Estudios de Economía. Vol. 25 - Nº 1, Junio 1998. Págs. 71-98

THE STRUCTURE OF WAGES IN CHILE 1960-1996: AN APPLICATION OF QUANTILE REGRESSION*

CLAUDIO E. MONTENEGRO

Abstract

This paper applies newly developed techniques in the estimation of earnings functions to compute private rates of return for education in Chile. Although studies concerning the rate of return for education in Chile are available, the quantile regression method used here permits a conditional breakdown of the wage structure that is of crucial importance in an economy which has experienced important changes in political regimes that have had different impacts on different groups of the population. The results show that: (i) mean and median wage estimation equations are stable; (ii) the differences in the rates of return to education by quantiles are systematic; (iii) wage inequality is more volatile than what we usually believe; and (iv) the labor market is more heterogeneous than originally thought.

Resumen

En este trabajo se aplican técnicas recientemente desarrolladas para la estimación de funciones de ingreso para computar tasas privadas de retorno a la educación en Chile. Aun cuando existen estudios acerca de la tasa de retorno a la educación en Chile, el método de regresión "quantile" usado en este trabajo permite hacer una desagregación condicional de la estructura de salarios que es de crucial importancia en una economía que ha experimentado importantes cambios en los regímenes políticos que han tenido diversos impactos sobre diferentes grupos de la población. Los resultados muestran que: (i) las ecuaciones de las estimaciones de media y mediana del salario son estables; (ii) las diferencias en las tasas de retorno a la educación por "quantiles" son sistemáticas; (iii) la desigualdad salarial es más volátil de lo que usualmente se ha creído; y (iv) el mercado del trabajo es más heterogéneo que lo que originalmente se pensaba.

* Responsibility for the contents of this paper is entirely that of its author and should not be attributed to The World Bank, its Executive Directors or the countries they represent. I am grateful to Alejandra Cox-Edwards, Indermit Gill, Partha Mukhopadhyay, Lant Pritchett, Claudia Sepulveda, Glenn Sheriff, Raimundo Soto and two anonymous referees of this Journal for their helpful comments. I am also in debt to the University of Chile's Economics Department, which provided the necessary assistance for this research. Needless to say, any remaining errors are my own.

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1. Introduction

Differences in earnings among workers have long been noted and debated. People with higher education tend to earn more than less educated people; people with more experience earn more. There are even "disturbing" earnings differences according to sex or race. The causes for such variations in wages and earnings are complex and controversial. An approach to explain such differences, known as the human capital hypothesis, suggests that individuals would invest in schooling only if they were to receive sufficiently higher lifetime earnings to compensate them for the foregone earnings, the tuition paid and the effort of going to school. On the demand side, this hypothesis postulates that employers pay premium wages for more highly educated workers (assumed to be more productive). Finally, it is assumed that in the long run, equilibrium earnings must be such that the supply and demand for workers at each level of schooling are equated, and that no worker wishes to alter his level of education.

The purpose of this study is to analyze the conditional wage distribution of Chilean workers over time. The basic theoretical background is the one postulated by Mincer (1974) in his seminal work summarized in the previous paragraph. Though there are other studies that use the same theoretical structure to analyze wages in Chile (Corbo and Stelcner 1983, Riveros 1990), this study stands out in three ways. First, the analysis is carried out year by year using a comparable and representative sample of annual surveys from 1960 to 1996,[1] which permits us to study the stability of the wage function. Second, the analysis uses regression quantile analysis, a novel approach. Although this methodology was developed some twenty years ago by Koenker and Basset (1978), applications to developing countries do not exist. Finally, the breakdown of the analysis into groups based on experience, public-private sector and blue-white collar is unprecedented in the case of Chile.

The analysis of the fluctuations in the rate of return[2] is particularly interesting in Chile, where there have been major changes in policies and severe external shocks during the period under study.[3] These are likely to affect the output composition and hence the profitability of education and the wage structure, since the changes in productive sector and public sector policies alter sectoral labor demands and skill requirements. One very pertinent question to assess is to what extent the economic policies and the shocks to which the economy was exposed affected the rates of return to schooling and the wage dispersion. Such analysis is beyond the scope of this paper, which is the more modest one of characterizing the wage structure over time.

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1 Because of incomplete data the years 1963, 1964 and 1965 had to be excluded from the sample. The years 1963 and 1964 do not include the education variable and the year 1965 does not include the income variable.

2 By "rate of return" we shall mean nothing more than the effect of one variable (education, experience) on some aspect of the conditional distribution of earnings.

3 The Chilean economic policies have been extensively documented by French-Davis (1973), Edwards and Cox-Edwards (1987), de la Cuadra and Hachette (1991), Wisecarver D. (1992), Bosworth, Dornbusch and Labán (1994), Hudson R. (1994), Soto R. (1995), Cortazar and Vial (1998).

In this paper we estimate the private return to education in Chile using a "Mincerian" specification that involves the fitting of a semi-log curve using hourly wages as the dependent variable, and years of schooling and potential years of labor market experience (and its square) as independent variables. Two estimation techniques are used: mean and quantile regressions.

The structure of the paper is as follows. In the second section, we discuss the theoretical model. In the third section, we discuss the econometric methodology. In the fourth section, we present the data. The fifth section presents and interprets the results. Finally, the last section collects the main conclusions.

2. THE MODEL

The model used to analyze the rates of return and also used to derive our quantile-inequality measure is based on the standard human capital earnings function developed by Mincer (1974) that has the form:

$$\ln y_i = \varphi(s_i, x_i, z_i) + u_i \tag{1}$$

where $\ln y_i$ is the log of earnings or wages for individual i, s_i is a measure of schooling or educational attainment, x_i is a measure of the stock of experience, z_i represents other factors that affect earnings such as race, gender, abilities, etc., and u_i is a random i.i.d. disturbance term that reflects unobserved characteristics. Notice that in equation (1) nothing is said about the functional form of the equation. It is possible to obtain a functional form for equation (1) if one makes certain assumptions (see for instance, Willis, R., 1986; Polachek and Siebert, 1993). The usual econometric equation estimated (and we are not an exception) can be written as:

$$\ln y_i = \beta_0 + \beta_1 s_i + \beta_2 E_1 + \beta_3 E_i^2 + u_i \tag{2}$$

where E_i is the level of experience, E_i^2 is the square of the level of experience (included to account for the commonly observed effect of a declining age earning profile for a given level of experience), and β_1 is the rate of return of one additional year of schooling.

In this specification, β_1 and β_2 are expected to be positive, and β_3 negative. It is important to recall that equation (2) is based on some restrictive assumptions: it assumes that individuals are of equal abilities and face equal opportunities (i.e., it assumes perfect capital and labor markets, which allows us to take earnings as a proxy for marginal productivity), it ignores direct costs of schooling, it overlooks earnings while attending school, and it assumes a constant return per year of schooling. A closer look at equation (2) also shows us that the parameter β_1 is an estimate of the impact of schooling on wages rather than an internal rate of return on investment. If it were an internal rate of return it would be a private one, since this specification ignores any subsidization of schooling and omits any positive or negative externalities to schooling.

As is usual in econometrics, there are some problems that arise with the estimation of equation (2). One is the omission of a relevant variable in this case abilities. Abilities are likely to be positively correlated with schooling, so omitting ability measures from the regression equation will bias the estimated returns to schooling upward. However, abilities are difficult to conceptualize and measure, and there is no consensus as to whether they are significant enough to differentiate earnings. Because of these reasons and because the sample does not include any variable that could conceivably be used as a proxy of abilities, this problem is ignored in our estimations. Another problem associated with the estimation of equation (2) is that we have to proxy experience by its potential term: age minus years of education minus six. This is a poor proxy. Furthermore, potential experience is a even poorer proxy for women than for men because women tend to have a more unstable participation in the labor force. An additional problem is that equation (2) assumes that education is assigned randomly across the population. In reality education is endogenous and the estimation of the relationship between earnings and education may be biased upward or downward depending on the way individuals make their education choices. We recognized the presence of this problems, but they don't invalidate our analysis because there is, a priori, no reason why they should have any trend in time.

3. Methodology

Traditionally, mean regression has been used to estimate equation (2). But when disturbances are non-normal or there is a relatively large proportion of outliers, then the mean regression method is not robust. This has led to the study of the other alternative methods of estimation. The l-estimator technique is particularly useful for our objective not only because it is a robust method, but also because it permits us to compute several regression curves corresponding to different "cuts" in the distribution (see explanation below).

The traditional mean regression method involves the minimization of the squared sum of errors which allows one to identify the value of the parameters. The minimization implies that the fitted curve is the prediction of the mean of Y (the dependent variable) given the values of a certain vector of independent variables X. In the same vein, instead of taking the square of the error, it is possible to take their absolute value and to minimize their sum. In this case the minimization implies that the fitted curve is the prediction of the median of Y given the values of a certain vector of independent variables X. This can also be seen as fitting a curve that implies that half of the errors will be positive and half negative. A natural extension of this concept is the fitting of a curve that implies that θ% of the errors will be negative and (100-θ)% will be positive, and this gives rise to the quantile regression estimation method. This extension permits us to have different "snapshots" of the distribution of wages, which may be a very informative device, since it is reasonable to assume that due to the presence of heterogeneity, the dependent variable is not identically distributed across individuals.

In a regression analysis where the errors are i.i.d., the conditional quantiles become a set of parallel hyperplanes and thus, we would expect the estimated coefficients be the same for different quantiles (with the obvious exception of

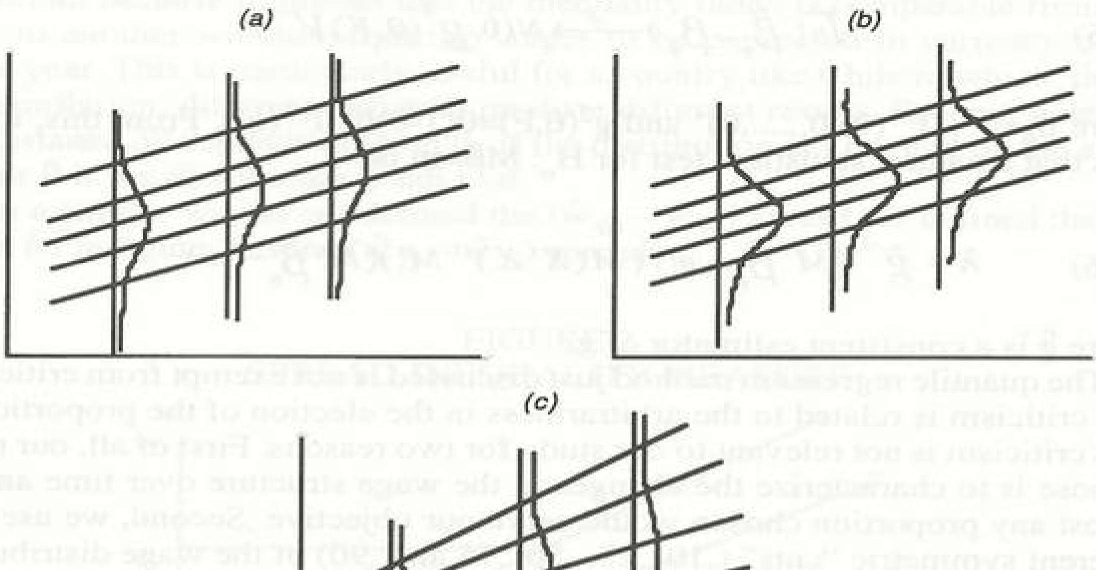
β_0). In this case, not much information is lost just using simple OLS. But even in i.i.d. settings, the regression quantile method gives us a device that we can use to measure the asymmetry and dispersion of the conditional distribution.

Figure 1 permits us to show graphically the idea behind quantile regression estimation. Panel (a) graphs the relationship between Y and X with i.i.d. errors. Panel (b) shows us another relation between Y and X with i.i.d. errors, but with a smaller variance[4]. Panel (c) shows us a relation between Y and X that has heteroskedasticity. Note that by using the quantile regression method it is possible to obtain a measure of the conditional dispersion that is equivalent to what in the one dimensional analysis is called "interquartile range". This can be measured as the vertical distance (evaluated at some point) between two quantile adjusted lines[5].

Let us formalize what we have just discussed. Let w_i (i=1,.....,n) be the wage of individual i and let X_i be a known vector of covariates. Let us assume that the θth quantile of the conditional distribution of w_i given X_i is linear, that is,

$$w_i = X_i'\beta_\theta + u_{\theta i} \text{ with } Q_{UANT\theta}(w_i \mid X_i) = X_i'\beta_\theta \quad i=1, 2, \ldots, n \tag{3}$$

FIGURE 1
ERROR DISTRIBUTION AND QUANTILE REGRESSION



[4] Note that the different quantile lines estimated are still parallel, but the distance between them is smaller.

[5] This measure depends not only on the "rate of return" but also on the intercept.

where X_i is a k x 1 vector of covariates with $X_{i1}=1$, and β_θ for all i, and is an unknown kx1 parameter vector whose estimation, for different values of θ $[0<\theta<1]$ is in our interest. The term $Q_{UANT\theta}(w_i|X_i)$ denotes the conditional quantile of w_i given X_i. In this specification u_θ is defined by $u_i=w_i-X_i'\beta_\theta$, from where it follows that $Q_{UANT\theta}(u_\theta|X)=0$.

The qth quantile regression based on a sample (w_i, X_i) i=1....,n, is a vector β_θ that minimizes:

$$L=\theta \sum_{[i|w_i\geq X_i'\beta_\theta]} |w_i - X_i'\beta_\theta| + (1-\theta) \sum_{[i|w_i<X_i'\beta_\theta]} |w_i - X_i'\beta_\theta| \tag{4}$$

The estimation of β_θ is a linear programming problem that can be solved using linear programming techniques as it is shown in Koenker and Bassett (1978, 1982). The solution does not have an explicit form. The estimation of β_θ can also be shown to fit into a Generalized Method of Moments framework. When the linear model errors $[u_\theta=w_i-X_i'\beta_\theta]$ are i.i.d. there is a well-developed asymptotic theory leading to the construction of tests. It is possible to show (Koenker and Basset, 1982) that if $\lim[(X'X)/n]\rightarrow V$ with $X_{i1}=1$ for all i, and the error distribution, F, has strictly positive density at the qth quantile [i.e., $f(F^{-1}(\theta))>0$], then β_θ is asymptotically normal, i.e.,

$$\sqrt{n}(\hat{\beta}_\theta-\beta_\theta) \xrightarrow{d} N(0, g^2(\theta,F)V^{-1}) \tag{5}$$

where $\beta_\theta=\beta+(F^{-1}(\theta),0,.....,0)'$ and $g^2(\theta,F)=\theta(1-\theta)/f^2(F^{-1}(q))$. From this, it follows that a natural statistical test for H_o: $M\beta=m$ is:

$$\lambda=\hat{g}^{-2}(M\hat{\beta}_\theta-m)'(M(X'X)^{-1}M')(M\hat{\beta}_\theta-m) \tag{6}$$

where $\hat{g}$ is a consistent estimator of g.

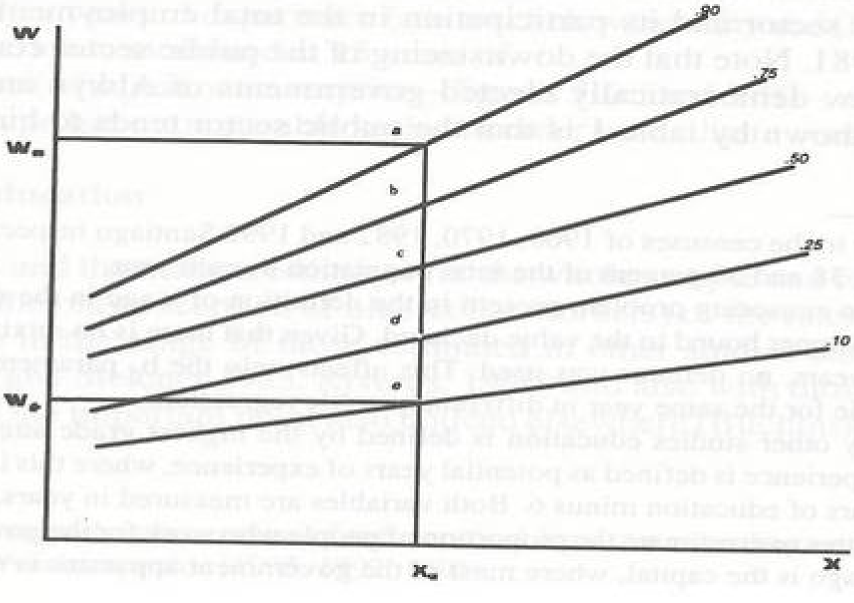
The quantile regression method just discussed is not exempt from criticism. One criticism is related to the arbitrariness in the election of the proportion θ. This criticism is not relevant to our study for two reasons. First of all, our main purpose is to characterize the changes in the wage structure over time and so almost any proportion chosen would serve our objective. Second, we use five different symmetric "cuts" (.10, .25, .50, .75 and .90) of the wage distribution which we believe permits us to characterize sufficiently the underlined distribution. Another problem associated with quantile regression estimation is that the final solution may not be unique, but uniqueness can always be achieved by selecting an appropriate design or by using an arbitrary rule to select from any set of multiple solutions (this problem is exactly similar to selecting the median among a sample that has a pair number of observations).

The quantile regression estimation technique also permits us to define a measure of inequality that we will call the spread. In the one dimensional analysis of a variable, the difference in two quantiles can be used as a natural measure of dispersion. In the case at hand, the model predicts different values of the 'average wage' depending on the quantile that we are interested in, given certain values of the covariates. Given this we can predict the value of the average wage for a given vector of covariates and then calculate their difference. The vector of covariates chosen here corresponds to the median of education and experience in each year. The precise definition of the inequality index used here is S_p=antilog $(\hat{w}_{.90} - \hat{w}_{.10})$-1. This, evaluated at the median values of education and experience, corresponds to the times that the 'representative' agent will earn in addition to its wage if he were in the upper tail of the distribution instead of being in the lower tail (i.e., a number like 2 means that he would earn three times as much if he were in the upper tail compared to what he would earn if he were in the lower tail).

The spread-inequality index can be illustrated using figure 2. Let X_e be the median of X. Let the line .90 be the estimated line when we estimate the quantile regression and we fix Θ=.90. Also let also .10 be the estimated line when we estimate the quantile regression and we fix Θ=.10. If we evaluate the predicted value for the "average wage" using these two different lines and we call $\hat{w}_{.90}$ the predicted value when Θ=.90 and $\hat{w}_{.10}$ when Θ=.10, then our spread-inequality index is S_p=antilog $(\hat{w}_{.90} - \hat{w}_{.10})$-1. Our dispersion measure is a monotonic transformation of these two values (i.e. the distance $\vec{a}\vec{e}$ in figure 2). Two things are worth nothing here. First, note that the difference in the predicted value for two different quantiles (i.e. $(\hat{w}_{.90} - \hat{w}_{.10})$) given a vector of covariates, is independent of the units in which the predicted wages are measured. This is extremely important because it implies that the inequality index is comparable from one year to another without requiring wages to be expressed in currency of the same year. This is particularly useful for a country like Chile in which, due to hyperinflation, different deflators produce different results. Second, note that the distance $\vec{a}\vec{e}$ depends only on β_0 if the distribution is i.i.d. and on the entire vector β if the distribution is not i.i.d.

In a similar way as we defined the $(\hat{w}_{.90} - \hat{w}_{.10})$ spread we defined the distance $\vec{b}\vec{d}$ in figure 2 as the $(\hat{w}_{.75} - \hat{w}_{.25})$ spread.

FIGURE 2
SPREAD-INEQUALITY MEASURE



4. The data

The data employed were obtained from the University of Chile Household Surveys. These are comparable and representative annual surveys for Santiago. Each survey has between 10,000 and 16,000 people and around 3,700 and 5,400 active labor force participants. During this period, Santiago represented about one third of Chile's total population,[6] and a higher proportion of GDP.

The sample was defined as male workers who worked at least 35 hours per week and were not self-employed. The sample only includes "empleados" (white-collar workers) and "obreros" (blue-collar workers). Self-employed workers, domestic servants and military personnel also were eliminated from the sample. Women were eliminated due to the usual reasons in these studies: "... their substantial commitment to non-market household activities and the high degree of variability of market labor over the life cycle" (R. Willis, 1986, pg. 528). Self-employed workers were eliminated because the data base did not allow the separation of income into returns to labor and returns to capital; domestic servants were eliminated because their recorded earnings could mislead their labor income, which for live-in domestic servants includes room and board, which are difficult to value; and military personnel was eliminated because their salaries do not correspond to a market productivity criteria. The unemployed and people who work in voluntary services were also excluded. The same type of survey and variable definitions are used throughout the entire period, which gives us comparable year by year results. The dependent variable is defined as the log of the hourly wage.[7]

Table 1 gives some stylized facts concerning the sample. The first six columns show the number of observations, the mean, the median and the standard deviation of the hourly wage and the means of education and years of experience for the total sample.[8] The rest of the columns show the same variables for the three breakdowns employed in this study. Here it is possible to note some facts such as the highly volatile participation of the public sector in total employment. Between 1960 and 1970 the public sector employed approximately 22 percent of the workers. Under Allende's government this percentage increased up to 28 percent in 1973. In 1973 the Pinochet's government started a reduction in the public sector and its participation in the total employment fell to a 16 percent in 1981. Note that the downsizeing of the public sector continued even under the new democratically elected governments of Alwyn and Frei.[9] Another point shown by table 1 is that the public sector tends to hire more edu-

6 According to the censuses of 1960, 1970, 1982 and 1992 Santiago respectively accounts for 32, 35, 38 and 39 percent of the total population in each year.

7 There is no censoring problem present in the definition of wage in the sample because there is no upper bound to the value declared. Given that there is no mixing of data from different years, no deflator was used. This affects only the b_0 parameter, but it is still comparable for the same year in different quantile regressions.

8 Like many other studies education is defined by the highest grade attended and completed; experience is defined as potential years of experience, where this is defined as age minus years of education minus 6. Both variables are measured in years.

9 These figures overestimate the proportion of people who work for the government, given that Santiago is the capital, where most of the government apparatus is situated.

cated people than the private sector. It has also started to hire more experienced people during the eighties and specially during the nineties. Table 1 also highlights the relatively stable partition of the sample between white and blue collar workers: blue-collar workers are a stable 50 percent of the sample. It is interesting to note that white-collar workers are for the whole period more educated on average than blue-collar workers, but the difference decreases as time progresses: in 1960 white collar workers had almost twice the years of education of the blue collar workers. By 1996 this gap steadily reduced to 1.5 times. This fact casts some doubts on the usual distinction between high and low skilled workers based on the blue-collar versus white-collar type of job (so common in some branches of the recent labor literature).

5. Empirical analysis

In this section the results of the estimation of equation (2) using mean and quantile regression are analyzed. The standard quantiles used in other studies of the same kind are reproduced here: .10, .25, .50, .75 and .90 (Buchinsky 1994a, Chamberlain 1991). The same equation is estimated yearly from 1960 to 1996 for the total sample, and partitions defined by experience, type of sector and job type (blue-collar or white-collar).

The results of the estimations are reported in figures 3 to 9. Figure 3 presents the results for the whole sample. Figures 4 and 5 present the results when a breakdown by years of experience is performed (figure 4 includes only individuals with less than 9 years of experience and figure 5 includes individuals with 20 or more years of experience). Figures 6 and 7 present the results when a breakdown by public and private sector is carried out. Figures 8 and 9 present the results when a breakdown by job type is performed. In each figure, the graphs on the left side present the estimation of the parameters using mean and median regression methods (i.e. mean estimation and quantile .50 estimation), and those on the right side present the estimation for the other quantiles considered in this study (i.e., .10, .25, .75, .90). For each figure, graphs (a) and (b) present the return to education, (c) and (d) present the return to experience evaluated at five years of experience (see text below) and (e) and (f) present the return to experience evaluated at 15 years of
experience (with just one exception –figures 5-(e) and 5-(f)–, all the graphs of the same type have comparable scales in order to facilitate comparisons).

Return to Education

The mean and the median estimates for the whole sample and for the breakdowns (with the only exception of blue-collar workers) of the rates of return to education are in the range of those estimated in other studies carried out for Chile (Corbo and Stelcner 1983, Riveros, 1990) and also with those calculated elsewhere.[10] One important point also noticed elsewhere (Buchinsky, 1994a) is

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10 For a very comprehensive review of the empirical literature regarding returns to education see G. Psacharopoulos (1985, 1992, 1993).

TABLE 1
BASIC STATISTICS OF THE SAMPLE (1)

YEAR	Total Sample						Breakdown by Experience: 0 - 9						Breakdown by Experience: 20 +					
	nobs	Y	Ye	std.	educ	exp.	nobs	Y	Ye	std.	educ	exp.	nobs	Y	Ye	std.	educ	exp.
60	1356	0.89	0.64	1.54	7.45	21.3	247	0.67	0.43	1.62	9.83	5.4	677	0.99	0.65	1.49	6.44	31.4
61	1442	1.10	0.71	1.56	8.20	20.6	314	0.93	0.64	1.68	10.56	5.5	669	1.19	0.76	1.52	7.08	31.6
62	1565	1.11	0.72	1.43	8.01	20.4	339	0.88	0.54	1.50	10.00	5.4	710	1.24	0.77	1.41	6.94	31.8
66	2134	1.19	0.76	3.93	7.95	20.5	470	1.02	0.65	4.09	10.50	5.2	1010	1.29	0.78	3.82	6.83	31.7
67	2284	1.33	0.87	0.34	8.23	20.1	552	1.12	0.70	0.37	10.43	5.4	1044	1.43	0.92	0.32	7.07	31.6
68	2045	1.43	0.86	2.84	8.72	19.7	532	1.21	0.69	3.07	10.91	5.4	930	1.54	0.92	2.70	7.49	31.2
69	1942	1.46	0.91	2.15	8.53	20.8	457	1.14	0.69	2.20	10.61	5.2	945	1.57	0.99	2.04	7.35	32.0
70	2000	1.60	1.00	16.61	8.77	20.4	492	1.36	0.77	17.74	10.99	5.4	941	1.72	1.08	15.76	7.46	32.0
71	2229	2.14	1.32	14.03	9.36	20.9	501	1.76	1.08	14.30	11.55	5.2	1080	2.28	1.36	13.77	8.18	32.2
72	2124	2.16	1.48	9.45	9.53	20.4	493	1.97	1.42	9.69	12.06	5.3	1000	2.21	1.51	9.26	8.14	31.7
73	2199	1.67	1.11	2.47	9.29	20.4	530	1.47	0.92	2.54	11.57	5.4	1024	1.73	1.21	2.41	7.94	32.1
74	1685	1.30	0.92	2.67	8.70	20.2	410	1.25	0.88	2.94	11.56	5.3	754	1.36	0.96	2.65	7.18	32.5
75	1845	1.18	0.88	5.31	9.14	21.4	384	1.16	0.79	5.71	11.95	5.4	944	1.20	0.88	5.05	7.86	31.8
76	1606	1.54	0.94	1.92	9.13	21.1	360	1.59	0.94	2.09	12.40	5.3	809	1.52	0.99	1.84	7.33	31.9
77	1868	2.15	1.26	1.01	9.36	20.3	444	1.98	1.10	1.05	12.06	5.2	872	2.11	1.28	0.98	7.53	31.7
78	1919	2.62	1.52	0.74	9.67	19.6	499	2.30	1.33	0.74	11.85	5.5	866	2.55	1.52	0.71	7.97	31.2
79	1897	2.90	1.66	0.57	9.75	19.3	540	2.71	1.53	0.58	11.94	5.2	801	2.88	1.71	0.55	8.01	32.3
80	1676	2.82	1.69	4.11	9.75	19.2	456	2.50	1.45	4.25	11.98	5.2	715	2.69	1.69	3.76	7.92	31.7
81	1821	3.18	1.99	3.22	9.63	18.9	537	2.80	1.91	3.09	11.86	5.2	768	3.12	2.05	3.18	7.81	31.6
82	1429	3.96	2.29	3.42	10.27	18.7	410	3.64	2.29	3.45	12.60	5.5	599	4.23	2.29	3.45	8.35	31.0
83	1369	2.81	1.49	2.65	10.12	18.8	370	2.33	1.23	2.60	12.02	5.7	569	2.60	1.49	2.54	8.31	31.0
84	1423	2.80	1.45	2.27	10.40	18.8	370	2.50	1.21	2.28	12.50	5.6	581	2.43	1.45	2.09	8.33	31.3
85	1600	2.26	1.26	1.58	10.55	19.1	433	1.71	0.95	1.43	12.43	5.2	675	2.51	1.40	1.63	8.96	31.9
86	1506	2.14	1.22	1.26	10.86	18.3	438	1.86	1.10	1.19	12.65	5.3	617	2.35	1.37	1.28	9.18	30.7
87	1631	2.63	1.22	1.22	10.87	18.3	492	2.02	1.03	1.13	12.30	5.4	654	2.71	1.27	1.20	9.21	31.2
88	1667	2.42	1.30	0.99	10.75	18.3	502	1.95	1.15	0.90	12.62	5.2	660	2.59	1.33	1.03	8.90	31.7
89	1764	2.77	1.53	0.81	11.34	17.5	568	2.50	1.43	0.79	13.09	5.3	638	2.99	1.60	0.83	9.62	31.5
90	1720	3.20	1.53	0.68	11.58	18.1	510	2.70	1.40	0.64	13.30	5.0	674	3.25	1.65	0.67	10.06	31.2
91	1822	3.19	1.65	0.54	11.55	18.1	572	2.91	1.48	0.54	13.30	5.1	712	3.17	1.73	0.52	9.95	31.7
92	1849	2.95	1.77	0.42	11.21	18.8	530	2.42	1.56	0.38	12.97	4.8	727	3.13	1.89	0.43	9.56	33.0
93	1874	3.42	2.15	0.37	11.64	18.8	566	3.09	2.01	0.36	13.45	5.0	756	3.60	2.30	0.38	9.96	32.5
94	1795	3.72	2.31	0.33	11.60	18.9	556	3.30	2.18	0.31	13.34	5.0	742	4.02	2.55	0.34	10.10	32.3
95	1712	3.93	2.37	0.31	11.59	18.8	505	3.29	1.97	0.30	12.94	5.0	675	4.05	2.56	0.30	10.14	32.7
96	1709	4.23	2.62	0.29	11.76	19.1	480	3.79	2.55	0.26	13.25	5.0	718	4.51	2.73	0.30	10.52	31.9

YEAR	Breakdown by Public-Private Sector: public nobs	Y	Ye	std.	educ	exp.	private nobs	Y	Ye	std.	educ	exp.	Breakdown by White-Blue Collar: white nobs	Y	Ye	std.	educ	exp.	blue nobs	Y	Ye	std.	educ	exp.
60	332	1.31	0.86	1.48	9.26	22.4	1024	0.75	0.54	1.46	6.86	20.9	579	1.40	0.97	1.46	10.26	21.2	777	0.51	0.46	1.04	5.36	21.3
61	286	1.69	1.09	1.44	10.80	21.5	1156	0.96	0.64	1.50	7.55	20.4	654	1.74	1.19	1.48	11.44	19.4	788	0.58	0.53	1.01	5.50	21.6
62	339	1.76	1.16	1.41	10.70	21.1	1226	0.93	0.65	1.33	7.27	20.2	707	1.76	1.23	1.32	11.15	19.5	858	0.58	0.52	0.95	5.42	21.2
66	464	1.63	1.04	3.85	10.40	20.9	1670	1.06	0.70	3.80	7.27	20.4	923	1.89	1.25	3.90	11.21	19.3	1211	0.65	0.60	2.55	5.46	21.5
67	474	1.89	1.23	0.33	10.82	20.2	1810	1.19	0.79	0.33	7.55	20.0	1032	2.08	1.31	0.33	11.32	19.3	1252	0.72	0.65	0.23	5.68	20.7
68	445	2.03	1.21	2.87	11.31	19.9	1600	1.26	0.79	2.74	8.00	19.6	1018	2.14	1.38	2.82	11.58	19.0	1027	0.72	0.64	1.87	5.89	20.3
69	450	1.93	1.30	1.97	10.57	21.8	1492	1.31	0.78	2.11	7.91	20.5	946	2.20	1.46	2.08	11.25	19.7	996	0.75	0.65	1.49	5.94	21.8
70	468	2.29	1.50	16.26	10.93	20.9	1532	1.39	0.87	15.91	8.11	20.3	1008	2.36	1.60	15.94	11.33	19.6	992	0.83	0.72	11.63	6.17	21.2
71	583	3.12	2.07	13.42	11.55	20.7	1646	1.80	1.10	13.37	8.59	21.0	1272	3.04	2.15	13.17	11.81	19.8	957	0.96	0.83	8.79	6.12	22.4
72	585	2.77	1.98	9.05	11.61	19.9	1539	1.93	1.42	9.27	8.74	20.5	1233	2.91	2.24	9.02	11.81	19.0	891	1.13	0.99	6.63	6.37	22.2
73	611	2.15	1.48	2.54	11.18	20.6	1588	1.49	1.02	2.38	8.56	20.3	1227	2.26	1.64	2.46	11.66	19.3	972	0.94	0.77	1.79	6.29	21.7
74	432	1.63	1.14	2.85	10.96	19.9	1253	1.18	0.84	2.54	7.92	20.4	791	1.83	1.38	2.76	11.54	18.8	894	0.83	0.73	1.94	6.18	21.5
75	468	1.37	1.00	5.31	10.85	21.5	1377	1.12	0.79	5.26	8.56	21.4	1005	1.59	1.19	5.16	11.63	20.2	840	0.69	0.61	3.88	6.16	22.8
76	402	1.66	1.13	1.82	10.40	22.0	1204	1.50	0.94	1.94	8.70	20.9	786	2.31	1.54	1.87	12.01	19.3	820	0.80	0.71	1.31	6.36	22.9
77	418	2.59	1.47	1.08	10.97	20.6	1450	2.03	1.22	0.99	8.89	20.2	900	3.35	2.20	0.98	12.25	18.6	968	1.04	0.92	0.64	6.67	21.9
78	401	3.14	1.68	0.85	11.16	21.2	1518	2.49	1.45	0.71	9.28	19.1	906	4.18	2.61	0.71	12.64	18.0	1013	1.24	1.11	0.48	7.02	21.0
79	373	3.64	2.00	0.65	11.52	20.7	1524	2.72	1.60	0.55	9.32	19.0	920	4.46	2.84	0.57	12.40	17.6	977	1.44	1.26	0.39	7.25	20.9
80	257	3.27	2.03	4.37	11.86	19.1	1419	2.74	1.62	4.05	9.37	19.2	789	4.47	2.89	3.94	12.61	17.6	887	1.35	1.21	2.71	7.21	20.6
81	243	3.72	2.30	3.60	11.88	18.5	1578	3.10	1.99	3.15	9.28	19.0	789	5.06	3.32	3.27	12.54	17.0	1032	1.75	1.56	2.27	7.41	20.3
82	204	4.16	2.75	3.54	12.35	18.0	1225	3.92	2.29	3.39	9.93	18.9	732	5.98	3.79	3.43	12.85	17.2	697	1.83	1.54	2.23	7.56	20.3
83	296	2.36	1.30	2.65	10.22	18.7	1073	2.93	1.59	2.63	10.09	18.9	655	4.53	2.89	2.62	12.87	17.1	714	1.23	1.04	1.63	7.59	20.4
84	262	3.33	1.58	2.58	11.15	20.4	1161	2.68	1.45	2.20	10.23	18.5	682	4.59	2.91	2.19	13.09	17.0	741	1.15	0.97	1.36	7.93	20.5
85	315	2.65	1.44	1.76	11.17	20.0	1285	2.17	1.20	1.53	10.40	18.8	745	3.70	2.45	1.54	12.94	18.4	855	1.01	0.86	0.93	8.47	19.7
86	230	2.76	1.61	1.43	12.09	19.3	1276	2.03	1.22	1.22	10.64	18.1	739	3.33	2.29	1.21	13.12	17.9	767	0.99	0.92	0.74	8.69	18.6
87	222	3.19	1.62	1.24	12.45	19.5	1409	2.54	1.15	1.21	10.62	18.2	782	4.41	2.24	1.27	13.47	16.8	849	1.00	0.88	0.65	8.47	19.8
88	195	3.92	2.00	1.14	12.64	20.1	1472	2.22	1.20	0.96	10.50	18.1	742	4.07	2.22	1.06	13.14	17.2	925	1.09	0.95	0.59	8.84	19.2
89	169	3.95	2.47	0.82	13.56	18.1	1595	2.64	1.43	0.80	11.10	17.4	835	4.40	2.75	0.82	13.66	16.4	929	1.30	1.15	0.49	9.25	18.5
90	186	4.26	2.18	0.67	13.47	20.5	1534	3.07	1.53	0.67	11.35	17.8	840	5.14	2.95	0.71	13.94	16.6	880	1.35	1.15	0.36	9.32	19.5
91	177	3.94	2.23	0.53	13.15	20.0	1645	3.11	1.59	0.54	11.38	17.9	922	4.94	2.78	0.56	13.95	16.8	900	1.40	1.24	0.30	9.09	19.5
92	174	4.19	2.43	0.46	13.05	21.9	1675	2.83	1.70	0.41	11.01	18.5	837	4.63	2.70	0.46	13.51	17.8	1012	1.57	1.35	0.25	9.30	19.7
93	153	3.59	2.76	0.34	12.93	21.6	1721	3.41	2.13	0.37	11.52	18.5	905	5.15	3.59	0.37	13.94	17.3	969	1.81	1.61	0.23	9.49	20.2
94	171	4.34	2.96	0.32	12.96	22.0	1624	3.65	2.26	0.33	11.45	18.5	879	5.48	3.77	0.35	13.69	17.2	916	2.02	1.72	0.21	9.59	20.5
95	148	4.89	2.96	0.32	13.18	21.3	1564	3.84	2.37	0.31	11.44	18.6	839	5.91	3.94	0.32	13.77	17.7	873	2.03	1.80	0.18	9.49	19.8
96	134	6.16	4.37	0.29	13.98	23.2	1575	4.06	2.55	0.28	11.58	18.7	849	6.22	4.37	0.29	13.95	18.0	860	2.26	1.99	0.18	9.61	20.1

Source: Author's calculations.

(1) Y represents the mean of the hourly real wage; Ye the median of the hourly real wage; std. is the standard deviation of the hourly real wage; educ is the average of complete years of education and exp is the average of years of experience (all real values are in pesos of June of 1989. The deflator used is the CPI).

that the mean estimation and the median estimation show very similar patterns for the return to education. The same pattern of movements is followed by the rate of return calculated in each one of the quantile regressions. From our estimates for the whole sample (fig. 3-(a)), it is possible to see that the rate of return to education was relatively stable at around 12 percent until to 1971, declined until 1974 to a level of 10 percent, started rising again until 1987 (reaching a peak of around 17 percent), declined until 1992 to around 12 percent and from then on stabilized around 14 percent. The same pattern of movements are followed by the quantile regression estimates, but the levels differ, showing that the higher rate of return is to education the higher the quantile. It is possible to see from figure 3-(b) that between 1960 and 1970 there was a relatively stable return to education per quantile. Between 1970 and 1974 there was a big decline in all the quantile returns. Between 1975 and 1980 there was a recovery in all the quantile returns, but this increase was higher in the two upper quantiles, increasing the spread in the returns between the upper two quantiles and the lower two. During the eighties the rates of return between upper and lower quantiles moved quite differently: the rates of return of the upper quantiles went up and that of the lower two quantiles went down, increasing the spread. During the nineties the rate of return of the upper quantiles has declined and, instead, the rate of return of the two lower quantiles have remained relatively stable implying a decrease in the spread.

Now looking at the breakdown by level of experience (fig. 4-(a)-(b) and 5-(a)-(b)), we notice two very important facts. First, the rates of return to education estimated using mean and median estimates are higher for new workers (zero to nine years of experience) than for old workers (20 plus years of experience), with the difference being especially large after 1980, but this difference declines sharply in the nineties. Second, it is possible to observe the same effects observed for the whole sample: the differences in return to education by quantiles increase with the quantile (the higher the quantile, the higher the rate of return), and this is independent of the group being considered. Looking at figures 4-(b) and 5-(b), it is possible to notice that the differences estimated by quantiles are getting larger as time progresses particularly in the case of new workers after 1983, but again these differences tend to decrease in the nineties.

If we now look at the breakdown by public and private sector (figs. 6-(a)-(b) and 7-(a)-(b)), we see that the estimations of the rate of return to education using mean and median regression estimates show a very stable pattern in the case of the public sector from 1960 to 1976, followed by an increase until 1984 to around 18 percent, then an unstable pattern of changes up and down between 1984 and 1993, followed by a big decline in 1993, and finally a stable recovery to a rate of around 16 percent in 1996. In the case of the private sector, the same estimates produce a rate of return to education that was very stable from 1960 to 1971, a decline from 1971 to 1974 to a level of 10 percent, a rise again until 1987, then a decline until 1992, and a very stable level since then at around 13 percent. A closer look will also show that the rate of return to education is slightly higher in the public sector than in the private sector and also more volatile. Looking at the quantile regression estimations it is possible to see that the differences in the rate of return to education in the top two quantiles with respect to the lower two quantiles are higher in the private sector than in the public sector, and the differences seem to be growing bigger in the private sector, with the exception of the nineties in which the opposite is true. The same differences in the public sector are amazingly narrow between 1977 and 1983, but they also seem to be increasing thereafter. These estimates also show a more stable return to education by quantiles in the case of the private sector than in the public sector.

The last breakdown performed is between blue-collar and white-collar workers. Here there are some surprising results. Figure 8-(a) shows that white-collar workers have a rate of return to education that is relatively stable between 1960 and 1971. It then declines to a level of around 9 percent in 1975. Since then on it increases (although not steadily), and reaches a peak of 20 percent in 1987. It declines again until 1993 and it seems to stabilize around 16 percent at the end of the period. Figure 9-(a) shows a very different pattern for the rate of return on education to the blue collar workers: it is much lower (around 5 percent) and also very stable during the whole period. The quantile regressions also show that quantile estimates of the rate of return to education in the case of white-collar workers (fig. 8-(b)) are very similar to those of the whole sample, being higher, the higher the quantile. The same quantile estimates show a very different pattern for the blue-collar workers, where it is impossible to distinguish any pattern before 1984. Since that year it seems that the rate of return to education is higher for the higher quantiles. Still, the rate of return for the higher quantiles in the case of blue-collar workers is lower than the rate of return to education for the lower quantile in the case of white-collar workers. I have no explanation for this fact and it surely is a topic for further research. It should also be noticed that the differences (spread) in quantile returns are higher for the white collar workers than for the blue collar workers (see figs. 8-(b) and 9-(b)).

One striking point also noticed by Buchinsky (1994a) is the fact that the mean return to education and the returns estimated at each quantile behave in a similar manner. This is true in our study not only for the whole sample, but also for each one of the breakdowns performed.

Return to Experience

The marginal impact of one additional year of experience on the conditional wage distribution can be obtained from equation (2) and is equal to $\beta_2+2\beta_3\mathrm{Exp}$; hence, it needs to be evaluated at a specific level of experience. Following Buchinsky (1994a), two points were chosen: five years (representing new workers) and 15 years (representing experienced workers). The results are presented in figures 3 to 3 in graphs (c), (d), (e) and (f).

The estimations using mean and the median regression methods for the whole sample show a very stable pattern of return to experience of about five percent when evaluated at five years of experience and four percent when evaluated at 15 years of experience (see figs. 3-(c) and 3-(e)). The quantile estimates show no particular patterns besides a very concentrated distribution that tends to be less concentrated starting in 1986 (see figures 3-(d) and 3-(f)). The breakdown by years of experience produces a very different picture: for the group of zero to nine years of experience (the less experienced workers), the estimated regression evaluated at five years of experience produces a rate of return that is much higher than the average for the whole sample (even though the difference is declining as time progresses), and the quantile regressions show no particular order. The same regression evaluated at 15 years of experience produces wild changes in the estimates, which can be attributed to the imprecise estimation of parameter β_3 (see figure 4-(e)). The same estimations in the case of experienced workers produce estimates of the return to experience that are lower than those for the whole sample and especially lower compared to those for young and experienced workers (see figures 5-(c) and 5-(e)). The quantile regressions also show no particular pattern either for the less experienced worker or for the experienced workers (see figures 4-(d)-(f) and 5-(d)-(f)).

Figures 6-(c)-(d)-(e)-(f) and 7-(c)-(d)-(e)-(f) show that, in general, there are differences in the rate of return to experience if we divide the sample into public and private sectors. The rate of return to experience (evaluated either at 5 or 15 years) is less stable (and lower in level) in the public sector than in the private sector. In the case of the private sector the rate of return is very stable at around five percent with a slight decline starting in 1987. Similar decline can be observed in the case of the public sector. The quantile regressions also show the same patterns, but in the case of the private sector, show that starting in 1986, there has been a consistent pattern of being higher in the higher quantiles specially after 1986. This is true not only when evaluated at five years of experience but also when evaluated at 15 years of experience.

Looking at the disaggregation by job type, we see that the return to experience in the case of white-collar workers using media and median regression methods is very stable at around four percent (as for the whole sample), but the return for new blue-collar workers seems to be declining from five percent at the beginning of the period for new workers to around 2.5 percent at the end of the period (see figs. 8-(c) and 9-(c)). When evaluated at 15 years of experience, it went down from three percent at the beginning of the period to around one percent at the end of the period (graph 9-(e)). In the case of white-collar workers, the quantile regressions show no particular pattern, but in the case of blue-collar workers, there seems to be a pattern of being higher for the higher quantiles, especially when evaluated at five years of experience and at the end of the period. The same is observed when evaluated at 15 years of experience, but on a lower scale.

Wage Inequality

As we discussed in the methodological section, the quantile regression estimation technique permit us to define a measure equivalent of the interquartile range in the unidimensional analysis. We called it spread. In this section we present the empirical results and we compared to a more traditional measure of dispersion: the Gini coefficient. It is worthwhile to stress that the results obtained in this section are based on the sample definition already mentioned and on the distribution of the hourly wage. Two measures of dispersion of the conditional wage distribution are analyzed here: the .90 - .10 spread and the .75 - .25 spread. They are presented in figure 10.

When considering the whole sample we see that the .90 - .10 spread shows a tendency to increase from 1966 to 1974 (fig. 10-(a)), then drop in 1975, start to rise again until 1984 when it experiences a second drop. It then increases vigorously until 1989 and then again has a big drop in 1990 and from then on tends to decrease showing another big drop in 1993. From then on it decreases. Note that these results imply that inequality increased in Chile starting in the middle of the sixties and did so until 1989 (although not steadily). It is also interesting to note the order of magnitude of this phenomenon: in 1960 a person in the top of the distribution (θ=.90) would earn three times as much as a person in the lower tail (θ=.10). In 1988 (at the peak of the inequality) the same person would earn almost six times as much as a person of the lower tail. By 1993 this difference was reduced to almost 4.5 times.

The same general pattern can be observed in the case of the .75 - .25 spread for the whole sample (fig. 10-(b)), although it is remarkably more stable than the .90 - .10 spread. In here the inequality index stays relatively stable until 1966 and from then on it grows (although unsteadily) until 1987 when it decreases markedly in both 1988 and 1989, increases in 1990 and decreases heavily since then. The fact that the .75 - .25 spread is more stable than the .90 - .10 spread clearly suggests that the changes in wage inequality are mainly due to changes in the tails of the distribution.

The results also show that different breakdowns of the sample give very different pictures of the dispersion. In the case of the breakdown by experience (figs. 10-(c) and 10-(d)), we see that when we use the .90 - .10 measure of dispersion we note that until 1980 both groups have a relatively similar pattern of dispersion (even though in the case of people with less experience it is more volatile). After 1980 it is possible to observe that people with more than 20 years of experience have more inequality than people with less experience. This difference is particularly big around 1990 (4.5 versus 2.5). The .75 - .25 spread defined by experience sub-groups produces a pattern that follows the whole sample pattern very closely.

The breakdown by public and private sector (figs. 10-(e) and 10-(f)) confirms the results for the whole sample, i.e., inequality in both sectors started to rise around the mid sixties. Two facts are worth noting here: first, the rise in inequality in the private sector has been more stable than in the public sector and, second, the inequality in both sectors is relatively similar. It is interesting to note that since 1989 the inequality has been decreasing in both sectors. The behavior of the .75 - .25 spread in the cases of the private and the public sectors is very similar to the behavior of the .71 - .25 spread in the case of the whole sample.

When the sample is divided by type of job is possible to observe (figs. 10-(g) and 10-(h)) that inequality (measured either as the .90 - .10 spread or the .75 - .25 spread) is bigger in white-collar jobs than in blue-collar type of jobs. It is also possible to observe that inequality has been increasing during the whole period for the white-collar type of jobs, but this is not the case for the blue-collar type of jobs in which inequality is amazingly stable. This partition of the sample produces the most clear effect in inequality: blue collar workers have less inequality than white collar workers, regardless of the spread use to measure it. The .75 - .25 spread does not behave like the whole sample in this case: it is definitively higher for white collar than for blue collar.

In order to compare our measure or inequality, the Gini coefficient was calculated year by year for the whole sample and for each one of the partitions studied in this paper, and compare to the .90 - .10 spread. The results are shown in figure 11[11]. This figure show us that with the exception of the period 1960 - 1970 (in which the Gini coefficient shows a higher level of inequality) the Gini coefficient behaves in a very similar way to our .90 - .10 measure of inequality. This is true not only for the whole sample, but also for each one of the partitions analyzed here. Note that the Gini coefficient is also remarkably higher for white collar workers than for blue collar workers. All this reinforces our results on inequality.

Summary

There are different facts that appear very clearly from the analysis performed. We proceed to summarize them.

- First, the rate of return is very stable during the sixties, then presents a general declining from 1970 until 1974 and from then on grows until 1986 when it starts to decline until 1993, being relatively stable since then.
- Second, the *movements* of the rate of return to education calculated using OLS or using (any) quantile regression are very similar. This result is valid not only for the whole sample, but also for all of the breakdowns of the sample performed here.
- Third, it is clear that the returns to education are different depending on the quantile analyzed: the higher the quantile the higher the return to education.
- Fourth, the difference in the return to education using different quantiles increased during the eighties, and specially after 1986. This is especially true when we consider the cases of new workers, private sector and white-collar workers.
- Fifth, there are clear differences in the rates of return to education by group (the rate of return is higher for: less experienced workers compared to experienced workers; for public sector workers when compared to private sector workers; and especially for white collar workers when compared to blue collar workers). This shows a more heterogeneous labor market than originally thought.
- Sixth, there are differences in the rate of return to experience by groups, and there are also differences in the rate of return to experience by quantile: the higher the quantile the higher the return to experience, although these differences are much more smaller than the differences in the rate of return to education by quantiles.
- Seventh, the difference in the return to experience using different quantiles markedly increased after 1986. This is especially true in the cases of the whole sample, the private sector and the blue-collar workers.
- Eight, the rate of return on experience is systematically declining. This is true not only for the whole sample but almost for every partition defined in this study. For the whole sample it is obvious that the return on experience starts to decline in 1986 (figure 3(c)), for the less experienced workers it declines during the whole period considered here (figure 4-(c)), for the public and private sectors since 1986 (figure 6-(c) and 7-(c)), and for the white collar and blue collar workers it almost decline during the whole period, but the declines is more pronounced for blue collar workers.

[11] Note that thorough this figure all the graphs have comparable left and right scales.

- Ninth, inequality increased starting in the mid-sixties and continued to growth until around 1988, when it started to decrease. This decrease is especially pronounced during the period 1988-1993 and very stable since then.
- Tenth, the biggest difference in inequality by group is defined by white collar versus blue collar workers; the white collar workers have a remarkably unequal distribution when compared to blue collar workers.

6. Conclusions

How representative the mean is of a distribution depends on the variance. The bigger the variance the less representative the mean. The quantile regression proved to be a very useful device in analyzing the conditional distribution of wages when populations are heterogeneous. The results show that the return to education is higher, the higher the quantile, and that this conclusion is independent of the partitions used here. The results also show that there are significant differences in the rate of return by quantile and that those differences depend on the partition analyzed. Regarding experience, the distribution of wages conditional on experience is by far more concentrated than its equivalent for education.

Regarding inequality, the analysis performed shows that it started growing in the mid-sixties and until around 1989 and started to decline vigorously after 1990. This coincides in part with some other studies that have focused exclusively in income distribution (Solimano and Marcel, 1994).

As a general conclusion, we agree with Buchinsky (1994a) that the normal location model does not provide a good description of the conditional wage distribution. As mentioned, that model implies that the covariate slopes should be invariant as we go across quantiles, while the quantile analysis performed here shows that some coefficients differ systematically as we move along quantiles. This is particularly true for education.

Our results also indicate a strong pattern of differences by groups, showing that partitions of the sample might also explain differences in wage inequality, and that the labor market is more heterogeneous than originally thought.

Finally, this study shows that the impact of one additional year of education or experience on wages is not a parameter that we can consider given. We found that there are significant differences in the rate of return to education and experience for the whole sample in different periods. We also found even bigger differences in return to education and experience for the sub-groups defined here. This should be a matter for future research.

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FIGURE 3
RATES OF RETURN: WHOLE SAMPLE

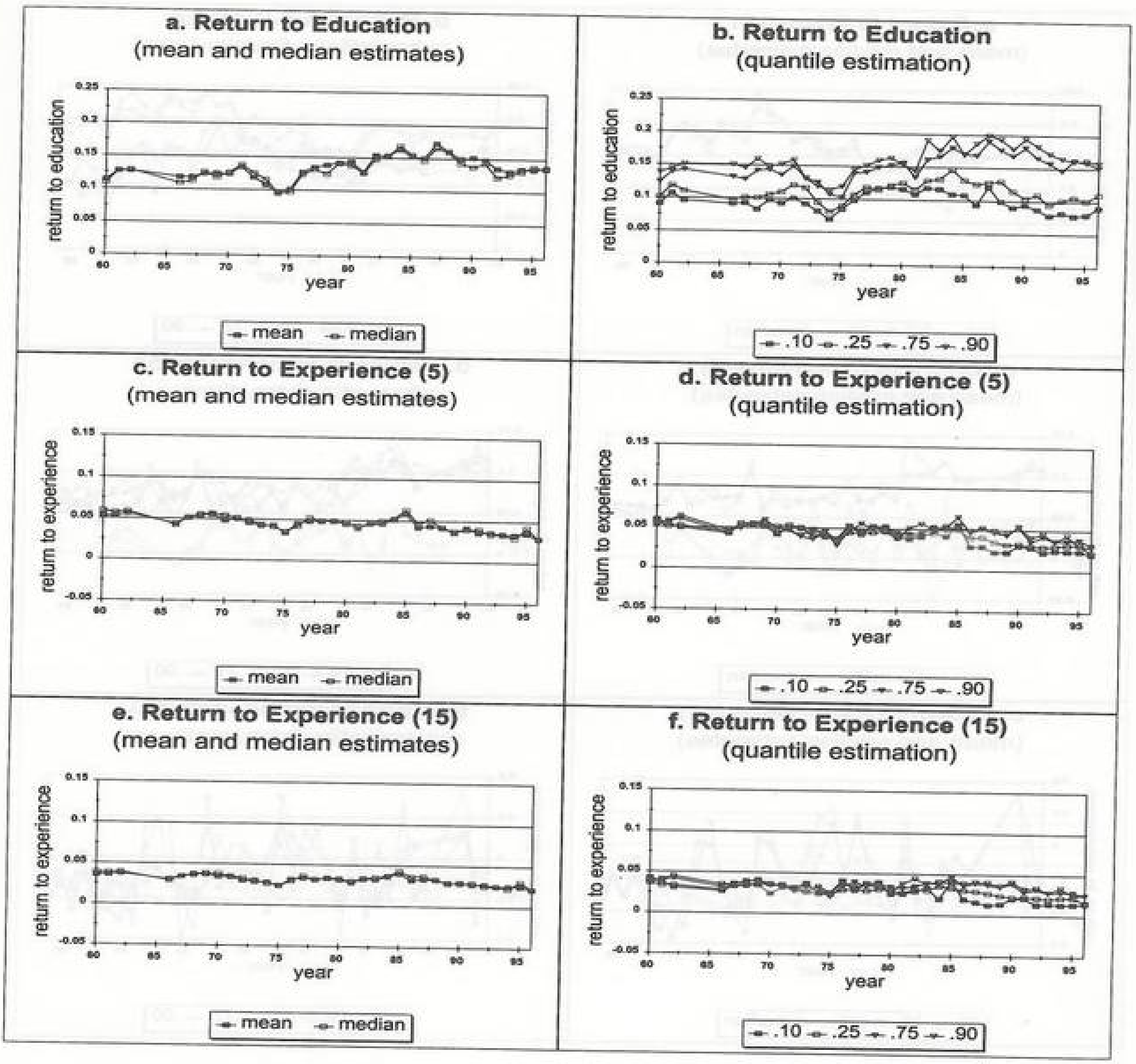

FIGURE 4
RATES OF RETURN: LESS EXPERIENCED WORKERS

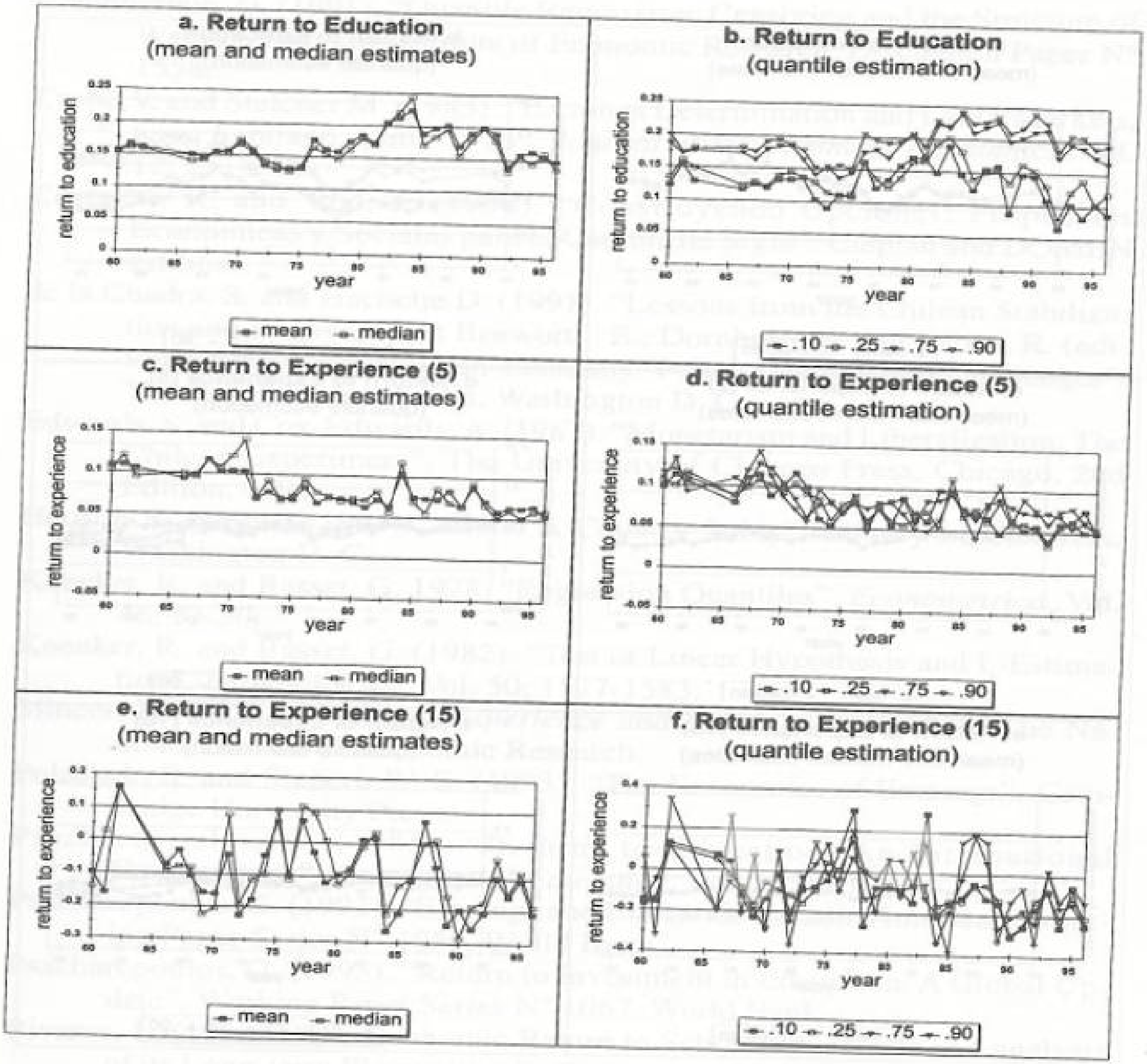

FIGURE 5
RATES OF RETURN: EXPERIENCED WORKERS

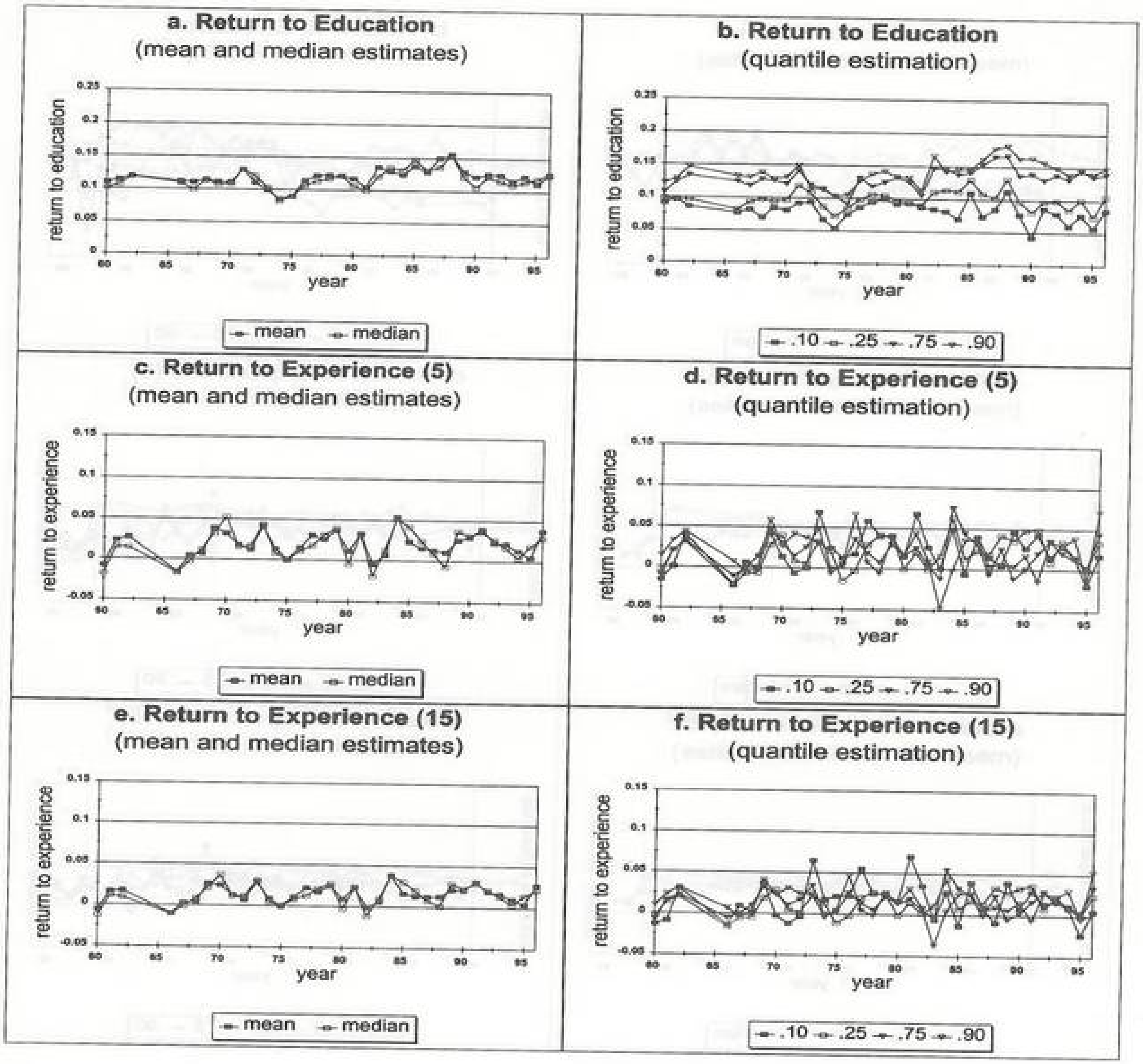

FIGURE 6
RATES OF RETURN: PUBLIC SECTOR WORKERS

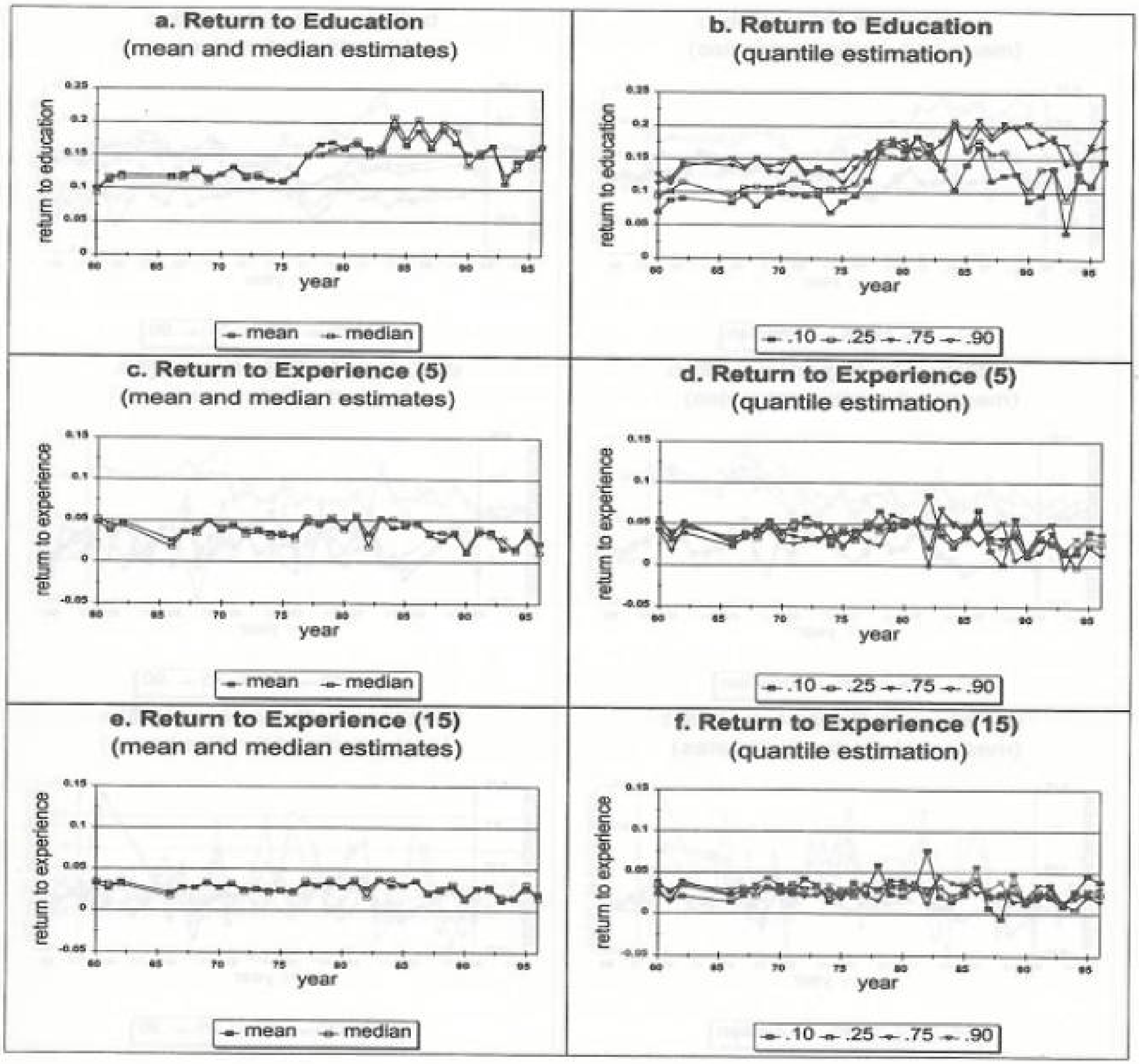

FIGURE 7
RATES OF RETURN: PRIVATE SECTOR WORKERS

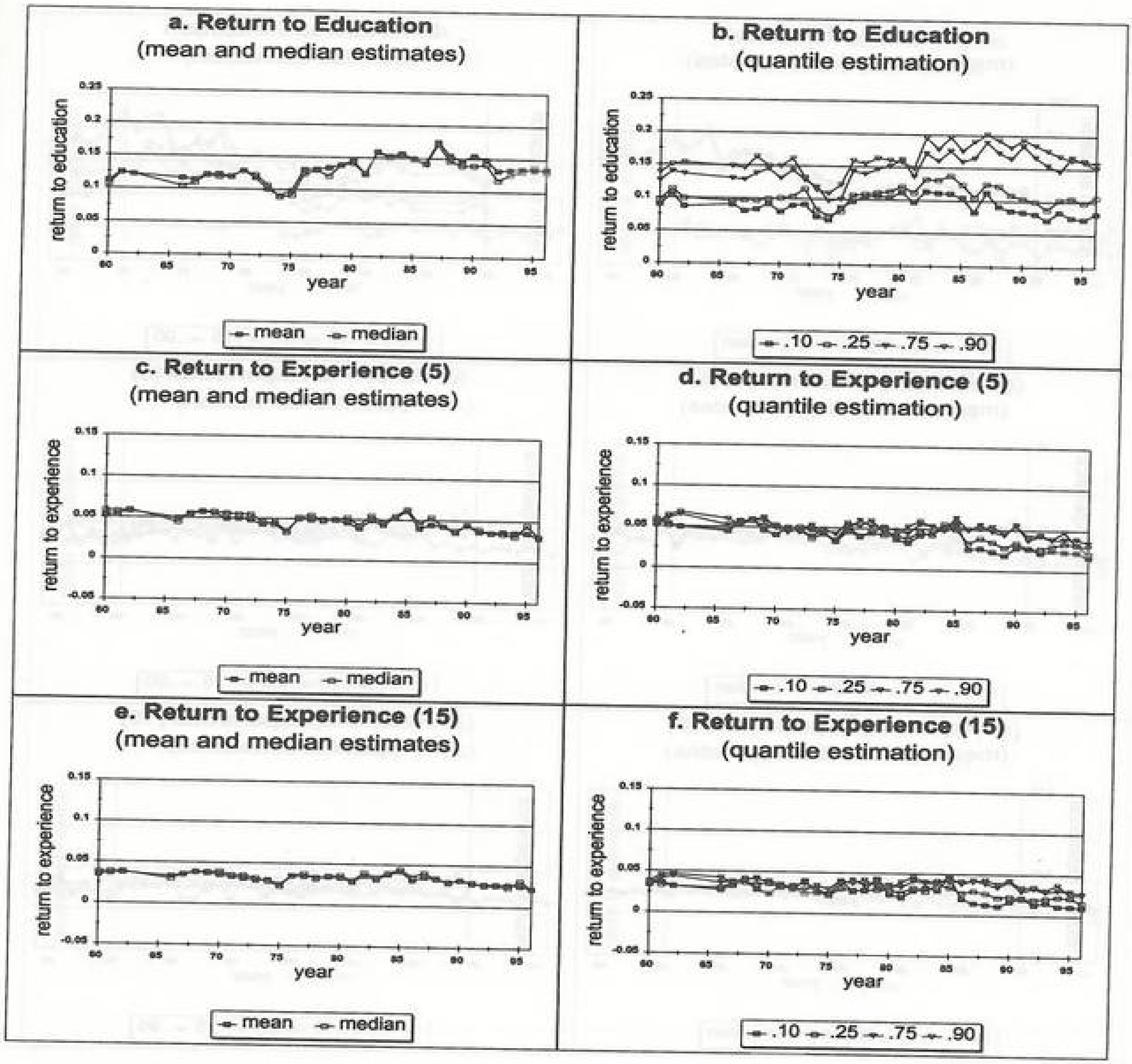

FIGURE 8
RATES OF RETURN: WHITE COLLAR WORKERS

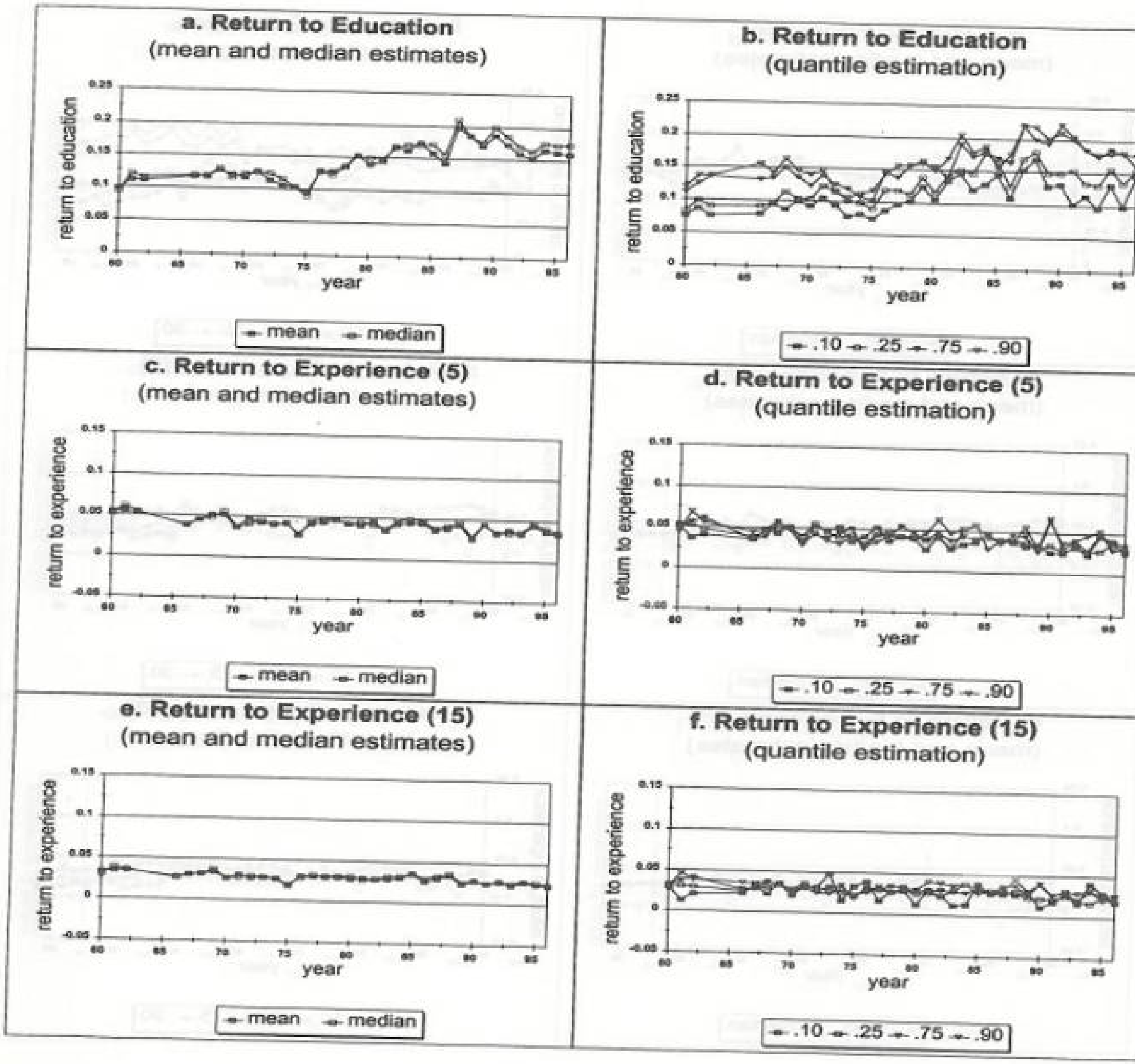

FIGURE 9
RATES OF RETURN: BLUE COLLAR WORKERS

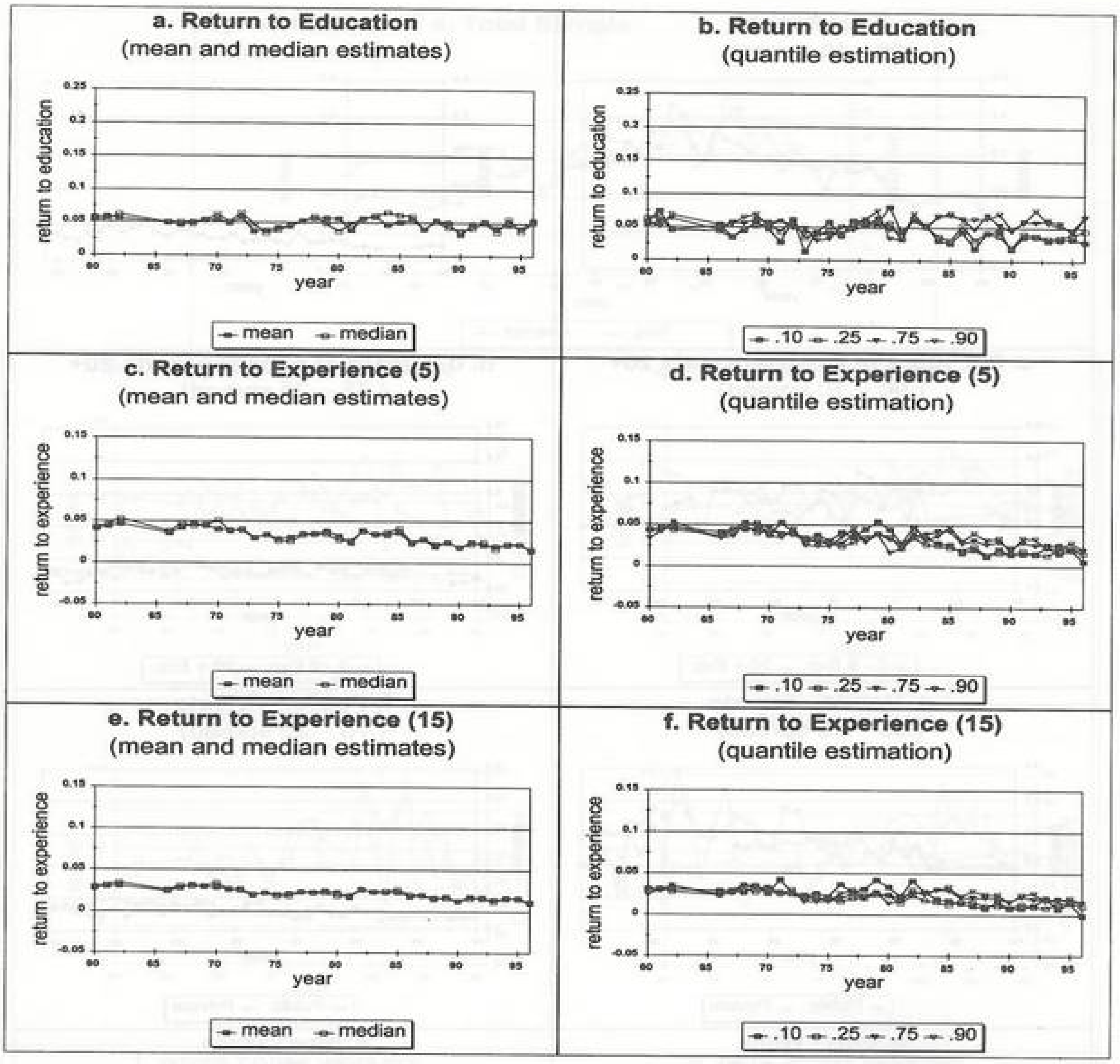

FIGURE 10
WAGE INEQUALITY

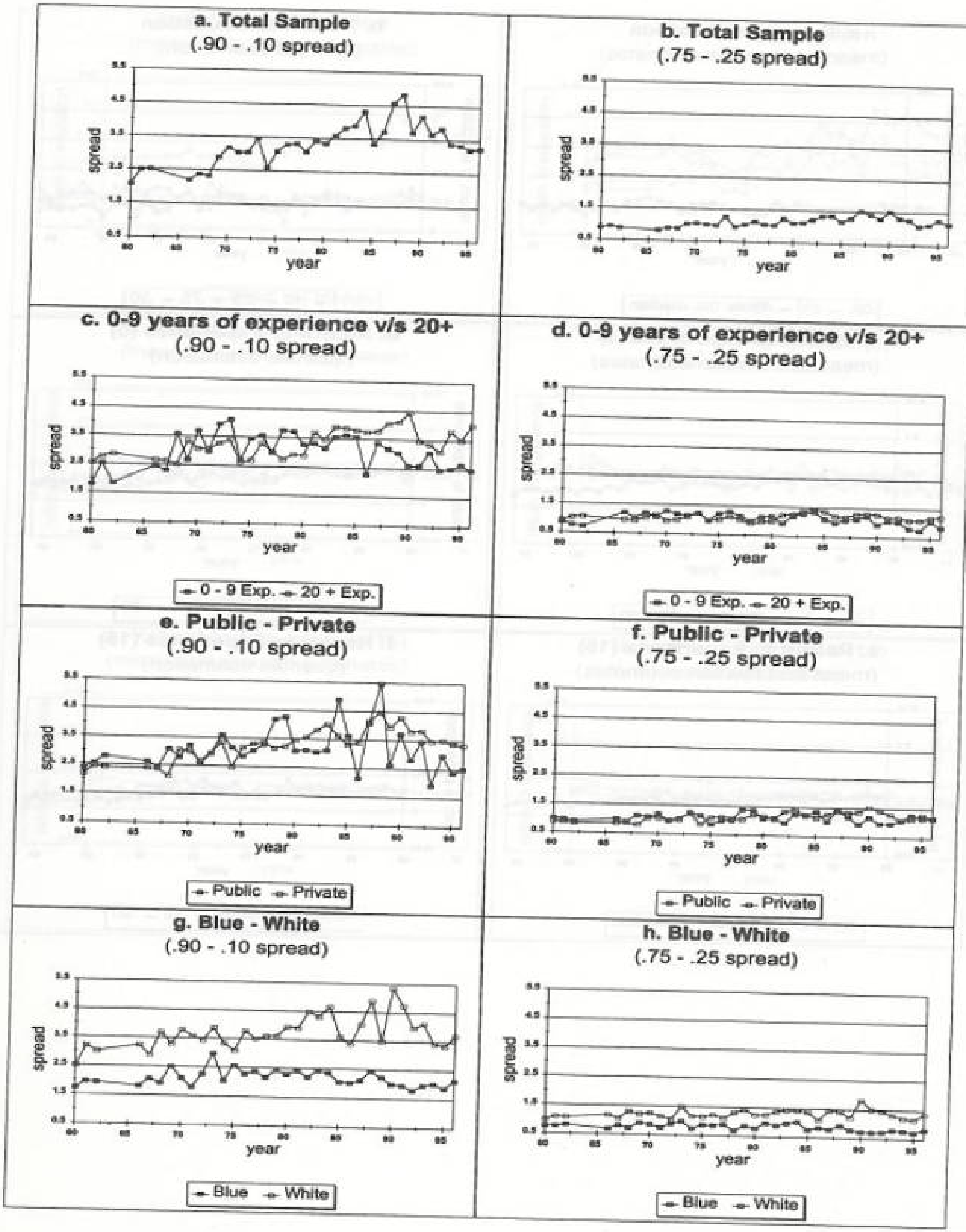

FIGURE 11
A COMPARISON OF TWO MEASURES OF WAGE INEQUALITY