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Earning Functions in Portugal 1982-1994: Evidence from Quantile Regressions *

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1 Introduction

The structure of wages and wage inequality have been under scrutiny in most developed countries for a long time. It is well established now that the 1970's and in particular the 1980's witnessed a reversal in the tendency towards a reduction in wage inequality that prevailed during the previous decade. An explanation that has been recurrently advanced for this change in the structure of pay is that there has been a shift in labor demand favoring high-skilled labor at the expense of low-skilled labor, primarily caused by changes in the technology, notably by the use of computers (Juhn, Murphy and Pierce 1993, Bound and Johnson 1992). Another explanation relates the increase in the pay spread to the increase of foreign competition (Borjas and Ramey 1995). A third explanation suggests that demographic factors, such as reduction in the number of colleges graduates among the working population, may be responsible for the increase of the premium to education (Murphy and Welch 1989).

All of these three factors were subject to important changes in Portugal in the last decade. Foreign competition increased, largely due to European Union membership in 1986. At the same time, and largely financed with European funds, very substantial resources were devoted to policies designed to modernize the industrial structure, both by subsidizing investment in modern technologies and by creating widespread training programs. These changes have certainly had an impact on the wage structure.

It comes therefore as no surprise that this topic has also attracted considerable attention in Portugal in recent years. As in the other developed economies, wage inequality increased during the last decade, in particular since the mid 1980's (Cardoso 1996). In addition, educational levels have been continuously increasing, largely as a result of successive increases in the number of years of mandatory schooling, which led to a shift in the supply of labor towards more skilled workers. At the same time, however, increasing returns to schooling are observed (Vieira, Hartog and Pereira 1997a).

In this paper, we do not go into the details of the changes that have occurred in the Portuguese labor market, nor do we offer explanations for the changes that have occurred. Our goal in the paper is rather to offer a detailed description of the conditional wage distribution and of its evolution over the 1980's.

Analysts of the determinants of wages have acknowledged that work places are highly heterogeneous. As a consequence, the returns to education (or, more generally, to human capital) may vary across individuals with the same observed human capital. To account for this heterogeneity, researchers control for region, industry and employer characteristics, which is typically done by including the explicitly observed characteristics of the employer or firm, industry and regional dummies in wage equations. Recent research, however, suggests that this may be insufficient to capture the real effect of employer heterogeneity and found that employee and employer characteristics interact in the process of the determination of salaries (see for example Cardoso 1997). A more primitive form of heterogeneity affecting the wage distribution is employee's heterogeneity. This type of heterogeneity has been long recognized in labor economics, and panel data is commonly employed in the estimation of earning functions, in order to obtain unbiased estimates of the returns to human capital. However, conventional panel data techniques only deal with the effect of unobserved heterogeneity upon the mean wage. In this sense, the use of panel data is not helpful to study, for example, the effects of gender or formal education on wage inequality.

Rather than exploring the intricate set of relationships stemming from employers and employee's heterogeneity, our analysis takes a different path. We use quantile regression techniques, to document the heterogeneity in the way wages respond to variations in those variables which are normally expected to affect them. Unlike the mean (least squares) regression, these techniques allow the study of the effect of each of the covariates along the whole distribution and, consequently, the estimation of the effect of employer's and workers' heterogeneity upon wages. One point of particular interest is the effect of workers' attributes upon wage inequality. Our analysis will enable us to answer questions such as the following. Consider two samples of identical individuals, except that in one sample all the individuals are men, while in the other they are all women. In which of the samples are wages more dispersed? Take a sample of identical individuals and give them an additional year of education. Will their wages become more or less dispersed? By how much will wage inequality change?

The paper is structured along the following lines. Section 2 gives a brief introduction to the statistical methodology employed in the analysis. The exposition is at a non-technical level, and it is aimed at readers which are not familiar with the technique. The focus are the potential informative gains of using regression quantiles in the context of the analysis of the structure of wages. An appendix in the end of the paper sketches the estimation procedures. There are no novelties on this front, and readers with previous knowledge of the technique may want to skip this discussion, and go directly into the data analysis. This analysis begins in Section 3, which presents the data source and describes the samples employed. At this point, we give an overview of the evolution of wages and characteristics of the working population over the period 1982-1994. Regression results appear in Section 4. The results at different quantiles of the distribution are discussed, with particular emphasis on the impact of covariates upon the dispersion of wages, and on the returns to education. Having quantified the impact of the covariates at different points of the wage distribution, we are able to estimate the resulting conditional distribution, that is the distribution of wages that would result in a sample of individuals which are all identical with respect to the observed attributes. The evolution of this distribution over time is discussed. Finally, Section 5 offers concluding comments.

2 Quantile Regression

The interest in estimating earning functions lies, to a large extent, in the interest in obtaining estimates of the returns to education or, more generally, to human capital. The usual approach for such an exercise is to specify a regression equation of the form

$$y = x'\beta + u$$

where y is the logarithm of wages and x includes variables measuring human capital together with other variables which are expected to impact wages as well (gender, for instance). The last term in this equation (u) is a disturbance satisfying $E[u|x] = 0$. Owing to this assumption, the regression above may be called mean regression as, in fact, it models the conditional expectation of y given x. That is, it states that

$$E[y|x] = x'\beta.$$

This type of exercise is very useful in that, using the estimated coefficients and supplying values for the independent variables, one can estimate the mean wage earned by individuals with these characteristics. Moreover, by direct inspection of the estimated $\beta's$, one can evaluate the percent change in mean wage caused by changes in one variable, say education. Of course, these models do not imply that all the individuals with a given set of attributes earn the same wage. The remaining variability, however, is treated as nuisance and left to the error term. As a consequence, all of the inferences with the regression model above pertain only to the mean wage.

The limitations of this approach have been clearly highlighted by Mosteller and Tukey (1977 p. 266), when they say that "just as the mean gives an incomplete picture of a single distribution, so the regression curve gives a correspondingly incomplete picture for a set of distributions." They add that "what the regression curve does is give a grand summary for the averages of the distributions corresponding to the set of $x's$. We could go one step further and compute several regression curves corresponding to the various percentage points of the distribution and thus get a more complete description of the set. Ordinarily this is not done, and so regression often gives a rather incomplete picture" (Mosteller and Tukey 1977 p. 266).[1]

[1] This suggestion was pursued by Koenker and Bassett (1978), who developed estimators for quantile regressions

Figure 1: here

This informative gain in estimating quantile regressions can be easily grasped by means of simple graphical illustrations. Consider, for instance, the distribution of wages (y) for men and women in Figure 1. In this context, we have a single regressor x, which can only take two values, 0 for women, and 1 for men. For each sex, there is a distribution of values of y. Figure 1 shows the probability density function (pdf) of y for the two x's. Point A represents the mean of y given $x = 0$, $E(y|x = 0)$ and, analogously, $A' = E(y|x = 1)$. Connecting these points one gets the (population) mean or least squares regression. Quite in the same way, one may connect $B = Q_{75}(y|x = 0)$ and $B' = Q_{75}(y|x = 1)$ representing the 75-th quantile of the conditional distribution of y for different values of x that is, the 75-th (population) quantile regression. Of course, the same can be done for other quantiles yielding a whole set of quantile regressions ($Q_\theta(y|x)$ for $\theta \in (0,1)$). Because, in this example, wages are identically distributed for men and women, all the regression lines are parallel, irrespectively of the quantile being considered. Therefore, the different regression lines convey the same information on the way the covariates impact the distribution of y. For instance, if mean regression indicates that, on average, men are paid 10% more than women, then the 25-th quantile regression says that a man in the 25-th percentile of the men's wage distributions is also paid 10% more than a woman in the same place of women's wage distribution.

A common example in econometrics of this set-up is the linear regression model with *i.i.d.* errors. Let, $y = \alpha + \beta x + u$ with u *i.i.d.*. Then, $E(y \mid x) = [\alpha + E(u)] + \beta x$ and $Q_\theta(y \mid x) = [\alpha + Q_\theta(u)] + \beta x$ where $E(u)$ and $Q_\theta(u)$ represent the mean and the θ-th quantile of the errors. That is, the regression lines differ only in the intercept. The message in these two examples is completely general. Whenever the dependent variable is identically distributed around a known function of the regressors (i.e., whenever the conditional distribution belongs to a translation family) all location functions such as mean, median or quantiles, are parallel (see, for instance, Mansky 1988). In this context, there will be no gain in going beyond the estimation of the mean regression.

The situation is quite different outside this statistical framework, when attributes of the distribution of y other than location also depend on the covariates. A common case is heteroskedasticity, represented in Figure 2. The marked points have the same interpretation as in

that generalize to the regression case the ordinary sample quantiles. These models have been recently applied to the study of the wage distribution by Chamberlain (1994), Buchinsky (1994, 1996) and Fitzenberger and Kurz (1997).

Figure 2: here

Figure 3: here

Figure 1, as it is quite clear that now the regression lines are not parallel. This means that the gap between men's and women's wages is larger at the third quartile than at the first. An economic meaningful interpretation of this figure is to say that the men's wages are more dispersed than are women's. Heteroskedasticity can be easily accommodated in mean regression models and, in fact, in particular in cross-section work, its treatment is completely routine. However, despite its informative value, the different variances are commonly regarded as mere nuisance parameters, and the modeling of heteroskedasticity is typically seen as a way of improving the efficiency of the estimates of the mean effect or of getting correct interval inferences, rather than a way of recovering that information.

By the same token, the third and fourth moments or even the whole distribution may depend on the regressors as well. Figure 3 illustrates this case. Here the two distributions are totally different. As in the previous case, the mean and the quantiles regressions lines are not parallel and, therefore, they provide different information about the way y varies with x. Unlike in the heteroscedastic case, however, it is not easy to see how the information of how does y vary with x can be recovered using a simple parametric form. Quantile regression allows one to recover this information while imposing a minimum of structure.

The basic point in these two examples is that, in this general setting, the marginal effect of sex on the wage depends on the point of the conditional wage distribution where the individual is located. This is, indeed, a very likely case to hold in the context of the distribution of wages, being entirely conceivable that difference in mean wages of men and women is smaller than the difference in the wages corresponding to the 9-th decile. To illustrate this last point, consider a random coefficients model relating the log wage (y) to a measure of workers' human capital (x): $y_i = \alpha + \beta_i x_i$ with $\beta_i = \beta + \epsilon_i$, with ϵ being a *i.i.d.* random variable. The random coefficient, β_i, captures the fact that wages are heterogeneously determined and, that returns to human capital may differ in workers with the same observed human capital. Then, $Q_\theta(y \mid x) = \alpha + [Q_\theta(\epsilon) + \beta]x$ and, consequently, the slope coefficient depends on the quantile being estimated. To reduce the amount of this unaccounted heterogeneity, wage equations often include an array of individual, industry and employers characteristics. Yet, it seems pretentious to argue that the heterogeneity is completely controlled for and, therefore, the essential message of the very simple illustrative

Table 1: here

model remains valid for more general regressions.[2]

Practical implementation of quantile regression models, in general, does not proceed along the lines indicated by the previous quotation of Mosteller and Tukey and suggested by Figures 1, 2, 3. This can be done in cases where there repeated observations on y for each regressor (see Chamberlain 1994), but becomes infeasible when the model includes a large number of continuous variables, as ours does. Fortunately, the estimation method suggested by Koenker and Bassett (1978) allows to handle the general case without much difficulty. This procedure (outlined in the appendix) was the one employed here.

3 Data

In this work we estimate regressions of the logarithm of wages on covariates representing gender, human capital (as measured by education, experience and tenure), firm attributes (size and ownership status) and industry dummies. The data employed were obtained from a survey (Quadros de Pessoal, hereafter QP) conducted by the Portuguese Ministry of Employment, covering the work force of all firms employing paid labor in Portugal. The survey records information on salaries as well on workers attributes such as sex, education, age and tenure for over 2 million people every year. Moreover, it also records information on the employer, from which we used firm size and ownership status (whether the firm is majority owned by private domestic, foreign, and state) and industry. Individuals for which the data base has complete information with respect to all the variables above are about 1.5 million every year.

We use data from 1982 and 1994, respectively the first and the last year for which we had information available when the study was started. For each year, we selected a random sample of about 5,000 full-time wage earners employed by firms located in mainland Portugal. These samples are described in Table 1, which documents with clarity a number of changes that have occurred in the Portuguese labor market.

Table 1 documents an important increase in real wages over the period. In fact, the average wage increased by about 38%, which amounts to about 2.7% per year. This wage increase,

[2]Notice, however, that quantile regressions are quite different from random coefficients models. With the random coefficients model we simply recognize that the $\beta_i's$ are random and would try to estimate its mean. By using quantile regression, we will learn about how the $\beta's$ vary across the distribution, and will thus be able to analyze the impact of each covariate upon, for example, the dispersion of the distribution.

however, was very unevenly distributed. While wages at the bottom of the distribution (first decile, first quartile and median) increased about by 20%, the salaries at the third quartile and at the ninth decile increased by 35% and 52%, respectively. This increase in the dispersion is also visible in the increase in the standard deviation of the wage distribution, and in the differences of the percentiles of the log wage distribution.

There were also important changes in the composition of the labor force. First of all, women represent an increasing proportion of the labor force. Starting from a level near 30% in 1982, they are about 40% of the total working population in 1994. During this period, the educational level of the labor force increased quite substantially, starting from an average of five years of schooling to an average of over six, reflecting the increased years of mandatory schooling. This is also visible in the distribution of the working population across the schooling classes. There is a marked increase in the percentage of people in the educational classes at or above six years of education, with the corresponding decrease in the classes corresponding to the lowest educational levels. On the whole, individuals with 4 years of education or less, which were almost 70% of the working population in 1982, were no longer the majority in 1994.

Our data does not contain direct information on the individuals' experience in the labor market. Therefore, our measure of experience is defined as age minus the number of years of schooling minus 6. The evolution of this variable thus reflects the combined evolution of schooling and age. As the average age of individuals in the sample remains pretty constant around 35 years, experience displays a decrease over time. Unlike experience, our data contains direct observation on the tenure within a firm. The data shows that the average tenure also decreased during this period. During this period, the economy experienced very important flows of entry and exit of firms, leading to a reduction both in the average age of firms and in the average tenure.[3]

This turnover is also associated with the evolution of the number of employees per firm, which experienced a decrease over the period under scrutiny. This is reflected in the evolution of the variable Firm Size, which was measured here by the logarithm of the employment in the firm. The variables Foreign and State are dummy variables indicating whether the firm for which the individual works has a majority of foreign/state capital. Table 1 indicates that foreign owned firms increased their importance, while state owned firms became less important over time. The averages of these firm variables should, however, be interpreted with care, as they are computed from a sample of individuals rather than firms.

[3]This pattern of entry of new firms in Portugal is documented, for example, in Mata (1996).

Table 2: here

Table 3: here

4 Results

This section discusses the results of the analysis of the impact of the covariates presented above upon the distribution of the log of the hourly wages for 1982 and 1994. First, we will present the quantile regressions for these years. Second, we will provide some global characterization of the wage distributions and their evolution over time.

4.1 Wage Regressions

The first two tables in this section summarize the major characteristics of the conditional wage distributions. Table 2 presents the quantile regression estimates for selected values of θ. The estimated coefficients measure the impact of each covariate on the whole actual distribution; for instance, the coefficient of schooling at the median represents the percentage pay increase that would keep an "average" worker's wage on the median if his number of school years had increased by one year. To allow a comparison with the effects upon the mean, we also present the OLS estimates in the first column of this table. In Table 3 we use the estimates of quantile regressions to provide two measures the marginal effect of the covariates on the dispersion of the wage distributions. As measures of the (relative) dispersion in the wage distribution we use the difference in log wages at different quantiles (the 25-th *versus* the 75-th and the 10-th *versus* the 90-th percentiles). Our estimates of the marginal impact of covariates upon these measures are therefore obtained simply by computing the differences of the quantile regression coefficients at the relevant quantiles and the associated standard errors.

■ **Sex** The first column in Table 2 shows that, on average, women make 15% less than otherwise comparable men and that this figure has experienced a slight increase (1% in absolute value) from 1982 to 1994. The information retrieved from the columns pertaining to the quantile regressions confirm that, *ceteris paribus*, the distribution of women's wages is clearly to the left of men's (all the coefficients are negative). However, it also indicates very clearly that the estimate of a 15%

pay penalty is not an accurate description of the differences between the wage distributions for men and women. In fact, in 1994 the first decile of women's wages is only 9% lower than the corresponding decile of men's wages, but the median is already 14% lower and, at the 9-th decile, the difference reaches 17%. The fact that the wage differentials are much larger at the top than at the bottom of the wage distribution translates into men having a relatively more dispersed wage distribution than women. As Table 3 documents, the wage distribution for women not only suffers a location shift, but it is also significantly less spread out than men's.

In addition, although the same qualitative results also hold for 1982, the impact of sex on the wage distribution has not had an uniform evolution in the 12 years period under scrutiny. Indeed, while the sex differentials appear to have increased slightly for individuals earning wages in the middle of the distribution, they are smaller for the top and bottom of the pay scale. Our result for central location is consistent with Cardoso (1997), who finds that the distribution (across firms) of the mean gender effect has shifted to the left from 1983 to 1992. However, our findings for the overall wage distribution clearly show that the estimate of 1% increase in the mean pay spread (provided by OLS) is only a very crude estimate of the changes that have actually occurred.

The **"human capital"** covariates - years of schooling, tenure and experience - are significant at all the quantiles and they all cause a shift of the entire wage distribution to the right. That is, there are positive returns on human capital at every point of the wage distribution, which conforms well to the general indication provided by the OLS estimates. However, as we shall see, the changes induced by a greater endowment of human capital are far more complex than a simple overall shift to the right.

■ **Education** Starting with education, it is visible that the mean effect of 7.7% return to an additional year of education observed in 1994 is an "averaging" of very different results, starting from a return of 3.6% at the 10-th quantile, which increases to 6.5% at the median and reaches 11.4% at the top decile. Once again, the fact that the effect is increasing with the quantiles suggests - and Table 3 formally confirms - that schooling has a positive impact on the wage dispersion.

As with sex, the broad picture does not change much from 1982 to 1994, the returns being increasing across quantiles. Nevertheless, the differences in the evolution at the different points of the distribution are striking. While the mean and median returns are roughly constant (both increased about 0.5%), the impact of education at the tails of the distribution was quite distinct, as the return at the 90-th quantile has increased by 3% and the returns at the low quantiles have

Table 4: here

decreased by 1.5%. In plain English, one may then say that more educated workers earn more but education is relatively more valued for high-pay jobs. Moreover, the tendency for education to be more valued at relatively high pay jobs has sharpened over this 12 years period, which led to a dramatic increase in the effect of education upon dispersion observable in Table 3. Interestingly, this tendency contrasts with the findings of Buchinsky (1994) that, for the U.S., the returns have increased over time at all quantiles at about the same rate, but is consistent with Cardoso (1997) who noticed that the distribution across firms of the mean return on education has shifted to the right from 1983 to 1992.

As an alternative specification for the effect of education, we re-run the quantile regressions measuring now formal education in a discrete fashion. Although the continuous variable "years of schooling" of Table 2 is easier to interpret - as it provides a single description for the returns on education - the use of "schooling classes" highlights the nonlinearities of the response of wages to additional education. Results are in Table 4.[4]

The returns of having just the "primary education" have dramatically decreased from 1982 to 1994 at all quantiles. Moreover, in 1994 these returns are statistically different from zero only at the 25-th quantile.[5] At the bottom of the formal education scale, the number of years in school does not have much bearing on the reasons why an individual has a relatively high pay job. This also holds for the top decile of the "6 years class".

Apparently, the returns from the 9 years mandatory schooling have also decreased over the whole wage distribution. However, a significant part of this decline is due to the fall of the returns associated with the "primary education" classes. Indeed the incremental return on having 9 years of schooling rather than just 6 has declined somewhat on the left tail but has increased at the 75-th and 90-th quantiles.

The returns of holding a university degree (14 years of schooling) are the only ones which, on average, have increased from 1982 to 1994. This increase in the returns to university education, however, is only observed at the median and quantiles above. Nevertheless, largely due to the decrease in the returns to the 9 years of schooling, one observes an increase in the incremental

[4]Only the coefficients associated to the "schooling classes" are displayed in this table. The results for the other variables remain largely unchanged.

[5]Due to the high number of observations in our samples, the tests should not be performed at the usual significance levels. The significance level implied by the Schwarz Information Criterion, which takes the sample size into account, is 0.4%.

Table 5: here

returns on having a university degree at every point of the wage distribution.

The different schooling classes in Table 4 are of different lengths, which makes the comparison of the returns of the different classes difficult to make. However, it is straightforward from Table 4 to compute estimates of the returns to one additional year of schooling at different levels of education. These estimates are displayed in Table 5. They show very clearly a change in the structure of pay that has not been uncovered yet. While in 1982 the returns to one additional year of schooling were roughly constant (except for the class of 4 years of schooling), in 1994 one observes that returns are clearly increasing with the level of education. Moreover, it becomes also apparent that in 1994, each additional year of education contributes towards the increase in wage dispersion as, for each educational class, there is a much wider dispersion in the estimates of the returns to education in 1994 than in 1982.[6]

One may then conclude that, returns on education are not necessarily positive: it makes virtually no difference to have no formal education or just 4 or even 6 years of schooling, at least for those individuals which are in the top of the wage distribution. Only after a certain degree does education pay off. When it does, education is more valued for high-pay jobs.

■ **Experience and Tenure** We employed a simple specification in the tradition of Mincerian wage equations, in which both labor market experience and tenure are allowed to have nonlinear effects on the quantile function. Our specification includes both a linear and a quadratic term for these variables. The linear terms are always significant (both years at all quantiles) and the same holds for the squared term for experience. In the case of tenure, however, the squared term becomes non-significant at the 75-th and 90-th quantiles, which means that the effect that was found to be convex at the left tail of the distribution becomes linear at the right tail. This pattern for the effects of either variable is similar to that estimated by Fitzenberger and Kurtz (1997) for Germany.

The global effects of these two covariates as functions of their level are depicted in Figures 4 and 5. It is very clear that the effect of either variable is positive over the entire wage distribution. Moreover, in spite of its convexity, wages increase with either variable over the relevant range (recall from Table 1 that the average experience in the sample is about 23/24 years and the

[6]Note that, with the exception of the returns at the 90-th percentile for individuals with 4 years of education, the returns in 1994 increase monotonically with the quantiles, which does not happen in 1982.

Figure 4: here

Figure 5: here

average tenure 8/9 years).

In 1982 the returns to experience are roughly constant all over the distribution, but in 1994 they are higher for the highest quantiles. The marginal effect of experience upon dispersion is not easy to grasp from Table 3 (compare the derivatives of the functions at different quantiles). Due to the non-linearities involved, the effect varies across the distribution, but it is easy to evaluate this effect at each particular point. We computed these marginal effects at the sample's mean. These statistics (which are not reported here) show a positive and increasing effect of experience over time.[7]

Tenure, on the other hand, exhibits both in 1982 and 1994 approximately constant returns on the mid-part and left tail of the wage distribution but with a significant reduction at the top quantiles. Notice, for instance, that the return to tenure at the 90-th quantile is smaller than at the 10-th: tenure is thus more valued at relatively low paid jobs.

It is also apparent from Figure 5 that, at the 10-th and 90-th percentiles, the effect of tenure (evaluated at its average level) did not change much from 1982 to 1994. Therefore its impact upon dispersion (measured at these quantiles) remained roughly constant.[8] With respect to the quartiles, it is very clear from Figure 5 that, although the estimates of returns are higher at the first quartile than at the third, the differences in the derivatives are minor (in fact, they are never statistically significant).[9] Overall, therefore, our results suggest that the effect of tenure experienced a very modest change during the period under scrutiny and that, at least in 1994, there is no evidence that tenure has an impact upon wage dispersion.

We turn now our attention to the variables which are intended to capture heterogeneity in work places, at the firm and industry level.

■ **Firm effects** Larger firms pay more to workers with the same attributes. Table 3 also

[7] All of these statistics are highly significant, except the effect upon the difference between the 25-th and the 75-th quantiles in 1982, which is only marginally significant (p-value of 9.9%).

[8] The precision associate with this measurement is somewhat lower in 1994 than in 1982 (p-value change from 0.4% to 7.1%.)

[9] The lack of significant changes in returns over time contrasts with the findings of Cardoso (1997), that the mean return to tenure has deceased.

Table 6: here

reveals that, notably in 1982, larger firms tend to have a larger wage spread even controlling for workers observed characteristics.

The impact of the covariates reflecting the type of firms ownership - "state" and "foreign" - is quite diverse. State ownership is much more relevant at the lower tail of the wage distribution: relatively low-paid workers earn more in state owned firms, but the impact of this attribute dies out as one moves along the wage distribution and is statistically insignificant for the higher wages. Not surprisingly, state ownership tends to compress the wage spread. This results are qualitatively similar to that reported by Poterba and Rueben (1994) for the U.S., although they report positive premia only for the 10-th and 25-th quantiles in the case of men, a result which extends to the median in the case of women.[10]

On the contrary, the presence of foreign capital not only shifts the whole distribution to the right but increases proportionately more relatively high-pay jobs, especially in 1994.

■ **Industry Effects** All of the regressions estimated in Table 2 include a set of 24 sector dummies whose estimated coefficients are presented in Tables 6 and 7 together with some test statistics. The first statistic refers to the joint significance of industry effects, and tests whether the industry dummies can be reduced to a single intercept. In these tests, the null is always rejected, so we conclude that industry matters for the determination of wages. The second statistic is relative to the hypothesis of equality of coefficients between adjacent quantiles, and compares the effects across the distribution. The statistic displayed in each column refers to the comparison between the effects at the quantile corresponding to that column and the quantile corresponding to the previous one. The null hypothesis of identical effects is always rejected, although the comparison between the median and the 3rd quartile in 1982 is rejected only at levels of significance greater than 2.1%. Therefore, we conclude that the impact of industry upon wages goes well beyond the mere location shift.

The point estimates of the industry effects are displayed at the top of Tables 6 and 7. The coefficients are displayed as deviations from the average industry effect, industries being ranked according to the magnitude of the industries's effect at the mean (given by OLS). The first

[10]An important difference between the two studies, however, is that Poterba and Rueben are dealing with employment in the state and local governments, while we are dealing only with employment in state owned enterprises, as our data does not cover the public administration sector.

Table 7: here

Table 8: here

thing one notes from Tables 6 and 7 is that, despite the equality of effects across quantiles being systematically rejected, the two digit figures are concentrated at the top and the bottom of the tables, and the negative values are concentrated at the top, while positive values are concentrated at the bottom of the tables. That is, sectors that pay positive premia tend to pay positive premia across the whole distribution, and those that have negative coefficients tend to have them all over the wage distribution. This is reflected in the positive correlations between the industry coefficients displayed in Table 8.

That does not mean that there are not very important differences in the industry effects in different quantiles. For example, the sector which has the highest effect (51% higher than the average) at the 90-th percentile in 1982 (Social and community services) pays no more than 11% higher than the average at the 10-th percentile. In contrast, the communications sector pays a premium of 33% at the 10-th percentile, but only 12% at the 90-th. In 1994, the gap in this sector has even increased. While the estimate for the 10-th quantile remains roughly unchanged, at the top of the wage distribution, the 12% premium has changed to a 10% penalty.

It is also important to keep in mind that, unlike the effect of workers' attributes, which typically displays a monotonic pattern across the distribution, the effect of industries is somewhat unstable in some cases. One can, nevertheless, identify industries which are more (less) "egalitarian", in the sense that their wage distribution is less (more) dispersed that the one in the reference industry.

There are, of course, a number of ways to identify the more "egalitarian" industries. A possible way for doing that is to look for sectors in which our two measures of dispersion are consistently negative or positive in both periods. Among the less "egalitarian" sectors according to this definition, one finds retail trade, social and community services, business services, paper and publishing and chemicals. Among the more "egalitarian" one finds textiles and clothing, mechanical engineering, communications, insurance and banking. It is interesting to note that in this group one finds both the sector which is ranked at the bottom in both years according to the mean effect (textiles and clothing), and the two sectors which are ranked at the top (banking

Table 9: here

Table 10: here

and insurance). Although it is not our purpose to go into the details of intra sectoral wage determination, it is tempting to suggest that this more "egalitarian" propensity is related to the high levels of unionization in the industry (see Vieira, Hartog and Pereira 1997b for estimates of unionization levels).[11]

4.2 The Wage Distribution

Having discussed the determinants of wages at different points of the wage distribution, we are now in a good position to analyze the conditional wage distribution and its evolution over the period under scrutiny. The estimates in the first column of Table 9 were obtained using the 1982 regression coefficients and the 1982 regressors sample averages. Analogously, the second column presents estimates evaluated at the 1994 averages and coefficients. That is, the data for each year refers to the distribution of wages of a sample of individuals, which are all identical with respect to the attributes considered in our models. It is, therefore, unsurprising that these distributions are less dispersed than their empirical counterparts, as part of the dispersion in the empirical distribution is due to the dispersion in workers' attributes across the sample.

As we had already observed with the empirical distribution, the whole conditional distribution of wages has shifted to the right between 1982 and 1994. Moreover, this shift was much more pronounced on the right than on the left tail: the median wage and wages on the left tail increased about 22% while the top decile increased 35%. This lead to an increase in wage inequality which, however, was quite smaller than the observed in the empirical distribution. In fact, the dispersion in the growth rates in the conditional distribution is far smaller than the corresponding dispersion in the empirical distribution (compare the first two columns of Table 10).

Finally, the last column of Table 9 presents the estimates obtained using the coefficients from the 1994 regressions but the 1982 average values of the covariates. Those estimates attempt to

[11] In preliminary runs, we also included dummy variables to control for different bargaining regimes, but the estimates became very unstable. See Vieira, Hartog and Pereira (1997a, 1997b) for an analysis of the impact of unionization and bargaining regimes upon the industry mean effect. What our results indicate is that industry effect is not identical across the distribution of wages and that there remains a lot to be investigated.

provide a counterfactual depiction of what would be the 1994 wage distribution if the covariates would have remained constant at their 1982 average values. The last column of Table 10 presents the estimates of growth at different points of the conditional distribution in this case.

Comparison of the two last columns in Tables 9 and 10 enables to disentangle two types of factors that may have caused the estimated shifts in the conditional wage distribution: changes in the level of covariates, that is, changes in the amounts of human capital and other inputs, and changes in the returns to these inputs.

What comes out very clearly from this exercise is that both changes contribute towards increased inequality, as growth at the top quantiles is always larger than growth at the bottom ones. However, the overall contribution of changes in returns is relatively modest, as compared with changes in the quantity of inputs. Both the growth rates in Table 10 and the inequality index in Table 9 clearly reveal that most of the estimated change in the wage inequality was due to the way the average level of the covariates evolved that is, to changes in the distribution of the worker's attributes, rather than to an increased inequality within workers with the same characteristics.

5 Conclusion

The paper uses quantile regressions to describe the conditional wage distribution for Portugal and its evolution from 1982 to 1994. Quantile regressions provide "snap-shots" of different points of a conditional distribution and, thus, constitute a parsimonious way of describing the whole distribution. The estimation of Mincer type equations at several points of the wage distribution revealed several interesting aspects that would not be apparent by just looking at single regression equation, such as the mean.[12]

As to the effects of gender, we conclude that the wage distribution for women is shifted to the left of men's. Moreover, the gender gap is bigger for high paid jobs and, consequently, the women's wage distribution is less spread out than men's. The impact of sex on the wage distribution has not had an uniform evolution in the 12 years period under scrutiny. While the sex differentials appear to have increased slightly for individuals earning wages in the middle of the distribution, they became smaller for the top and bottom of the pay scale.

Tenure and experience have a positive effect on wages over the entire distribution. In 1982 the returns to experience are roughly constant all over the distribution, but in 1994 they are higher for the highest quantiles. Tenure, on the other hand, exhibits both in 1982 and 1994

[12]Our own results for the mean regression models are in general, consistent with those of previous studies on Portugal. See Pereira and Lima (1997) for a survey.

approximately constant returns on the mid-part and left tail of the wage distribution but with significant reduction at the top quantiles, that is, tenure is thus more valued at relatively low paid jobs.

The size and type of firms ownership was also found to exert significant influence on the wage distribution. Larger firms pay more to workers with the same attributes; the presence of foreign capital increases wages at all levels but proportionately more so at the relatively higher ones; quite the opposite happens with public capital which is much more relevant at the lower end of the distribution.

One of the most interesting results of our study refers to the returns to formal education. We found that, although returns to schooling are positive at all quantiles, education is relatively more valued for high-pay jobs. Consequently, schooling has a positive impact on the wage inequality. Moreover, the tendency for education to be more valued at relatively high pay jobs has sharpened over this 12 years period, which led to an increase in the effect of education upon wage dispersion. One of the most important changes in the characteristics of workers that have occurred during the period 1982-1994 is a remarkable increase in their educational levels. An expected consequence from this increase in an increase in the level of pay in the economy and, indeed, we observe this rise in pay. What our results show, however, is that this increase comes at a cost, at least if one believes that increases in wage inequality represent a cost for society.

A finer analysis of the education variable reveals even more interesting features of the response of wages to additional education. The returns of having just the "primary education" have dramatically decreased from 1982 to 1994 at all quantiles and are no longer significant in 1994. On the other end of the educational spectrum, the incremental returns on having a university degree have increased at every point of the wage distribution, but with a much sharper rise for the top quantiles.

What makes these results particularly interesting is that the observed increase in returns to education goes hands in hands with an increase in the average level of education of the working population. Unlike in the U.S., where the increase in returns to education may have been provoked by a reduction in the number of college graduates (Murphy and Welch 1989), in Portugal we had an increase in returns to university education, despite the remarkable increase in the number of college graduates. What this necessarily suggests is that, simultaneously to the shift in labor supply, there was a more than compensating shift in labor demand towards more skilled workers, which probably reflect changes in the underlying technology.

Our results for education have implications for the ongoing debate about private vs. public financing of university education. The rates of return estimated in the paper are private and, therefore, do not reflect the potential external effects of education. We are not aware of any study that has estimated social rates of return to education in Portugal and, therefore, we will not comment on the relative merits of public financing of the different levels of schooling. However, what seems to emerge very neatly from our results is that, as the private returns to college education have increased across all of the wage distribution, there is clearly a case for increasing the private contribution towards the costs of university education.

Finally, with respect to the observed increase in wage inequality, our results document very clearly the impact of heterogeneity in the worker force. Should there be no variability in workers' characteristics in the economy, wages would have increased more than they did at the bottom of the wage distribution, and less at the top. If, moreover, their characteristics have remained constant over time, the dispersion in wage growth between the top and the bottom of the distribution would have been even smaller. Nevertheless, our results indicate that, even in this case, dispersion would have increased, due to changes in the structure of pay.

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Appendix: Estimation of quantile regressions

The quantile regression estimators proposed by Koenker and Bassett (1978, 1982) allow a comprehensive and yet parsimonious description of the whole conditional distribution, enabling the analysis of the effect of the covariates on the whole wage distribution. To summarize the econometric framework, let y_i denote the (log) wage of worker i and x_i a vector of covariates representing individual and firm attributes and industry dummies. The statistical model used in this paper specifies the θ-th quantile of the conditional distribution of y_i given x as a linear function of the covariates,

$$Q_\theta(y_i \mid x) = \alpha(\theta) + x'\beta(\theta), \quad \theta \in (0,1). \tag{1}$$

This model subsumes as special cases the illustrations in Section 2 since the slope coefficients are allowed to vary from quantile to quantile. It is well known that the population mean of a random variable y is a solution of $\min_c E(y-c)^2$. However, all the other location measures of y may also be obtained as solutions to optimization problems (e.g., Mansky 1988). In particular the θ-th quantile of the distribution of y solves

$$\min_c E[\rho_\theta(y-c)]$$

where,

$$\rho_\theta(u) = \begin{cases} \theta u & \text{for } u \geq 0 \\ (\theta - 1)u & \text{for } u < 0. \end{cases}$$

is the so called "check" function. The analogy principle suggests to estimate the θ-th population quantile by solving $\min_c \sum_i \rho_\theta(y_i - c)$ which, indeed yields the ordinary sample quantiles. This same ideas generalize to conditional distributions. For each $\theta \in (0,1)$, the coefficients $\alpha(\theta)$ and $\beta(\theta)$ in model (1) can be estimated by minimizing in a and b, (Koenker and Bassett, 1978),

$$n^{-1} \sum_{i=1}^{n} \rho_\theta(y_i - a - x_i'b). \tag{2}$$

Asymptotic interval inferences about the coefficients $\beta(\theta)$ can be performed using the asymptotic distribution theory for quantile regressions, (*e.g.* Koenker and Bassett 1978, 1982 and Hendricks and Koenker 1992).

Figure 1: Wage distribution for men and women: Identically distributed wages

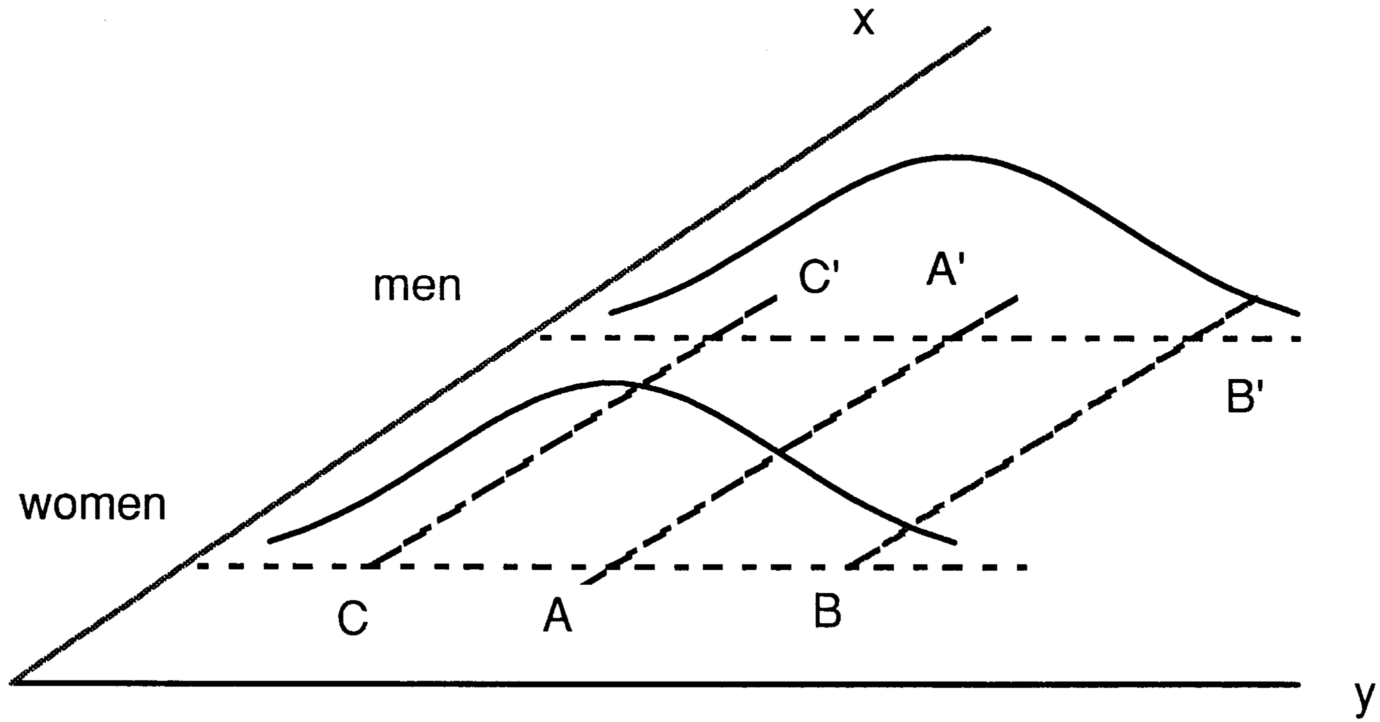

Figure 2: Wage distribution for men and women: Heteroskedasticity

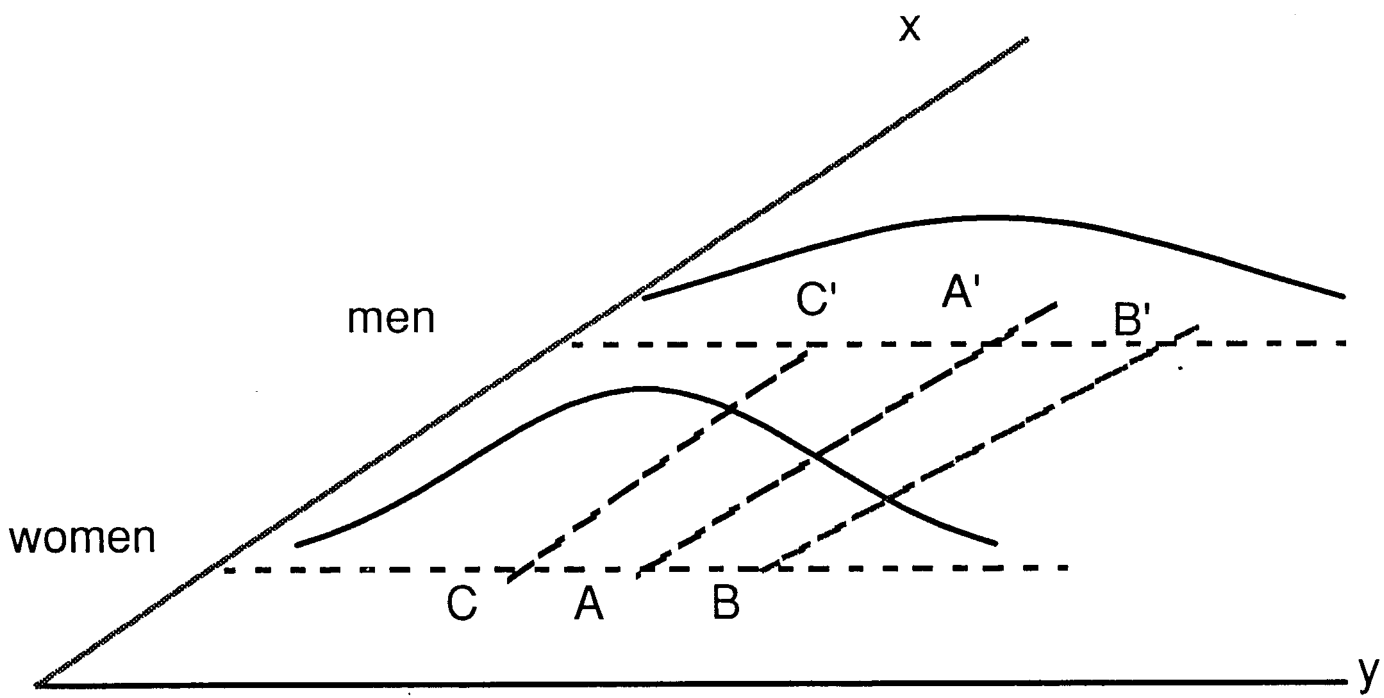

Figure 3: Wage distribution for men and women: Non-identically distributed wages

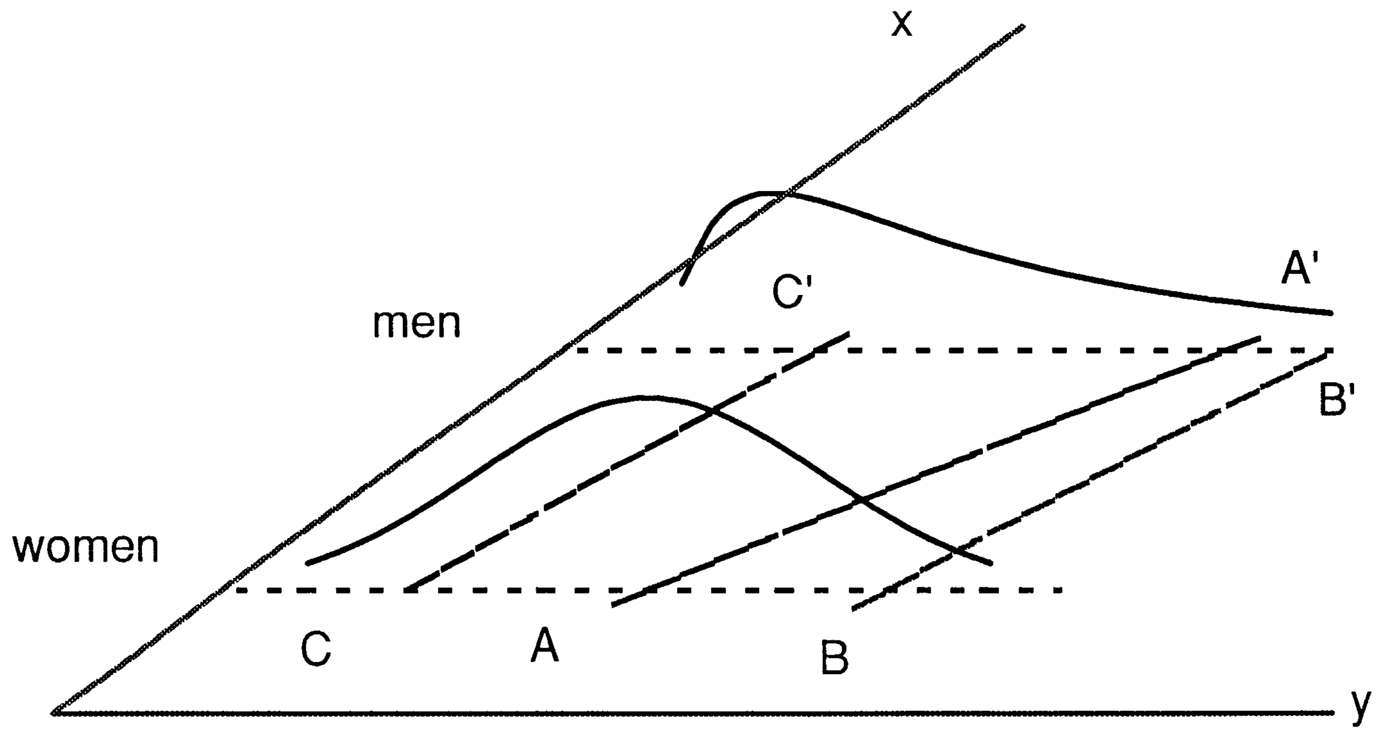

Figure 4: The Effect of Experience

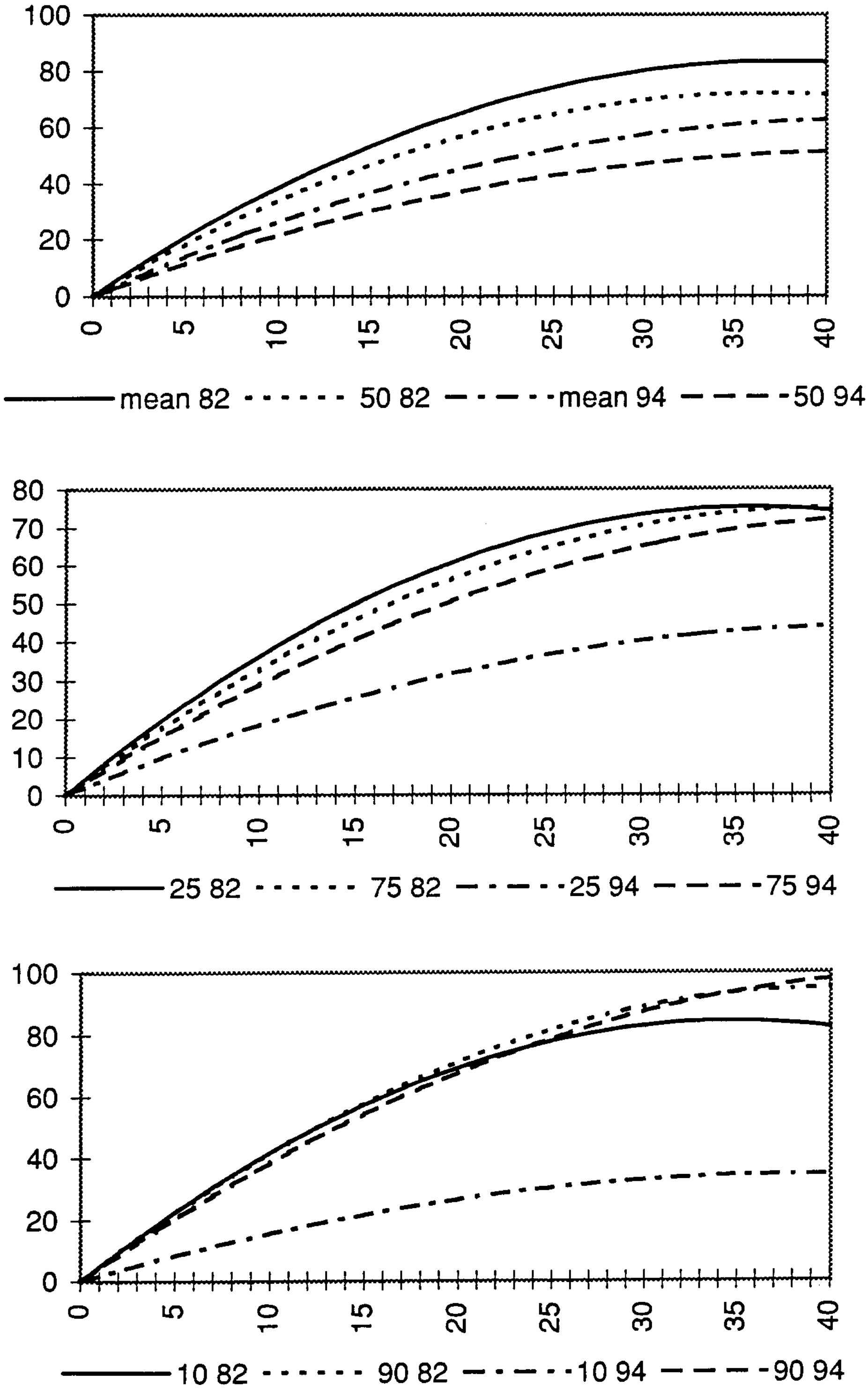

Figure 5: The Effect of Tenure

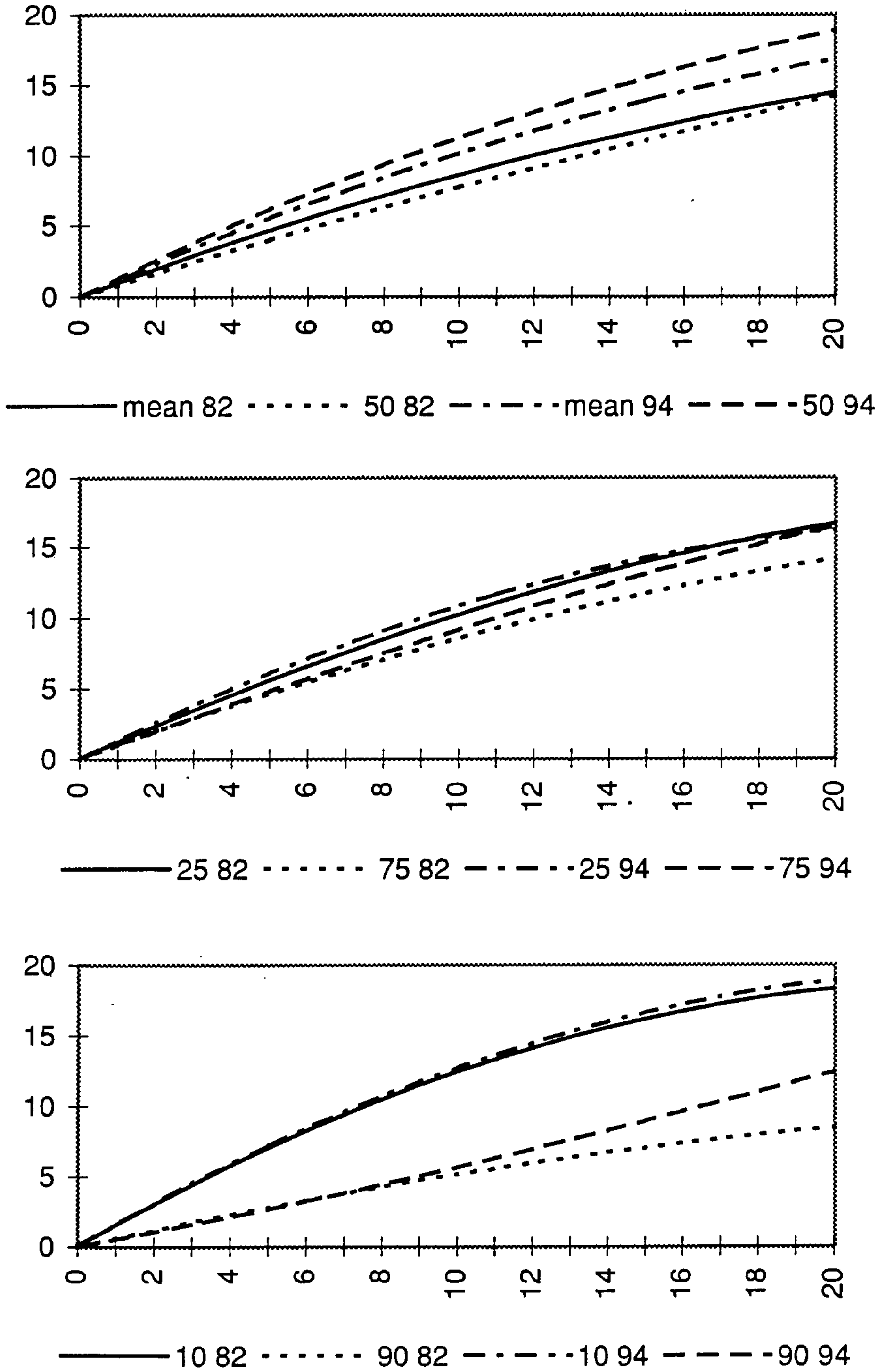

Table 1: The samples

	1982	1994
Wages		
Mean	396.1	554.9
Standard deviation	291.3	522.0
Quantiles		
q10	197.3	237.6
q25	240.3	286.7
q50	319.4	389.3
q75	453.5	610.7
q90	692.5	1054.2
Dispersion		
log(q90)-log(q10)	1.26	1.49
log(q75)-log(q25)	0.64	0.76
log(q25)-log(q10)	0.20	0.19
log(q50)-log(q25)	0.28	0.31
log(q75)-log(q50)	0.35	0.45
log(q90)-log(q75)	0.42	0.55
Sex (% of females)	0.29	0.39
Years of Schooling	5.05	6.33
Schooling Classes (% in each class)		
less than 4 years	10	3
4 years	59	45
6 years	14	26
9 years	15	28
14 years	2	4
Experience	23.84	22.70
Tenure	8.50	7.79
Size	5.14	4.50
Foreign	0.06	0.07
State	0.12	0.09
Observations	4690	4974

Table 2: Quantile Regressions

	OLS	10	25	50	75	90
1982						
Sex	-14.546	-10.679	-10.434	-13.191	-15.846	-19.909
	(1.073)	(1.442)	(1.175)	(1.095)	(1.140)	(1.529)
Schooling	7.062	5.091	5.549	6.117	7.261	8.340
	(0.224)	(0.228)	(0.196)	(0.208)	(0.249)	(0.316)
Experience	4.446	4.856	4.200	3.928	3.752	4.745
	(0.171)	(0.244)	(0.186)	(0.157)	(0.172)	(0.261)
Experience2	-0.059	-0.070	-0.059	-0.053	-0.047	-0.059
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
Tenure	0.997	1.566	1.207	0.832	1.001	0.609
	(0.156)	(0.232)	(0.179)	(0.172)	(0.194)	(0.269)
Tenure2	-0.014	-0.032	-0.019	-0.006	-0.015	-0.009
	(0.004)	(0.009)	(0.005)	(0.006)	(0.006)	(0.008)
Size	5.196	4.770	4.289	4.607	5.612	6.287
	(0.325)	(0.378)	(0.327)	(0.283)	(0.326)	(0.495)
Foreign	19.733	18.846	16.979	16.558	22.406	16.968
	(2.074)	(2.267)	(2.115)	(1.761)	(2.208)	(1.842)
State	8.335	17.599	13.115	10.758	4.186	-0.681
	(2.085)	(2.156)	(1.567)	(2.053)	(2.851)	(4.162)
1994						
Sex	-15.614	-8.629	-11.926	-14.321	-16.844	-17.183
	(1.185)	(0.756)	(0.808)	(0.936)	(1.343)	(2.149)
Schooling	7.696	3.587	4.862	6.498	8.636	11.415
	(0.262)	(0.170)	(0.181)	(0.183)	(0.276)	(0.461)
Experience	2.975	1.797	2.064	2.433	3.238	4.314
	(0.169)	(0.147)	(0.128)	(0.113)	(0.213)	(0.377)
Experience2	-0.035	-0.023	-0.024	-0.029	-0.036	-0.047
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.006)
Tenure	1.193	1.601	1.352	1.321	1.007	0.508
	(0.210)	(0.151)	(0.159)	(0.123)	(0.285)	(0.488)
Tenure2	-0.017	-0.033	-0.027	-0.019	-0.009	0.006
	(0.007)	(0.005)	(0.006)	(0.003)	(0.011)	(0.017)
Size	6.143	5.358	5.290	5.684	6.001	7.014
	(0.350)	(0.291)	(0.245)	(0.258)	(0.425)	(0.742)
Foreign	23.395	11.206	16.968	20.018	25.442	25.380
	(2.699)	(3.520)	(1.997)	(1.827)	(3.595)	(5.513)
State	5.132	11.829	8.704	5.427	3.706	-1.631
	(2.770)	(2.200)	(1.897)	(2.578)	(5.043)	(4.775)

All coefficents are in percent. Standard errors are in parenthesis.

Table 3: Impact Upon Dispersion

	1982		1994	
	25-75	**10-90**	**25-75**	**10-90**
Sex	-5.412	-9.231	-4.918	-8.554
	(1.343)	(1.989)	(1.320)	(2.200)
Schooling	1.712	3.249	3.774	7.827
	(0.263)	(0.369)	(0.276)	(0.474)
Experience	-0.449	-0.111	1.175	2.517
	(0.209)	(0.339)	(0.209)	(0.390)
Experience2	0.012	0.011	-0.012	-0.023
	(0.003)	(0.006)	(0.004)	(0.007)
Tenure	-0.206	-0.957	-0.345	-1.093
	(0.216)	(0.336)	(0.277)	(0.496)
Tenure2	0.004	0.023	0.018	0.038
	(0.006)	(0.011)	(0.010)	(0.017)
Size	1.325	1.516	0.710	1.656
	(0.378)	(0.589)	(0.415)	(0.767)
Foreign	5.427	-1.878	8.474	14.174
	(2.499)	(2.772)	(3.485)	(6.207)
State	-0.089	-0.183	-0.050	-0.135
	(0.028)	(0.045)	(0.048)	(0.051)

All coefficents are in percent. Standard errors are i
parenthesis.

Table 4: The Effect of Schooling

Educ. (years)	OLS	10	25	50	75	90
1982						
4	5.228	1.798	4.396	7.193	10.606	7.623
	(1.816)	(1.861)	(1.141)	(2.844)	(2.313)	(3.577)
6	19.839	12.319	17.255	20.228	27.019	25.939
	(2.377)	(2.299)	(1.944)	(3.285)	(2.672)	(4.256)
9	49.884	40.829	43.421	45.529	55.905	57.909
	(2.480)	(2.238)	(1.364)	(3.711)	(2.854)	(4.226)
14	102.080	76.605	96.275	107.482	117.413	112.787
	(5.071)	(8.089)	(2.076)	(12.223)	(4.630)	(9.243)
1994						
4	1.682	1.266	4.726	5.452	7.851	-2.622
	(3.207)	(1.086)	(1.457)	(2.657)	(3.491)	(9.334)
6	12.071	5.690	11.624	15.253	19.699	14.046
	(3.492)	(1.363)	(1.518)	(2.783)	(3.654)	(9.537)
9	38.882	19.937	28.856	39.168	52.168	55.895
	(3.730)	(1.564)	(1.751)	(2.952)	(4.021)	(9.803)
14	109.324	63.158	91.753	115.295	135.294	147.132
	(5.543)	(7.395)	(4.799)	(4.092)	(6.774)	(10.164)

All coefficents are in percent. Standard errors are in parenthesis.

Table 5: Returns to One Additional Year of Schooling

Educ. (years)	OLS	10	25	50	75	90
1982						
4	1.282	0.447	1.081	1.752	2.552	1.854
6	7.056	5.129	6.235	6.318	7.895	8.773
9	9.152	8.721	8.056	7.808	8.827	9.688
14	8.763	6.308	8.857	10.123	10.062	9.144
1994						
4	0.418	0.315	1.161	1.336	1.907	-0.662
6	5.066	2.188	3.391	4.786	5.758	8.013
9	8.239	4.540	5.443	7.409	9.826	12.359
14	11.254	7.449	10.251	11.986	12.863	13.845

Table 6: Industry Effects - 1982

Industry	OLS	10	25	50	75	90
Textiles and clothing	-21.5	-17.8	-21.4	-22.1	-24.3	-25.3
Wood and cork	-17.8	-14.7	-18.0	-18.5	-18.4	-21.5
Other manufacturing	-15.6	-15.8	-5.1	-18.7	-26.6	-11.8
Household services	-15.1	-26.5	-16.2	-9.9	-9.4	-13.7
Cleaning services	-9.3	-3.6	-9.4	-16.7	2.6	-9.6
Mechanical engineering	-5.1	-0.7	-1.2	-2.7	-5.8	-8.9
Hospitality	-3.3	-4.2	-6.2	-2.8	-1.4	-4.2
Food	-2.5	0.0	-5.1	-4.9	-2.5	-3.6
Retail trade	-2.4	-5.9	-4.8	-2.4	-1.0	-3.1
Basic metals	0.6	2.9	3.9	1.8	0.5	-8.3
Paper and publishing	2.9	-3.6	-4.1	-1.7	3.1	16.3
Chemicals	5.4	5.4	3.6	6.9	3.6	9.8
Nom metal minerals	6.8	8.2	6.8	7.9	5.6	2.6
Cultural and amusement services	7.3	-4.6	16.3	14.4	10.3	-0.7
Construction	9.1	11.7	9.5	8.0	6.1	5.2
Mining	9.2	2.1	1.3	8.3	13.1	20.8
Wholesale trade	9.5	8.1	11.0	9.2	9.6	11.2
Transport	10.2	-5.7	3.9	7.0	17.2	23.4
Business services	18.9	10.8	15.3	19.5	23.0	23.2
Electricity, gas, and water	20.1	17.4	25.7	26.3	21.1	24.4
Communications	20.7	33.2	34.7	23.9	16.0	11.5
Social and community services	24.2	10.8	15.7	22.6	27.6	50.8
Banking	26.5	34.6	33.5	25.4	27.7	31.0
Insurance	51.7	73.4	65.4	59.5	55.9	51.7
Tests						
Joint significance of industry effects						
Wald chi square	760.0	710.8	2531.4	903.2	726.9	587.2
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Equality between adjacent quantiles						
Wald chi square			53.2	49.2	38.9	85.5
p-value			(0.000)	(0.001)	(0.021)	(0.000)

Table 7: Industry Effects - 1994

Industry	OLS	10	25	50	75	90
Textiles and clothing	-20.1	-18.2	-18.5	-21.3	-22.0	-21.4
Wood and cork	-17.1	-16.2	-19.4	-20.4	-17.0	-11.9
Other manufacturing	-14.9	-13.0	-14.7	-15.1	-7.8	-22.2
Cleaning	-12.6	-8.3	-15.5	-9.6	-11.0	-15.2
Hospitality	-12.2	-12.7	-13.8	-13.8	-12.3	-13.5
Household services	-11.0	-12.5	-12.2	-11.9	-10.7	-15.3
Food	-7.0	-12.1	-10.6	-7.4	-4.7	-1.9
Retail trade	-4.3	-3.5	-7.4	-5.7	-2.7	0.0
Social and community services	-4.0	-7.5	-6.0	-4.9	-3.2	-2.4
Mechanical engineering	-1.7	-0.3	1.0	1.2	-1.6	-6.2
Nom metal minerals	2.2	-7.2	0.7	2.7	7.8	8.0
Construction	2.9	-0.6	1.4	0.9	-0.1	10.3
Basic metals	6.4	9.4	5.8	4.9	6.0	6.2
Business services	9.1	4.3	4.3	10.7	13.5	22.8
Cultural and amusement services	9.3	14.7	14.9	11.8	4.9	3.2
Transport	9.6	7.3	10.2	9.1	9.4	10.7
Wholesale trade	10.0	3.5	5.6	9.0	10.0	8.0
Paper and publishing	10.9	2.3	9.1	13.3	17.2	13.9
Communications	15.0	32.5	29.6	20.8	10.9	-9.8
Chemicals	17.6	4.4	9.7	21.8	22.7	20.9
Mining	19.0	10.6	22.6	19.4	18.5	29.3
Electricity, gas, and water	35.3	55.1	48.8	44.0	35.3	19.3
Insurance	48.0	80.2	67.4	55.8	36.5	11.1
Banking	50.8	68.9	60.4	54.0	49.8	41.4
Tests						
Joint significance of industry effects						
Wald chi square	760.0	710.8	2531.4	903.2	726.9	587.2
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Equality between adjacent quantiles						
Wald chi square			53.2	49.2	38.9	85.5
p-value			(0.000)	(0.001)	(0.021)	(0.000)

Table 8: Correlations Between Industry Effects

	OLS	10	25	50	75	90
OLS	1.00	0.94	0.98	0.99	0.98	0.80
10	0.91	1.00	0.98	0.95	0.87	0.58
25	0.95	0.95	1.00	0.98	0.93	0.68
50	0.99	0.91	0.96	1.00	0.97	0.76
75	0.97	0.86	0.88	0.95	1.00	0.86
90	0.92	0.73	0.78	0.86	0.91	1.00

Figures below (above) the diagonal refer to 1982 (1994)

Table 9: The Conditional Wage Distribution

	1982	1994	1994 at 1982 averages
Wages			
Quantiles			
q10	237.3	292.3	295.5
q25	279.0	339.4	340.5
q50	332.3	406.1	401.9
q75	400.6	507.9	492.3
q90	492.8	666.5	628.1
Dispersion			
log(q90)-log(q10)	0.73	0.82	0.75
log(q75)-log(q25)	0.36	0.40	0.37
log(q25)-log(q10)	0.16	0.15	0.14
log(q50)-log(q25)	0.17	0.18	0.17
log(q75)-log(q50)	0.19	0.22	0.20
log(q90)-log(q75)	0.21	0.27	0.24

Table 10: Growth Rates
at Different Points of the Distribution (%)

Quantile	Empirical	Conditional	Conditional at 1982 averages
10	20.4	23.2	24.5
25	19.3	21.7	22.0
50	21.9	22.2	20.9
75	34.7	26.8	22.9
90	52.2	35.3	27.5

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