The Dynamics of Earnings in Chile

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Uncertainty is a key dimension of individual decisionmaking. Individuals cannot insure against certain contingencies under incomplete markets. 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. Individuals who are identical ex ante 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 on the dynamics of earnings, health outcomes, investment opportunities, and general 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, 2004). Our data are drawn from a survey of Chilean households—namely, the *Encuesta Suplementaria de Ingresos* (ESI) carried out by the National Institute of Statistics (INE) (see INE, various years). Whether consumers in an emerging economy face levels of uncertainty similar to those in developed economies is an empirical matter that is

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addressed in this paper. The welfare consequences of uncertainty may be much larger than our findings indicate, however: individuals operating in underdeveloped markets have fewer opportunities than their counterparts in developed countries to share risks through the marketplace, and the public welfare system is much smaller in developing countries, offering little possibility of offsetting negative shocks.

Our modeling structure allows us to distinguish between a predictable and an unpredictable component of income. We further 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 disturbances, and we evaluate whether they correlate with the business cycle. Since the ESI data set is a repeated cross-section, we construct synthetic panels to perform our estimations. Our synthetic panels contain annual observations from 1990–2000, based on five-year birth cohorts.

Our results for men between the ages of twenty-five and sixty indicate that the age profile of labor income has the typical hump shape and that there are very large educational effects. At age fifty, a college-educated individual expects to earn 2.5 times the earnings of a person who finished high school and 3.8 times the earnings of an individual who only completed eight 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 a high persistence but low variance of permanent shocks, together with a negligible variance of the transitory shock. These low variances may be an artifact of our synthetic panel technique, since averaging reduces the observed variability. We investigate this hypothesis by comparing our results to those obtained using U.S. data from the Panel Study of Income Dynamics (PSID) (see SRC, various years). When we replicate our cohort estimation procedure with U.S. data, we find a similar process for the dynamics of income, but the variance of earnings is significantly higher in the United States than in Chile. We interpret this as evidence of the relative rigidity of the Chilean labor market vis-à-vis the U.S. labor market. Another result is that averaging within cohorts reduces the estimated variance of the permanent shock by one order of magnitude. We cannot provide an estimate of the variance of the transitory shock, as all our benchmark estimates turn out to be insignificant.

If markets are complete, individuals can perfectly share their good and bad fortunes. The measurement of individual uncertainty then becomes irrelevant. However, vast evidence shows that in practice, many important events are not insured and 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 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 income process, although earned income has a negative effect on the likelihood that any given individual receives a transfer.

The paper also provides a number of applications. We analyze income inequality and earnings mobility simulating the life-cycle income profiles of individuals who face the process we have estimated. Since income is estimated to be highly persistent, we should expect to observe little mobility of individuals across the distribution of income. 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 still be 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 income distribution 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. The next section describes the data and compares the ESI to the *Encuesta de Caracterización Socioeconómica Nacional* (or CASEN survey), which is the most widely used survey for the analysis of Chilean household behavior (see MIDEPLAN, various years). Section 2 then presents the model and estimation techniques. In section 3, we provide our estimates of mean income and then use the unexplained portion of income to fit different dynamic processes. We also compare the results on Chile to a similar sample of U.S. workers. Section 4 provides a number of applications of our results, and section 5 concludes.

1. Data

The data used in this paper are drawn from the *Encuesta Suplementaria de Ingresos* (ESI), which 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 fifteen years old. Data are registered on all types of income perceived during the previous month, as well as on a number of individual characteristics such as educational attainment, marital status, gender, and employment status. Population weights are also provided. Data are available for the 1990–2000 period, with the exception of 1994 when the survey was not conducted. The use of the ESI as a source of income data has been fairly limited; one exception is Granados (2001).

Our analysis considers men between the ages of twenty-five and sixty who are not self-employed. We deflate all nominal variables using the consumer price index (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 170,000 pesos each month. The median is just above 100,000 pesos, reflecting the skewness of the Chilean income distribution. About 17 percent of individuals report income below the monthly minimum wage. The typical individual in the sample is thirty-eight years old, married, and has completed nine years of education (corresponding to an education level of one year of high school).

Table 1. Sample Descriptive Statistics: ESI

Variable	*Mean*	*Standard deviation*	*Minimum*	*Maximum*	*Median*
Monthly labor income[a]	168,534	191,520	6	4,189,475	107,729
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
Geographical location (fraction)					
Metropolitan Region	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: ESI survey data (INE, 1990–2000).
a. In December 1999 Chilean pesos.

Finally, the median household has four 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 is analyzed extensively elsewhere. The figure also shows the distribution of income in the 1996 CASEN (taken from Baytelman, Cowan, and De Gregorio, 1999).[1] These two distributions are not directly comparable, as the CASEN figures include transfers and represent different sample years.[2] Furthermore, the ESI distribution is built from our data set on men. Even so, 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: the ratio of the income share of the 20 percent of individuals with the highest income to the share of the bottom 20 percent is 7.9 in the ESI versus 13.8 in the CASEN, while the ratio of the share of the highest decile to the share of the lowest decile is 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 percent in the period 1990–2000.[3] The figure breaks the sample down by educational attainment: individuals identified as having a primary education have completed eight years of schooling; those with a high school education have completed twelve years of schooling; and those with a college education have completed seventeen years of education.[4] In all cases the path of mean earnings is

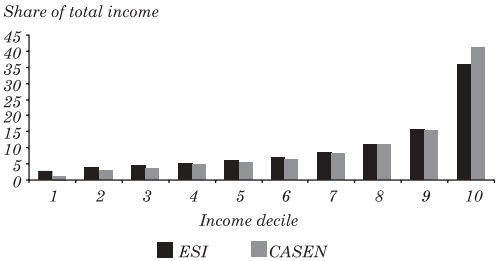
1. The CASEN is the most widely used survey for the analysis of Chilean household and individual income and earnings. The survey began in 1985, and it has been carried out almost every two years since then. The CASEN measures household and individual income for a representative sample of the Chilean population; it sampled 48,107 households in 1998. Like the ESI, the survey gathers information on all types of income and on a number of demographic characteristics. It also collects information on in-kind transfers, such as public programs in education, housing, and health, and on housing and durable goods ownership. This type of information supports detailed studies of poverty, and the survey has mainly been used to examine income inequality and the role of social policies in reducing it (Anríquez, Cowan, and De Gregorio, 1998; Larrañaga, 1994; Contreras and others, 2001). 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. The appendix provides a formal demonstration of this point.

2. Nevertheless, the distribution of income has hardly changed over the last decade. See Baytelman, Cowan, and De Gregorio (1999).

3. Per capita gross domestic product (GDP) grew at about 5 percent over this period.

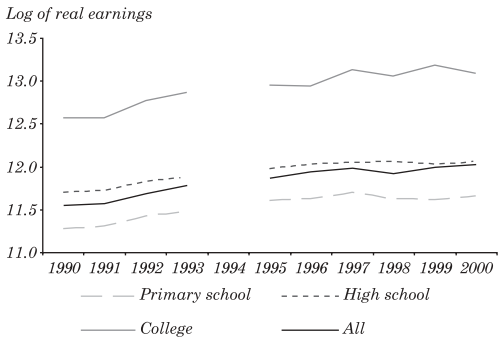
4. Universities in Chile simultaneously grant a college degree and a professional title. Most programs last about five years.

Figure 1. Distribution of Labor Income: ESI versus CASEN



Source: Authors' calculations, based on ESI and CASEN survey data (INE, 1990–2000; Baytelman, Cowan, and De Gregorio, 1999).

Figure 2. Mean of Log Real Earnings



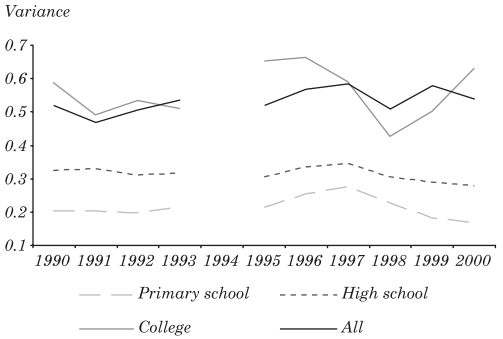
Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

upwardly trended, although the annual growth rates correlate positively with educational attainment. Chile, like other countries, has thus experienced a widening of the earnings distribution.[5]

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; that is, 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

5. For U.S. 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 (2002).

Figure 3. Variance of Log Real Earnings



Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

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 the ESI survey represents cross-sections of households, we build synthetic panels based on five-year birth cohorts. Table 2 presents the number of observations available for each cohort and year.

2. 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.[6] Income consists of the sum of a predictable component and a stochastic component. Let y_{it} represent the logarithm of the real measured income of individual i in year t. Let $\mathbf{Z}_{it}$ represent a vector of demographic characteristics, and η_{it} the stochastic component of income. We assume that the unexplained component can be decomposed into a permanent shock, y_{it}^{p} (such as health shocks that affect earnings capacity in a long-lasting way and

6. Recent literature modeling earnings processes allows for heterogeneity between agents. See Alvarez, Browning, and Ejrnæs (2002).

Table 2. Number of Available Observations by Cohort and Year

	Year										
Cohort[a]	*1990*	*1991*	*1992*	*1993*	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*	*Total*
56–60	808	652	503	323	0	0	0	0	0	0	2,286
51–55	1,226	1,186	1,071	979	843	589	451	312	148	0	6,805
46–50	1,642	1,640	1,524	1,492	1,179	1,181	1,167	983	958	972	12,738
41–45	2,045	2,032	1,945	1,832	1,615	1,607	1,617	1,545	1,478	1,437	17,153
36–40	2,471	2,370	2,346	2,215	1,994	2,274	1,881	1,782	1,697	1,860	20,890
31–35	3,054	2,952	2,745	2,680	2,620	2,436	2,640	2,462	2,404	2,435	26,428
26–30	3,520	3,370	3,134	3,091	2,767	2,950	2,847	2,819	2,783	3,030	30,311
21–25	702	1,333	1,955	2,671	2,928	3,004	2,849	2,729	2,715	2,818	23,704
16–20	0	0	0	0	573	1,101	1,691	2,114	2,530	2,873	10,882
Total	15,468	15,535	15,223	15,283	14,519	15,142	15,143	14,746	14,713	15,425	151,197

Source: ESI survey data (INE, 1990–2000).
a. Age in 1990.

long-term unemployment), and a transitory innovation, μ_{it} (such as bonuses and overtime pay). We also allow for classical measurement error, ω_{it}. Finally, we assume that y^p and μ_{it} are uncorrelated at all leads and lags. We thus propose the following model for individual income:

$$y_{it} = \mathbf{Z}_{it}\beta + \eta_{it} \text{ and}$$

$$y_{it} = \mathbf{Z}_{it}\beta + y_{it}^p + \mu_{it} + \omega_{it} \ .$$

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

$$y_{it}^p = y_{it-1}^p + \upsilon_{it} \text{ and}$$

$$\mu_{it} = \varepsilon_{it} - \theta\,\varepsilon_{it-1} \ .$$

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 in which permanent shocks follow a first-order autoregressive, or AR(1), process whereas the transitory component is independent and identically distributed (i.i.d.); that is,

$$y_{it}^p = \rho y_{it-1}^p + \upsilon_{it} \text{ , for } 0 < \eta < 1, \text{ and}$$

$$\mu_{it} = \varepsilon_{it} \ .$$

We estimate our complete model in two stages. In the first stage, we use individual-level data to estimate η and to compute

$$\hat{\eta} = y - \mathbf{Z}\hat{\beta}$$

for each observation in our sample. In the second stage, we classify all observations on the basis of the year of birth and take averages of $\hat{\eta}$ to build a synthetic panel of cohort/year means.[7] That is,

7. We use the survey's population weights to build the means.

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

where the superscript c indexes birth-year cohorts and n_t^c 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 modeling structure allows for time-varying variances. We estimate these parameters using equally weighted generalized method of moments (GMM) by minimizing the distance between the theoretical and the empirical autocovariances of the first difference of the stochastic component of income.[8]

Assume that there is no measurement error and that the dynamics of earnings are characterized by a random walk plus a first-order moving average, or MA(1), transitory shock.[9] Then,

$$\Delta \eta_{it} = \eta_{it} - \eta_{it-1} = \upsilon_{it} + \varepsilon_{it} - (\theta + 1)\varepsilon_{it-1} + \theta\varepsilon_{it-2} .$$

The theoretical autocovariances are thus given by

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

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

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

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

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

$\mathrm{cov}(\Delta\eta_{it}, \Delta\eta_{it-j}) = 0$, for $j > 2$, and

$\mathrm{cov}(\Delta\eta_{it}, \Delta\eta_{it+j}) = 0$, for $j > 2$.

8. See Altonji and Segal (1996) for an analysis of alternative weighting procedures.

9. In our procedure, we assume that measurement error cancels out when we collapse our individual data set into cohort means. We thus ignore measurement error in what follows.

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. We thus expect to underestimate the true uncertainty level that individuals face in Chile. In the analysis below, we provide estimates from a comparable sample taken from U.S. data to show how much the estimated process changes when we follow cohorts instead of individuals.

3. Results

We report our first-stage estimation results in table 3. In the regression, we control for age, education, marital status, and household size, as well as for interaction terms and nonlinear effects of these variables. We also control for the region of residence and the 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 identified above. All the other variables have been set at their average sample levels. The magnitude of the educational effect becomes evident when we consider three individuals who are identical except for their level of schooling. At age twenty-five, an individual who has completed eight years of schooling earns,

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

Explanatory variable	*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	

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).
a. The dependent variable is the log of monthly labor income. The regressions include a full set of dummies for the year and month of the interview and the region of residence.

on average, about 85,000 pesos per month, whereas an individual with twelve years of education earns almost 120,000 pesos per month—that is, a difference of 40 percent. A college-educated individual earns, on average, about 280,000 pesos at age twenty-five, or 2.3 times the earnings of a high-school-educated individual. These differences increase with age. At age fifty, a college-educated individual earns 2.5 times the earnings of a person who finished high school and 3.8 times the earnings of an individual who only completed eight years of schooling. These differences widen further when we take into account the findings that education and household size are negatively related and that household size has a negative impact on earnings. Educated people are less likely to be married than individuals with incomplete schooling, but this correlation is quite small in the sample.

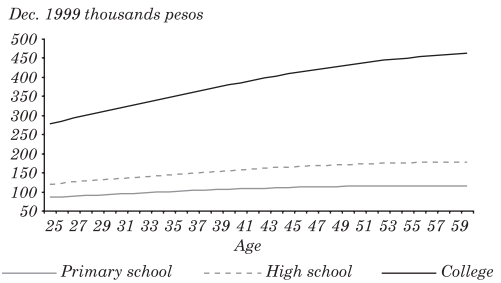
3.1 The Dynamics of Income

Since we do not follow the same individuals over time, we estimate the income process using a synthetic panel approach. For each individual in the sample, we take the unexplained component of the log of income as

$$\hat{\eta} = y - \mathbf{Z}\,\hat{\beta}\,.$$

We then classify all observations according to birth cohort to form our synthetic panel. Figure 5 tracks the variance of the unexplained portion of earnings within each cohort observed from 1990 through 2000. The variance clearly increases with age, which reflects the fact that individuals who are identical ex ante may follow quite different paths of income. In other words, in a sample of ex ante identical

Figure 4. Mean Monthly Labor Income



Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

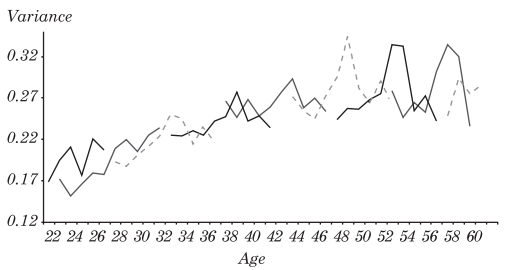
agents, income inequality increases over time whenever there is a permanent component in uncertainty. If all shocks were i.i.d., the distribution of income would be age independent. Furthermore, individuals actually start off at very different levels, as the initial variance is quite high.

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 individuals born in different years should not expect different levels of uncertainty at a given age. For all cohorts, the variance tends to 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.

Table 4 displays the sample autocovariance matrix of the residual of log income changes. The upper right triangle shows the covariances; the lower left triangle 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 modeled as an MA(1) process.

Our benchmark estimates are reported in table 5, where we define income as annual individual earnings (without government transfers). Three cases are analyzed depending on 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) process. In all cases, the transitory component is not significant at the 5 percent 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 negligible

Figure 5. Residual Variance across Cohorts: ESI, 1990–2000[a]



Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).
a. The nine cohorts are defined by their age in 1990; from left to right, they are sixteen to twenty years of age; twenty-one to twenty-five years of age; twenty-six to thirty years of age; thirty-one to thirty-five years of age; thirty-six to forty years of age; forty-one to forty-five years of age; forty-six to fifty years of age; fifty-one to fifty-five years of age; and fifty-six to sixty years of age.

Table 4. Covariance Matrix of Log Income Changes: ESI[a]

Year	*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	0.00053	–0.000029
1992	0.70860	0.00005	–0.00004	–0.00007	–0.00002	0.00004	0.00001	0.00003
	(0.0491)							
1993	–0.54160	–0.87000	0.00022	–0.00019	–0.00009	0.00027	–0.00011	–0.00006
	(0.1656)	(0.005)						
1996	–0.07240	–0.53340	–0.03530	0.00042	0.00010	–0.00041	0.00011	–0.00001
	(0.8774)	(0.2175)	(0.9402)					
1997	0.2951	–0.27810	0.41300	0.32160	0.00017	–0.00019	–0.00004	0.00011
	(0.5205)	(0.5459)	(0.3571)	(0.4373)				
1998	–0.10130	0.31320	0.23720	–0.86830	–0.55230	0.00050	–0.00014	–0.00003
	(0.8289)	(0.4939)	(0.6086)	(0.0052)	(0.1558)			
1999	0.28160	0.13170	–0.53580	0.21680	–0.34050	–0.33580	0.00019	–0.00015
	(0.5406)	(0.7784)	(0.2152)	(0.6061)	(0.4091)	(0.4162)		
2000	–0.19110	0.26450	–0.23820	–0.11660	0.49230	–0.01620	–0.59620	0.00032
	(0.7169)	(0.6124)	(0.6494)	(0.8033)	(0.2617)	(0.9725)	(0.1577)	

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).
a. Correlations are below the diagonal; covariances are above the diagonal. Statistical significance is in parentheses.

when we average within cohorts. In other words, the transitory component is 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, but it is an order of magnitude smaller than the variance estimated by several authors using a panel of individual U.S. data from panel sets such as the PSID.[10] This large difference can also be explained by the fact that we track cohorts and not individuals over time.[11] We further investigate this hypothesis below.

Table 5 also estimates the dynamics of Chilean earnings using labor income plus government transfers. This exercise identifies the extent to which the government provides insurance through its monetary

10. See Meghir and Pistaferri (2004) for the most recent results.

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

Table 5. The Dynamic Process of Labor Income: ESI[a]

Definition of income and income process[b]	*Permanent component*		*Transitory component*	
	Variance	*Autocorrelation*	*Variance*	*MA(1) coefficient*
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)		(0.00264)	
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)	

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).
a. Standard errors are in parentheses.
b. Income is defined as annual individual earnings, with and without government transfers. The assumed income processes vary depending on 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) process.

transfers. A number of papers analyze the role of government transfers in alleviating poverty and reducing income inequality in Chile (Baytelman, Cowan, and De Gregorio, 1999; Engel, Galetovic, and Raddatz, 1999). We analyze whether public transfers reduce the uncertainty faced by individuals.

The estimated income 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.[12] However, a probit regression of a dummy indicating whether the individual received a positive transfer on the level of real earnings, as well as year, month, and regional dummies, yields a highly significant negative effect of

12. Only about 1.5 percent 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, which may lead individuals to incorrectly report transfers as part of their labor earnings.

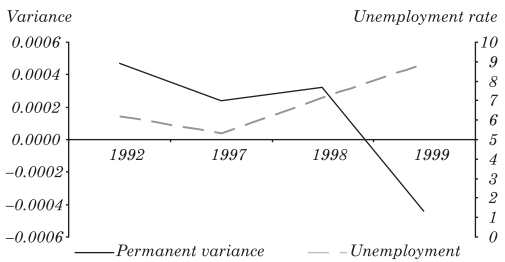
perceived income on the probability of receiving a transfer. Hence, public transfers do play a limited redistributive role in our sample.[13]

We have thus far restricted the variances of the shocks to be constant over time, although our modeling structure allows for time-varying variances. Following Meghir and Pistaferri (2004), we can identify the evolution of the variance of the permanent shock using the following moment condition:

$$E\left[\Delta\eta_t^c\left(\sum_{j=-(1+q)}^{(1+q)}\Delta\eta_{t+j}^c\right)\right]=E\left(\sigma_{\upsilon t}\right),$$

where c indexes cohorts, t indexes years, and q is the order of the MA (transitory) component. Figure 6 plots the estimated evolution of the variance of the permanent component, along with the unemployment rate. Unfortunately, our sample is short and was interrupted in 1994, so we are only able to estimate the variance for 1992, 1997, 1998, and 1999. Except for 1999, the unemployment rate and permanent variance behave in a synchronized manner. Our point estimate of the 1999 variance is negative, but not statistically significant. Our results thus show that income uncertainty correlates with the business cycle.

Figure 6. Variance of Permanent Shock and Unemployment



Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

13. The marginal effect is $-2.08 \bullet 10^{-8}$, so each additional 200,000 pesos of income (about one standard deviation in the sample) reduces the chance of receiving a public transfer by 0.42 percentage points.

3.2 Synthetic Cohorts and Variance Underestimation: Comparing Chile and the United States

To further investigate the hypothesis that cohort averaging leads to a large underestimation of the variances, we study whether our estimation process leads to similar results when we use data from the United States. Specifically, we compare our results to those obtained from a comparable sample taken from U.S. data, using a synthetic panel and individual-level data. Our source of information is the Panel Study of Income Dynamics (PSID), which is a representative longitudinal survey of nearly 8,000 households. The PSID started collecting data on individuals and households in 1968, and it 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 U.S. data replicates the analysis of Chilean data. We first restrict our samples to men between the ages of twenty-five and sixty. We deflate wage income by the consumer price index for all urban consumers (CPI-U) and then estimate the predictable component of labor income using the same variables and functional form reported for Chile in the previous subsection. We 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.

Table 6. Sample Descriptive Statistics: PSID

Variable	*Mean*	*Standard deviation*	*Minimum*	*Maximum*	*Median*
Annual labor income[a]	39,714	40,119	1,076	1,274,859	32,617
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	0.8	0.4	0	1	1

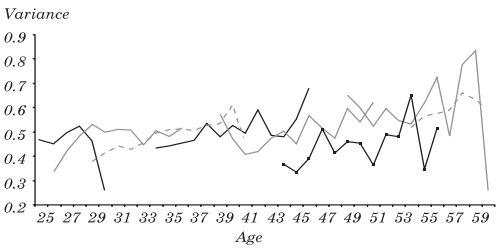
Source: PSID survey data (SRC, 1988–97).
a. In 1996 U.S. dollars.

Figure 7 plots the behavior of the U.S. within-cohort residual variance over the sample period. 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 U.S. profiles. First, the variance is quite flat over most of the life-cycle in the United States, whereas it increases with age in Chile. Second, the variance is much larger in the United States 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, as income is measured in logs.[14]

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 U.S. labor market. As shown by Bertola and Ichino (1995), wage inequality is reduced in markets where workers move across firms, occupations, and regions in response to productivity and demand shocks. Wage dispersion differences may thus reflect different labor market institutions, labor reallocation costs, and wage contract structures.

Alternatively, once we allow for the endogeneity of earnings, a pos-

Figure 7. Residual Variance across Cohorts: PSID, 1988–97[a]



Source: Authors' calculations, based on PSID survey data (SRC, 1988–97).
a. The eight cohorts are defined by their age in 1988; from left to right, they are nineteen to twenty-four years of age; twenty-five to twenty-nine years of age; thirty to thirty-four years of age; thirty-five to thirty-nine years of age; forty to forty-four years of age; forty-five to forty-nine years of age; fifty to fifty-four years of age; and fifty-five to sixty years of age.

14. Survey methodologies and the extent of measurement error might partly explain these differences. However, the U.S. variance of log real earnings is higher than the Chilean variance even before conditioning on worker characteristics. Furthermore, the R^2 of the regression is much higher for the Chilean data than for the U.S. data, so a larger portion of total income variability in Chile is explained by the predictable part of earnings. Both facts are consistent with the notion that Chilean workers face much less income uncertainty than do their American counterparts. We obtained similar results using the 1990–2000 Current Population Survey (CPS); these results are available on request.

sible explanation is that U.S. 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 given their better-developed markets. Furthermore, the public welfare system is much larger in the United States than in Chile, and female labor force participation is much higher. Both of these circumstances provide insurance against negative shocks. Therefore, our results are consistent with the hypothesis that workers in the United States can afford to take more risks than workers in Chile, and they thus choose riskier occupations and jobs.

The gap between the variance in Chile and the United States is reduced as individuals age. This fact might also have an institutional explanation: minimum wage laws might have a larger effect on young workers in Chile than in the United States. Indeed, the Chilean real minimum wage rose 72 percent over the sample years, whereas the U.S. real minimum wage rose only 18 percent.

In table 7 we estimate the dynamics of income using the information on U.S. workers, assuming the process is described by a random walk plus an i.i.d. transitory disturbance. For comparison, the table repeats the results obtained using the ESI and then presents the results using synthetic cohorts from the PSID. As with the Chilean case, we find

Table 7. The Dynamic Process of Labor Income: Chile and the United States[a]

Data source and level of aggregation	*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)

Source: Authors' calculations, based on ESI and PSID survey data (INE, 1990–2000; SRC, 1988–97).
a. The simulations assume a random walk plus an i.i.d. transitory disturbance. Standard errors are in parentheses.

that the process can be described solely by a random walk, as the transitory shock averages out in the aggregate. Moreover, the variance of the permanent shock is much larger in the United States than in Chile,

which confirms the results in figures 5 and 7.[15]

Finally, 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 variance estimated using cohort data. We also find a significant variance of the transitory shock.[16] Our results are consistent with other analyses. For instance, Meghir and Pistaferri (2004) 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 0.008 and 0.03.[17]

If we extrapolate the information in the PSID exercises to the Chilean case, the variance of the permanent shock is one order of magnitude larger than the variance estimated using the panel of cohorts, that is, about 0.0209. The variance of the transitory shock is also likely to be 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 to illustrate these points. We first simulate life-cycle paths of income using our estimated processes. We then use the simulated outcomes to build income distributions and estimate the likelihood that an individual will move along the income distribution.

4. 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. The first set estimates transition matrices—the conditional probability that an individual will move along the income distribu-

15. The qualitative results are similar if we assume either an AR(1) plus an i.i.d. shock or a random walk plus an MA(1) shock.

16. Since we estimated the processes using a nonlinear 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.

17. Meghir and Pistaferri (2004) 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.

tion—that results from the estimated persistence of the dynamics of income. The second set of exercises estimates the distribution of income that results from the estimated variances.

To compute the transition matrices and the income distributions, we first generate 5,000 lifetime income streams based on our estimates. We assume a life-cycle of thirty-five years (ages twenty-five through sixty) and set the parameters of the model equal to the values estimated in table 5. We assume all individuals are identical at age twenty-five. 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 earnings mobility is very limited. 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, but the persistence is still quite high. Table 9 shows the simulated ten-year transition matrices (that is, 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, mobility is rather limited even over a ten-year horizon. Figures 8 and 9 show the chance that an individual at any given point in life will be at the third and lowest quintiles, respectively, under the two alterna-

Table 8. Simulated Income Mobility: One-year Transition Matrix, ESI[a]

Income process and income quintile in period t	*Income quintile in t + 1*				
	1	*2*	*3*	*4*	*5*
Random walk					
Quintile 1	0.84	0.14	0.01	0.00	0.00
Quintile 2	0.14	0.65	0.19	0.02	0.00
Quintile 3	0.01	0.19	0.60	0.18	0.01
Quintile 4	0.00	0.02	0.19	0.65	0.15
Quintile 5	0.00	0.00	0.01	0.15	0.84
AR(1)					
Quintile 1	0.77	0.20	0.03	0.00	0.00
Quintile 2	0.20	0.50	0.25	0.05	0.00
Quintile 3	0.03	0.25	0.45	0.25	0.03
Quintile 4	0.00	0.05	0.25	0.50	0.20
Quintile 5	0.00	0.00	0.03	0.20	0.76

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).
a. The simulations assume a random walk and an AR(1) process with first-order autocorrelation coefficient equal to 0.93095.

Table 9. Simulated Income Mobility: Ten-year Transition Matrix, ESI[a]

Income process and income quintile in period t	*Income quintile in t + 10*				
	1	*2*	*3*	*4*	*5*
Random walk					
Quintile 1	0.58	0.25	0.11	0.05	0.02
Quintile 2	0.25	0.32	0.24	0.13	0.05
Quintile 3	0.11	0.24	0.29	0.24	0.11
Quintile 4	0.04	0.14	0.24	0.32	0.26
Quintile 5	0.01	0.05	0.12	0.25	0.56
AR(1)					
Quintile 1	0.40	0.24	0.18	0.12	0.06
Quintile 2	0.25	0.24	0.21	0.18	0.12
Quintile 3	0.18	0.22	0.22	0.21	0.18
Quintile 4	0.12	0.18	0.21	0.24	0.25
Quintile 5	0.06	0.12	0.18	0.25	0.39

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).
a. The simulations assume a random walk and an AR(1) process with first-order autocorrelation coefficient equal to 0.93095.

Figure 8. Income Mobility and Lifetime Persistence: Third Quintile

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

Figure 9. Income Mobility and Lifetime Persistence: Lowest Quintile

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

tive levels of persistence. 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 percent of individuals at age thirty receive a share of income that is 1.41 times the share of the poorest 20 percent, assuming our uncorrected benchmark estimates. This ratio increases to 2.48 when 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

Table 10. Simulated Income Distributions

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

Source: Authors' calculations, based on ESI survey data (INE, 1990–2000).

assumption that all individuals start off with the same characteristics. In particular, we assume the same educational attainment across workers. As discussed earlier, 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.

5. Concluding Remarks

In this paper, we have estimated the dynamic process of individual income using the *Encuesta Suplementaria de Ingresos*. We found the income process to be characterized by high persistence but low variability. We also showed that the low variance is an artifact of our cohort technique. Using data for U.S. workers, we 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. Different organizations in Chile have collected rich panel data sets that follow workers over long periods of time and on a monthly basis. Unfortunately, these data sets currently are not publicly available.

APPENDIX
Estimating Dynamics Using the CASEN Data

Most of the existing analyses of Chilean household income are based on data from the CASEN survey. Unfortunately, the CASEN only gathers information every other year. Based on the ESI, our results show that the dynamics of earnings is highly persistent. The CASEN thus misses most of the action in the two-year lag. We formally show in this appendix that it is not possible to estimate our income processes using this survey.

Our benchmark model assumes that the stochastic component of income can be decomposed into permanent and transitory shocks:

$$\eta_{it} = y_{it}^{p} + \mu_{it} + \omega_{it} \ .$$

If the permanent shock follows a random walk and the transitory shock follows an MA(1) process, then

$$y_{it}^{p} = y_{it-1}^{p} + \upsilon_{it} \text{ and}$$

$$\mu_{it} = \varepsilon_{it} - \theta\varepsilon_{it-1} \ .$$

We identify the model's parameters using GMM by matching population and sample moments. To use the CASEN, we would then need to match the covariances of second differences; that is,

$$\Delta_2\eta_{it} = \eta_{it} - \eta_{it-2} = \upsilon_{it} + \upsilon_{it-1} + \varepsilon_{it} - \theta\varepsilon_{it-1} - \varepsilon_{it-2} + \theta\varepsilon_{it-3} \ .$$

The relevant population moments are thus as follows:

$$\text{var}\left(\Delta_2\eta_{it}\right) = \sigma_{\upsilon t} + \sigma_{\upsilon t-1} + \sigma_{\varepsilon t} + \theta^2\sigma_{\varepsilon t-1} + \sigma_{\varepsilon t-2} + \theta^2\sigma_{\varepsilon t-3} \ ,$$

$$\text{cov}\left(\Delta_2\eta_{it}, \Delta_2\eta_{it-2}\right) = -\sigma_{\varepsilon t-2} - \theta^2\sigma_{\varepsilon t-3} \ , \text{ and}$$

$$\text{cov}\left(\Delta_2\eta_{it}, \Delta_2\eta_{it-j}\right) = 0 \text{, for } j \geq 4 \ .$$

Assume that variances are time independent. The identification conditions then reduce to

$$\text{var}\left(\Delta_2\eta_{it}\right) = 2\sigma_{\upsilon} + 2\left(1+\theta^2\right)\sigma_{\varepsilon} \ ,$$

$\text{cov}\left(\Delta_2\eta_{it}, \Delta_2\eta_{it-2}\right) = -\left(1+\theta^2\right)\sigma_\varepsilon$, and

$\text{cov}\left(\Delta_2\eta_{it}, \Delta_2\eta_{it-j}\right) = 0$, or $j \geq 4$.

This model does not have a unique solution: only the first two equations provide useful information, but there are three unknown parameters to solve for. Thus, the CASEN does not have enough information to estimate the underlying parameters of our model.

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