The Educational Transition and Decreasing Wage Inequality in Chile

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Abstract

The wage of the 90th (richest) percentile of the wage distribution in Chile increased faster than the median wage and the wage of the 10th percentile between 1975 and 1990. By contrast, from 1990 onwards the wage of the 10th percentile and the median wage grew faster than the 90th percentile. This is one of many findings showing that wage inequality in Chile has been falling, first slowly, then faster, over the last two decades. This pattern emerges clearest once cyclical components of wage inequality measures are removed.

To understand the driving forces behind the decrease in wage inequality, we group workers according to their cohort and educational attainment, and decompose the variance of log-wages into the sum of the within- and between-group variances. We find that the significant decrease in inequality observed since the mid 1990s is due mainly to a decrease in the between-group variance. We present evidence suggesting that this decrease was due to a secular decrease of the skill premium for tertiary education that resulted from the deregulation of this market in 1980. Somewhat surprisingly, the marked decrease in the skill premium can be found in the data one decade earlier, yet the corresponding decrease in wage inequality was canceled by a Kuznets-type effect, where an increasing but still small fraction of workers with tertiary education led to more inequality, during the 1985–1995 period.

Keywords: Skill premium, educational transition, Kuznets effect, Tinbergen effect, between- and within-group standard deviation and variance, cohort analysis, removing cyclical components.

JEL classification: I20, J21, J31.

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1 Introduction

The fraction of the population living under the poverty line in Chile fell from 45.1 to 13.7% between 1987 and 2006. This is an impressive achievement by any measure, probably related to Chile's high growth rates during this period. Yet while poverty decreased at a fast pace, income inequality remained pretty much unchanged: the Gini coefficient for autonomous incomes oscillated between 0.56 and 0.58 during most of this period, with a significant fall only in the most recent (2006) survey, when this inequality measure fell to 0.54.[2]

While, by most accounts, the military government that ruled Chile between 1973 and 1990 put little emphasis on improving the income distribution, this challenge was central in the electoral platform that brought to power in 1990, with the return of democracy, the coalition of political parties known as the Concertación (see Meller, 1996, for details). *"Crecimiento con equidad"* ("growth with equity") was Patricio Aylwin's slogan during the campaign that led to his election as president of the first Concertación government. Consistent with campaign promises, shortly after being inaugurated the Aylwin administration passed through Congress a significant tax increase aimed at financing new social programs. That income inequality remained unchanged during the decade that followed, despite this and other efforts, was puzzling to many and a major source of embarrassment and frustration for Concertación governments.[3]

This motivates our study of the dynamics of one of the main determinants of the distribution of income, the wage distribution, during the 1975–2006 period in Chile (Gran Santiago to be precise). We find that the wage of the 90th (richest) percentile of the wage distribution increased faster than the median wage and the wage of the 10th percentile between 1975 and 1990. By contrast, from 1990 onwards the wage of the 10th percentile and the median wage grew faster than the 90th percentile. This is one of many findings we present showing that wage inequality in Chile has been falling, first slowly, then faster, over the last two decades.

The pattern of decreasing wage inequality, which precedes the decrease in autonomous income inequality mentioned in the introductory paragraph by more than a decade, emerges clearest once cyclical components of wage inequality measures are removed. We first do this

[2]Source for poverty and inequality statistics: *Encuesta de Caracterización Socioeconómica* (CASEN). Planning Ministry (Mideplan).

[3]Engel, Galetovic and Raddatz (1997) point out that the attention given to income inequality in Chile may be overdone, since the income distribution improves significantly after taxes are collected and spent. For example, Mideplan reports, based on the 2006 CASEN survey, that the ratio of incomes for the richest and poorest quintile decreases from 13.1 when considering only autonomous income, to 7.1 after incorporating monetary subsidies and imputing the cost of health and education. Yet the public debate focuses mainly on the income distribution before applying redistributive measures ('autonomous income'), and many analysts argue that households value more goods and services they buy with their own means, all of which justifies focussing on the determinants of autonomous income, as we do in this paper.

using the Hodrick-Prescott (HP) filter, as is commonly done in macroeconomics.

The main part of the paper uses a more sophisticated approach to remove the cyclical component of the standard deviation of the log-wage distribution, based on modeling the mean and standard deviation of log-wages, for a given educational level (primary, secondary and tertiary), as a function of cohort, age and time. We use the estimated equations to decompose the variance of log-wages into the sum of the within- and between-group variances, finding that the significant decrease in inequality observed since the mid 1990s is due mainly to a decrease in the between-group variance. By contrast, the slight decrease in wage inequality between the mid 1980s and mid 1990s is due mainly to a slow decrease in within-group inequality.

To explain the role of the between-group variance in the reduction in wage inequality, we study the relation between this measure and the significant increase in workers with tertiary education that resulted from the deregulation of this segment of the education market in 1980. A series of legislative changes led to a major reduction in entry barriers for private suppliers, as long as they were politically acceptable to the government (Brunner, 2008). Over the decades that followed this led to a significant increase in tertiary enrolment, which more than tripled between 1989 and 2002.[4] This resulted in the share of workers with university education doubling between 1975 and 2005, reaching 25%. The major increase in supply of tertiary education that took place in 1980 was amplified by the fact that university enrollment had been falling during preceding years, by more than 30% between 1973 (the year universities in Chile were intervened by the military regime that came to power that year) and 1980.

When the increase in workers with tertiary education becomes apparent during the second half of the 1980s, initially the reduction in inequality due to the lower skill premium that resulted from higher supply (we call this the Tinbergen effect) was canceled by the increase in inequality associated with a larger (but still small) fraction of workers receiving this premium (the Kuznet's effect). The between-group variance therefore remained pretty much constant between 1987 and 1997. Yet from 1997 onward, the fraction of workers with tertiary education was sufficiently large for the supply effect on the skill premium to dominate, and the wage inequality decreased at a fast pace.

The remainder of the paper is organized as follows. Section 2 discusses the relation of this paper to the literature. Section 3 describes our data set —the Employment and Unemployment Survey (EUS) from the University of Chile— and provides a series of descriptive aggregate inequality statistics. We explore the effect of removing cyclical components from inequality measures using the HP filter in this section. Section 4 presents our estimation

[4]Source: Uribe (2004) and González (2000).

strategy which builds on Gosling, Machin and Meghir (2000). The paper's results are discussed in Section 5, which is followed by a conclusion and several appendices.

2 Relation to the Literature

There is a substantive literature explaining the evolution of the U.S. and U.K. wage distributions, see Katz and Murphy (1992), Juhn, Murphy and Pierce (1993) and Katz, Loveman, and Blanchflower (1995) for the U.S. and Gosling et al. (2000) for the U.K.

The methodology we use follows closely that developed in Gosling et al. (2000) to describe and explain wage inequality in the U.K. They estimate separate equations for the average log-wage and 13 quantiles of the wage distribution (the 5-th, the 25-th, the 75-th, the 95-th and the 9 deciles). as a smooth function of age and cohort. Separate equations are estimated for different educational groups (primary, secondary and tertiary) but years of schooling do not enter as explanatory variables for a given educational group. Identification is achieved by assuming additive time-effects that are independent from the age-cohort explanatory variables.[5] Time-effects can then be interpreted as a cyclical component.

Gossling et al. (2000) extract information about the location of the distribution from the median, and information about the dispersion of the distribution mostly through the standard deviation and its between- and within-group components, calculated from their 13 quantile equations. We take the short-cut of estimating directly an equation for the standard deviation, thereby avoiding the mean and 13 quantile equations. This equation, together with the mean equation, allows us to perform the same decompositions into between- and within-group standard deviations.

Our use of the standard deviation of log-wages as inequality measure may be controversial, since this measure does not satisfy the Dalton-Pigou principle (see Foster and Ok, 1999). Nonetheless, the standard deviation of log-wages (or log-consumption) has been used widely, both in the labor literature (see, for example, Juhn et al., 1993, and Katz and Murphy, 1992) and, more recently, in the macroeconomics literature studying the increase in wage inequality in the U.S. in recent decades (see, for example, Krueger and Perri, 2003 and 2006, Heathcote, Storesletten and Violante, 2005, and for an early and important example, Deaton and Paxson, 1994).

Regarding work on the income distribution in Chile during the period we consider here, Cowan and De Gregorio (1996) concluded that the early 1990s saw a clear improvements in

[5]See Deaton (1997) for an insightful exposition on the identification problem when the dynamics of a moment of the wage distribution (or the distribution of consumption or income) is explained via linear models with cohort, age and time as dependent variables.

social indicators, despite a history of high inequality. By contrast, Ruiz-Tagle (1999) argued that improvements in social indicators have been modest while agreeing that high inequality has been persistent. Also, Bravo and Contreras (2004) concluded that inequality measures changed little between 1990 and 1996, due to changes in the labor market and social policies that canceled each other. The same conclusion was reached by Solimano and Torche (2007). Robbins (1994) showed that the increase in the relative wages of skilled workers, between the years 1975 and 1990, was associated with occupational shifts toward industries where workers' schooling level increased faster than average.

In a paper where cohorts also play an important role, Sapelli (2007) studies the dynamics of cohort effects for the Gini coefficient of the wage distribution and their relation to changes in the distribution of years of schooling.[6] By contrast with Sapelli, we study the dynamics of an overall inequality measure, focusing on the decomposition of this measure into the sum of its between- and within-group components. We find most of the action in between-group inequality, a component that is unrelated to the cohort-specific inequality measures emphasized by Sapelli.

Our paper also is related to a vast literature studying the relationship between the distribution of human capital (as proxied, e.g., by educational attainment) and the distribution of income. Bourgignon, Ferreira and Lustig (2004) survey this literature, paying particular attention to possible explanations for situations where an overall increase in educational attainment can lead to an increase in wage inequality, as observed in a number of empirical studies. They call this phenomenon the "paradox of progress." In our case wage inequality did not deteriorate when the share of tertiary education began to increase, but instead remained unchanged during an entire decade, before it began to fall. In a sense, then, what we find is a weak version of the paradox of progress.

3 Descriptive Statistics

This section begins with a description of the wage data we use throughout the paper (Section 3.1). The trusting reader can skip to Section 3.2, where we discuss the time-evolution of various inequality measures. We find that inequality increased during roughly the first half of our sample and decreased thereafter (our sample period is 1975–2006). Furthermore, during the first half of our sample the wage of the 90th percentile of the wage distribution increased much faster than both the median wage and the 10th percentile wage. This pattern reversed

[6]The first version of this paper, Sapelli (2005), misinterpreted the increase in inequality that takes place over time for a given cohort as shocks accumulate, as documented in Deaton and Paxson (1994), as a reduction in wage inequality for younger cohorts.

during the second half of our sample, when the wage of the 10th percentile increased faster than the median and 90th percentile wages.

Standard techniques from macroeconomics —the Hodrick-Prescott (HP) filter— are applied to take a first pass at removing the cyclical components from inequality measures. The pattern that emerges suggests that the wage distribution began to improve sometime during the second half of the 1980s. Applying the HP-filter is a somewhat mechanical approach to removing cyclical components of a time-series, these findings should therefore be viewed with caution. Yet they motivate the more ambitious analysis we undertake in Section 4.

3.1 Data Description

The data is extracted from the annual Employment and Unemployment Survey (EUS) conducted by the Universidad de Chile. This survey covers the city of Santiago and surrounding areas (Gran Santiago). This accounts for approximately 40% of Chile's population. Available information includes wages, gender, and education level; there is no information on hours worked.[7,8,9]

Our sample consists of male workers between 25 and 59 years of age, during the 1975–2006 period. Focussing on male workers avoids having to model the labor market participation decision and its implications for male-female wage differentials, both important topics but largely unrelated to the issues that concern us here.[10] Leaving out the youngest and oldest workers allows us to abstract from the decision between studying and working faced by younger workers, and the retirement decision faced by older workers.

Even though the available data covers from 1957 to 2006, we drop the data prior to 1975 for three reasons. First, the information on schooling is lacking for some of the pre-1975 years; we need this information to apply the methodology we discuss in the next section. Second, the wage data for the years 1973–1974 show strange patterns, for example, some of the wage inequality measures almost double between 1973 and 1974, dropping back to their pre-1973 values in 1975. Third, focussing on the evolution of inequality during the last three decades suffices to address the issues that concern us in this paper.

So as to have a larger sample and more statistical power, we include self-employed workers. The results we obtain when excluding these workers are qualitatively the same, and

[7]Following what has become standard in the literature, we impute 1.2 times the maximum annual declared earnings of the sample to the top coded workers. Reasonable variations of this factor do not affect the results.

[8]The methodology described in Section 5 requires real wage data, which we calculate using the Cortázar-Marshall adjustment for the CPI series, thereby correcting for the well documented misreporting of inflation during the 1973–1978 period.

[9]In Appendix B.1 we work with the *Encuesta de Caracterización Socioeconómica* (CASEN) survey, which has national coverage over a considerably shorter time-period sampled at a lower frequency.

[10]Most papers cited in Section 2 also ignore female workers.

quantitatively very similar, except for larger standard deviations. We also exclude retirees, individuals that worked for less than a week in the previous calendar year, individuals for whom we have no information on their educational attainment, and workers attending school or participating in the armed forces for part of the year under consideration. Excluded workers add up to slightly less than 20% of the sample. To limit the influence of outliers, we work with Winsorized samples. That is, for each cohort-education-year cell we replace the 5% highest wages by the 95-th percentile wage, and the 5% lowest wages by the 5th percentile wage. As a robustness check, we recompute our results with the actual samples and obtain essentially the same results (see Appendix B.2).

We consider three educational attainment levels: 8th grade or less, between 9th and 12th grade, and more than 12th grade. These categories correspond to the Chilean educational system levels: the first is *Educación Básica* (Elementary Education), the second is *Educación Media* (Secondary Education) and the third is *Educación Superior* (Tertiary Education).[11] We exclude from the sample workers with tertiary education that graduated from institutions that offer technical training (called *Institutos Profesionales* and *Centros de Formación Técnica*), or from programs that last less than 4 years. These institutions (and programs) supply workers with a skill level that belongs somewhere between the second and third educational attainment level we consider. The number of workers belonging to this category is very small in most years of our sample, we therefore do not have enough statistical power to create a separate category for them.

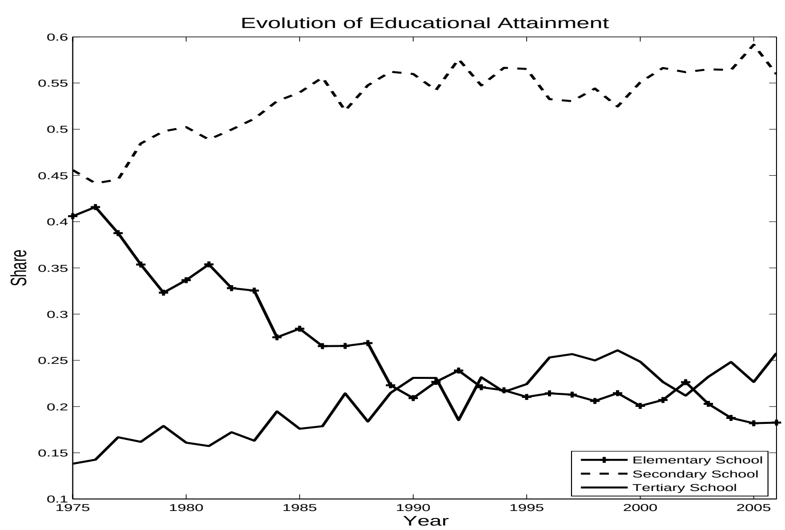

Figure 1: Evolution of the Educational Attainment Groups

[11]The latter category includes students that attended college, graduate school, and professional schools.

Figure 1 shows the evolution of the share for these three groups in our sample. The proportion of workers with secondary and tertiary education shows an increasing trend during this period, reflecting government policies expanding access to secondary education, and the effect of deregulation of tertiary education following the reform law passed in 1980.

3.2 Basic Facts

We begin our study of the dynamics of wage inequality in Chile by considering some of the classical inequality measures: the Gini coefficient, the interquartile range, the difference between the 90th and 10th percentile and the standard deviation. All these measures are calculated for the log-wage. The solid lines in Figure 2 depict the evolution of these measures from 1975 to 2006. All of them exhibit a fall toward the end of the period, this fall is more pronounced for measures that put less weight on the tails of the distribution (the interquartile range and the 90th to 10th percentile range).

Interesting insights are obtained by plotting the evolution of specific percentiles over different time periods. This is done in Figure 3, which displays the cumulative log-change for the 90th (relatively rich), 50th (median) and 10th (relatively poor) percentile in the log-wage distribution over the 1975–1989 and 1990–2006 periods. In the first period, the wage of the 90th percentile increased more than the median wage and more than the wage of the 10th percentile. By contrast, the right panel shows that this trend reversed after 1990.

Cyclical fluctuations in economic conditions impact the wage distribution, we would like to remove these fluctuations when answering questions that involve long term trends in inequality, such as whether the decrease in wage inequality observed in the second half of our sample is likely to continue in the future. We use standard techniques from macroeconomics and take a first pass at removing cyclical components by applying the Hodrick-Prescott (HP) filter to the various inequality measures considered above (see Hodrick and Prescott, 1980).[12]

The dashed lines in Figure 2 show the evolution of the inequality measures after applying the HP filter. Once cyclical fluctuations are removed using simple filters popular in macroeconomics, the inequality measures present a downward trend from around the year 1987 onward. Moreover, measures with less weight on the tails display a steeper slope than alternatives that put more weight on the tails. In the following sections we use a more sophisticated approach to remove cyclical components from the standard deviation, and also find a downward trend in inequality.

[12]Ravn and Uhlig (2002) argue convincingly that the bandwidth to be used when applying the HP filter to annual data that best corresponds to using the standard bandwidth of 1,600 for quarterly data is any value between 6.25 and 8.25. Varying values within this range makes no discernible difference. We use a bandwidth value of 8.25.

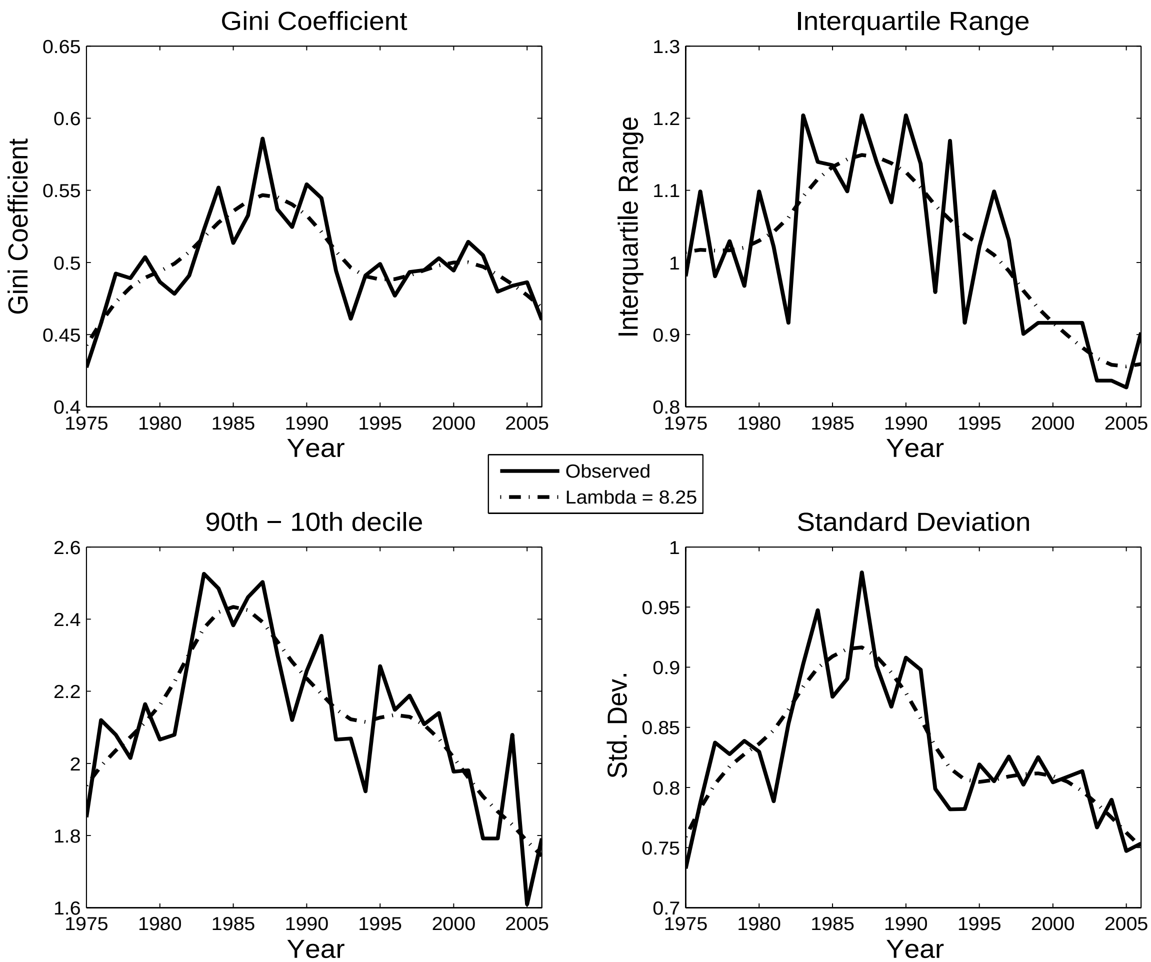

Figure 2: HP-filtered Inequality Measures.

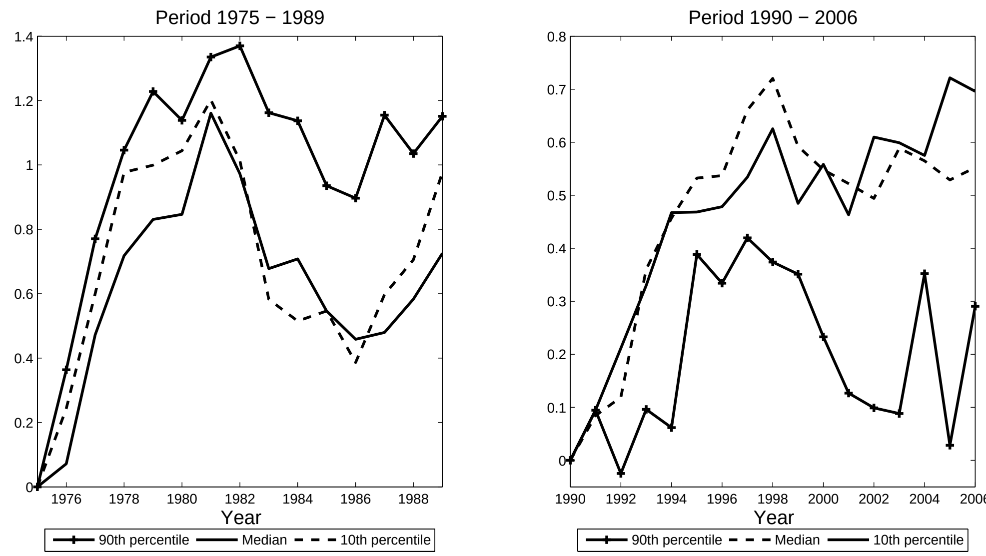

Figure 3: Evolution of the Median, 90th and 10th percentiles. 1975–1989 and 1990–2006

4 Estimation Strategy

Our estimation strategy builds on the fact that cohorts are a useful unit of analysis when understanding the dynamics of the wage distribution. For example, the quality of education varies across cohorts because members within a cohort are subject to the same fundamental changes in the educational system. Similarly, the history of major macroeconomic shocks faced by the members of a given cohort is the same, as are the changes in labor market regulations, all of which are likely to impact the mean and dispersion of cohort members' wage earnings.

4.1 Overview

As discussed in Section 2, our estimation strategy follows closely that of Gosling et al. (2000). We assume that human capital for individual i in education group ed in year t takes the form:

$$H_{it}^{\mathrm{ed}} = \exp(\phi^{\mathrm{ed}}(\mathrm{Age}_{it}, \mathrm{Cohort}_i) + u_{it}^{\mathrm{ed}}),$$

where u_{it}^{ed} represents unobserved characteristics. The aggregate production function depends on total human capital employed for each education group and $\exp(T_t^{\mathrm{ed}})$ denotes the equilibrium price of human capital for education group "ed" in year t. It then follows that the wage of individual i in group ed in period t, W_{it}^{ed}, satisfies:

$$W_{it}^{\mathrm{ed}} = H_{it}^{\mathrm{ed}} \exp(T_t^{\mathrm{ed}}).$$

This leads to the first equation we estimate:

$$w_{it}^{\text{ed}} = T_t^{\text{ed}} + \phi^{\text{ed}}(\text{Age}_{it}, \text{Cohort}_i) + u_{it}^{\text{ed}} \tag{1}$$

where $w = \log W$. Note that T_t^{ed} is associated to wage shocks common across all workers in a given education group.

Our identifying assumption is that T_t^{ed} is orthogonal to ϕ and u, this implies that any trend in wages is captured entirely by ϕ^{ed} while T_t^{ed} captures the cyclical component. That is, we are assuming that the cyclical component of wage inequality is orthogonal to the economic determinants of inequality (that is, age, cohort and educational attainment group). It then follows that the variance of log-wages within an educational group during year t satisfies:

$$\begin{aligned}
\text{Var}_i(w_{it}^{\text{ed}}) &= \text{Var}_i(\phi^{\text{ed}}(\text{Age}_{it}, \text{Cohort}_i)) \;+\; \text{Var}_i(u_{it}^{\text{ed}}) \\
&= \text{Var}_i(\text{observables}) \;+\; \text{Var}_i(\text{unobservables}) \\
&= \text{between-group variance} \;+\; \text{within-group variance.}
\end{aligned}$$

If the distribution of u is independent of age, education and cohort, then the within-group variance is constant and observables account for all the fluctuations in the distribution of wages. In this case fluctuations in the variance of log-wages are equal to fluctuations in the between-group variance. The data strongly rejects this hypothesis, suggesting the second equation we estimate:

$$\sigma(u_{it}^{\text{ed}}) = \eta_t^{\text{ed}} + \psi^{\text{ed}}(\text{Age}_{it}, \text{Cohort}_i). \tag{2}$$

Summing up, we estimate the mean and standard deviation equations (1) and (2), assuming that the yearly components, T_t^{ed} and η_t^{ed}, are orthogonal to the cohort-age components ϕ and ψ. The details are discussed next, the trusting reader can skip to Section 5 where we present our results.

4.2 Details

To estimate (1) we use a two step procedure, which we apply separately to each educational attainment group. We approximate ϕ by a third order polynomial expansion and in the first step use OLS to estimate:

$$w_{ijt} \;=\; C^{\text{ed}_i} + \alpha_1^{\text{ed}_i}\text{Age}_{jt} + \alpha_2^{\text{ed}_i}\text{Age}_{jt}^2 + \alpha_3^{\text{ed}_i}\text{Age}_{jt}^3 + \beta_1^{\text{ed}_i}\text{Coh}_j + \beta_2^{\text{ed}_i}\text{Coh}_j^2 + \beta_3^{\text{ed}_i}\text{Coh}_j^3$$

$$+ \gamma_1^{\mathrm{ed}_i} \mathrm{Age}_{jt} \mathrm{Coh}_j \; + \; \gamma_2^{\mathrm{ed}_i} \mathrm{Age}_{jt}^2 \mathrm{Coh}_j \; + \; \gamma_3^{\mathrm{ed}_i} \mathrm{Age}_{jt} \mathrm{Coh}_j^2 \; + \; u_{it}^{\mathrm{ed}_i}. \tag{3}$$

Next we obtain the first set of estimates for time effects by regressing the estimated residuals, $\hat{u}_{it}^{\mathrm{ed}_i}$, on a set of time dummies using OLS.[13]

$$\hat{u}_{it}^{\mathrm{ed}_i} = \delta_1^{\mathrm{ed}_i} D_{1977} + \delta_2^{\mathrm{ed}_i} D_{1978} + \cdots + \delta_{30}^{\mathrm{ed}_i} D_{2006} + \epsilon_{it}.$$

The second step of our estimation procedure estimates (3) again, this time using log-wages adjusted for time-effects estimated in the first step as dependent variable. Estimation is via GLS this time, with weights equal to the variance of log-wages adjusted for time-effects. This leads to our definitive estimates for the αs, βs and γs in (3). To obtain the final estimates for time-effects, we regress the residuals of the GLS regression against time-dummies, using GLS with weights given by the variance of the estimated log-wages after removing time effects.[14] By construction, the time effects we obtain will sum to zero and be orthogonal to the included age and cohort effects.

As noted in the introduction to this section, the fact that the estimated standard deviations varies substantially with cohort, age and education suggests we estimate an equation of the form (2) for this moment as well. We use the same two step strategy described above to estimate a specification analogous to (3) with $\sigma(u_{it}^{\mathrm{ed}})$ as dependent variable.[15]

5 Results

In Section 5.1 we present our estimates for the mean equation (1) followed by the estimates of the standard deviation equation (2) in Section 5.2. We use these estimated equations as inputs for the main part of this section, Section 5.3, where we decompose the variance of log-wages into the sum of its within- and between-group components to help us understand the dynamics of wage inequality.

5.1 Mean Equation

Table 1 presents our estimates for the mean-equation (1). Standard errors are reported in parenthesis and cohorts are measured as the difference between the cohort's year of birth and 1934. The estimated quadratic terms for age and cohort are negative for each educational group; this is consistent with a hump shaped wage profile and with a diminishing marginal

[13]Following Deaton (1997) we drop two years to achieve identification.

[14]More details about this procedure can be found in Chamberlain (1993).

[15]The procedure described above is valid for any moment of the wage distribution, see Appendix A.3 in Gossling et al. (2000).

increase on the entry wage for younger cohorts, at least in the range of values where the quadratic term dominates over the cubic term. The coefficients for the cross terms involving cohorts and age differ significantly from zero, making the analysis of cohort and age effects harder. We therefore present some figures that display the main findings varying one variable while keeping the other variable fixed.

Table 1: Estimates for the Mean Equation

	Left school before 9th grade	Left school between 9th and 12th grade	More than 12th grade
Cohort	0.90643	1.04191	0.95116
	[0.00584]**	[0.01786]**	[0.00900]**
Cohort^2	-0.02509	-0.03044	-0.02438
	[0.00033]**	[0.00149]**	[0.00047]**
Cohort^3	0.00023	0.00027	0.00021
	[0.00000]**	[0.00003]**	[0.00001]**
Age	0.98775	1.02839	1.1449
	[0.00753]**	[0.01153]**	[0.01373]**
Age^2	-0.02918	-0.02881	-0.03383
	[0.00050]**	[0.00069]**	[0.00087]**
Age^3	0.00029	0.00026	0.00034
	[0.00001]**	[0.00001]**	[0.00001]**
Age $\times$ Cohort	-0.05171	-0.0597	-0.05311
	[0.00036]**	[0.00054]**	[0.00061]**
Age^2 $\times$ Cohort	0.00075	0.00084	0.00075
	[0.00001]**	[0.00001]**	[0.00002]**
Age $\times$ Cohort^2	0.00071	0.00088	0.00066
	[0.00001]**	[0.00002]**	[0.00001]**
Observations	13097	10499	10328
R^2	0.9977	0.9966	0.9968

* significant at 5%; ** significant at 1%.

Figure 4 shows the cohort effect for different ages. The panels display the cumulative changes of the predicted mean of the log-wage at 25 and 40 years of age for workers of each educational attainment group, as a function of the cohort. The differences between the curves represent the cumulative cohort-specific skill premia at the time workers enter the labor market (age 25, left panel) and later in their life (age 40, right panel).

The skill premia at the entry wage has been decreasing for the secondary educational level. This reflects a dramatic increase in the fraction of workers with secondary education following the year 1966 when completing eighth grade became mandatory.[16] Another possible explanation for this phenomenon, especially for younger cohorts, is the increase of the

[16]For a description of the evolution of the Chilean labor market conditions from 1975 to 1995, see Mizala (1998).

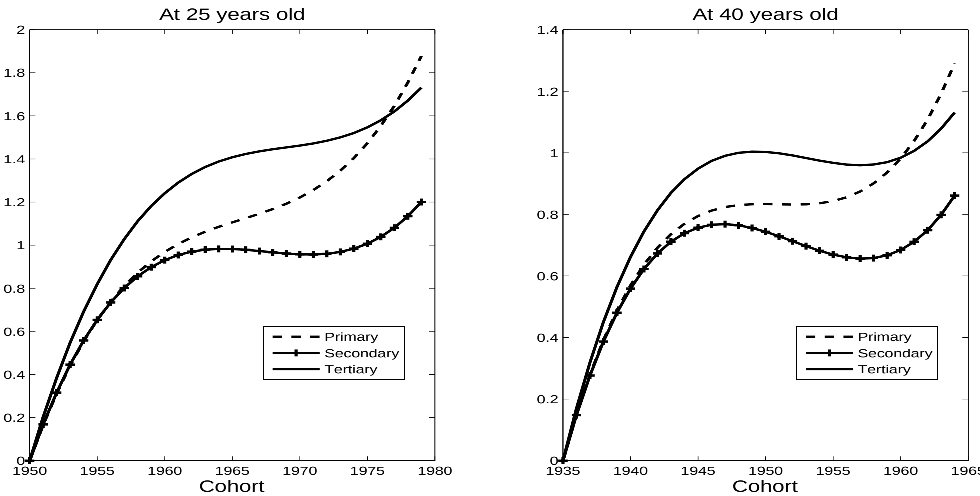

Figure 4: Evolution of the Cohort Effect.

minimum wage that began in the 1990s and accelerated toward the end of that decade. Since workers with primary education are more likely to earn the minimum wage, those that did not loose their job saw a significant increase in their wages (recall that the sample we work with includes only employed workers).[17]

For workers with more than 12th grade, the skill premium reaches a peak around the 1970 cohort. The increase in the supply of college graduates after 1980 probably is the main candidate to explain the drop in the skill premium that followed for this group (we return to this issue in Section 5.3 below). Another interesting phenomenon is the change in the trend of the skill premia around 1985, toward the end of the recession of 1982–1984. Similar trends, but attenuated, are present for workers at 40 years of age.

Figure 5 displays the cumulative age effect for the cohorts of 1935, 1950, 1965 and 1975. For older cohorts the growth rate of the log-wage of high skill workers is higher than for other groups. The difference in growth rates is less pronounced for younger cohorts, implying that the inequality across educational groups has been decreasing over time, because for more recent years the sample contains more individuals of younger cohorts (we return to this topic in Section 5.3).

[17]See Cowan, Micco and Pages (2004) for evidence on an increase in unemployment among unskilled workers due to the significant increase in the minimum wage that was approved by the Chilean congress shortly before the East Asian crisis of 1998.

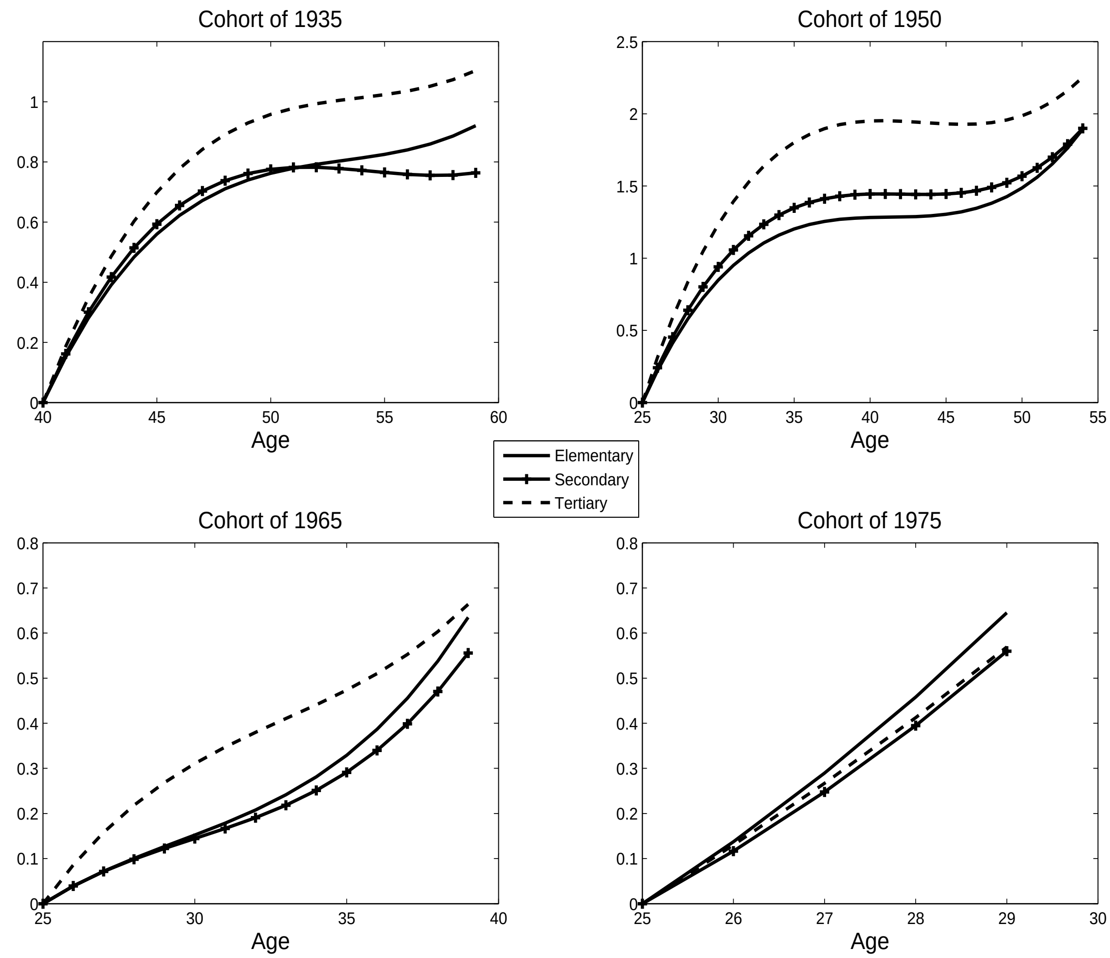

Figure 5: Evolution of the Age Effect.

5.2 Standard Deviation Equation

Table 2: Estimates for the Standard Deviation Equation

	Left school before 9th grade	Left school between 9th and 12th grade	More than 12th grade
Cohort	0.05496	0.05103	0.05047
	[0.00086]**	[0.00061]**	[0.00102]**
Cohort2	-0.0018	-0.0016	-0.00156
	[0.00005]**	[0.00003]**	[0.00006]**
Cohort3	0.00002	0.00002	0.00002
	[0.00000]**	[0.00000]**	[0.00000]**
Age	0.05225	0.06376	0.06461
	[0.00155]**	[0.00133]**	[0.00230]**
Age2	-0.00126	-0.00194	-0.00203
	[0.00010]**	[0.00008]**	[0.00014]**
Age3	0.00001	0.00002	0.00002
	[0.00000]**	[0.00000]**	[0.00000]**
Age × Cohort	-0.0025	-0.00284	-0.00283
	[0.00007]**	[0.00006]**	[0.00010]**
Age2 × Cohort	0.00003	0.00004	0.00004
	[0.00000]**	[0.00000]**	[0.00000]**
Age × Cohort2	0.00003	0.00004	0.00003
	[0.00000]**	[0.00000]**	[0.00000]**
Observations	930	579	915
$R2$	0.98	0.98	0.98

* significant at 5%; ** significant at 1%.

Table 2 reports our estimates for the standard deviation equation (2).[18] Standard errors are reported in parenthesis and, as before, cohorts are measured as the difference between the cohort's year of birth and 1934. The coefficients for product terms are again significant, we therefore present figures where we vary one variable while fixing the other variable at a given value to illustrate the main findings.

Figure 6 displays the age effect for the cohorts born in 1935, 1950, 1965 and 1975. According to the literature,[19] cohort-specific inequality increases with age, as can be observed for elementary and secondary education in most cases. By contrast, for most cohorts we find an inverse U-shaped standard deviation curve for workers with tertiary education. Moreover, the standard deviation for younger cohorts in this educational group is decreasing. One possible explanation begins by noting that the standard deviation curves begin to decrease at a point in time close to the major 1982–1984 recession. The drop in economic activity and the structural change that followed may have destroyed accumulated human capital,

[18]The results are quantitatively similar if we use the variance instead.

[19]Deaton and Paxson (1994) find this result for consumption, Farber and Gibbons (1997) in a learning by doing context.

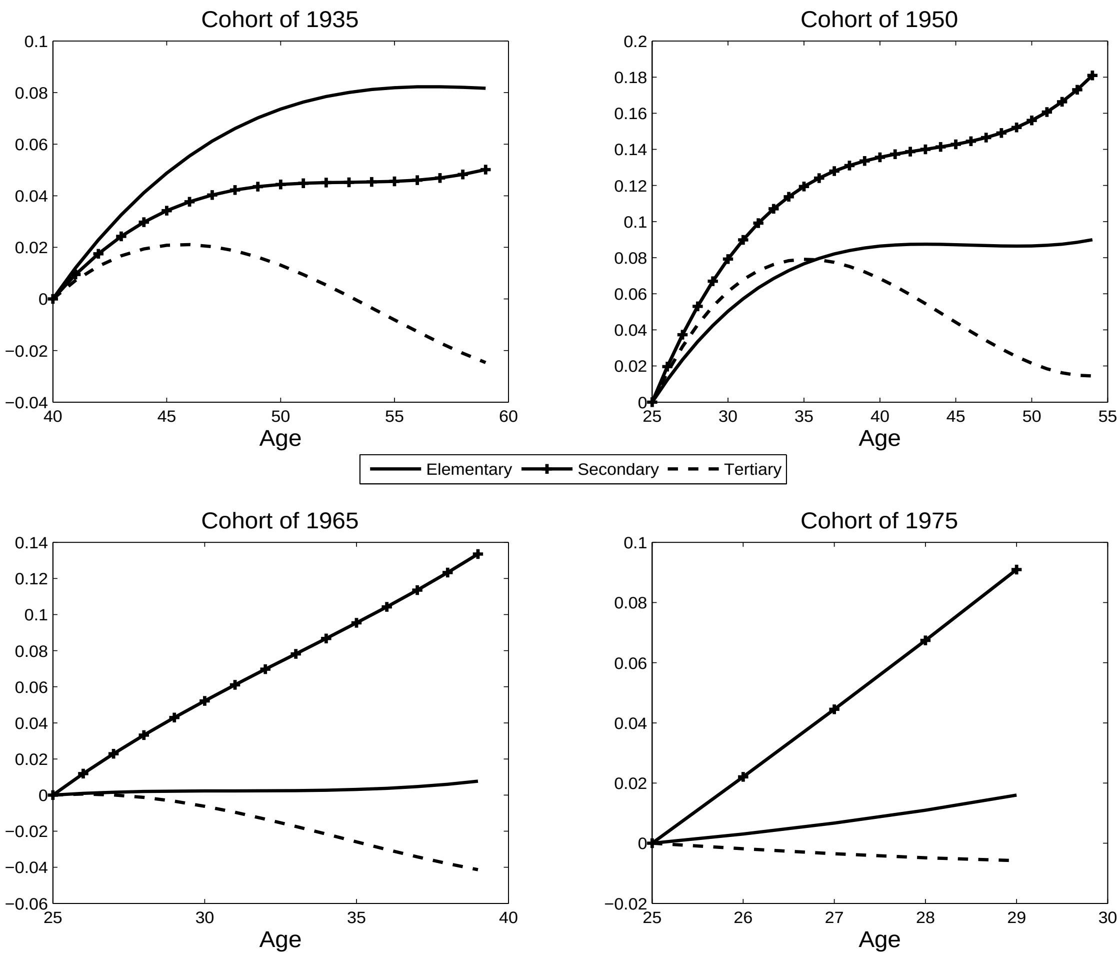

Figure 6: Evolution of the Age Effect.

thereby making workers within this cohort "more equal" and reducing wage heterogeneity within a cohort. Figure 6 suggests that, if present, this effect was more prominent for high skilled workers.

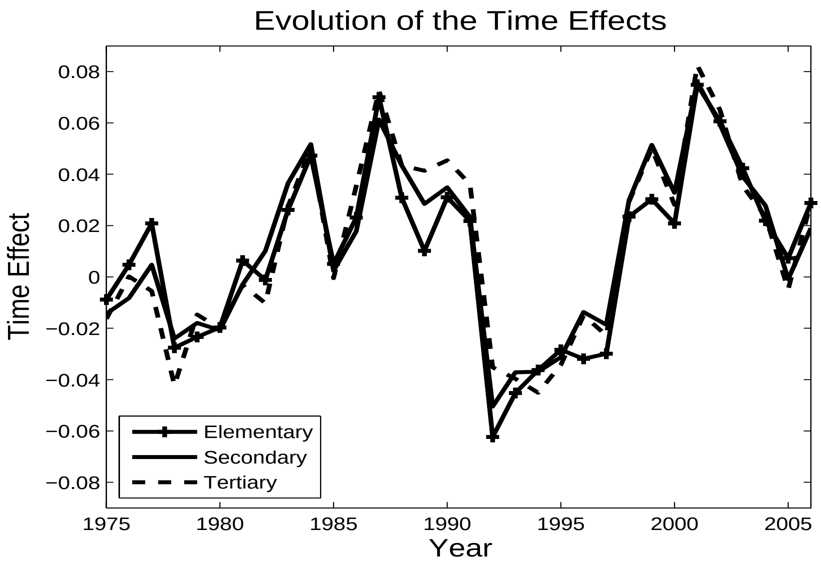

Figure 7: Evolution of Time Effects.

Figure 7 displays the time effects estimated for the standard deviation equation. As mentioned above, Chile suffered a major recession in the early 1980s, followed by a major expansion between 1986 and 1997, followed by a minor recession in 1998. It is apparent that the estimated time effects are highly countercyclical. A possible explanation is that low earning workers (within a given educational group) are more likely to loose their jobs during downturns, so that the fraction of high wage earners in our sample increases during these periods, leading to more wage inequality.

5.3 Variance Decomposition

Based on the fact that the total variance is equal to the sum of the within- and between-group variances, we use the estimates for our mean and standard deviation equations to study the evolution of the within- and between-group standard deviation, after removing cyclical effects. We find that most of aggregate inequality dynamics is explained by fluctuations in the between-group standard deviation. We also study the relation between the dynamics of this inequality measure and the educational transition, from a workforce with a majority of workers with secondary education to a workforce with a majority of workers with tertiary education, that began after the tertiary education market was liberalized in 1980.

Figure 8 displays the evolution of the standard deviation predicted by the equations we estimated, after removing time effects, together with the standard deviation for our entire

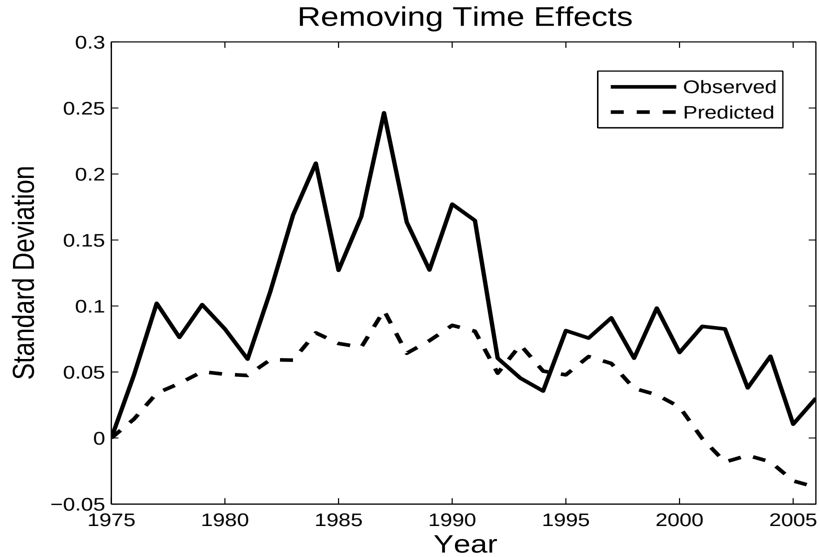

Figure 8: Removing Time Effects.

sample. Both curves are in deviation from their initial values. Note that the decreasing trend exhibited by our estimate of the trend of the standard deviation coincides with that observed for the HP-filtered version (see Figure 2), even though the HP-filtered standard deviation decreases faster initially and slower toward the end of the sample period.

Figure 9 displays the evolution of the predicted standard deviation, and the predicted standard deviation between and within age-skill groups, both in deviation from their initial values and after removing the cyclical component. The slow downward trend in overall inequality observed during the second half of the 1980s and first half of the 1990s is accounted for mainly by a slow decrease of the within-group standard deviation during this period. By contrast, the marked decrease in inequality from the mid 1990s onward is associated mainly to a decrease in the between-group standard deviation. This contrast is particularly remarkable if we note that the average value of the within-group variance equals 57% of the average overall variance, thus the decrease in the between-group standard deviation that begins in 1995 is large: it decreases by around 24% between 1996 and 2006. We argue next that the behavior of the between-group standard deviation can be explained, to a large extent, by the liberalization of the tertiary education market that took place in 1980.

The right panel of Figure 10 displays the share of workers with tertiary education, as a fraction of workers with either secondary or tertiary education (for simplicity, we ignore the fraction of workers with primary education in what follows). The left panel shows the evolution of the standard Mincerian skill premium for tertiary education over secondary

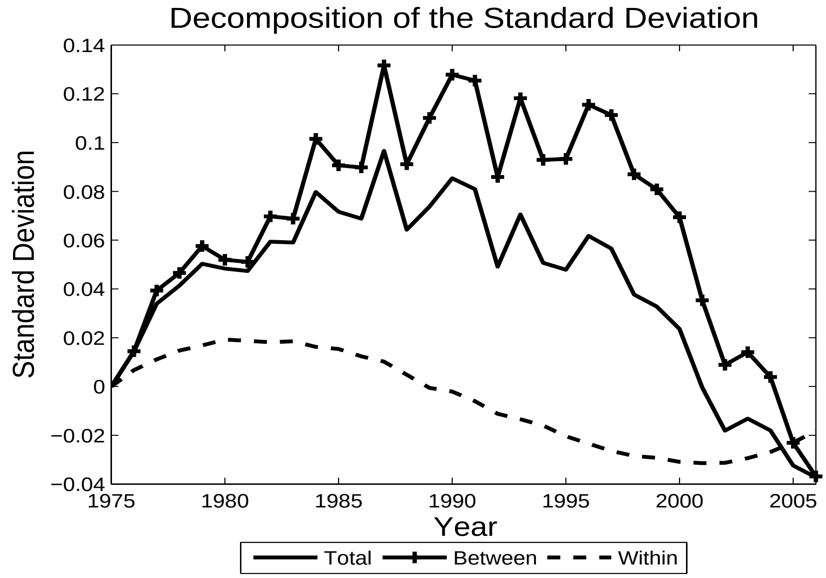

Figure 9: Decomposition of the Standard Deviation.

education (see Appendix A for details on how this premium is calculated).[20] The right panel shows that an increase in the fraction of workers with tertiary education becomes apparent sometime during the second half of the 1980s. This is consistent with the liberalization of the tertiary education market that took place in 1980—the lag is due to the time that elapses between the moment the number of students attending tertiary education institutions increases and the time they reach the labor market. The left panel shows that the skill premium also began to fall during the second half of the 1980s, which again is consistent with the increase in the supply of workers with tertiary education mentioned above.

To gauge whether the educational transition toward tertiary education explains the evolution of the between-group standard deviation, note that if we denote by p_t the fraction of workers with tertiary education in year t, and by R_t their skill premium, then the between-group standard deviation is given by:

$$\sigma_t^B = R_t\sqrt{p_t(1-p_t)}. \tag{4}$$

If R_t remains constant, (4) implies that σ_t^B increases with p_t as long as $p_t < \frac{1}{2}$, and decreases

[20]Our estimates for this return are higher than those obtained by other authors (for a survey of these estimates see Mizala and Romaguera, 2004) because, for reasons explained in Section 3.1, we exclude workers with lower level tertiary education (those coming from Institutos Profesionales and Centros de Formación Técnica).

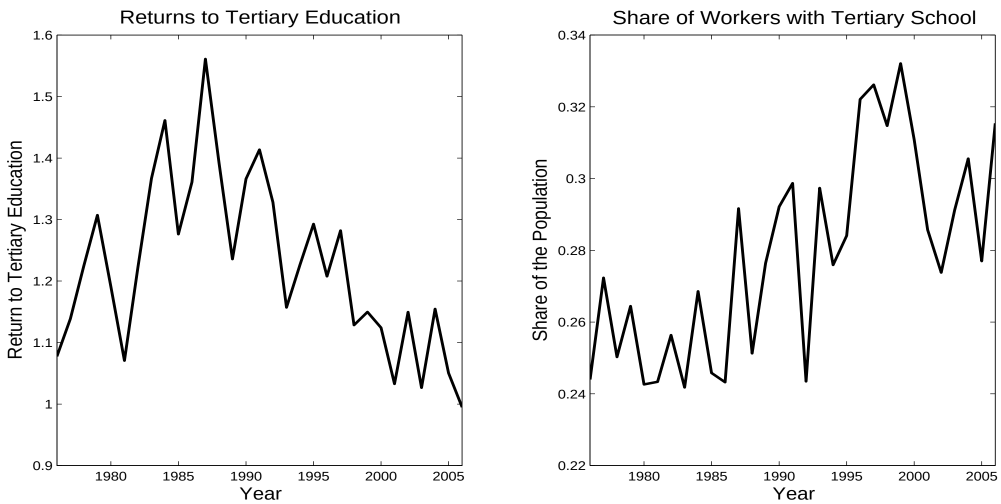

Figure 10: Explaining the between-group SD

thereafter. That is, when R_t remains unchanged, the educational transition first leads to an increase in wage inequality, as measured by the between-group standard deviation, as the fraction of workers with higher education increases, while still being a minority of workers. Only after a majority of workers have tertiary education do further increases in the fraction of tertiary workers lead to less wage inequality. It is natural to describe this pattern as the Kuznets effect (see Bourgignon et al., 2004).

Acting in the opposite direction is an effect highlighted by Tinbergen (1975), that emphasizes the reduction of the wage premium as the relative supply of workers with tertiary education increases.[21] That is, R_t in (4) will be decreasing in p_t and the threshold of p_t beyond which σ_t^B is decreasing in p_t can therefore be considerably smaller than $p_t = \frac{1}{2}$. We refer to this supply effect on the skill premium as the Tinbergen effect.[22]

From (4) it follows that:

$$\frac{d \log \sigma_t^B}{dp_t} = \frac{d \log R(p_t)}{dp_t} + \frac{1 - 2p_t}{p_t(1 - p_t)}. \tag{5}$$

The first term on the right hand side is negative and captures the strength of the Tinbergen effect. The second term is positive as long as $p_t < \frac{1}{2}$ and captures the size of the Kuznets

[21] Anecdotal evidence suggests that average quality of education in universities created after 1980 is lower than in older institutions. If this is the case, the reduction in the wage premium may partly reflect this phenomenon. We do not know of any study quantifying this supposed quality deterioration, and therefore cannot correct for this effect. In any case, the implications for our interpretation of the dynamics of the wage distribution would be minor.

[22] Our analysis ignores variations in demand or, alternatively, assumes that changes in supply dominate over demand changes.

effect. It follows that there exists a value $p_t^* \in (0, \frac{1}{2})$ beyond which σ_t is decreasing in p_t, our digression below suggests this value is around 0.3.

Figure 9 suggests that the between-group standard deviation remained pretty much constant between 1985 and 1997. This may reflect that the improvement in the income distribution associated with the decrease in the tertiary education wage premium (left panel of Figure 10) was canceled by the increase in the fraction of workers with tertiary education. That is, during this period the Kuznets and Tinbergen effects had approximately equal magnitude and opposite signs and therefore canceled each other. By contrast, from 1997 onward the Tinbergen effect begins to dominate, most likely because the Kuznets effect had weakened due to the growth in the fraction of workers with tertiary education: the second term on the right hand side of (5) is decreasing in p_t and negative for $p_t > \frac{1}{2}$.[23]

Figure 11 shows that, even though more volatile, the estimate of the between-group standard deviation obtained from (4) follows the between-group standard deviation estimated from (3) pretty closely. We conclude that a simple back-of-the-envelope calculation, that uses the Mincerian skill premium and the fraction of tertiary workers to calculate (4), provides a surprisingly good approximation for the actual evolution of the between-group standard deviation.

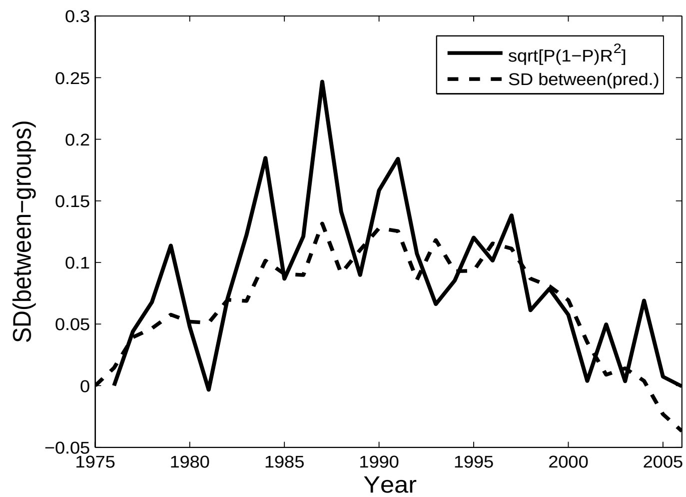

Figure 11: Evolution of Between-group SD

6 Conclusion

We summarize our findings, point out the main caveats, and make a forecast.

[23]Even though we know little about the first term, its sign may be expected to remain negative throughout.

Findings

1. Wage inequality has decreased in Chile since the mid 1980s. This downward trend emerges clearly once the cyclical component of inequality measures is removed using the HP filter.

2. Removing the cyclical component of the standard deviation of log-wages via a more sophisticated procedure than the HP filter, based on estimating an equation where the wage depends on cohorts, age, and an additive orthogonal time-effect, suggests that the underlying trend in inequality decreased at a slow pace between 1985 and 1995, and then at a significantly faster pace from 1995 onwards (our sample ends in 2006).

3. Most of the downward trend in inequality from 1995 onward is explained by the dynamics of the standard deviation *between* cohort-age groups.

4. Fluctuations in the between-group standard deviation during the last decade can be attributed to a major increase in the share of workers with tertiary education that originates with the deregulation of this market in 1980. The evidence for this relation is twofold:

   (a) First, the liberalization of tertiary education in 1980 is arguably the largest supply shock in education policy with implications for the wage distribution during the last three decades in Chile. Not only because it led to a doubling of the share of workers with tertiary education during the decades that followed, but also because enrollment had been constrained artificially by the military government during the period prior to the reform.

   (b) Second, even though the between-group standard deviation is calculated based on a model that incorporates cohort and age effects, the evolution of this inequality measure can be explained by a back-of-the-envelope calculation based only on the share of workers with tertiary education and a simple Mincerian estimate their skill premium.

Limitations

1. Our interpretation for the dynamics of inequality is based on supply shocks and therefore ignores shifts in demand. The supply shock that drives our results is large, but we may still be missing important elements of the dynamics of the wage distribution.

2. We use the standard deviation as inequality measure, which does not satisfy some properties we would like of inequality measures.[24] Of course, the standard deviation has the advantate that there exists a decomposition (for its square) into the sum of its within- and between-group components, a decomposition that does not exist for alternative inequality measures. This decomposition plays a central role in our analysis.

3. We provide a couple of conjectures to explain the slow decrease in the standard deviation of log wages during the 1985–1995 period, which is due to a downward trend in within-group inequality. but fail to make an entirely convincing case for any of them. More research is clearly needed on this front.

Forecasts

Next, let us risk a forecasts. The increase in the fraction of workers with tertiary education that is expected for the coming decade —Salamanca and Uribe (2007) estimates that by 2012 more than 50% of students in the 18–24 age group will be attending college— suggests that the improvement in wage inequality observed during the last decade is likely to continue into the future. Of course, at some point in the future we will have to begin worrying about the distribution of wages *within* the group of workers with tertiary education, but it is safe to say that the Tinbergen effect can provide substantial reductions in the wage premium for some time to come.[25]

Final Comment

Finally, a methodological point. The educational transition that took place in Chile during the last two decades illustrates a point that is relevant generally when studying distributional dynamics: A transition from a workforce with a majority of workers with secondary education, to one where most workers have tertiary education, may initially lead, to a period where the distribution of income remains unchanged (or even deteriorates, should the Kuznets effect be dominant). Only once the fraction of workers with tertiary education is sufficiently high can we expect the reduction in the skill premium to translate into lower wage inequality. Yet the period with constant (or deteriorating) wage inequality is necessary to reach the period where inequality decreases. Making welfare statements based on a static examination of inequality measures can be highly misleading.

[24] One might argue, along the lines of Arrow's impossibility theorem, that *any* inequality measure has some undesirable property, but this is beyond the scope of this paper.

[25] A major demand shift —such as an increase in the skill premium akin to what has been observed in industrialized countries— could render this forecast wrong as well.

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Appendix

A Estimating Returns to Education

In section 5.3 we used (4) to compute an alternative between-group standard deviation, using returns to education and the share of tertiary education workers (out of workers with secondary or tertiary education). The return to education we used was based on a standard Mincerian equation:

$$w_{it} = \alpha\delta_0 \text{ter} + \beta_0 x_{it} + \beta_1 x_{it}^2 + \Gamma_{0t}\text{time}_t + \Gamma_{1t}\text{time}_t \times \text{ter} + \epsilon_{it}$$

where ter a dummy for tertiary schooling, and time_t a dummy for year t.[26]

It follows that the estimated annual return to tertiary education in year t is $\delta_0 + \Gamma_{1t}$. Note that, by contrast with the approach we used in Section 5, the measure of return to education we obtain ignores cohort effects and instead is year-specific.

B Robustness

In this section we conduct a series of robustness checks, focussing in each case on whether the steep decrease in wage inequality that began in the mid 1990s continues being explained, mainly, by a decrease of between-group inequality (as depicted in Figure 9 in the main text).

B.1 Using the CASEN Data Set

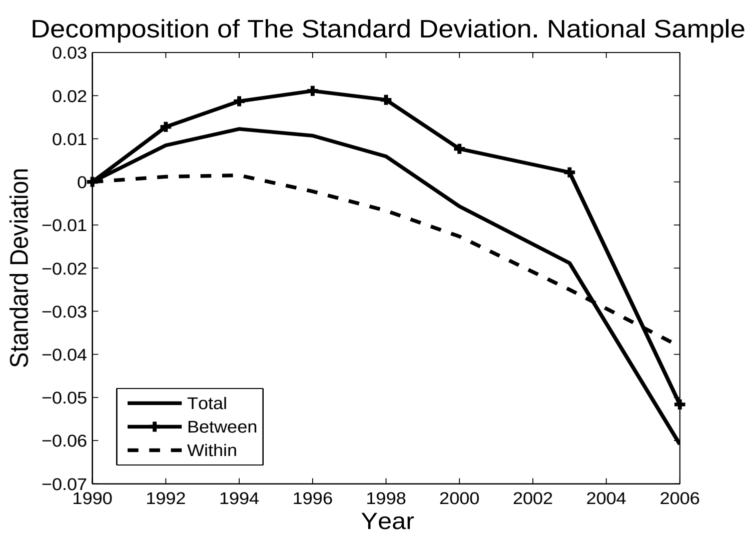

Figure 12: Decomposition of SD. CASEN and EUS.

[26]Working with alternative proxies for schooling level, for example, years of schooling, and dummies for completed level, and obtained similar results.

One of the shortcomings of the EUS database we use in the main text is that it covers only Santiago and surrounding areas (Gran Santiago)., By contrast, CASEN (*Encuesta de Caracterización Socioeconómica*) database has national coverage, even though it is applied less frequently and does not cover the entire period.

To check whether our main findings are valid at the national level, we use the CASEN for the years 1990, 1992, 1994, 1996, 1998, 2000 and 2003, and apply the same methodology that led to Figure 9 in the main text. Even though the magnitude of the effects are smaller, possibly because of differences in coverage and methodologies, the qualitative behavior, as shown in Figure 12, is similar. Inequality began to fall significantly in 1998 and this fall is explained mainly by a fall in the between-group standard deviation.

B.2 Non-Winsorized Sample

Figure 13 shows the predicted standard deviation, and the between- and within-group standard deviations, all in deviation from their initial values and after removing the cyclical components, when the non-Winsorized sample is used. A comparison of this figure with Figure 9 shows that the results we obtain are the same. It follows that our results are robust to outliers.

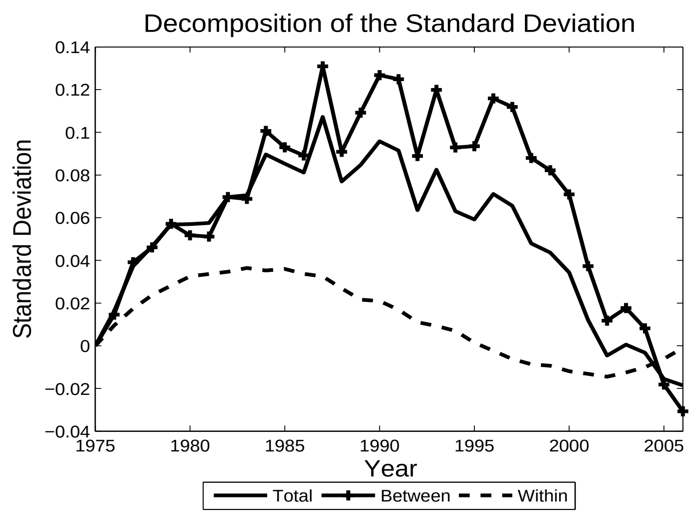

Figure 13: Decomposition of SD. Non-Winsorized Sample