3 we present the model and estimation techniques. In Section 4 we start by providing our estimates of mean income, to then use the unexplained portion of income to fit different dynamic processes. We also compare the results on Chile to a similar sample of American workers. In Section 5 we provide a number of applications of our results. We conclude in Section 6.

Data

The data used in this paper are drawn from the *Encuesta Suplementaria de Ingresos*, ESI. The ESI is a supplement to the National Employment Survey conducted monthly by the INE. The main goal of the ESI is to provide information on individual and household income. The ESI collects information over the last quarter of every year on a sample of roughly 36,000 households. These households are representative of the Chilean population. The survey gathers information on all household members that are at least 15 years old. Data on all types of income perceived during the previous month, and a number of individual characteristics such as educational attainment, marital status, gender and employment status is registered. Population weights are also provided. Data is available for years 1990-2000, except for year 1994 when the survey was not conducted. The use of the ESI as a source of income data has been fairly limited. An exception is Granados (2001).

Our analysis considers men between ages 25 and 60 who are not self-employed. We deflate all nominal variables using the CPI of the corresponding month of the interview. Real variables are reported in December 1999 Chilean pesos. Table 1 reports the sample's basic statistics. On average, individuals in our sample earn almost 170 thousand pesos each month. The median is just above 100 thousand pesos, reflecting the skewness of the Chilean income distribution. About 17% of individuals report income below the monthly minimum wage. The typical individual in the sample is 38 years old, married, and has completed 9 years of education (corresponding to an education level of just over secondary school). Finally, the median household has 4 residents, and most individuals live in the V, VIII, and Metropolitan administrative regions.

Figure 1 plots the distribution of personal labor income. The distribution shows the extent of income inequality in Chile, which has been extensively analyzed elsewhere. The figure also shows the distribution of income in the 1996 CASEN taken from Baytelman et al (1999).[2] These two distributions are not directly comparable, as the CASEN figures include transfers and represent different sample years.[3] Furthermore, the ESI distribution is built from our data set on men. However, the graph shows that the distributions are quite alike, especially for the middle deciles. Most of the differences are concentrated at the bottom and top of the distribution. As a matter of fact, the ratio of the income share of the 20% individuals with highest income to the share of the bottom 20% is 7.9 in the ESI. This same ratio is equal to 13.8 in the CASEN. Similarly, the ratio of the share of the highest decile to the share of the lowest decile is equal to 13.2 in the ESI and 29.5 in the CASEN.

Figure 2 shows the evolution of the mean of (the log of) real earnings over the sample period. On average, real earnings grew at an annual rate of 4.7% in the period 1990-2000.[4] The line labelled "Primary" plots the evolution of average income for individuals who have attained 8 years of schooling; the line labelled "High" shows the evolution of individuals who have completed 12 years of education; finally, the line labelled "College" takes individuals who have completed 17 years of education.[5] In all cases the path of mean earnings is upwardly trended, although the

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[2] The CASEN is the most widely used survey for the analysis of Chilean household and individual income and earnings. The survey begun in 1985, and it has been carried almost every two years since then. The CASEN measures household and individual income for a representative sample of the Chilean population, and it has been mainly used to study income inequality and the role of social policies in reducing it (Anríquez et al, 1998; Larrañaga, 1994; Contreras et al, 2001). The CASEN had a sample size of 48107 households in year 1998. Like the ESI, the survey gathers information on all types of income, and on a number of demographic characteristics. Futhermore, it collects information on in-kind transfers, such as public programs in education, housing and health, and housing and durables ownership, allowing for detailed studies of poverty. We are precluded from the use of the CASEN because of its two-year frequency. As we show below, the dynamics of earnings is highly persistent, and thus the CASEN misses most of the action in the two year lag.

[3] Nevertheless, the distribution of income has hardly changed over the last decade. See Baytelman et al (1999).

[4] GDP per capita grew at about 5% over this period.

[5] Universities in Chile grant simultaneously a college degree and a professional title. Most programs last about 5 years.

annual rates of growth correlate positively with educational attainment. Thus, as other countries, Chile has experienced a widening of the earnings distribution.[6]

Figure 3 plots the evolution of the variance of log earnings over the sample period, for all individuals and for three different education groups. Highly educated workers face a much larger variance of earnings; i.e. there are large private returns on university education at the cost of increased earnings risk. The variance of the earnings of low education groups is quite stable over the period. This stability contrasts with the behavior of the earnings variance of those who have attained college education, which experienced large swings over the ten year span.

In the next subsections we use the ESI dataset to estimate mean income profiles over the life-cycle for the typical Chilean individual. We then use the unexplained portion of income to estimate the dynamic process of earnings. The use of the ESI survey has a major shortcoming: the analysis of income dynamics requires following the same individuals over time. Since both surveys represent cross-sections of households, we build synthetic panels based on 5-year birth cohorts. Table 2 presents the number of observations available for each cohort and year.

The Earnings Model

In this paper we consider models in which all individuals within an educational category have identical income processes, but face different realizations of this process.[7] Income consists of the sum of a predictable component and a stochastic component. Let $y_{i,t}$ represent the logarithm of individual's i real measured income in year t. Let $Z_{i,t}$ represent a vector of demographic characteristics, and $\eta_{i,t}$ the stochastic component of income. We assume that the unexplained component can be decomposed into a permanent shock $y^p_{i,t}$ -- e.g. health shocks that affect earnings capacity in a long lasting way and long-term unemployment -- and a transitory innovation $\mu_{i,t}$ -- e.g. bonuses and overtime pay. We also allow for classical measurement error, $\omega_{i,t}$. Finally, we assume that y^p and μ are uncorrelated at all leads and lags. We thus propose the following model for individual income

$$y_{i,t} = Z_{i,t}\beta + \eta_{i,t}$$

$$y_{i,t} = Z_{i,t}\beta + y^p_{i,t} + \mu_{i,t} + \omega_{i,t}$$

We allow for different assumptions on the process that both the permanent and transitory innovation follow. For instance, in the benchmark case we assume that the permanent component is a random walk, whereas the transitory shock has some persistence:

$$y^p_{i,t} = y^p_{i,t-1} + \upsilon_{i,t}$$

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[6] For US evidence, see Bound and Johnson (1992), Katz and Murphy (1992), and Murphy and Welch (1992); for Chilean evidence, see Bravo and Marinovic (1997), and Beyer and Le Foulon (2001).

[7] Recent literature has modelled earnings processes allowing for heterogeneity between agents. See Alvarez, Browning and Ejrnæs (2001).

$$\mu_{i,t} = \varepsilon_{i,t} - \theta\, \varepsilon_{i,t-1}$$

We allow for persistence in transitory shocks to account for innovations, such as overtime pay and bonuses, that may last for a while but do not have long lasting effects.

Alternatively, we explore a model where permanent shocks follow an AR(1) process whereas the transitory component is i.i.d.; i.e.,

$$y^p_{i,t} = \rho y^p_{i,t-1} + \upsilon_{i,t}$$

with $0 < \rho < 1$, and

$$\mu_{i,t} = \varepsilon_{i,t}$$

We estimate our complete model in two stages. In the first stage we use individual level data to estimate β and to compute $\hat{\eta} = y - Z\hat{\beta}$ for each observation in our sample. In the second stage we classify all observations on the basis of their year of birth, and take averages of $\hat{\eta}$ building a synthetic panel of cohort/year means.[8] That is,

$$\hat{\eta}_t^{\,c} = \frac{\sum_{i \in c,t} \hat{\eta}_{i,t}^{\,c}}{n_t^c}$$

where the superscript c indexes birth-year cohorts, and n^c_t represents the number of available observations in cohort c in year t. We use this synthetic panel to estimate the variances of the permanent and transitory components of income shocks ($\sigma_{\upsilon,t}$ and $\sigma_{\varepsilon,t}$, respectively) and the persistence of the transitory innovation (θ). Our modelling structure allows for time-varying variances.[9] We estimate these parameters using equally weigthed GMM by minimizing the distance between the theoretical and the empirical autocovariances of the first difference of the stochastic component of income.[10]

Assume there is no measurement error, and that the dynamics of earnings is characterized by a random walk plus an MA(1) transitory shock.[11] Then

[8] We use the survey's population weights to build the means.

[9] Nevertheless, in this paper we restrict the variances of the shocks to be constant over time. Given the short span of our data set, and the fact that 1994 data is unavailable, we were able to estimate the permanent variances for only 4 years (1992, 1997, 1998, and 1999). Although the estimated variances seem to correlate with the unemployment rate, they are not tightly identified. Results are available upon request.

[10] See Altonji and Segal (1996) for an analysis of alternative weighting procedures.

[11] In our procedure we assume that measurement error cancels out when we collapse our individual data set into cohort means. In what follows we thus ignore measurement error.

$$\Delta \eta_{i,t} = \eta_{i,t} - \eta_{i,t-1} = \upsilon_{i,t} + \varepsilon_{i,t} - (\theta + 1)\varepsilon_{i,t-1} + \theta\varepsilon_{i,t-2}$$

The theoretical autocovariances are thus given by

$$\mathrm{Var}(\Delta \eta_{i,t}) = \sigma_{\upsilon,t} + \sigma_{\varepsilon,t} + (\theta + 1)^2 \sigma_{\varepsilon,t-1} + \theta^2\sigma_{\varepsilon,t-2}$$

$$\mathrm{Covar}(\Delta \eta_{i,t}, \Delta \eta_{i,t-1}) = -(\theta + 1)\sigma_{\varepsilon,t-1} - \theta (\theta + 1)\sigma_{\varepsilon,t-2}$$

$$\mathrm{Covar}(\Delta \eta_{i,t}, \Delta \eta_{i,t+1}) = -(\theta + 1)\sigma_{\varepsilon,t} - \theta (\theta + 1)\sigma_{\varepsilon,t-1}$$

$$\mathrm{Covar}(\Delta \eta_{i,t}, \Delta \eta_{i,t-2}) = \theta\, \sigma_{\varepsilon,t-2}$$

$$\mathrm{Covar}(\Delta \eta_{i,t}, \Delta \eta_{i,t+2}) = \theta\, \sigma_{\varepsilon,t}$$

$$\mathrm{Covar}(\Delta \eta_{i,t}, \Delta \eta_{i,t-j}) = 0, \qquad j > 2$$

$$\mathrm{Covar}(\Delta \eta_{i,t}, \Delta \eta_{i,t+j}) = 0, \qquad j > 2$$

We follow a similar procedure to estimate the underlying parameters when we assume alternative dynamic specifications.

The fact that we construct a synthetic panel, and follow cohorts but not individuals over time implies that our analysis is based on averages. Thus, we expect to underestimate the true uncertainty level individuals face in Chile. In the analysis below, we provide estimates from a comparable sample taken from US data (Panel Study of Income Dynamics), to show how much the estimated process changes once we move from following individuals to following cohorts.

Results

The predictable component of income

We report our first stage estimation results in Table 3. In the regression we control for age, education, marital status, household size, and for interaction terms and nonlinear effects of these variables. We also control for the region of residence, and year and month of the interview.

Our results show that the age profile of labor income has the typical hump-shape found for other countries. We also find very large educational effects. Figure 4 plots the estimated age profiles for three different educational groups. The line labelled “Primary School” plots the average life cycle profile of income for individuals who have attained 8 years of schooling; the line labelled “High School” assumes the individual has completed 12 years of education; finally, the line labelled “College” assumes 17 years of education. All the other variables have been set at their average sample levels. To illustrate the magnitude of the education effect, consider three identical individuals, except for their level of schooling. At age 25, an individual with 8 years of completed schooling on average earns about 85000 pesos per month, whereas an individual with 12 years of education earns almost 120 thousand pesos per month; i.e. a difference of 40%. A college educated individual earns on average at age 25 about 280000 pesos; that is, 2.3 times the earnings of a high school educated individual. These differences increase with age. At age 50, a college educated individual earns 2.5 times the earnings of a person who attained up to high school, and 3.8 times the earnings of an individual who only completed 8 years of schooling. These differences further widen up once we realize that education and household size are negatively related, and that household size has a negative impact on earnings. On the contrary, educated people are less likely to be married, but this correlation is quite small in the sample.

The dynamics of income

Since we do not follow the same individuals over time, we estimate the process of income using a synthetic panel approach. For each individual in the sample, we take the unexplained component of (log) income as $\hat{\eta}$= y-Z$\hat{\beta}$. We then classify all observations according to birth cohort, forming our synthetic panel. Figure 5 tracks the variance of the unexplained portion of earnings within each cohort observed from 1990 through to 2000. The variance clearly increases with age, which reflects the fact that ex-ante identical individuals end up with quite different paths of income. In other words, in a sample of ex-ante identical agents, income inequality increases over time whenever there is a permanent component in uncertainty. If all shocks were i.i.d., the distribution of income would be age independent. Furthermore, individuals do start off at very different levels, as the initial variance is quite high.

The figure does not show important differences across cohorts. Except for the younger cohorts, the time path of the variance of earnings for any two consecutive cohorts typically cross, with no clear pattern. This means that at the same age, individuals born in different years should not expect different levels if uncertainty. For all cohorts, the variance tends to have a peak around 1996, indicating the presence of time effects in the cross-sectional variance of income -- perhaps, aggregate fluctuations that change the dispersion of income.

In Table 4 we display the sample autocovariance matrix of the residual of log income changes. The upper right triangle shows the covariances; the lower traingle shows the correlations. We find high autocorrelations at the first order, followed by a steep decline at higher orders. These patterns suggest that income changes may be modelled as an MA(1) process.

Our benchmark estimates are reported in the top panel of Table 5, where we define income as annual individual earnings. Three cases are analyzed depending upon whether the permanent component follows a random walk or an AR(1) stationary process, and whether the transitory shock is i.i.d. or an MA(1). In all cases the transitory component is not significant at a 5% significance level. The transitory shock does not show any persistence either. These findings are consistent with the hypothesis that the transitory component is i.i.d at the individual level, and that this component becomes neglegible when averaging within cohorts. In other words, the transitory component in indistinguishable from classical measurement error. The permanent component follows an AR(1) process, as the autocorrelation coefficient is statistically smaller than 1. The estimated variance of the permanent component is much larger than the variance of the transitory shock. However, it is an order of magnitude smaller than the variance estimated by several authors using a panel of individual US data from panel sets such as the PSID.[12] This large difference can also be explained by the fact we track cohorts and not individuals over time.[13] We further investigate this hypothesis below.

In the second panel of Table 5 we estimate the dynamics of Chilean earnings using labor income plus government transfers. In this exercise we ask to what extent the government provides insurance through its monetary transfers. A number of papers have analyzed the role of government transfers in alleviating poverty and in reducing income inequality in Chile (Baytelman et al (1999) and Engel et al (1999)). We analyze whether public transfers do reduce the uncertainty faced by individuals.

The estimated processes with and without transfers are very much alike. This is due to the fact that very few individuals report having received transfers in our data set.[14] However, a probit regression of a dummy indicating whether the individual received a positive transfer on the level of real earnings, and year, month and regional dummies, yields a highly significant negative effect of perceived income on the probability of receiving a transfer. Hence, in our sample, public transfers do play a (limited) redistributive role.[15]

To further investigate the hypothesis that due to cohort averaging, we largely underestimate the variances, we study whether our estimation process leads to similar results using data from the US. Specifically, we compare our results to those obtained from a comparable sample taken from US data, using a synthetic panel and individual level data. Our source of information is the Panel Study of Income Dynamics (PSID). The PSID is a representative longitudinal survey of nearly 8000 households. The PSID started collecting data on individuals and households in 1968, and has followed the same households and their split-offs on a yearly basis since then. The survey has rich data on a large number of economic and demographic variables. Below we exploit the fact that the PSID has a panel structure, which allows us to estimate the dynamics of income using individual data directly. We then reestimate the process using cohort data to analyze the way estimated parameters are affected by using a synthetic panel technique. We use the surveys from 1988 to 1997. Table 6 reports some sample descriptive statistics.

Our analysis of the US data replicates the analysis of Chilean data. We first restrict our samples to men between ages 25 and 60. We deflate wage income by the CPI-U. We then estimate the predictable component of labor income using the same variables and functional form reported for Chile in the previous subsection. We then construct a series for the unexplained portion of labor income for every individual in our sample. We use the sample weights to perform our estimates.

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[12] See Meghir and Pistaferri (2003) for the most recent results.

[13] See Pischke (1995) for a comparison of the variability and persistence of aggregate and individual income.

[14] Only about 1.5% report a positive level of transfers. This underreporting of transfers might be explained by the fact that most monetary subsidies are paid through the worker's paycheck. Thus individuals may incorrectly report transfers as part of their labor earnings.

[15] The marginal effect is $-2.08 \bullet 10^{-8}$, so every additional 200 thousand pesos of income (about one standard deviation in the sample) reduce the chance of receiving a public transfer in 0.42 percentage points.

Figure 6 plots the behavior over the sample period of the US within-cohort residual variance. As in the Chilean case, the figures do not reveal the presence of a cohort effect. Two properties are not shared by the Chilean and American profiles. First, the variance is quite flat over most of the life-cycle in the US. Second, the variance is much larger in the US than in Chile -- almost 2.05 times larger on average. This result seems counterintuitive, and it is not an artifact of the different currency denominations used to measure income.[16, 17]

This striking gap in earnings risk may be the result of institutional rigidities that reduce wage dispersion in the Chilean labor market relative to the American labor market. As shown by Bertola and Ichino (1995), there is much less wage inequality in markets where workers do move across firms, occupations, and regions in response to productivity and demand shocks. Thus wage dispersion differences may be the reflect different labor market institutions, labor reallocation costs, and wage contract structures.

Alternatively, once we allow for the endogeneity of earnings, a possible explanation is that American workers are willing to face a much larger level of uncertainty than their Chilean counterparts, as they have more opportunities to share risks through the marketplace when markets are more developed. Furthermore, the public welfare system is much larger in the US, and female labor force participation is much higher. Both provide insurance against negative shocks. Therefore, our results are consistent with the hypothesis that in the US workers can afford to take more risks, and choose occupations and jobs that are more risky.

The gap between the variance in Chile and the US is reduced as individuals age. This fact might also have an institutional explanation: minimum wage laws might have a larger effect on Chilean young workers. As a matter of fact, the Chilean real minimum wage rised in 72% over the sample years, whereas the US real minimum wage rised in only 18%.

In Table 7 we estimate the dynamics of income using the information on American workers, assuming the process is described by a random walk plus an i.i.d. transitory disturbance. For comparison, the first panel of the Table repeats the results obtained using the ESI. In the second panel we present the results using synthetic cohorts from the PSID. Similar to the Chilean case, we find that the process can be solely described by a random walk, as the transitory shock averages out in the aggregate. Moreover, we find that the variance of the permanent shock is much larger in the US than in Chile, confirming the results in Figures 5 and 6. [18]

The last panel of Table 7 reports the estimated parameters using individual level data from the PSID. We find that the variance of the permanent shock is one order of magnitude larger than the

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[16] Recall that all variables are measured in natural logs. We obtained similar results using the 1990-2000 Current Population Survey (CPS). The results are available upon request. However, survey methodologies and the extent of measurement error might partly explain these differences.

[17] The US variance of log real earnings is higher than the Chilean variance (before conditioning on worker characteristics). Furthermore, the R^2 of the regression on Chilean data is much higher, thus a larger portion of total income variability is explained by the predictable part of earnings. Both facts are consistent with the notion that Chilean workers face much less income uncertainty than their American counterparts.

[18] The qualitative results are similar if we assume an AR(1) plus an i.i.d. shock, or a random walk plus an MA(1) shock.

one estimated using cohort data. We also find a significant variance of the transitory shock.[19] Our results are consistent with other analyses. For instance, Meghir and Pistaferri (2003) use a similar sample from the PSID, and find that the variance of the permanent shock is 0.0313, whereas the variance of the transitory shock is between 0.00779 and 0.03.[20]

If the information in the PSID exercises can be extrapolated to the Chilean case, we would find that the variance of the permanent shock is one order of magnitude larger than the one we estimate using the panel of cohorts, i.e., about 0.0209. It is also likely that the variance of the transitory shock is different from zero. These results have important behavioral implications. First, if innovations are permanent and individuals are prudent, then precautionary savings can become quantitatively very important (Deaton, 1992). Second, the distribution of labor income can be persistently very unequal. Finally, the position of an individual on the income distribution is also highly persistent, as good and bad fortunes last forever. Below we provide simulation exercises that intend to illustrate these points. We first simulate life-cycle paths of income using our estimated processes. Then we use the simulated outcomes to build income distributions and to estimate the likelihood that an individual will move along the income distribution.

Application to Earnings mobility

Our application refers to income inequality and earnings persistence over the life cycle. We provide two sets of exercises that illustrate the effects of shock variance and persistence, using our benchmark estimates. In our first set we estimate transition matrices – the conditional probability that an individual will move along the income distribution – that results from the estimated persistence of the dynamics of income. In our second set of exercises, we estimate the distribution of income that results from the estimated variances.

To compute the transition matrices and the income distributions, we first generate 5000 lifetime income streams based on our estimates. We assume a life-cycle of 35 years (ages 25-60) and set the parameters of the model equal to the values estimated in Table 5. We assume all individuals are identical at age 25. Table 8 shows the simulated one-year transition matrices that result from assuming a random-walk and an AR(1) process with first order autocorrelation coefficient equal to 0.93095. The high persistence of the shocks implies that there is very limited earnings mobility. For instance, an individual who starts-off at the lowest quintile of the distribution has a 0.77-0.84 chance of staying there for another period. The likelihood of an individual at the richest quintile staying at that same quintile is quite similar. As expected, mobility is concentrated at the middle of the distribution. However, the persistence is still quite high at that position of the distribution. Table 9 shows the simulated ten year transition matrices; i.e, the chance that an individual starting-off at any given quintile will be at the same or at another quintile ten years ahead. Since the processes we estimate are highly persistent, we find that even over a ten year horizon, mobility is rather limited. Figures 7 and 8 show the chance that an individual is at any given point in life at the third and

[19] Since we estimated the processes using a non-linear methodology, we should not expect to find that the cohort level variance is equal to the individual level variance divided by the number of individuals in the cohort.

[20] Meghir and Pistaferri (2003) allow for measurement error, and show that the process for measurement error and for the transitory shock cannot be identified without external information. They find that the variance of the error in measurement must be between 0.01 and 0.03, assuming an MA(1) transitory shock. They estimate that the MA(1) coefficient is bounded between -0.18 and -0.25.

lowest quintiles, respectively, under the two alternative levels of persistence. Thus a major implication of our results is that poverty and the distribution of income in Chile should be quite persistent.

The variance level of the income process has important implications for the skewness of the income distribution. Table 10 shows the share of total income of individuals at different positions of the income distribution, and at different ages. The first column reports the simulation results using the estimated variance. The second column uses the scaled ESI variance to account for the underestimation implied by our cohort technique. For instance, the richest 20% individuals at age 30 receive a share of income that is 1.41 times the share of the poorest 20%, assuming our uncorrected benchmark estimates. This ratio increases to 2.48 if we scale the variance according to our PSID results. Because of the persistence of our estimates, simulated inequality increases with age. Nevertheless, our simulations cannot match actual income disparities. According to the CASEN, the richest quintile receives a share of about 13.8 times the share of the lowest quintile. Our underestimation is the result of the assumption that all individuals start off with the same characteristics. In particular, we assume the same educational attainment across workers. Figure 4 shows that schooling might explain a large portion of income inequality. Still, once we take the scaled variances, a large portion of actual inequality is explained by the underlying variability of the process of individual income.

Concluding Remarks

In this paper we have estimated the dynamic process of individual income using the *Encuesta Suplementaria de Ingresos*. We have found a highly persistent, but low variability income process. We have also shown that the low variance is an artifact of our cohort technique. Using data for American workers, we have found that averaging over cohorts leads to variance underestimation of one order of magnitude. Future work should directly address the issue of underestimation, which requires long panel sets of data on individual income. In Chile there exist rich panel sets that have followed workers over long periods of time and on a monthly basis. Unfortunately, these data sets are not publicly available as of today.

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Table 1. Sample Descriptive Statistics - ESI

	Mean	Std. Dev.	Min	Max	Median
Monthly Labor Income (Dec.99 pesos)	168534	191520	6	4189475	107729
Age	38.8	9.4	25	60	38
Years of Schooling	9.3	4.2	0	20	9
Household Size	4.6	2.0	1	26	4
Married	0.70	0.46	0	1	1
% of individuals living in					
RM	0.22	0.42	0	1	0
V Region	0.11	0.31	0	1	0
VIII Region	0.13	0.34	0	1	0

Source: 1990-2000 ESI.

Table 2. Number of Available Observations by Cohort and Year

Cohort	Year									
(age in 1990)	1990	1991	1992	1993	1995	1996	1997	1998	1999	2000
56-60	808	652	503	323	0	0	0	0	0	0
51-55	1226	1186	1071	979	843	589	451	312	148	0
46-50	1642	1640	1524	1492	1179	1181	1167	983	958	972
41-45	2045	2032	1945	1832	1615	1607	1617	1545	1478	1437
36-40	2471	2370	2346	2215	1994	2274	1881	1782	1697	1860
31-35	3054	2952	2745	2680	2620	2436	2640	2462	2404	2435
26-30	3520	3370	3134	3091	2767	2950	2847	2819	2783	3030
21-25	702	1333	1955	2671	2928	3004	2849	2729	2715	2818
16-20	0	0	0	0	573	1101	1691	2114	2530	2873
Total	15468	15535	15223	15283	14519	15142	15143	14746	14713	15425

Table 3. Mean Income
(Dependent variable: log of monthly labor income)

	Coefficient	Robust Standard Error
Age	0.030152	0.002192
Age^2	-0.000312	0.000025
Years of schooling	-0.024810	0.004483
Years of $schooling^2$	0.003484	0.000285
Age*Years of schooling	0.000641	0.000062
Years of $schooling^4$	0.000006	0.000001
Household size	-0.009955	0.001391
Married	0.190891	0.010351
Household size*married	-0.002730	0.001902
Constant	10.93174	0.052274
R^2	0.56	

Authors' estimation based on the 1990-2000 ESI.
The regressions also include a full set of year dummies, a
full set of month of the interview dummies, and region of residence
dummies.

Table 4. Covariance Matrix of Log Income Changes - ESI

	1991	1992	1993	1996	1997	1998	1999	2000
1991	0.000075	5.40E-06	2.20E-06	-0.000051	-3.10E-06	7.40E-06	0.000053	-0.000029
1992	0.70860 (0.0491)	0.00005	-0.00004	-0.00007	-0.00002	0.00004	0.00001	0.00003
1993	-0.54160 (0.1656)	-0.87000 (0.005)	0.00022	-0.00019	-0.00009	0.00027	-0.00011	-0.00006
1996	-0.07240 (0.8774)	-0.53340 (0.2175)	-0.03530 (0.9402)	0.00042	0.00010	-0.00041	0.00011	-0.00001
1997	0.29510 (0.5205)	-0.27810 (0.5459)	0.41300 (0.3571)	0.32160 (0.4373)	0.00017	-0.00019	-0.00004	0.00011
1998	-0.10130 (0.8289)	0.31320 (0.4939)	0.23720 (0.6086)	-0.86830 (0.0052)	-0.55230 (0.1558)	0.00050	-0.00014	-0.00003
1999	0.28160 (0.5406)	0.13170 (0.7784)	-0.53580 (0.2152)	0.21680 (0.6061)	-0.34050 (0.4091)	-0.33580 (0.4162)	0.00019	-0.00015
2000	-0.19110 (0.7169)	0.26450 (0.6124)	-0.23820 (0.6494)	-0.11660 (0.8033)	0.49230 (0.2617)	-0.01620 (0.9725)	-0.59620 (0.1577)	0.00032

Correlations below the diagonal, covariances above the diagonal.
Significance in parentheses.

Table 5. The Dynamic Process of Labor Income - ESI

		Permanent Component		Transitory Component	
		Variance	Autocorrelation	Variance	MA(1) Coeff.
Without Transfers					
	Permanent AR(1)	0.00395	0.93095	-0.00028	
	Transitory i.i.d.	(0.00062)	(0.02830)	(0.00028)	
	Permanent random walk	0.00326		0.00014	0.15868
	Transitory MA(1)	(0.00080)		(0.00067)	(2.64100)
	Permanent random walk	0.003028		0.000303	
	Transitory i.i.d.	(0.00067)		(0.000264)	
With Transfers	Permanent AR(1)	0.00394	0.93077	-0.00026	
	Transitory i.i.d.	(0.00062)	(0.02900)	(0.00028)	
	Permanent random walk	0.00327		0.00014	0.15871
	Transitory MA(1)	(0.00081)		(0.00068)	(2.6169)
	Permanent random walk	0.00304		0.00031	
	Transitory i.i.d.	(0.00069)		(0.00027)	

Standard errors in parentheses.

Table 6. Sample Descriptive Statistics - PSID

	Mean	Std. Dev.	Min	Max	Median
Annual Labor Income (96 dollars)	39714	40119	1076	1274859	32617
Age	39.3	8.5	25	60	38
Years of Schooling	13.1	2.8	0	21	12
Household Size	3.2	1.5	1	13	3
Married	0.79	0.40	0	1	1

Source: 1988-1997 PSID.

Table 7. The Dynamic Process of Labor Income
Chile and the US

	Permanent Variance	Transitory Variance
ESI - Cohorts	**0.00303**	**0.00030**
	(0.00067)	**(0.00026)**
PSID - Cohorts	**0.01181**	**0.00080**
	(0.00362)	**(0.00157)**
PSID - Individuals	**0.08150**	**0.11173**
	(0.00839)	**(0.00644)**

Standard errors in parentheses.

Table 8. Simulated Income Mobility
a. One Year Transition Matrix - ESI - Random Walk

	Quintile in t+1				
Quintile in t	1	2	3	4	5
1	0.84	0.14	0.01	0.00	0.00
2	0.14	0.65	0.19	0.02	0.00
3	0.01	0.19	0.60	0.18	0.01
4	0.00	0.02	0.19	0.65	0.15
5	0.00	0.00	0.01	0.15	0.84

b. One Year Transition Matrix - ESI - AR(1)

	Quintile in t+1				
Quintile in t	1	2	3	4	5
1	0.77	0.20	0.03	0.00	0.00
2	0.20	0.50	0.25	0.05	0.00
3	0.03	0.25	0.45	0.25	0.03
4	0.00	0.05	0.25	0.50	0.20
5	0.00	0.00	0.03	0.20	0.76

Table 9. Simulated Income Mobility

a. Ten Year Transition Matrix - ESI - Random Walk

	Quintile in t+10				
Quintile in t	1	2	3	4	5
1	0.58	0.25	0.11	0.05	0.02
2	0.25	0.32	0.24	0.13	0.05
3	0.11	0.24	0.29	0.24	0.11
4	0.04	0.14	0.24	0.32	0.26
5	0.01	0.05	0.12	0.25	0.56

b.Ten Year Transition Matrix - ESI - AR(1)

	Quintile in t+10				
Quintile in t	1	2	3	4	5
1	0.40	0.24	0.18	0.12	0.06
2	0.25	0.24	0.21	0.18	0.12
3	0.18	0.22	0.22	0.21	0.18
4	0.12	0.18	0.21	0.24	0.25
5	0.06	0.12	0.18	0.25	0.39

Table 10. Simulated Income Distributions

	Income Shares		Share V / Share I	
	ESI	Scaled ESI	ESI	Scaled ESI
Age 30	0.17	0.12	1.41	2.48
	0.19	0.16		
	0.20	0.19		
	0.21	0.23		
	0.24	0.30		
Age 40	0.15	0.08	1.80	4.62
	0.18	0.13		
	0.20	0.17		
	0.22	0.23		
	0.26	0.38		
Age 50	0.13	0.06	2.14	7.43
	0.17	0.11		
	0.19	0.16		
	0.22	0.23		
	0.28	0.45		
Age 60	0.12	0.05	2.46	10.59
	0.16	0.09		
	0.19	0.14		
	0.23	0.22		
	0.30	0.50		

Figure 1. The Distribution of Labor Income
ESI vs. CASEN

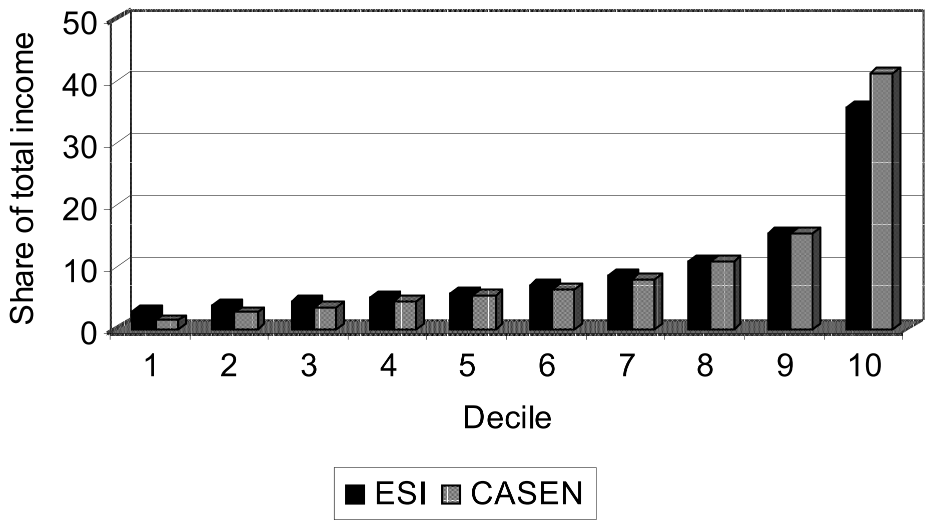

Figure 2. The Mean of Log Real Earnings

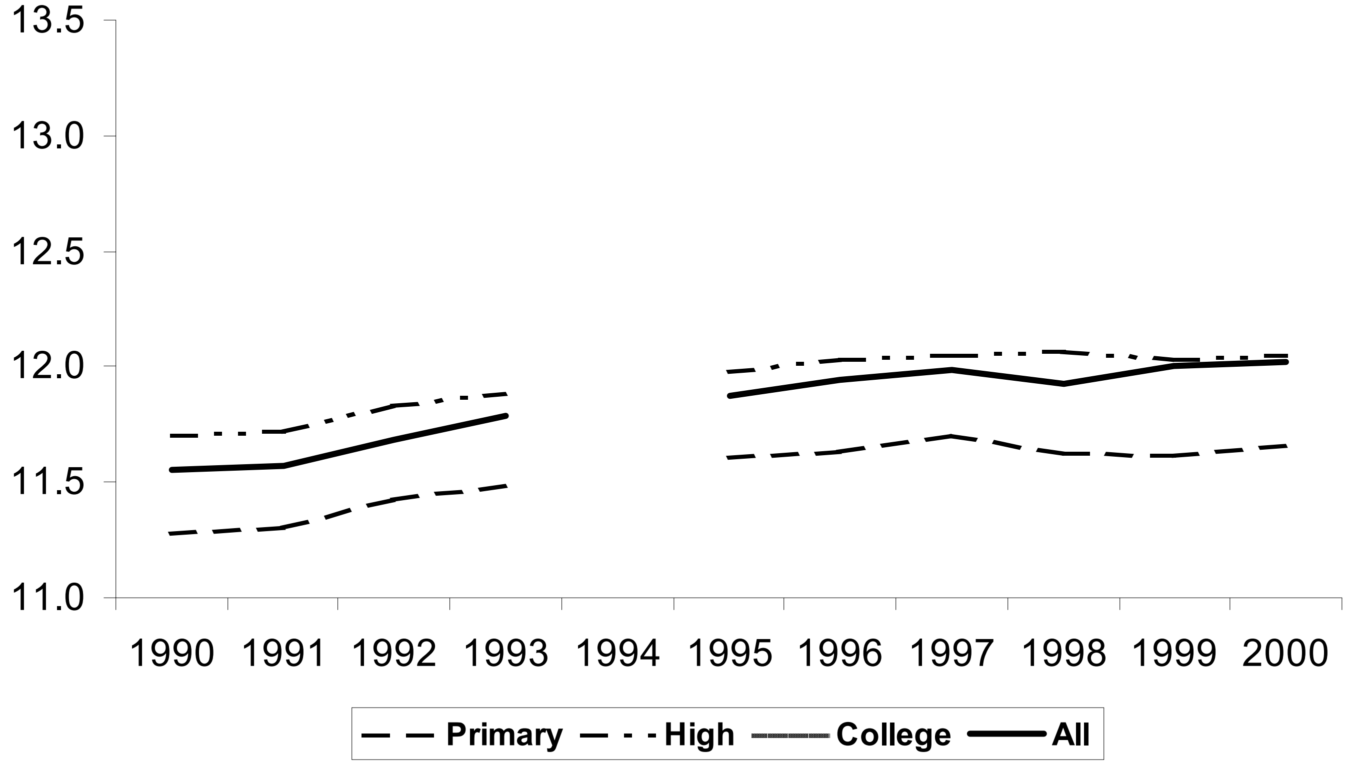

Figure 3. The Variance of Log Real Earnings

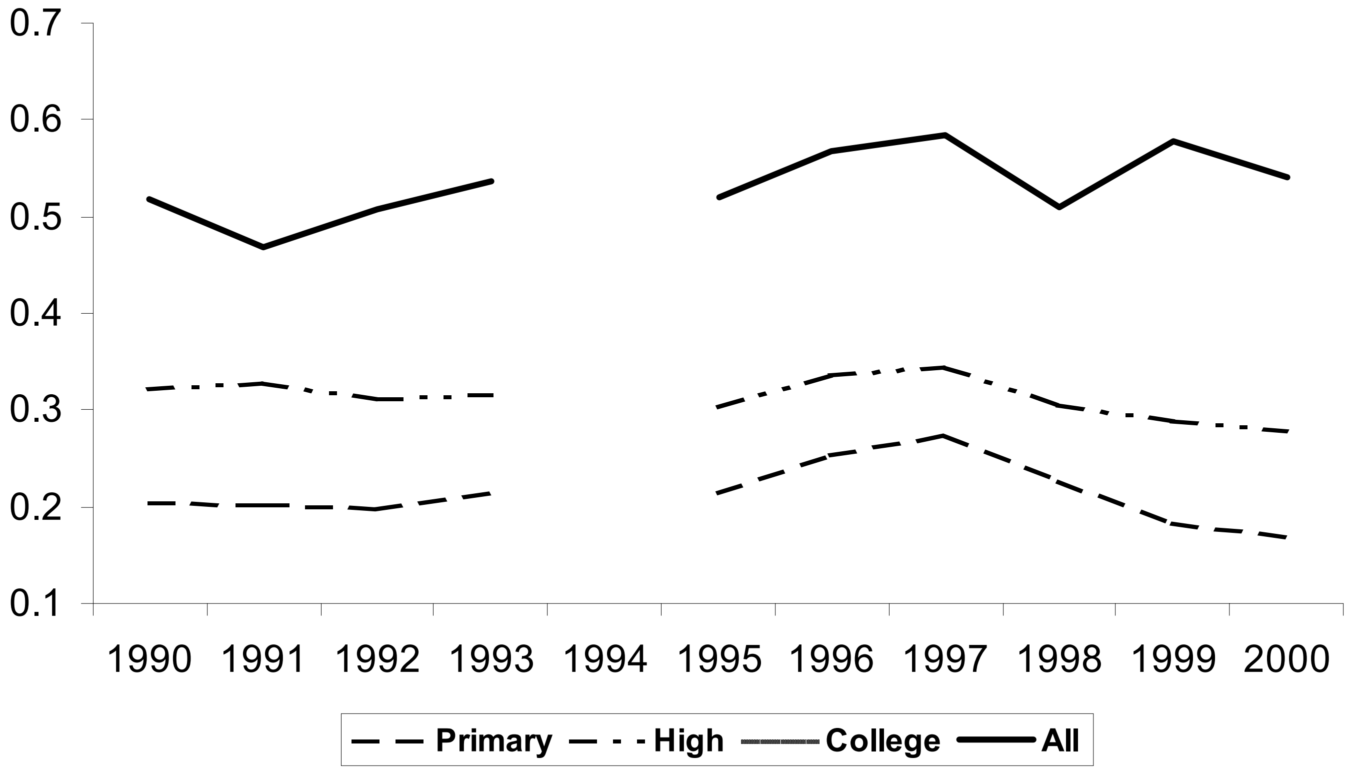

Figure 4. Mean Monthly Labor Income

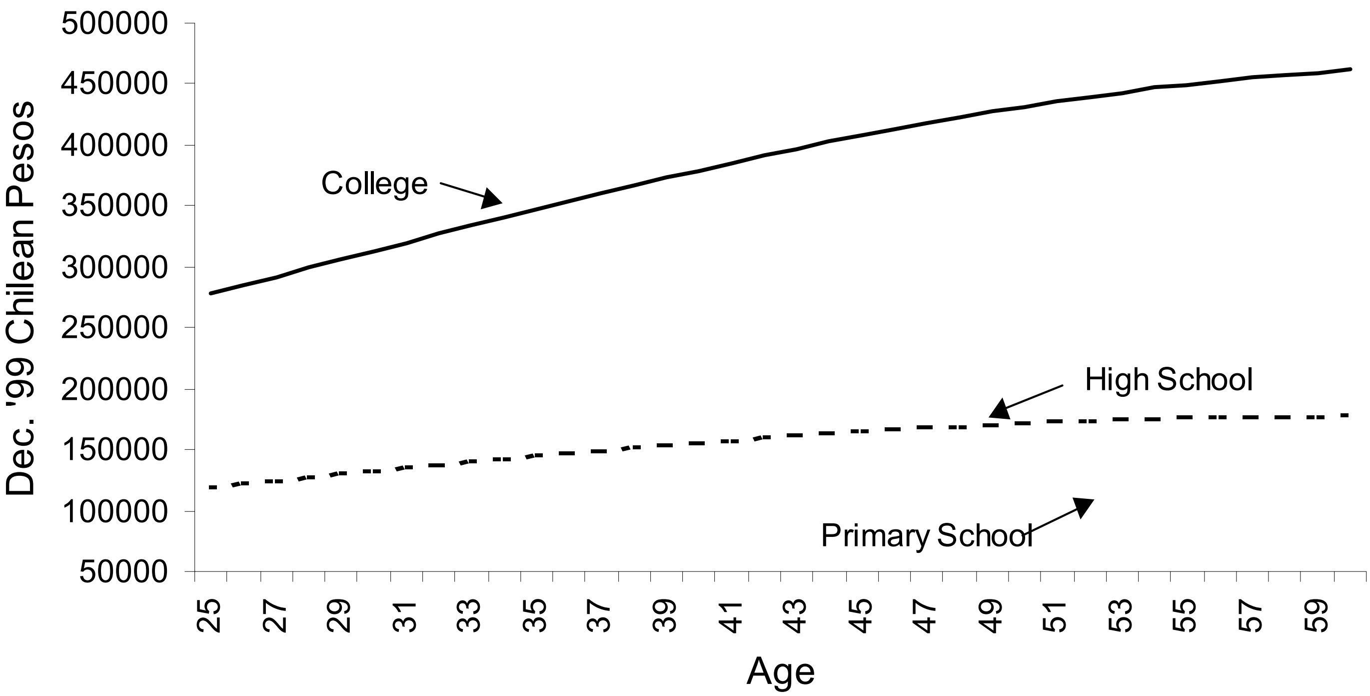

Figure 5. Residual Variance Across Cohorts
ESI 1990-2000

Figure 6. Residual Variance Across Cohorts
PSID 1988-1997

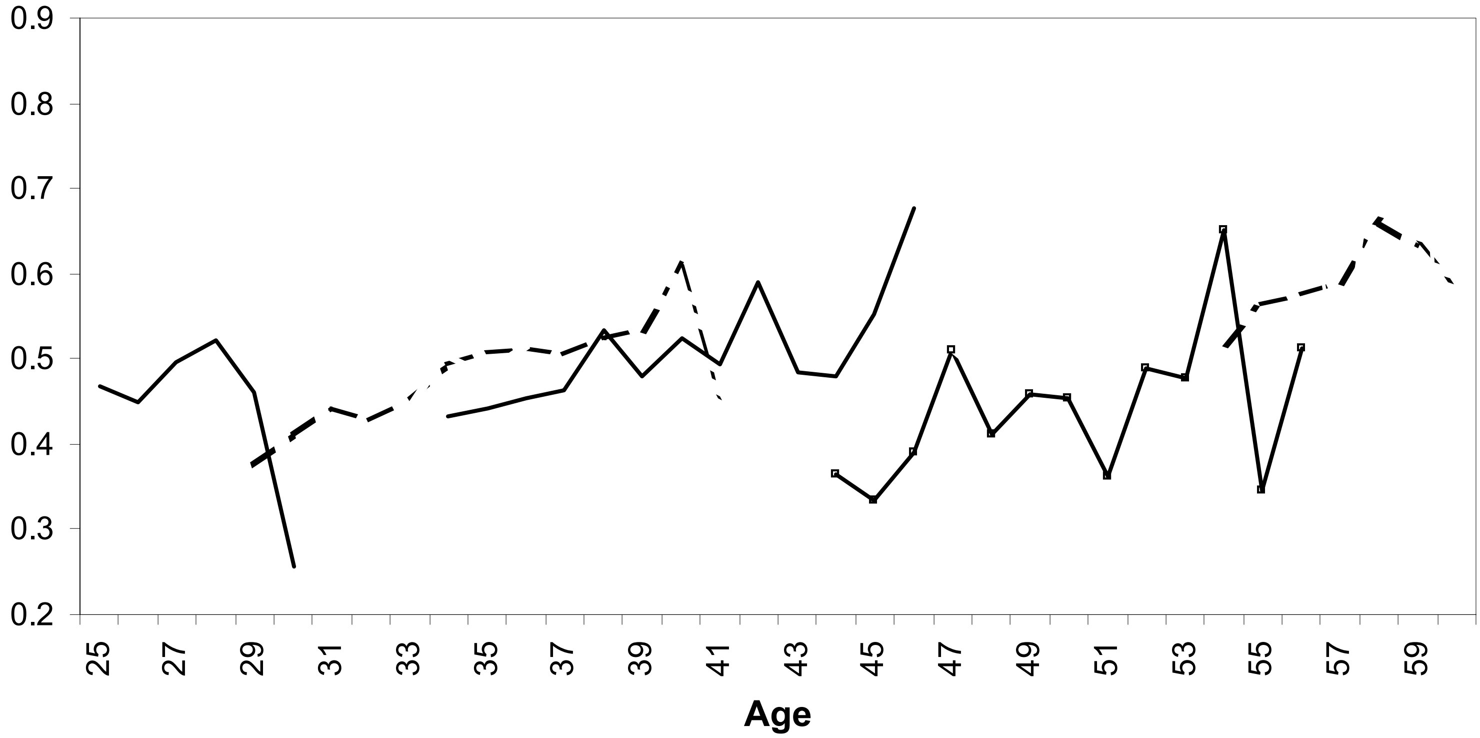

Figure 7. Income Mobility and Lifetime Persistence Third Quintile

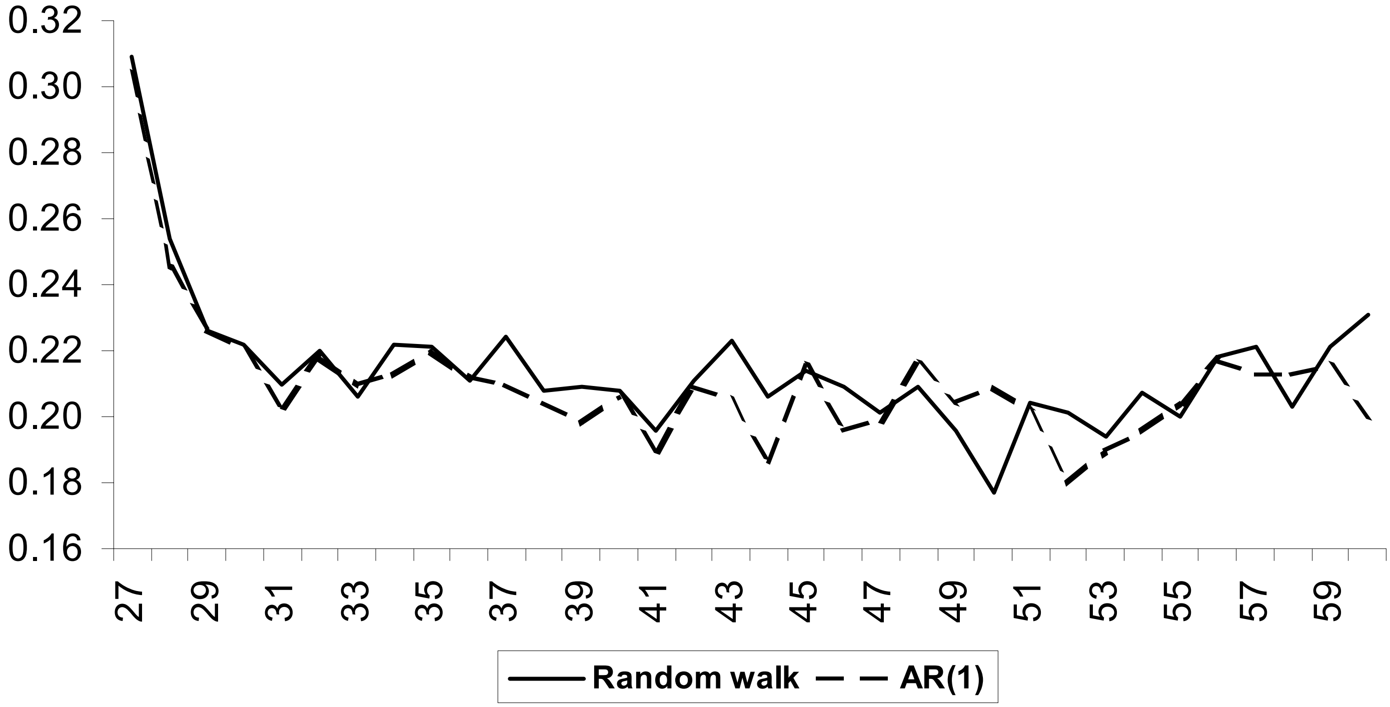

Figure 8. Income Mobility and Lifetime Persistence
Lowest Quintile