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# New insights on earnings trends across skill groups and industries in West Germany — Source link

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# New Insights on Earnings Trends across Skill Groups and Industries in West Germany

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Abstract

This paper provides an empirical analysis of the structure of earnings in West Germany across skill groups and industries. Our analysis is based on data from the German Socioeconomic Panel for the period 1984 to 1994. We estimate quantile regressions, both for the entire sample period and for each year separately, in order to obtain a finer picture of the earnings structure compared to conventional least squares methods. For robust standard error estimation, this study uses a block bootstrap procedure taking account of heteroskedasticity and autocorrelation in the error term. We also suggest a simple one–step procedure to obtain a consistent estimate of inter–industry earnings variability. Our main findings are: first, pooled estimation comprising a uniform time trend is not rejected by the data, and second, the effects of human capital variables and industry dummies on earnings differ considerably across quantiles.

Keywords : Earnings Structure across Skill Groups and Industries, Quantile Regression, Block Bootstrap

JEL–Classification : J31, C23

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# Contents

# 1 Introduction

This paper is concerned with the structure of earnings across skill groups and industries. The analysis is based on individual data from the German socio–economic Panel (GSOEP) from 1984 to 1994. We estimate earnings functions by means of quantile regression techniques in order to allow for a finer investigation of the earnings structure compared to least squares approaches. This analysis addresses the following questions. How does the entire earnings distribution differ between sets of workers defined by some observable characteristics? And, are these conditional distributions shifted uniformly over time? As part of this analysis, we also consider two methodological aspects. First, we are concerned about robust inference on our estimates motivating the use of a flexible block bootstrap method for standard error estimation. Second, we develop a versatile procedure for estimating consistently the inter–industry variability of earnings which applies both to least squares and quantile regression estimates on industry dummies.

The economic policy debate in Germany is discussing intensively whether the high level of unemployment is due to the general wage level being too high and due to a lack of flexibility in the German wage structure caused by the prevailing wage bargaining system. Yet, until fairly recently, there existed surprisingly little evidence on wage trends in Germany taking account of compositional effects and on the actual flexibility (or inflexibility) of the wage structure.[1] In fact, Siebert (1995) forcefully demands more empirical research on the German wage structure. It is likely that due to potential composition effects an analysis of aggregate wage data is not sufficient. On an international level, a considerable increase in earnings inequality since the early 1980's has been observed for various industrial countries, the most prominent ones being the United States and the United Kingdom, see OECD (1993, 1996). Compared to developments in other countries, the latter study (based, however, on a fairly small set of descriptive statistics) shows that West Germany exhibits an exceptionally stable wage structure since the mid 1980's. This perception motivated some of the recent empirical studies on the wage structure in Germany and its flexibility.

A large strand of literature has emphasized the importance of wage differences across industries. The studies by Krueger and Summers (1987, 1988) initiated a considerable research effort to investigate whether in fact labor is paid differently even after controlling for observable and unobservable differences. If inter–industry wage differences prove consistent, this raises doubts about competitive wage explanations and opens the floor for non–competitive considerations like efficiency wage theory. A related issue is the perception that due to industry level wage bargaining in Germany wage growth is fairly uniform across individuals within an industry. However, it is often argued that pattern bargaining occurs, i.e. one industry sets the trend for the annual wage increases which then other industries follow, see Franz (1996, chapter 8).

[1] Exceptions are Abraham and Houseman (1994), Fitzenberger et al. (1995), and OECD (1993, 1996) concerned with trends in wages across skill groups; Bellmann and Möller (1993) and DeNew and Schmidt (1994) concerned with trends in wages across industries; Kurz (1995), Möller and Bellmann (1996), and Möller (1996) both concerned with trends in wages across skill groups and across industries.

Studies for Germany[2] have reached quite different conclusions on whether a uniform and stable inter–industry wage structure, in fact, exists for observationally equivalent workers.

The goal of this paper is to provide a comprehensive description of earnings trends across skill groups and industries. Rather than restricting ourselves to mean effects, as most of the previous literature, our empirical approach examines changes of the entire within distribution across groups of workers (cells), who exhibit the same observable characteristics. We estimate linear least squares and quantile regressions and investigate whether the entire earnings distribution is affected uniformly by human capital variables, industry dummies, and time, such that a least squares perspective (disregarding outlier problems) on modelling average (uniform) effects is sufficient to describe the data. Our results indicate that some new insights on the earnings structure can be obtained this way.

This study introduces also some methodological innovations. As a first innovation, we suggest a simple one–step–procedure for estimating employment weighted industry effects around the mean across industries, which automatically yields a consistent estimate of the covariance matrix of the centered dummy coefficients. This simplifies the consistent estimation of the weighted standard deviation across industries, compared to the two–step procedures suggested in the literature, cf. DeNew–Haisken and Schmidt (1996) and Möller (1995). A second innovation is to use a block bootstrap procedure for inference both on least squares and quantile regressions based on panel data, cf. Fitzenberger (1997), which provide standard error estimates which are consistent under heteroskedasticity and autocorrelation of the error term for a given individual. Standard approaches in panel econometrics, such as fixed–effects estimation, do not appear attractive to us, since we want to model the structure of wage levels and not some form of deviation around an individual location measure. Granted, we do not necessarily claim to estimate a structural model. However, our results indicate that inference has to take account of autocorrelation.

The remainder of this paper is organized as follows. Section 2 surveys the recent literature focusing on empirical studies on the inter–industry wage dispersion. Section 3 develops the estimation approach taken in this study. Section 4 describes the data used. Section 5 presents the estimation results and section 6 concludes. A final appendix provides further information on the data set used, and further estimation results. In addition, it supplements the description of the estimation approach.

# 2 Previous Studies

This section discusses results of previous empirical studies. We focus on studies based on individual data attempting to control for individual characteristics in order to compare wage differentials between (observationally) equivalent types of labor. We put a great emphasis on inter–industry wage differentials. First, studies concerning Germany will be considered. Second, we add an international comparison of results

[2]Cf. Bellmann and Möller (1995), Burda (1993), DeNew and Schmidt (1994), Fels und Gundlach (1990 a,b), Kurz (1995), Möller and Bellmann (1996), Schmidt (1992), Schmidt and Zimmermann (1991), and Wagner (1990).

to evaluate the influence of different labour market institutions on the inter–industry wage dispersion.

## 2.1 Studies for Germany

Gerfin (1977) provides an early analysis of the inter–industry wage structure based on aggregate data in West Germany for the 60's and 70's. He finds considerable wage differentials across industries and changing trends. In order to explain these developments, Gerfin discusses various market forces and the influence of institutions. Whereas wage differentials were narrowing until the mid 60's, they started widening again afterwards. In contrast, Fels and Gundlach (1990 a,b) used aggregate data for different qualification groups and they find a stable industry wage structure for Germany during the last thirty years. The inter–industry wage structure exists for all types of qualifications and the authors interpret these findings as a confirmation of the hypothesis that certain branches pay wages above the market clearing level. Winker (1993) develops a dispersion measure based the entropy concept and he finds an upward trend in the coefficient of variation of aggregate wages across industries but not in his entropy measure.

Aggregate data might be plagued by composition effects. In particular, differences in the level of human capital of the workers in different industries might explain differences in aggregate wages (even if captured to some extent by taking aggregate data for different qualification groups). Human capital effects on wages are well established in labor economics based on Mincer type earnings functions, whereas the existence of persistent sectoral wage dispersion is often disputed. Estimating earning functions for the year 1978, Schmidt and Zimmermann (1991) do not find significant inter–industry wage differentials.

On the contrary, examining data from the German Socioeconomic Panel Hübler and Gerlach (1990) as well as Burda (1991) report significant wage differentials between industries for the years 1984 and 1985. But Burda reports also, that the inter–industry earnings differentials disappear for workers with less than five years job tenure. This seems to confirm a variant of the efficiency wage hypothesis stating that some industries depend more on firm specific human capital than others and therefore pay wages above the market clearing level to workers with considerable firm specific human capital (proxied by tenure) in order to avoid quits.

Schmidt (1992) estimates earnings functions with data from the first four waves of the German Socioeconomic Panel. Even after controlling for unobserved heterogeneity by using fixed and random effect methods the coefficients of the industry dummies remain jointly significant and their estimated standard deviation is growing over the period of observation by 2 percentage points.

These results are confirmed by the studies of Bellmann and Möller (1995), Möller and Bellmann (1996) and Möller (1996) based on the German Social Security data. For the period from 1979 to 1989, they observe a stable ordinal ranking of inter–industry earnings, but they report an increase of the standard deviation of the coefficients of the industry dummies (effect on log earnings) from 0.06 to 0.11, [3] which they interpret

[3] Using the correction for sample variability described in the appendix of this study.

as strong support for the hypothesis of rising wage inequality in the Federal Republic of Germany during the eighties (Bellmann and Möller (1995)). Möller (1996) indicate an increase of the employment weighted standard deviation (corrected for sampling variability) of the industry dummy coefficients for all skill groups, whereby unskilled employees exhibit the greatest earnings dispersion. In 1989, the standard deviation of industry coefficients is estimated as 0.08 for unskilled workers as compared to 0.065 for skilled workers. The theory of a growing standard deviation is somehow in contrast to our results indicating a stable wage dispersion in West Germany from 1984 to 1994.

DeNew and Schmidt (1994) investigate the German industrial wage structure during the eighties with data from ALLBUS [4] estimating earnings functions based on a pooled sample. They calculate the industry effects as deviations from the mean and obtain significant inter–industry wage differentials, but with fluctuations in the relative position of individual industries in the wage hierarchy.

This finding is questioned in the studies by Möller and Bellmann (1996) and Kurz (1995). The analysis by Kurz is based on the first ten waves of the German Socioeconomic Panel (in fact the same basic data set as used in this study). Kurz applies fixed– and random–effects methods in order to control for unobserved heterogeneity. In contrast to Schmidt (1992), these corrections reduce the inter–industry wage dispersion but the coefficients of the sector dummies remain jointly significant. Therefore unobserved individual effects seem to be partly responsible for the observed inter–industry wage differences. The wage dispersion between sectors remains stable in this sample and there is no evidence for intertemporal changes in the industry wage stucture (except for changes involving very small industries). Even though, a closer look shows rather great fluctuations in the cross–section coefficients of the sector dummies, intertemporal stability of almost all industry dummies cannot be rejected. These results are confirmed by our analysis of the data set, but using quantile regressions rather than ordinary least squares, we find significant differences in the inter–industry wage structure between the earnings quantiles.

Based on German Social Security data from 1976 to 1984, Fitzenberger et al. (1995) analyze wage trends across skill groups by means of a cohort analysis using quantile regression techniques. The main findings are that wages of workers with intermediate education levels, among them especially those of young workers, deteriorated slightly relative to both high and low education levels. Wage inequality within age-education groups stayed fairly constant below the median and increased slightly above the median. Overall, the German wage structure was fairly stable, especially in international comparison. The results appear consistent with a skill bias in labor demand trends, together with skill-specific trends in employment and labor supply, and recognizing that union wages are only likely to be binding floors for low-wage earners.

## 2.2 International Studies

Potentially, international studies can distinguish between common effects on wage trends across countries in reaction to common shocks and the influence of country

[4] ALLBUS is an abbreviation for "Allgemeine Bevölkerungsumfrage der Sozialwissenschaften"

specific shocks and different labour market institutions. Our paper fits into a series of recent studies which have analyzed the trends in wages across skill groups in various industrialized countries during the 1970s and 80s, documenting the growth of wage inequality in several dimensions.[5] Katz and Murphy (1992) list the following stylized facts (among others) of wage trends in the United States: (i) the relative wages of more educated workers exhibit a decline during the 70s and a substantial increase in the 80s, (ii) the relative wages of older workers increase sharply among workers without a college degree during the 70s and 80s, but only during the 70s among workers with a college degree, and (iii) wage inequality within gender , education, and age groups rises continuously during the 70s and 80s. Finding (iii) is questioned in the study by MaCurdy and Mroz (1995), who do not find an increase in within-inequality.

Katz and Murphy discuss supply and demand factors which could potentially explain the observed trends. The baby boom and immigration may have increased the relative supply of unskilled labor. Skill biased technological change and an intensified international competition may have increased the relative demand for skilled labor. Further issues raised in the literature relate to institutional changes, namely the decline of unionism and the decline of real minimum wages in the United States during the 80s. The inability to discriminate sharply between different hypotheses for the United States motivated recent cross-country studies, see OECD (1993, 1996), since some but not all of the hypotheses are relevant to all industrialized countries. For instance, OECD (1993, 1996), Abraham and Houseman (1994), and Fitzenberger et al. (1995) find quite different patterns for Germany compared to the United States.

The inter-industry wage dispersion of the US is investigated by Krueger and Summers (1988) with individual data from the Current Population Survey for 1974, 1979 and 1984. Their estimates of earnings functions involve individually and jointly significant coefficients of the industry dummies with a rather stable standard deviation between 0.11 and 0.14. In a further study (1987), they investigate the development of American industrial wages for the period from 1915 to 1984. They find an intertemporally stable industry structure with correlation coefficients of 0.76 and 0.98 between different years. The wage dispersion does not exhibit an apparent trend, but it appears to be countercyclical in the short run. Similar results for the US are also obtained by Helwege (1992) for the years of 1940 to 1980 with deviations of the industry effect from the mean ranging -0.31% to +0.40%.

Various empirical studies analyze the earnings structure in different countries in order to compare the effects of labour market institutions. Krueger and Summers (1987) observe similar industry wage structures in the capitalistic countries and report correlations of the industry effects between these countries of about 0.8. Similar results are obtained by Holmlund and Zetterberg (1991) comparing Austria, Germany, Norway, Sweden and the USA. Hereby, Sweden, a country with a rather centralized labour market, exhibits the smallest wage dispersion. The greatest earnings differences between industries are found in the USA. If wage dispersion indicates the flexibility of labour markets, this study confirms the hypothesis, that the flexibility of the labour market rises with institutional decentralization.

A different result is obtained by Wagner (1990) who examines the labour mar-

[5] Cf. among others Buchinsky (1994), Katz and Murphy (1992), MaCurdy and Mroz (1995), and OECD (1993, 1996).

kets of Austria, Germany, Great Britain, Switzerland and the USA. His estimates of earnings functions exhibit great differences in the industrial wage structures of the countries. An exception are Credit and Insurance institutions being high wage industries and Construction, Transportation, and Communication being low wage industries in almost every country.

# 3 Estimation Approach

This section describes our estimation approach. Most previous studies on wage differences across skill groups and industries discussed in section 2 were typically using least squares regressions (or tobit models in the presence of censoring) to estimate Mincer type earnings functions including industry dummies as part of the regressor set. Such an approach amounts to modeling the mean of earnings conditional on the set of regressors. However, it has been shown recently that restricting the analysis to "average" effects misses some of the important features of the wage or earnings structure, cf. Buchinsky (1994), Chamberlain (1994), and Fitzenberger et al. (1995). Thus, in addition to estimating conventional least squares earnings regressions, we choose to model the earnings distribution at various quantiles $\theta \in (0,1)$ conditional on standard human capital variables (education, experience, tenure) and conditional on the industry the worker belongs to. Estimating such quantile regressions, we obtain a more detailed picture of the earnings structure across workers with different skill levels and belonging to different industries. For the special case of the median, $\theta = 0.5$, this amounts to least absolute deviations (LAD) regression which implies minimization of the sum of the absolute values of the residuals instead of their squares as in the least squares case. Quantile regressions were introduced by Koenker and Bassett (1978). Chamberlain (1994) is a recent reference for a survey on the method. Koenker and d'Orey (1987) provide an efficient algorithm in Fortran to do the estimation. Further details of our specific estimation approach can be found in the appendix.

### Estimation of Quantile Regressions

For the general case $\theta \in (0,1)$, we estimate conditional quantiles of earnings by means of quantile regressions

$$q_{\theta,t}(ln(w_{i,t})|x_{i,t},\mu_t^\theta) = x_{i,t}'\mu_t^\theta \quad , \tag{1}$$

where $q_{\theta,t}(ln(w_{i,t})|x_{i,t},\mu_t^\theta)$ denotes the $\theta$–quantile of the earnings of individual $i$ at time $t$ conditional on the set of regressors $x_{i,t}$ and $\mu_t^\theta$ the coefficient vector. For our empirical analysis, we decided to model the following quantiles, $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$.

Quantile regressions are conceptually quite analogous to least squares regressions. In the least squares case, the regression coefficients measure the influence of the regressor variables on the conditional mean of the dependent variable, whereas in the quantile regression case the regression coefficients $\mu_t^\theta$ represent the influence of the regressor variables on the conditional $\theta$–quantile of the dependent variable.

For the median case $\theta = 0.5$, the estimation of the coefficients $\mu_t^{0.5}$ involves minimization of the sum of the absolute values of the residuals (LAD)

$$S_{0.5}(\mu_t^{0.5}) = \sum_{i,t} |ln(w_{i,t}) - x'_{i,t}\mu_t^\theta| \ , \tag{2}$$

where the absolute value can be rewritten as

$$|ln(w_{i,t}) - x'_{i,t}\mu_t^\theta| \equiv sgn(ln(w_{i,t}) - x'_{i,t}\mu_t^\theta)\ (ln(w_{i,t}) - x'_{i,t}\mu_t^\theta)$$

and $sgn(.)$ represents the sign function. Thus, the absolute value of the residual is equal to the residual if the latter is positive and otherwise it is equal to the negative of the residual.

Now, the general quantile regression case differs from the LAD case by weighting the residual differently depending on its sign. For general $\theta$, positive residuals enter the distance function with a weight of $\theta$ and negative residuals with a weight of $-(1-\theta)$.[6] Estimation of the quantile regression coefficients $\mu_t^\theta$ involves minimization of[7]

$$S_\theta(\mu_t^\theta) = \sum_{i,t} sgn_\theta(ln(w_{i,t}) - x'_{i,t}\mu_t^\theta)\ (ln(w_{i,t}) - x'_{i,t}\mu_t^\theta) \ . \tag{3}$$

$$= \sum_{i,t\,:\,ln(w_{i,t})-x'_{i,t}\mu_t^\theta>0} \theta \cdot |ln(w_{i,t}) - x'_{i,t}\mu_t^\theta| + \sum_{i,t\,:\,ln(w_{i,t})-x'_{i,t}\mu_t^\theta<0} (1-\theta) \cdot |ln(w_{i,t}) - x'_{i,t}\mu_t^\theta|$$

where the $\theta$–weighted sign function $sgn_\theta(\epsilon_{i,t}^\theta)$ is defined as

$$sgn_\theta(\epsilon_{i,t}^\theta) \ \equiv \ \theta I(\epsilon_{i,t}^\theta > 0) \ - \ (1-\theta) I(\epsilon_{i,t}^\theta < 0)$$

and $I(.)$ denotes the indicator function. The expression $\rho(\epsilon_{i,t}^\theta) \equiv sgn_\theta(\epsilon_{i,t}^\theta)\,(\epsilon_{i,t}^\theta) = (\theta - I(\epsilon_{i,t}^\theta < 0))\epsilon_{i,t}^\theta$ is often referred to as the check function. By variation of $\theta$, different quantiles can be obtained.

Fitzenberger (1997) provides a general treatment of the asymptotic distribution of the least squares and quantile regression coefficients estimates when heteroskedasticity and autocorrelation of the error term is present in the time series context. Analogous to least squares regression, the basic structure of the asymptotic covariance matrix

[6] As a motivation, note that for a sample of size N, $\{y_1, ..., y_N\}$, the minimization of the sum

$$\sum_{i=1}^{N} [\theta I(y_i - q_\theta > 0) - (1-\theta) I(y_i - q_\theta < 0)]\ (y_i - q_\theta)$$

with respect to $q_\theta$ is a formalized way to determine the empirical $\theta$–quantile $q_\theta$ where $I(.)$ denotes the indicator function.

[7] Chamberlain (1994), Buchinsky (1994), and Fitzenberger et al. (1995) also use a simplified minimum–distance approach to the estimation of quantile regressions when the data on the regressors can be grouped into cells and censoring is not too severe. The approach consists of calculating the respective cell quantiles in a first stage and regressing (by generalized least squares) those empirical quantiles on the set of regressors in the second stage. However, for the data set used in this study the cell sizes would be too small to make this a fruitful approach (Chamberlain suggests cell sizes of at least 30).

presented in Fitzenberger (1997) generalizes to the cross–section and time series case involving an unbalanced panel. Under standard regularity conditions in the presence of heteroscedasticity and correlation of the error terms, the asymptotic covariance matrix of the quantile regression coefficient estimator $\hat{\mu}_t^\theta$ minimizing the distance function (3) is given by

$$\sqrt{N}\,(\hat{\mu}_t^\theta - \mu_t^\theta) \overset{A}{\sim} N(0, L_{\theta,N}^{-1} J_{\theta,N} L_{\theta,N}^{-1}) \tag{4}$$

where $N$ denotes the sample size and the matrices $L_{\theta,N}$ and $J_{\theta,N}$ are given by

$$L_{\theta,N} = E\,\frac{1}{N}\sum_{i,t} f_{\theta,i,t} x_{i,t}\, x'_{i,t}$$

and

$$J_{\theta,N} = Cov\left\{\frac{1}{\sqrt{N}}\sum_{i,t} sgn_\theta(\epsilon_{i,t}^\theta)x_{i,t}\,,\,\frac{1}{\sqrt{N}}\sum_{i,t} sgn_\theta(\epsilon_{i,t}^\theta)x_{i,t}\right\} .$$

The above result requires the assumption that the $\theta$–quantile of $\epsilon_{i,t}^\theta$ conditional on the regressors is equal to zero and $f_{\theta,i,t}$ denotes the density of $\epsilon_{i,t}^\theta$ at zero conditional on the regressors. Heteroscedasticity enters the covariance matrix through $f_{\theta,i,t}$ differing across observations. Autocorrelation of the error term $\epsilon_{i,t}^\theta$ affects $J_{\theta,N}$ through correlation of the $\theta$–weighted sign function across observations.

In our case, we assume the error terms to be independent across individuals but we allow for correlation of the error term for a given individual over time, which is the standard form of correlation considered by panel data methods. Therefore, $J_{\theta,N}$ becomes

$$J_{\theta,N} = \frac{1}{N}\sum_i \sum_{j=-T+1}^{T-1} \sum_t Cov(sgn_\theta(\epsilon_{i,t}^\theta)x_{i,t}, sgn_\theta(\epsilon_{i,t+j}^\theta)x_{i,t+j}) \quad ,$$

where $T$ represents the number of waves and for individual $i$ the summation $\sum_t$ is only taken for the available observations in the data set.

The asympotic distribution of the quantile regression estimator is quite analogous to the least squares case, when the error term exhibits heteroscedasticity and autocorrelation. In the well–known least squares case, the term $f_{\theta,i,t}$ is missing in the expression for the matrix $L_N$ and the matrix $J_N$ takes account of variances and covariances in $\{\epsilon_{i,t}^\theta x_{i,t}\}$ instead of $\{sgn_\theta(\epsilon_{i,t}^\theta)x_{i,t}\}$, cf. Fitzenberger (1997).

At this point, we should mention two objections against our estimation approach. Based on panel data of full–employed male workers, our analysis attempts to describe the structure of earnings levels rather than to identify structural parameters. Therefore, we neither estimate a fixed–effects model nor do we attempt to control for the selection bias involved by our sample restriction. First, estimating a fixed–effects model in order to control for individual autocorrelation over time would effectively amount to describing the deviations of earnings levels around some individual location measure (mean, quantile) instead of describing individual levels. Especially in the quantile case, such deviations do not seem very meaningful. Second, we do not control for the sample selection involved by ignoring the employment decision, since we are specifically interested in describing the wage distribution conditional on being employed. However, attrition is a serious issue in our data set, cf. section 4. We assume that attrition occurs purely at random without affecting the consistency of our regression estimates.

### Robust Estimation of Asymptotic Covariance Matrix: Block Bootstrap Estimator

Robust estimation of the asymptotic covariance matrix would involve estimation of the conditional density differing across observations and taking account of the dependency in $sgn_\theta(\epsilon^\theta_{i,t})$ across observations. Facing these difficulties, researchers have resorted to bootstrap methods as a viable alternative, see Chamberlain (1994), Buchinsky (1994), and Fitzenberger et al. (1995). Fitzenberger (1997) establishes the asymptotic validity of the Moving Blocks Bootstrap method (and therefore the standard bootstrap as a special case) for quantile regressions in the time series context.

In this paper, we use a flexible Block Bootstrap approach allowing for standard error estimates which are robust against fairly arbitrary heteroscedasticity and autocorrelation of the error term. The Block Bootstrap approach employed in this paper extends the standard bootstrap procedure in that it draws blocks of observations to form the resamples; for each observation in a block, the entire vector of endogenous variable and regressors is used, i.e., we do not draw from the estimated residuals. We draw the entire observation vector for one individual over time at random with replacement until the resample has reached the desired size. Due to attrition and integer problems, we might only take parts of the last block because of a fixed resample size. Since for the period specific quantile regressions reported in section 5, a large share of resamples would exhibit singular design matrices (due to the large number of dummy variables), we use resample sizes which are two times as large as the original sample size for the period specific estimates. The raw bootstrap covariance estimates are then rescaled according to the asymptotic rate of $\sqrt{N}$, i.e. for the period specific regressions the bootstrap covariance estimates are multiplied by a factor of two. The results presented in section 5 indicate that allowing for correlation between individual error terms over time when forming the blocks changes the estimated standard errors considerably. Thus, it is very likely that such correlation is present.

### Estimating the Standard Deviation of Inter–Industry Wage Differences

The literature on the inter–industry wage (or earnings) structure has been very concerned about obtaining an unbiased estimate of the standard deviation of the true inter–industry wage differences. Krueger and Summers (1988) showed that an unbiased estimator based on a least squares regression has to take account of the sampling variability of the dummy coefficient estimates. Thus, robust estimation of the coefficient covariance matrix, as discussed above, is also of great importance to obtain a reliable measure of the standard deviation of the true inter–industry wage differences. In order to obtain dummy coefficient estimates, which are deviations from a (employment–) weighted mean, the literature takes a two–step approach. In the first step, the dummy coefficients are estimated by means of a regression based on the raw dummies with one omitted category. In the second step, deviations from a (employment–) weighted mean are calculated based on the first step estimates.

Table 1: Number of Observations from the GSOEP used in Regression Analysis

| Year | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Number of Observations | 1468 | 1270 | 1181 | 1157 | 1092 | 956 | 1020 | 885 | 832 | 705 | 608 | 11174 |

When calculating appropriate standard errors for the second step, one has in fact to take account of the covariances of the first step estimates, which has been neglected by most of the literature. To our knowledge, this was observed independently by Haisken–DeNew and Schmidt (1996) and Möller (1995).

In the appendix, we develop a simple one–step procedure to estimate deviations from a (employment–) weighted mean. In the following, we implement this procedure both for linear least squares and quantile regressions. We also derive an appropriate estimator of the standard deviation of the true inter–industry wage differences which, in contrast to the suggestions in the literature, only requires an estimate of the variances but not the covariances of our one–step dummy coefficient estimates.

# 4 Description of the Data

The empirical part of this paper relies on data from the German Socio–economic Panel (GSOEP). This panel contains information from annual interviews of German and foreign households with residence in Germany. It started in 1984 with the interviews of 5921 households and in this study annual data until 1994 are employed. Table 1 provides the number of observations by year used for our estimations. Obviously panel mortality is quite severe: by 1994 the number of observations available is reduced by more than 50% compared to 1984. To minimize the losses of panel mortality, we choose an unbalanced panel design.

We concentrate on the earnings of men who live in western Germany and are fulltime employed. To exclude the periods of education and retirement, only persons between 25 and 55 years of age remain in the sample. The dependent variable in our regression analysis is the log of real gross monthly earnings which we deflate by the German CPI. This variable is drawn from the annual question concerning the gross labor income of the last month before the interview. It includes overtime compensation but no other extra payments as for example leave pay. We use this variable instead of the average monthly earning per year because it enables us to fit the earning to the current industry where the individual is employed. By using average values this would not be possible for job changes during the year.

To measure the influence of human capital on earnings we use as regressors the variables education (including the occupational degree), years of potential labor market experience (EX), and years of tenure (TEN) at the current employer. We define the potential labor market experience as the age of a person minus its years of education minus its first 6 years of childhood. This variable is supposed to capture the general human capital acquired during labor market experience. The years of tenure serve as an approximation of the level of firm–specific training which is only useful at the present employer. To allow for some heterogeneity in education and occupational degrees and to avoid imposing the linearity assumption involved when using years of schooling,[8] the data set is divided into four groups:

- workers without any completed occupational degree ("Ohne abgeschlossene Berufsausbildung", dummy variable $DQ_1$),
- workers with a completed apprenticeship ("Abgeschlossene Lehre", $DQ_2$),
- workers with an occupational degree from a vocational school or with a secondary school leaving certificate ("Sonstiger Berufsabschluß, Fachhochschulreife oder Abitur", $DQ_3$),
- and workers holding a university or technical college degree ("Universitäts- oder Fachhochschulabschluß", $DQ_4$).

See Fitzenberger et al. (1995) or Möller and Bellmann (1996) for a similar classification. In the regression analysis, the group $DQ_1$ serves as the reference category.

The industry effects are included into the regressions by generating a dummy variable for each industry where the observed persons are employed. We use the two-digit industry classification of the GSOEP, see the classification in the appendix. This allows us to distinguish between 35 different branches, but unfortunately some industries in our sample contain only very few observations. To get a more representative distribution of workers across industries, the dummy variables are weighted by aggregate employment in the regression analysis using the overall weights of full time employed men.[9] Since the industry classifications of the GSOEP and the aggregate statistics do not match exactly, some industries in the GSOEP had to be combined. Furthermore, some of the generated industries do not contain enough observations for a useful implementation of the estimation methods used here. Therefore a few more industries are combined. Thus, starting from the 35 industries available in the GSOEP the final number of industries used in this study is reduced to 27. In our regression analysis, the coefficients of the industry dummies are estimated as normalized deviations from the employment weighted mean. For the exact classification of industries and the implementation of the estimation of industry effects see the appendix.

Table 2 comprises the variables from the GSOEP used in our analysis and provides some descriptive statistics based on the entire sample from 1984 to 1994 in table 1. Average earnings are DM 3919 and median earnings DM 3500 indicating an earnings distribution that is skewed to the right. Since we are going to use quantile regression methods, we do not trimm the earnings data. [10] As it is typical for the German education system, $DQ_2$ is by far the largest group among the four education groups.[11]

[8] Linearity in years of schooling is typically rejected by the data, cf. Franz (1996, chapter 3), and Möller and Bellmann (1996).

[9] The employment weights are calculated from the employment statistics of the German "Statistisches Bundesamt". The numbers are reported in the appendix.

[10] Only two observations are dropped from the data set because their extremely low earnings seem not to fit to the other information give by these persons.

[11] In other studies – Fitzenberger et al. (1995), Möller and Bellmann (1996) – $DQ_2$ is combined with "Occupational Degree from a School", which results into a group comprising about 70% of male German workers. In order to avoid such a dominant group, we decided to use a different division. Our group $DQ_3$ combines naturally schooling at secondary schools and at vocational training schools.

Table 2: Definitions of Variables from GSOEP and descriptive Statistics[a]

| Variable | Abbrev. | Mean | Std.Dev. | Median | Min. | Max. |
|---|---|---|---|---|---|---|
| Real Monthly Gross Earnings | $w_{i,t}$ | 3919 | 1629 | 3500 | 868 | 31276 |
| No occupational degree | $DQ_{1,i,t}$ | 0.088 | 0.283 | 0 | 0 | 1 |
| Apprenticeship | $DQ_{2,i,t}$ | 0.549 | 0.498 | 1 | 0 | 1 |
| Vocational/Secondary School Certificate | $DQ_{3,i,t}$ | 0.202 | 0.402 | 0 | 0 | 1 |
| College/University | $DQ_{4,i,t}$ | 0.161 | 0.368 | 0 | 0 | 1 |
| Potential Labor Market Experience | $EX_{i,t}$ | 24 | 9.22 | 24 | 1 | 41 |
| Tenure | $TEN_{i,t}$ | 13.1 | 9.24 | 12 | 0 | 41 |
| Industry Dummy for Industry $s$ | $DS_{s,i,t}$ | –[b] | –[b] | –[b] | 0 | 1 |

a: $i$ is the index for individual $i$ and $t$ for time period $t$=1984,...,1994

b: see appendix for the industry classification and sample frequencies

On average, experience and tenure are fairly large at 24 and 13 years. Somewhat surprisingly, the standard deviations are of similar magnitude indicating considerable differences in tenure across workers. The appendix provides the GSOEP sample frequencies for the 27 industries. There are actually notable differencies between the sample frequencies and the aggregate employment weights, which are at least partly due to panel mortality. Therefore, we rather use the aggregate weights for our analysis in order to obtain a more representative picture for the later years.

# 5 Empirical Results

The section presents the results of our empirical investigation of the earnings structure across skill groups and industries. First, as a benchmark, we describe the raw earnings differences across skill groups and the raw inter–industry earnings differences, respectively, without controlling for other variables. Second, we estimate earnings regressions pooling the entire sample from 1984 to 1994. We find significant differences in the estimated regressions across quantiles with respect to earnings across industries, across education groups, and and with respect to tenure effects. This suggests that least squares estimation approaches focusing on mean effects are not sufficient to describe the data. Then, we compare inference based on the conventional bootstrap with block bootstrap standard error estimates. The results indicate considerable positive autocorrelation of the error term across time for the same individual. And third, we investigate whether the estimates based on the pooled sample are sufficient to describe the data. Using our bootstrap standard error estimates, we test for stability of the estimated coefficients across time. We find considerable movements of coefficients across time (especially of the coefficients on the industry dummies) but, in contrast to results in the literature, these movements prove to be insignificant, i.e. pooling over time is not rejected by our data.

### Raw Differences in Earnings across Occupational Degrees

Table 4 provides the raw differences in the mean and various quantiles of earnings across workers with different occupational degrees over time. These numbers were obtained as raw differences in log real earnings, e.g. in 1984 the difference between workers in skill group $DQ2$ (Workers with completed Apprenticeship) and $DQ1$ (Workers without occupational degree) in means was 12 percent (in logs) whereas the difference in medians was 11 percent. In 1994, these differences were both at 17 percent.

Over time, earnings differences between $DQ2$ and $DQ1$ tend to increase uniformly across the different location measures, the differences between $DQ4$ and $DQ2$ appear fairly constant and the differences between $DQ3$ and $DQ2$ tend to decrease. Also there is a slight tendency for differences to be higher at higher quantiles, i.e. not in all cases the between-differences of earnings across skill groups exhibit such a uniformity that one measure (typically the mean differences) is sufficient to describe earnings inequality across skill groups. However, the findings in table 4 are not very clear cut because the numbers prove fairly irregular over time and across the different location measures. One might conclude that the earnings structure across skill groups is fairly constant over time, since any trend is likely to prove insignificant in light of the noise in the data. Such a result corresponds to common findings in the literature based on GSOEP data, cf. OECD (1993, 1996) and Abraham and Houseman (1994).

### Raw Inter-Industry Differences in Earnings

Table 5 provides the raw standard deviations of the mean and various quantiles of earnings across industries. The standard deviation of the mean varies between 12 and 17 percent (in logs). However, we find notable differences across quantiles. The standard deviation tends to be higher at higher quantiles suggesting that inter-industry earnings differences are more pronounced for workers with higher earnings. Also, the standard deviation at the lower quantiles (10%, 30%) are typically lower than at the mean and it is typically higher at the higher quantiles (50%, 70%, 90%). One has to be cautious at this point, since quantiles typically exhibit a higher sampling variability compared to the mean, except for distributions with very fat tails. For the estimated quantile regressions discussed later in this section, we do take account of the sampling variability when calculating the standard deviation of the coefficients on the industry dummies. As it stands, the result suggests that inter-industry differentials in earnings are not uniform across quantiles and restricting oneself to the mean effect might hide an important heterogeneity between workers.

The dynamics of the estimated standard deviations are fairly erratic with an upward tendency both for the mean and the quantiles until 1994. It will be tested within the regression approach later in this section, whether, in fact, there is a significant trend in earnings differences across industries after controlling for various human capital variables. The size of the increase in the raw inter-industry differences over the time span 1984 to 1994 considered appears to be in the order of 2 to 6 percentage points. However, there is a considerable decline in 1994 for all location measures except for the 10%–quantile. The estimated trend from 1984 to 1994 would by no means be negligible.[12]

As for aggregate data, the analysis of raw differences across occupational degrees or industries might be plagued by composition effects, cf. the discussion in section 2. Therefore, we turn now to a regression approach controlling for some observable differences across workers which presumably exhibit an influence on earnings.

### Pooling Across Time: Least Squares and Quantile Regression Estimates, Standard Errors, and Standard Deviation of Inter-Industry Earnings Differences

We estimate the earnings equation specified in the appendix pooling the entire sample from 1984 to 1994. This specifiation allows for the human capital variables occupational degree, experience, and tenure, for the industry dummies, which are normalized such that they represent deviations form the employment weighted mean using aggregate weights, and for year dummies, which represent uniform time effects across workers with different observable characteristics. Quantile Regressions are estimated for the quantiles $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$. Details of the estimation approach are given in section 3 and in the appendix. In following, we first analyze the problem of standard error estimation. Then, we discuss the estimated quantile regressions.

In order to estimate appropriate standard errors for the regression coefficient estimates which are robust against heteroscedasticity and autocorrelation, we used the following two bootstrap procedures as described in section 3.

- **SERR1** (Standard Bootstrap) block consists of single observation (this only yields heteroscedasticity–consistent standard errors)
- **SERR2** block of time series for individual (this considers correlation for a given individual over time)

Whereas SERR1 does not take account of any correlation across observations, SERR2 encompasses the correlation for a given individual over time which can be attributed to unobserved characteristics of the individual worker. Each of our bootstrap estimates are based on 1000 resamples. For the specification pooled over time, the resample size is equal to the sample size. For the period specific (separate) quantile regressions reported later in this section, we take the resample size to be two times as large as the sample sizes because our regressor set contains a large number of dummy variables, cf. section 3.

For the least squares and the median regression ($\theta = 0.5$, LAD), table 6 contains the coefficient estimates and different standard error estimates. The qualitative results for the median discussed in the following are very representative for the other quantiles.[13] Compared to conventional standard error estimates, the standard error

[12] This can be illustrated by the following rough calcuation. If one assumes the log industry differences are normally distributed and one calculates the effect of an increase of the standard deviation from 0.11 to 0.14 (suggested by the figures for the mean and median), this would increase the interquartile difference from about 15% to about 19%.

[13] We obtained results for the other quantiles ($\theta = 0.1, 0.3, 0.7, 0.9$) analogous to table 6. These numbers are available upon request.

estimates for least squares typically increase when switching to the heteroskedasticity consistent estimates SERR1. Both for least squares and median, the estimates increase considerably for all regressor variables except for the year dummies ($D_{1985}, ..., D_{1994}$) when switching from SERR1 to SERR2, i.e. when allowing for autocorrelation of the error term of a worker over time. This is a strong indication of positive autocorrelation over time. The fact, that the standard error estimates for most of the year dummies decrease is perfectly consistent with positive autocorrelation, since the year dummies themselves are negatively correlated over time, cf. the expression for $J_{\theta,N}$ in the asymptotic covariance of the quantile regression estimator presented in section 3. The results suggest the presence of autocorrelation and heteroskedasticity in the error term. The finding of heteroskeasticity is consistent with the differences of certain coefficient estimates across quantiles, which is discussed later in this section. Since there is a need for reliable inference on the industry dummies when calculating the standard deviation of inter–industry earnings differentials, we base most of our analysis on the standard error estimates SERR2.

The estimates of the pooled quantile regressions are presented in table 7. Figures 1 to 4 contrast graphically the estimates for different sets of regressors across quantiles with the least squares estimates. In these graphs, the least squares estimates typically lie in between the respective quantile estimates. The results for the skill dummies indicate that higher occupational degrees induce higher earnings at all quantiles. Also the coefficient estimates change monotonically across quantiles. This is illustrated in figure 2 where the coefficient estimates on $DQ_2$, $DQ_3$, and $DQ_4$ (returns to occupational degree relative to $DQ_1$) are plotted across quantiles. For instance, relative to workers without an occupational degree ($DQ_1$), workers with university type education ($DQ_4$) earn 0.54 more at the 10%–quantile, 0.65 more at the mean, and 0.77 more at the 90%–quantile. Our findings strongly suggest that the within–dispersion (heteroscedasticity) of earnings is positively related to the occupational degree.

Experience exhibits the familiar concave profiles at all quantiles, whereas the tenure effect is almost linear at all quantiles, except for being insignificant at $\theta = 0.9$. In contrast to the skill variables, the estimated returns to experience and tenure in figures 3 and 4, respectively, generally do not imply increasing conditional earnings dispersion at higher levels of experience or tenure. The experience profiles donot appear monotonically related to the quantile considered and the tenure effect becomes smaller at higher quantiles.[14]

Tenure can be seen as a proxy for firm–specific human capital ("learning") as well as for the time the employer has had to screen the employee ("sorting"). The estimation results are consistent with at least three interpretations for the lower quantiles. First, workers with bad unobservable characteristics (at lower quantiles) might acquire more firm specific human capital. Second, it might take them more time to signal their true productivity, and third, they might face a higher risk of losing their job or exhibit a higher incentive to quit. The lack of significance for the tenure effect at $\theta = 0.9$ could imply that high productivity workers are able to show their true productivity from the start of their current job and they are also able to make use of their acquired human capital at other firms. The latter corresponds to the distinctly

[14] The results on experience are somewhat in contrast to Fitzenberger et al. (1995) who estimate age–profiles being positively related to the quantile considered for the time period 1976 to 1984.

higher returns to experience for $\theta = 0.9$. The productivity of these workers does not seem to increase with increasing tenure contradicting the "learning" effect. Thus, also considering the fact that the group of workers with increasing tenure basically consists of a shrinking subset of the same set of workers over time, the results appear more favorable to the "sorting" hypothesis.

The time effects in the estimated pooled quantile regressions prove quite uniform across quantiles, cf. figure 1. This corresponds to wages growing quite uniformly in the entire economy due to the institutional features of wage bargaining in West Germany (pattern bargaining). The coefficient estimates on the year dummies indicate a growth in real earnings of about 12 to 14 percent from 1984 to 1994. The wage hikes in 1991 and 1992 are quite noticeable in the data. Our results correspond to findings (also based on the GSOEP) on within-inequality in Abraham and Houseman (1994) and OECD (1993, 1996), who both notice a great stability of wage dispersion in West Germany across the 1980's. In contrast to these findings, Bellman and Möller (1995) and Möller and Bellmann (1996) found slightly increasing wage dispersion over this period based on German social security data.[15] It remains an open question whether these differences are due to differences in methods or due to the fact that different data sets are used. Obviously, the quality of inference also relies on the appropriateness of standard error estimates, an issue which has so far been neglected in most of the literature.

The estimated coefficients on the industry dummies also differ considerably across quantiles. Test results on the joint significance of industry dummies in the pooled quantile regressions indicate that there exist significant inter-industry differences at all quantiles.[16] However, inter-industry differences are far from being uniform across quantiles. As an extreme case, the (conditional) within-earnings-distribution in industry 14 (Retail trade) is much more dispersed compared to the employment weighted average since the 10%-quantile lies 8.3 percents below the average and the 90%-quantile lies 1.5 percents above the average (however, the latter figure proves insignificant). As an extreme polar case, the distribution in industry 2 (Electricity et al.) is much less dispersed compared to the average with the 10%-quantile at 8.9% above average and the 90%-quantile at 5.3% below average. This adds new evidence to the ongoing debate whether there "exist industries that consistently pay more than others". Table 8 provides the estimated weighted standard deviation of the industry effects at the different quantiles. Both the raw estimates and the estimates corrected for sampling variability indicate an increasing dispersion of industry effects at higher quantiles. Note that a similar effect is already present in the raw differences, see table 5. Accounting for sampling variability reduces the estimated standard deviations considerably, especially when based on the autocorrelation consistent estimates SERR2. The greater reduction for the quantiles at the tails partly reflects the greater sampling

[15] These findings are partly invalidated by a structural break in the social security data used by Bellmann and Möller. Recently, Steiner and Wagner (1996) have pointed out that from 1984 onwards all extra payments by employers to employees had become subject to the social security tax and that this institutional change produces incredible jumps in some measures of earnings inequality.

[16] Based on standard error estimate SERR2, the Wald test statistics ($\chi^2$ with 26 degrees of freedom) are 256.4 for least squares, 152.7 for $\theta = 0.1$, 116.8 for $\theta = 0.3$, 177.9 for $\theta = 0.5$, 262.0 for $\theta = 0.7$, and 229.8 for $\theta = 0.9$, which are all significant at the 1% level. Also for SERR1, the test results prove highly significant.

variability in these parts of the distribution. Comparing the results in table 5 based on raw differences with the results in table 8 shows that human capital variables account for a considerable part of the raw inter–industry earnings differential. Following Burda (1991) and adding more variables proxying unobserved differences in workers into the analysis based on quantile regressions might further reduce the estimated standard deviations of the industry effects. Overall, our findings raise further doubts on uniform inter–industry earnings differences.

### Can Pooling Across Quantiles be Rejected?

Based on the quantile regression estimates, which are based on the pooled sample from 1984 to 1994, table 9 provides the test results on pooling across quantiles. The findings are very clear cut, except for the tenure effect. The quantile regressions differ significantly across quantiles, i.e. pooling the estimation across quantiles is not warranted and the differences discussed above are statistically significant. The results confirm the working hypothesis of this paper that simple least squares regressions do not sufficiently describe the data. However, for SERR2 the time dummies and the tenure coefficients do not seem to differ significantly. The result on the time dummies implies that the dynamics in the data can be described by uniform shifts of the earnings distribution over time conditional on the set of other regressors. The tenure effects in table 9 are obtained both for the linear and the quadratic term. However, the results reported above for SERR2 showed that the coefficient on the linear term is significantly positive for lower quantiles and not significantly different from zero for higher quantiles.

### Dynamics in the Earnings Structure: Can Pooling over time be Rejected?

At last, we investigate whether in fact the pooled estimates described above are rejected by the data, i.e. whether period specific regressions are required. This is equivalent to testing whether earnings differences between skill groups or industries changed over time. We estimate period specific least squares and quantile regressions which correspond to pooled regressions over time where each regressor is interacted with a year dummy. Even though there are only period specific regressors, robust standard error estimates should accomodate autocorrelation in the error term, cf. the definition of $J_{\theta,N}$ in section 3.[17] Thus, we implement SERR2 analogous to the pooled estimation results reported above.

Table 10 provides the results of various Wald tests investigating the dynamic stability of the estimated regression coefficients. The findings can be summarized as follows. Despite a great apparent variability of coefficient estimates over time,[18] the formal test results reported in table 10 support dynamic stability of all regression coefficient estimates.[19] Given the noticeable movement of the period specific industry

[17]This is also true for the least squares case with $sgn_\theta(\epsilon^\theta_{i,t})$ in the formula for $J_{\theta,N}$ being replaced by $\epsilon^\theta_{i,t}$ and $f_{\theta,i,t}$ omitted in the formula for $L_{\theta,N}$, cf. Fitzenberger (1997).

[18]The period specific estimates are available upon request.

[19]For the industry dummies, there are three exceptions, which seems fairly innocuous given that we present a total of 36 test statistics.

effects, the apparent stability of the industry dummy coefficients is somewhat surprising. Overall, our result on the inter–industry effects corresponds to the general findings in Kurz (1995) but is in contrast both to findings in DeNew and Schmidt (1994) and in Möller and Bellmann (1996) for the 1980's. Methodologically, these studies focus on mean effects and rely on conventional inference methods, which tend to underestimate sampling variability in earnings (wage) regressions, see section 2. DeNew and Schmidt find industry effects which are not stable across time, whereas Möller and Bellmann find an ordinal stability of industry effects across time but a significant upward trend in the inter–industry dispersion.

# 6 Conclusions

This paper investigates earnings across occupational degrees, experience, tenure, industries, and time using quantile regression techniques, which allow for a finer picture on the structure of earnings compared to conventional least squares methods. In order to take account of dependencies across observations, the paper uses a flexible block bootstrap approach for inference. In addition, the paper suggests a modified approach to implement the estimation of industry effects on earnings as deviations from an employment weighted mean. When estimating the standard deviation of inter–industry wage differences, the paper notes that the same type of correction of the raw estimate taking account of sampling variability developed initially for least squares regressions applies to quantile regressions as well.

The empirical analysis in this paper is based on data from the German socio–economic Panel for the period from 1984 to 1994. The main results of the paper are as follows. First, the hypothesis of dynamic stability of the quantile regression estimates – apart from allowing for uniform time effects – cannot be rejected. This corresponds to results in the literature based on the same data set indicating that earnings inequality in Germany did not change during the 1980's. This result on the dynamic stability includes the industry effects which is in contrast to previous results in the literature. Second, we find considerable differences of the effects of human capital variables across quantiles. Wage dispersion increases with the formal level of education and decreases with tenure, whereas we do not find a monotonic effect of experience on wage dispersion. For workers with low earnings, tenure exhibits a positive influence on earnings, which is not true for workers with high earnings. And third, concerning inter–industry earnings differentials, we find that the inter–industry earnings structure is not uniform across quantiles and more dispersed at higher quantiles and that human capital variables explain a considerable part of raw inter–industry differences at all quantiles. Our results raise some doubts on the existence of a uniform inter–industry earnings structure, however, in contrast to DeNew and Schmidt (1994), our doubts reflect differences across quantiles rather than an intertemporal instability of the industry dummy estimates.

# A Appendix

**Estimation of linear regressions for wages using normalized weighted industry dummies**

The mean (least squares regression) and various conditional quantiles of log wages are estimated as

$$
\begin{aligned}
q_{\theta,t}(ln(w_{i,t})|x_{i,t},\mu_t^\theta) = x_{i,t}'\mu_t^\theta &= \alpha_{1t}^\theta + \sum_{j=2}^{4} \alpha_{j,t}^\theta \cdot DQ_{j,i,t} + \sum_{k=1}^{3} \beta_{k,t}^\theta \cdot EX_{i,t}^k \\
&\quad + \sum_{l=1}^{2} \gamma_{l,t}^\theta \cdot TEN_{i,t}^l + \sum_{s=1}^{27} \delta_{s,t}^\theta \cdot DS_{s,i,t} \\
\text{subject to} \quad g'\delta_t^\theta &= \sum_{s=1}^{27} g_s \cdot \delta_{s,t}^\theta = 0
\end{aligned}
$$

where expression without $\theta$ denotes least squares linear regression

$\theta$ : quantile considered ($\theta = 0.1, 0.3, 0.5, 0.7, 0.9$) for quantile regression

i : index for individual i

t : index for time period t = 1984, ... , 1994

$w_{i,t}$ : earnings of individual i at time t

$x_{i,t}$ : k $\times$ 1 vector of regressors

$\mu_t^\theta$ : k $\times$ 1 vector of time varying coefficients

$q_t(ln(w_{i,t})|x_{i,t},\mu_t)$ : conditional mean of $ln(w_{i,t})$ given $x_{i,t}$ (least squares regression)

$q_{\theta,t}(ln(w_{i,t})|x_{i,t},\mu_t^\theta)$ : conditional $\theta$–quantile of $ln(w_{i,t})$ given $x_{i,t}$

$DQ_{j,i,t}$ : dummy variables indicating level of formal qualification (schooling, vocational training)

$EX_{i,t}$ : length of potential labor market experience

$TEN_{i,t}$ : length of tenure at current employer

$DS_{s,i,t}$ : industry dummy

$g = (g_i, \ldots, g_{27})'$ : employment weights of 27 industries ($\sum_{s=1}^{27} g_s = 1$)

The vector of regressors is given by

$$
x_{i,t} = (1, DQ_{2,i,t}, DQ_{3,i,t}, DQ_{4,i,t}, EX_{i,t}, EX_{i,t}^2, EX_{i,t}^3, TEN_{i,t}, TEN_{i,t}^2, DS_{1,i,t}, \ldots, DS_{27,i,t}) \ ,
$$

the coefficient vector is given by

$$
\mu_{i,t}^\theta = (\alpha_{1,t}^\theta, \alpha_{2,t}^\theta, \alpha_{3,t}^\theta, \alpha_{4,t}^\theta, \beta_{1,t}^\theta, \beta_{2,t}^\theta, \beta_{3,t}^\theta, \gamma_{1,t}^\theta, \gamma_{2,t}^\theta, \delta_t^\theta) \ ,
$$

and the industry dummy coefficients are given by

$$
\delta_t^\theta = (\delta_{1,t}^\theta, \delta_{2,t}^\theta, \ldots, \delta_{27,t}^\theta) \ .
$$

The linear regressions are estimated subject to the constraint $g'\delta_t^\theta = 0$, i.e. the coefficients on the industry dummies denote deviations from an employment weighted mean.

Estimating linear regressions subject to $g'\delta_t^\theta = 0$

The restriction $g'\delta_t^\theta = 0$ ($g'\delta_t = 0$ for the least squares regression case) can be implemented by redefining the industry dummy variables. Let the industry effect for individual i at time t be

$$IE_{i,t}^\theta = \sum_{s=1}^{27} \delta_{s,t}^\theta DS_{s,i,t},$$

i.e. $IE_{i,t}^\theta$ denotes the deviation of the $\theta$–quantile (the mean) of log wages from the employment weighted mean of the $\theta$–quantile (the mean) across industries.
Choosing a reference industry (without loss of generality, let the reference industry be industry 27 with $g_{27} > 0$), the restriction $g'\delta_t^\theta = 0$ can be written as

(R) $$\delta_{27,t}^\theta = -\sum_{s=1}^{26} \frac{g_s}{g_{27}} \cdot \delta_{s,t}^\theta = -\sum_{s=1}^{26} \tilde{g}_s \cdot \delta_{s,t}^\theta \text{ where } \tilde{g}_s = \frac{g_s}{g_{27}} .$$

Replacing $\delta_{27,t}^\theta$ by the above expression (R), the industry effect becomes

$$\begin{aligned} IE_{i,t}^\theta &= \sum_{s=1}^{26} \delta_{s,t}^\theta \cdot DS_{s,i,t} - \sum_{s=1}^{26} \tilde{g}_s \cdot \delta_{s,t}^\theta \cdot DS_{26,i,t} \\ &= \sum_{s=1}^{26} \delta_{s,t}^\theta \{DS_{s,i,t} - \tilde{g}_s \cdot DS_{27,i,t}\} . \end{aligned}$$

Finally, defining the orthogonalized dummy variables

$$\widetilde{DS}_{s,i,t} = DS_{s,i,t} - \tilde{g}_s \cdot DS_{27,i,t}$$

the industry effect can be rewritten as

(IE) $$IE_{i,t}^\theta = \sum_{s=1}^{26} \delta_{s,t}^\theta \cdot \widetilde{DS}_{s,i,t} .$$

and the 26 orthogonalized industry dummies $\widetilde{DS}_{s,i,t}$ can be used directly in the regression equation to obtain an estimate of $(\delta_{1,t}^\theta, \ldots, \delta_{26,t}^\theta)$. The estimate for the reference industry 27 is obtained using equation (R).
Regressions involving orthogonalized industry dummies provide automatically an estimate of the Variance–Covariance matrix $\tilde{V}$ of all coefficient estimates – including $(\hat{\delta}_{1,t}^\theta, \ldots, \hat{\delta}_{26,t}^\theta)$ – except for $\hat{\delta}_{27,t}^\theta$.
Again using equation (R), one obtains an estimate of the variance of the estimate of $\delta_{27,t}^\theta$ and of all covariances with other coefficient estimates. Define the $k \times (k-1)$ transformation matrix

$$T = \begin{pmatrix} & & & I_{k-1} & & \\ 0 & \cdots & 0 & -\tilde{g}_1 & \cdots & -\tilde{g}_{26} \end{pmatrix} ,$$

let $I_{k-1}$ denote the $(k-1) \times (k-1)$ identity matrix and let $\tilde{V}$ be the $(k-1) \times (k-1)$ "automatic" covariance matrix estimate of all estimated coefficients $(\hat{\alpha}_{1t}^\theta, \ldots, \hat{\delta}_{26}^\theta)$ except $\hat{\delta}_{27,t}^\theta$ when using orthogonalized dummy variables $\widetilde{DS}_{s,i,t}$. Then the complete Variance–Covariance matrix of the entire coefficient vector $(\hat{\alpha}_{1t}^\theta, \ldots, \hat{\delta}_{27}^\theta)$ becomes

(CVE) $$V(\hat{\mu}_t^\theta) = T \cdot \tilde{V} \cdot T'$$

and the covariances for $\hat{\delta}_{27,t}^\theta$ can be found in the last row or the last column of $V(\hat{\mu}_t^\theta)$.

## Estimating the weighted standard deviation of inter-industry wage differences

The literature on inter–industry wage differentials has been very concerned about obtaining an unbiased estimate of the standard deviation of the true inter–industry wage differences. Krueger and Summers (1988) derived an unbiased estimate for least squares regressions based on the raw industry dummies and with one industry omitted. Based on these estimates they calculated the employment weighted (normalized) inter–industry differences but then used the variance estimates based on the original dummy estimates. However, the exact standard errors of the normalized dummy coefficients also involve the covariances and can be calculated by simple matrix operations based on the raw dummy estimates and their covariance estimate. To our knowledge, this was observed independently by Haisken–DeNew and Schmidt (1996) and Möller (1995). These two references consider a two–step procedure where the estimation in the first step is based on raw industry dummy variables. Then, in the second step, the deviations from the weighted mean are calculated based on the first step estimates and the variance–covariance matrix is estimated taking account of the relevant covariances. For the least squares estimation problem, Haisken–DeNew and Schmidt (1996) provide a characterization as a Restricted Least Squares problem. They show for concrete estimation problems that the Krueger and Summers (1988) approach, which disregards the normalization of the dummy coefficients, leads to a substantial overstatement of the standard errors of the coefficient estimates and, thus, to a downward bias in the estimate of their true variability.

Both for the linear least squares and quantile regressions, the two–step procedure can be circumvented by using the direct approach described above based on orthogonalized dummies. Building on the previous literature for least squares, we derive in the following a simple asymptotic estimate for the weighted standard deviation of the true inter–industry differences in the $\theta$–quantile of log wages. The procedure is based on the covariance estimate (CVE) developed above.

Take the raw employment weighted variance of the dummy coefficient estimates given by

$$s^2(\hat{\delta}^\theta_{s,t}) = \sum_{s=1}^{27} g_s \cdot (\hat{\delta}^\theta_{s,t})^2$$

since $\sum_{s=1}^{27} g_s \hat{\delta}^\theta_{s,t} = 0$ by construction. The expected value of $s^2(\hat{\delta}^\theta_{s,t})$ equals

$$Es^2(\hat{\delta}^\theta_{s,t}) = \sum_{s=1}^{27} g_s \cdot E(\hat{\delta}^\theta_{s,t})^2 = \sum_{s=1}^{27} g_s \cdot [Var(\hat{\delta}^\theta_{s,t}) + (E\hat{\delta}^\theta_{s,t})^2] \, .$$

Since $\hat{\delta}^\theta_{s,t}$ converges to $\delta^\theta_{s,t}$ for the sample size going to infinity, the expected value $E\hat{\delta}^\theta_{s,t}$ is asymptotically equal to the true $\delta_{s,t}$, i.e.,

$$\sum_{s=1}^{27} g_s \cdot (E\hat{\delta}^\theta_{s,t})^2$$

corresponds asymptotically to the employment weighted variance of the true inter–industry wage difference. An asymptotically unbiased estimate is given by

$$\hat{S}^2(\delta^\theta_{s,t}) = s^2(\hat{\delta}^\theta_{s,t}) - \sum_{s=1}^{27} g_s \cdot \widehat{Var}(\hat{\delta}^\theta_{s,t})$$

where $\widehat{Var}(\delta^\theta_{s,t})$, s=1, ..., 27, are the diagonal elements of the covariance matrix $V(\hat{\mu}^\theta_t)$ in expression (CVE) corresponding to $\hat{\delta}^\theta_{s,t}$, s=1, ..., 27.

Table 3: Industry Classification, Employment Weights, and Sample Frequencies[a]

| No. | Industry | Employment Weights in % | Sample Fre–quencies in % |
|---|---|---|---|
| 01 | Agriculture, forestry and fishing | 1.2 | 0.7 |
| 02 | Electricity, gas, steam and water supply, mining | 3.1 | 2.7 |
| 03 | Chemical industry and mineral oil refining | 3.5 | 5.4 |
| 04 | Rubber and plastic products | 1.7 | 1.5 |
| 05 | Stones and clays, ceramic and glass products | 2.0 | 1.7 |
| 06 | Machinery and equipment | 16.7 | 12.3 |
| 07 | Electrical engineering; precision and optical instruments; toys, games and jewellery | 8.6 | 7.4 |
| 08 | Wood and paper products; printing and duplicating | 4.6 | 3.8 |
| 09 | Leather goods; textile and clothing industries | 1.5 | 1.9 |
| 10 | Food, beverage and tobacco industries | 3.1 | 3.7 |
| 11 | Construction | 7.4 | 7.1 |
| 12 | Installation and building completion work | 3.1 | 3.0 |
| 13 | Wholesale and commission trade | 6.1 | 3.0 |
| 14 | Retail trade | 4.5 | 3.9 |
| 15 | Railroad transport (Deutsche Bundesbahn) | 0.9 | 1.2 |
| 16 | Communication (Deutsche Bundespost) | 0.8 | 0.8 |
| 17 | Other transport | 4.4 | 4.1 |
| 18 | Credit institutions | 2.2 | 2.8 |
| 19 | Insurance enterprises | 1.1 | 1.2 |
| 20 | Hotels and restaurants, homes and hostels | 2.0 | 0.5 |
| 21 | Other service enterprises | 5.6 | 2.1 |
| 22 | Education, science, culture services and publishing | 2.7 | 6.0 |
| 23 | Medical care and health services; veterinary services | 1.9 | 1.7 |
| 24 | Households and private non-profit institutions; other branches not fitting into this scheme | 1.3 | 1.9 |
| 25 | Central and local government | 5.2 | 8.7 |
| 26 | Social security funds | 0.5 | 0.9 |
| 27 | Iron and steel industry[b] | 4.2 | 10.0 |

a: The Employment Weights are the aggregate numbers from the employment statistics of the German Statistical Office ("Statistisches Bundesamt"). These figures correspond to the male full time employees in West Germany grouped by industries. The Sample Frequencies are based on the GSOEP according to table 1.

b: Sector 27 "Iron and steel industry" represents the reference industry in the estimations, see the details of estimation in section 3 and earlier in this appendix.

Table 4: Differences in Mean and various Quantiles (Q.) of Log Real Monthly Earnings across Skill Groups based on GSOEP sample[o]

| | Differences of the Location Measure across Skill Groups | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $DQ2^b$ relative to $DQ1^a$ | | | | $DQ3^c$ relative to $DQ2^b$ | | | |
| YEAR | Mean | 30%–Q. | 50%–Q. | 70%–Q. | Mean | 30%–Q. | 50%–Q. | 70%–Q. |
| 1984 | 0.12 | 0.10 | 0.11 | 0.09 | 0.16 | 0.12 | 0.14 | 0.16 |
| 1985 | 0.14 | 0.12 | 0.14 | 0.19 | 0.17 | 0.17 | 0.15 | 0.17 |
| 1986 | 0.15 | 0.09 | 0.10 | 0.12 | 0.18 | 0.16 | 0.15 | 0.21 |
| 1987 | 0.11 | 0.11 | 0.07 | 0.10 | 0.18 | 0.16 | 0.16 | 0.21 |
| 1988 | 0.12 | 0.10 | 0.10 | 0.11 | 0.16 | 0.11 | 0.17 | 0.19 |
| 1989 | 0.12 | 0.11 | 0.16 | 0.11 | 0.14 | 0.12 | 0.15 | 0.18 |
| 1990 | 0.15 | 0.12 | 0.12 | 0.18 | 0.11 | 0.09 | 0.11 | 0.14 |
| 1991 | 0.14 | 0.10 | 0.10 | 0.16 | 0.11 | 0.08 | 0.11 | 0.11 |
| 1992 | 0.17 | 0.14 | 0.15 | 0.19 | 0.12 | 0.11 | 0.10 | 0.08 |
| 1993 | 0.15 | 0.17 | 0.15 | 0.15 | 0.14 | 0.13 | 0.15 | 0.10 |
| 1994 | 0.17 | 0.15 | 0.17 | 0.19 | 0.13 | 0.12 | 0.11 | 0.13 |

| | $DQ4^d$ relative to $DQ2^b$ | | | |
|---|---|---|---|---|
| YEAR | Mean | 30%–Q. | 50%–Q. | 70%–Q. |
| 1984 | 0.41 | 0.41 | 0.47 | 0.46 |
| 1985 | 0.46 | 0.43 | 0.51 | 0.49 |
| 1986 | 0.46 | 0.45 | 0.49 | 0.54 |
| 1987 | 0.48 | 0.44 | 0.52 | 0.54 |
| 1988 | 0.49 | 0.47 | 0.55 | 0.54 |
| 1989 | 0.50 | 0.48 | 0.53 | 0.56 |
| 1990 | 0.45 | 0.47 | 0.51 | 0.50 |
| 1991 | 0.45 | 0.46 | 0.47 | 0.45 |
| 1992 | 0.49 | 0.48 | 0.48 | 0.48 |
| 1993 | 0.47 | 0.45 | 0.49 | 0.47 |
| 1994 | 0.46 | 0.44 | 0.47 | 0.49 |

o: The numbers reported in this table are the result of the following two steps. First, we calculate the average and the quantiles for all observations in each skill group and year. And second, we take the difference of the averages and quantiles across skill groups, respectively. Our calculations are based on the sample reported in table 1.

a: No occupational degree

b: Apprenticeship

c: Vocational/Secondary School Certificate

d: College/University

Table 5: Standard deviation of the Mean and various Quantiles (Q.) of Log Real Monthly Earnings across Industries based on GSOEP sample[a]

| YEAR | Standard Deviation of the Location Measure across Industries | | | | | |
|---|---|---|---|---|---|---|
| | Mean | 10%–Q. | 30%–Q. | 50%–Q. | 70%–Q. | 90%–Q. |
| 1984 | 0.107 | 0.091 | 0.101 | 0.114 | 0.146 | 0.159 |
| 1985 | 0.125 | 0.119 | 0.115 | 0.130 | 0.172 | 0.193 |
| 1986 | 0.133 | 0.097 | 0.125 | 0.128 | 0.179 | 0.208 |
| 1987 | 0.133 | 0.156 | 0.126 | 0.117 | 0.169 | 0.188 |
| 1988 | 0.110 | 0.089 | 0.107 | 0.114 | 0.157 | 0.196 |
| 1989 | 0.105 | 0.097 | 0.102 | 0.115 | 0.127 | 0.192 |
| 1990 | 0.115 | 0.121 | 0.114 | 0.126 | 0.141 | 0.167 |
| 1991 | 0.126 | 0.140 | 0.117 | 0.149 | 0.159 | 0.186 |
| 1992 | 0.122 | 0.120 | 0.129 | 0.132 | 0.141 | 0.181 |
| 1993 | 0.138 | 0.126 | 0.123 | 0.143 | 0.169 | 0.226 |
| 1994 | 0.116 | 0.152 | 0.117 | 0.125 | 0.147 | 0.205 |
| Total | 0.135 | 0.137 | 0.129 | 0.139 | 0.166 | 0.199 |

a: The numbers reported in this table are the result of the following two steps. First, we calculate the average and the quantiles for all observations in each industries. And second, we calculate the employment–weighted standard deviation of those industry averages and industry quantiles, respectively. Our calculations are based on the sample reported in table 1 using aggregate employment weights, cf. table 3. The numbers are not corrected for sampling error.

## Estimates for the Pooled Least Squares and Quantile Regressions for Log Real Monthly Earnings

Table 6: Estimates for the Pooled Least Squares and Median Regression and different Standard Error Estimates

| | Least Squares estimates | | | | Median estimates | | |
|---|---|---|---|---|---|---|---|
| Regressor | Coefficient Estimates | Standard Errors I.I.D.[a] | SERR1[b] | SERR2[b] | Coefficient Estimates | Standard Errors[a] SERR1[b] | SERR2[b] |
| $Intercept$ | 7.215 | 0.036 | 0.053 | 0.075 | 7.257 | 0.055 | 0.084 |
| $DQ_{2,i,t}$ | 0.141 | 0.009 | 0.008 | 0.019 | 0.130 | 0.009 | 0.019 |
| $DQ_{3,i,t}$ | 0.285 | 0.010 | 0.010 | 0.023 | 0.272 | 0.011 | 0.023 |
| $DQ_{4,i,t}$ | 0.671 | 0.012 | 0.011 | 0.028 | 0.680 | 0.011 | 0.027 |
| $EX_{i,t}$ [c] | 0.654 | 0.050 | 0.072 | 0.104 | 0.609 | 0.080 | 0.119 |
| $EX^2_{i,t}$ [c] | -0.187 | 0.022 | 0.031 | 0.045 | -0.177 | 0.034 | 0.050 |
| $EX^3_{i,t}$ [c] | 0.016 | 0.003 | 0.004 | 0.006 | 0.015 | 0.005 | 0.007 |
| $TEN_{i,t}$ [c] | 0.037 | 0.010 | 0.010 | 0.022 | 0.041 | 0.011 | 0.022 |
| $TEN^2_{i,t}$ [c] | -0.002 | 0.003 | 0.003 | 0.006 | -0.003 | 0.004 | 0.007 |
| $D_{1985}$ | 0.002 | 0.010 | 0.011 | 0.006 | -0.009 | 0.011 | 0.008 |
| $D_{1986}$ | 0.030 | 0.010 | 0.011 | 0.007 | 0.023 | 0.011 | 0.009 |
| $D_{1987}$ | 0.056 | 0.010 | 0.012 | 0.007 | 0.056 | 0.012 | 0.009 |
| $D_{1988}$ | 0.080 | 0.011 | 0.011 | 0.008 | 0.074 | 0.011 | 0.010 |
| $D_{1989}$ | 0.081 | 0.011 | 0.011 | 0.009 | 0.060 | 0.011 | 0.010 |
| $D_{1990}$ | 0.094 | 0.011 | 0.011 | 0.009 | 0.083 | 0.013 | 0.011 |
| $D_{1991}$ | 0.108 | 0.011 | 0.012 | 0.010 | 0.092 | 0.013 | 0.012 |
| $D_{1992}$ | 0.124 | 0.012 | 0.012 | 0.010 | 0.109 | 0.012 | 0.012 |
| $D_{1993}$ | 0.135 | 0.012 | 0.013 | 0.011 | 0.128 | 0.014 | 0.013 |
| $D_{1994}$ | 0.125 | 0.013 | 0.013 | 0.012 | 0.122 | 0.015 | 0.014 |
| $DS_{1,i,t}$ | -0.133 | 0.030 | 0.031 | 0.053 | -0.179 | 0.034 | 0.077 |
| $DS_{2,i,t}$ | 0.037 | 0.015 | 0.011 | 0.026 | 0.072 | 0.016 | 0.039 |
| $DS_{3,i,t}$ | 0.097 | 0.011 | 0.012 | 0.022 | 0.116 | 0.013 | 0.022 |
| $DS_{4,i,t}$ | -0.015 | 0.020 | 0.024 | 0.052 | -0.032 | 0.026 | 0.054 |
| $DS_{5,i,t}$ | 0.001 | 0.019 | 0.019 | 0.052 | 0.004 | 0.021 | 0.049 |
| $DS_{6,i,t}$ | 0.050 | 0.006 | 0.007 | 0.015 | 0.051 | 0.009 | 0.018 |
| $DS_{7,i,t}$ | 0.083 | 0.009 | 0.010 | 0.023 | 0.075 | 0.012 | 0.025 |
| $DS_{8,i,t}$ | -0.002 | 0.013 | 0.014 | 0.031 | -0.005 | 0.014 | 0.025 |
| $DS_{9,i,t}$ | -0.037 | 0.018 | 0.021 | 0.044 | -0.055 | 0.028 | 0.050 |
| $DS_{10,i,t}$ | -0.036 | 0.013 | 0.013 | 0.033 | -0.038 | 0.018 | 0.035 |
| $DS_{11,i,t}$ | -0.039 | 0.009 | 0.009 | 0.022 | -0.027 | 0.009 | 0.022 |
| $DS_{12,i,t}$ | -0.101 | 0.014 | 0.015 | 0.035 | -0.127 | 0.015 | 0.026 |
| $DS_{13,i,t}$ | -0.044 | 0.014 | 0.014 | 0.025 | -0.054 | 0.015 | 0.026 |
| $DS_{14,i,t}$ | -0.046 | 0.012 | 0.017 | 0.028 | -0.042 | 0.016 | 0.027 |

Table 6: Estimates of Pooled Least Squares and Median Regression and different Standard Error Estimates <continued>

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| $DS_{15,i,t}$ | -0.173 | 0.023 | 0.015 | 0.041 | -0.116 | 0.016 | 0.042 |
| $DS_{16,i,t}$ | -0.259 | 0.027 | 0.022 | 0.043 | -0.225 | 0.026 | 0.048 |
| $DS_{17,i,t}$ | 0.043 | 0.012 | 0.012 | 0.030 | 0.036 | 0.013 | 0.033 |
| $DS_{18,i,t}$ | 0.125 | 0.015 | 0.012 | 0.028 | 0.154 | 0.016 | 0.041 |
| $DS_{19,i,t}$ | 0.157 | 0.023 | 0.023 | 0.047 | 0.162 | 0.021 | 0.069 |
| $DS_{20,i,t}$ | -0.122 | 0.037 | 0.055 | 0.096 | -0.159 | 0.077 | 0.117 |
| $DS_{21,i,t}$ | 0.094 | 0.017 | 0.020 | 0.046 | 0.076 | 0.024 | 0.058 |
| $DS_{22,i,t}$ | -0.043 | 0.011 | 0.012 | 0.028 | -0.063 | 0.010 | 0.023 |
| $DS_{23,i,t}$ | -0.083 | 0.019 | 0.017 | 0.027 | -0.076 | 0.014 | 0.026 |
| $DS_{24,i,t}$ | -0.120 | 0.018 | 0.015 | 0.037 | -0.098 | 0.024 | 0.050 |
| $DS_{25,i,t}$ | -0.114 | 0.009 | 0.007 | 0.015 | -0.092 | 0.008 | 0.018 |
| $DS_{26,i,t}$ | 0.029 | 0.026 | 0.028 | 0.077 | 0.033 | 0.020 | 0.075 |

a: The Standard Error estimates I.I.D. represent the conventional estimates for least squares regressions ($s^2\ X'X^{-1}$).

b: The Standard Error estimates SERR1 and SERR2 are based on two different bootstrap estimation approaches which are described in section 5.

c: The variables experience and tenure are divided by 10.

Table 7: Pooled Quantile Regressions – Coefficient Estimates and t–statistics[a] for $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$ including the omitted industry 27

| | $\theta = 0.1$ | | $\theta = 0.3$ | | $\theta = 0.5$ | | $\theta = 0.7$ | | $\theta = 0.9$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| Regressor | Coeff. | (t-st) | Coeff. | (t-st) | Coeff. | (t-st) | Coeff. | (t-st) | Coeff. | (t-st) |
| *Intercept* | 6.982 | ( 62.7) | 7.184 | ( 89.9) | 7.257 | (86.3) | 7.438 | (100.6) | 7.525 | (67.7) |
| $DQ_{2,i,t}$ | 0.103 | ( 3.9) | 0.111 | ( 5.9) | 0.130 | ( 6.7) | 0.157 | ( 6.2) | 0.173 | ( 5.4) |
| $DQ_{3,i,t}$ | 0.209 | ( 7.1) | 0.235 | ( 10.7) | 0.272 | (11.6) | 0.313 | ( 10.8) | 0.352 | ( 8.1) |
| $DQ_{4,i,t}$ | 0.527 | ( 12.2) | 0.625 | ( 19.6) | 0.680 | (25.6) | 0.697 | ( 22.4) | 0.765 | (18.4) |
| $EX_{i,t}$ [b] | 0.684 | ( 4.8) | 0.561 | ( 5.0) | 0.609 | ( 5.1) | 0.480 | ( 4.6) | 0.597 | ( 3.7) |
| $EX^2_{i,t}$ [b] | -0.229 | ( 3.8) | -0.158 | ( 3.2) | -0.177 | ( 3.5) | -0.117 | ( 2.5) | -0.139 | ( 1.9) |
| $EX^3_{i,t}$ [b] | 0.024 | ( 3.0) | 0.013 | ( 1.9) | 0.015 | ( 2.3) | 0.007 | ( 1.1) | 0.008 | ( 0.8) |
| $TEN_{i,t}$ [b] | 0.069 | ( 3.1) | 0.053 | ( 2.6) | 0.041 | ( 1.9) | 0.038 | ( 1.5) | -0.019 | ( 0.5) |
| $TEN^2_{i,t}$ [b] | -0.007 | ( 1.2) | -0.004 | ( 0.7) | -0.003 | ( 0.5) | -0.005 | ( 0.6) | 0.009 | ( 0.8) |
| $D_{1985}$ | -0.003 | ( 0.3) | 0.007 | ( 0.9) | -0.009 | ( 1.1) | 0.014 | ( 1.6) | -0.001 | ( 0.1) |
| $D_{1986}$ | 0.023 | ( 1.9) | 0.022 | ( 2.5) | 0.023 | ( 2.6) | 0.038 | ( 4.1) | 0.032 | ( 2.2) |
| $D_{1987}$ | 0.060 | ( 4.5) | 0.060 | ( 6.7) | 0.056 | ( 5.9) | 0.057 | ( 5.8) | 0.050 | ( 3.3) |
| $D_{1988}$ | 0.083 | ( 6.7) | 0.074 | ( 7.7) | 0.074 | ( 7.2) | 0.092 | ( 8.7) | 0.083 | ( 5.0) |
| $D_{1989}$ | 0.087 | ( 6.1) | 0.081 | ( 7.4) | 0.060 | ( 5.8) | 0.075 | ( 6.8) | 0.089 | ( 5.1) |
| $D_{1990}$ | 0.087 | ( 6.0) | 0.086 | ( 8.2) | 0.083 | ( 7.5) | 0.096 | ( 7.7) | 0.090 | ( 5.2) |

Table 7: Estimates[a] for the Pooled Quantile Regressions for $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$ including the omitted industry 27 <continued>

| | | | | | |
|---|---|---|---|---|---|
| $D_{1991}$ | 0.110 ( 7.6) | 0.091 ( 8.0) | 0.092 ( 7.4) | 0.119 ( 8.7) | 0.096 ( 5.2) |
| $D_{1992}$ | 0.135 ( 8.4) | 0.127 ( 10.8) | 0.109 ( 8.8) | 0.123 ( 8.6) | 0.100 ( 4.9) |
| $D_{1993}$ | 0.123 ( 7.3) | 0.124 ( 9.4) | 0.128 (10.1) | 0.148 ( 9.1) | 0.125 ( 5.9) |
| $D_{1994}$ | 0.132 ( 7.5) | 0.119 ( 8.9) | 0.122 ( 8.7) | 0.131 ( 7.9) | 0.117 ( 5.4) |
| $DS_{1,i,t}$ | -0.123 ( 1.7) | -0.146 ( 2.6) | -0.179 ( 2.3) | -0.107 ( 1.2) | -0.110 ( 1.4) |
| $DS_{2,i,t}$ | 0.089 ( 3.9) | 0.050 ( 1.2) | 0.072 ( 1.9) | 0.046 ( 1.8) | -0.053 ( 1.6) |
| $DS_{3,i,t}$ | 0.039 ( 1.0) | 0.108 ( 3.3) | 0.116 ( 5.3) | 0.099 ( 4.5) | 0.087 ( 2.3) |
| $DS_{4,i,t}$ | -0.073 ( 0.8) | -0.051 ( 1.0) | -0.032 ( 0.6) | 0.037 ( 0.5) | 0.078 ( 1.1) |
| $DS_{5,i,t}$ | -0.042 ( 0.6) | 0.011 ( 0.3) | 0.004 ( 0.1) | -0.002 ( 0.0) | 0.033 ( 0.3) |
| $DS_{6,i,t}$ | 0.040 ( 2.9) | 0.038 ( 2.6) | 0.051 ( 2.8) | 0.056 ( 2.9) | 0.047 ( 1.6) |
| $DS_{7,i,t}$ | 0.046 ( 1.9) | 0.064 ( 3.0) | 0.075 ( 3.0) | 0.087 ( 2.5) | 0.149 ( 3.4) |
| $DS_{8,i,t}$ | -0.044 ( 1.4) | -0.001 ( 0.0) | -0.005 ( 0.2) | -0.015 ( 0.4) | 0.011 ( 0.2) |
| $DS_{9,i,t}$ | -0.093 ( 2.6) | -0.058 ( 0.9) | -0.055 ( 1.1) | -0.030 ( 0.6) | -0.033 ( 0.5) |
| $DS_{10,i,t}$ | -0.034 ( 0.6) | -0.048 ( 1.5) | -0.038 ( 1.1) | -0.052 ( 1.1) | 0.022 ( 0.3) |
| $DS_{11,i,t}$ | -0.046 ( 2.0) | -0.015 ( 0.8) | -0.027 ( 1.2) | -0.026 ( 0.9) | -0.017 ( 0.4) |
| $DS_{12,i,t}$ | -0.081 ( 2.8) | -0.089 ( 4.1) | -0.127 ( 4.9) | -0.153 ( 2.9) | -0.109 ( 0.9) |
| $DS_{13,i,t}$ | -0.017 ( 0.7) | -0.046 ( 2.0) | -0.054 ( 2.1) | -0.078 ( 2.1) | -0.038 ( 0.7) |
| $DS_{14,i,t}$ | -0.083 ( 2.5) | -0.074 ( 2.3) | -0.042 ( 1.5) | -0.026 ( 0.5) | 0.015 ( 0.3) |
| $DS_{15,i,t}$ | -0.110 ( 2.0) | -0.116 ( 1.7) | -0.116 ( 2.8) | -0.179 ( 4.2) | -0.259 ( 5.3) |
| $DS_{16,i,t}$ | -0.144 ( 1.6) | -0.206 ( 3.8) | -0.225 ( 4.7) | -0.256 ( 5.8) | -0.340 ( 7.8) |
| $DS_{17,i,t}$ | 0.017 ( 0.6) | 0.035 ( 1.1) | 0.036 ( 1.1) | 0.051 ( 1.3) | 0.032 ( 0.5) |
| $DS_{18,i,t}$ | 0.166 ( 7.3) | 0.144 ( 3.5) | 0.154 ( 3.7) | 0.125 ( 4.5) | 0.033 ( 1.1) |
| $DS_{19,i,t}$ | 0.173 ( 3.9) | 0.164 ( 2.4) | 0.162 ( 2.3) | 0.192 ( 2.9) | 0.096 ( 2.5) |
| $DS_{20,i,t}$ | -0.172 ( 1.3) | -0.115 ( 1.7) | -0.159 ( 1.4) | -0.060 ( 0.4) | -0.117 ( 0.5) |
| $DS_{21,i,t}$ | 0.069 ( 1.9) | 0.034 ( 0.9) | 0.076 ( 1.3) | 0.125 ( 2.5) | 0.128 ( 0.8) |
| $DS_{22,i,t}$ | 0.051 ( 1.4) | -0.006 ( 0.2) | -0.063 ( 2.8) | -0.108 ( 3.8) | -0.069 ( 1.3) |
| $DS_{23,i,t}$ | 0.026 ( 0.7) | -0.035 ( 1.8) | -0.076 ( 2.9) | -0.132 ( 4.4) | -0.192 ( 3.6) |
| $DS_{24,i,t}$ | -0.051 ( 0.9) | -0.076 ( 1.7) | -0.098 ( 1.9) | -0.134 ( 3.7) | -0.200 ( 4.2) |
| $DS_{25,i,t}$ | -0.027 ( 1.6) | -0.065 ( 4.3) | -0.092 ( 5.0) | -0.125 ( 7.2) | -0.226 ( 7.9) |
| $DS_{26,i,t}$ | -0.010 ( 0.1) | 0.020 ( 0.2) | 0.033 ( 0.4) | 0.057 ( 0.5) | 0.165 ( 1.3) |
| $DS_{27,i,t}$ | -0.037 ( 1.8) | -0.017 ( 1.1) | -0.023 ( 1.3) | -0.035 ( 1.7) | -0.036 ( 0.9) |

a: The t–statistics (t-st) in parentheses are based on the Standard Error estimate SERR2 which is described in section 5.

b: The variables experience and tenure are divided by 10.

Table 8: Estimated Weighted Standard Deviation of Coefficients on Industry Dummies based on the pooled Regression Estimates[a]

| | LS[b] | $\theta = 0.1$ | $\theta = 0.3$ | $\theta = 0.5$ | $\theta = 0.7$ | $\theta = 0.9$ |
|---|---|---|---|---|---|---|
| | Raw Estimates without Correction for Sampling Variance | | | | | |
| $s^2(\hat{\delta}^\theta_{s,t})$ | .0753 | .0652 | .0639 | .0768 | .0861 | .1025 |
| | Estimates involving Correction for Sampling Variance | | | | | |
| | based on Standard Error Estimate SERR1 | | | | | |
| $\hat{S}^2(\delta^\theta_{s,t})$ | .0734 | .0590 | .0619 | .0746 | .0838 | .0957 |
| | based on Standard Error Estimate SERR2 | | | | | |
| $\hat{S}^2(\delta^\theta_{s,t})$ | .0681 | .0521 | .0551 | .0676 | .0742 | .0716 |

a: For details of estimating the weighted standard deviation of inter-industry wage differences, see the first part of this appendix.

b: Least squares estimates.

Table 9: Wald $\chi^2$–Test Results on Stability of Coefficient Estimates across Quantiles[a] for Specification, which is pooled across Years

| Wald Test on stability of regression coefficients across quantiles $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$ based on different Standard Error Estimates SERR1 and SERR2 | | | | | |
|---|---|---|---|---|---|
| | | SERR1 | | SERR2 | |
| | Dof | $\chi^2$ | PV | $\chi^2$ | PV |
| Intercept | 4 | 39.1 | .000 | 19.2 | .000 |
| $DQ_{j,i,t}$ | 12 | 132.2 | .000 | 37.3 | .000 |
| $EX_{i,t}$ | 12 | 62.0 | .000 | 21.6 | .042 |
| $TEN_{i,t}$ | 8 | 46.2 | .000 | 9.3 | .314 |
| $D_t$ t=1985,...,1994 | 40 | 74.8 | .001 | 46.7 | .217 |
| $DS_{s,i,t}$ | 104 | 7155.8 | .000 | 207.4 | .000 |

a: $\chi^2$ denotes the value of the Wald test–statistic, Dof the corresponding degrees of freedom, and PV the corresponding probability value. For the hypothesis of stability of regression coefficients across quantiles, it is tested jointly whether the coefficients of different sets of regressors (the set of schooling dummies, the set of industry dummies, all powers of experience, all powers of tenure) are in fact constant across the quantiles considered using a Wald test on the quantile specific estimates.

## Pooling Tests

Table 10: $\chi^2$–Test Results on Period Specific Regressions[a]

| Wald Test on dynamic stability of coefficients on entire sets of regressors | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| based on Standard Error Estimate SERR1 | | | | | | | | | | | | | |
| | | LS[b] | | $\theta = 0.1$ | | $\theta = 0.3$ | | $\theta = 0.5$ | | $\theta = 0.7$ | | $\theta = 0.9$ | |
| | Dof | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV |
| $DQ_{j,i,t}$ | 30 | 4.1 | 1.00 | 19.3 | .933 | 21.8 | .861 | 18.9 | .942 | 19.1 | .937 | 21.7 | .864 |
| $EX_{i,t}$ | 30 | 10.7 | .999 | 27.8 | .581 | 26.0 | .675 | 41.5 | .078 | 28.7 | .533 | 24.3 | .758 |
| $TEN_{i,t}$ | 20 | 9.5 | .976 | 15.5 | .747 | 10.6 | .955 | 24.7 | .213 | 12.6 | .893 | 11.7 | .926 |
| $DS_{s,i,t}$ [c] | | | | | | | | | | | | | |
| 1984–1986 | 52 | 27.1 | .998 | 29.6 | .994 | 29.2 | .995 | 26.2 | .998 | 19.5 | .999 | 19.4 | .999 |
| 1986–1988 | 52 | 28.5 | .996 | 22.8 | .999 | 18.8 | .999 | 22.4 | .999 | 15.2 | 1.00 | 17.9 | 1.00 |
| 1988–1990 | 52 | 9.3 | 1.00 | 36.0 | .955 | 19.7 | .999 | 18.2 | 1.00 | 23.6 | .999 | 22.2 | .999 |
| 1990–1992 | 52 | 8.0 | 1.00 | 40.7 | .871 | 19.2 | .999 | 19.6 | .999 | 25.5 | .999 | 23.1 | .999 |
| 1992–1994 | 52 | 12.5 | 1.00 | 49.4 | .576 | 28.0 | .997 | 20.6 | .999 | 33.5 | .978 | 34.1 | .973 |
| 1984/1989/1994 | 52 | 26.2 | .998 | 58.8 | .240 | 34.1 | .973 | 41.4 | .853 | 45.4 | .729 | 88.0 | .001 |
| based on Standard Error Estimate SERR2 | | | | | | | | | | | | | |
| | | LS[b] | | $\theta = 0.1$ | | $\theta = 0.3$ | | $\theta = 0.5$ | | $\theta = 0.7$ | | $\theta = 0.9$ | |
| | Dof | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV | $\chi^2$ | PV |
| $DQ_{j,i,t}$ | 30 | 6.4 | 1.00 | 24.8 | .734 | 32.0 | .367 | 27.2 | .612 | 32.0 | .367 | 32.6 | .340 |
| $EX_{i,t}$ | 30 | 15.7 | .985 | 35.0 | .242 | 28.4 | .549 | 37.5 | .163 | 30.3 | .450 | 28.3 | .554 |
| $TEN_{i,t}$ | 20 | 13.9 | .835 | 20.8 | .408 | 13.4 | .859 | 26.7 | .143 | 16.7 | .672 | 15.5 | .747 |
| $DS_{s,i,t}$ [c] | | | | | | | | | | | | | |
| 1984–1986 | 52 | 84.5 | .002 | 49.7 | .564 | 41.7 | .845 | 39.3 | .902 | 37.2 | .939 | 36.2 | .952 |
| 1986–1988 | 52 | 69.7 | .051 | 40.0 | .887 | 32.5 | .984 | 44.2 | .770 | 27.8 | .997 | 31.7 | .988 |
| 1988–1990 | 52 | 16.0 | 1.00 | 41.8 | .843 | 28.1 | .997 | 33.9 | .975 | 30.9 | .991 | 50.5 | .533 |
| 1990–1992 | 52 | 10.4 | 1.00 | 66.7 | .082 | 37.4 | .936 | 37.4 | .936 | 43.2 | .802 | 42.2 | .832 |
| 1992–1994 | 52 | 12.9 | 1.00 | 58.6 | .246 | 38.9 | .910 | 39.4 | .900 | 56.6 | .307 | 70.1 | .047 |
| 1984/1989/1994 | 52 | 12.7 | 1.00 | 91.0 | .000 | 38.6 | .916 | 60.2 | .203 | 58.4 | .251 | 99.8 | .000 |

a: $\chi^2$ denotes the value of the Wald test–statistic, Dof the corresponding degrees of freedom, and PV the corresponding probability value. For the hypothesis of dynamic stability of regression coefficients, it is tested jointly whether the coefficients of different sets of regressors (the set of schooling dummies, the set of industry dummies, all powers of experience, all powers of tenure) are in fact constant over time using a Wald test on the period specific estimates.

b: Least squares estimates.

c: The Wald test statistic for the entire set of industry dummies over time could not be calculated for numerical reasons since it involves the inversion of a $260 \times 260$ matrix. Therefore, we tested sequentially whether the coefficients differed significantly between three adjacent years and between the years 1984, 1989, and 1994. For the first case, the different three years intervals are overlapping, such that sequential non–rejection in all cases would "imply" non–rejection for the entire time period 1984 to 1994.

## Graphical Illustrations of Estimated Pooled Regressions for Log Monthly Earnings

Figure 1: Estimated Intercepts for Least Squares and $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$

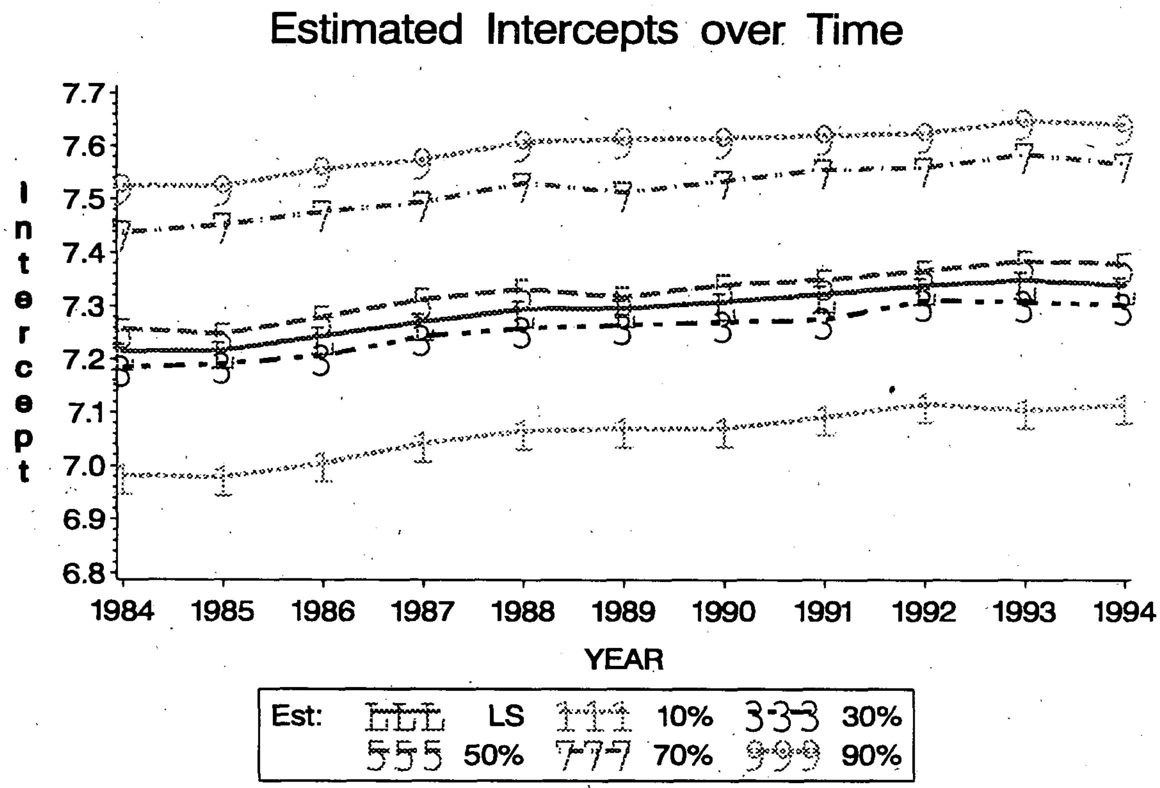



Figure 2: Estimated Returns to Schooling (Coefficients on $DQ_j$) relative to $DQ_1$ for Least Squares and $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$ and $j = 1, ., 4$

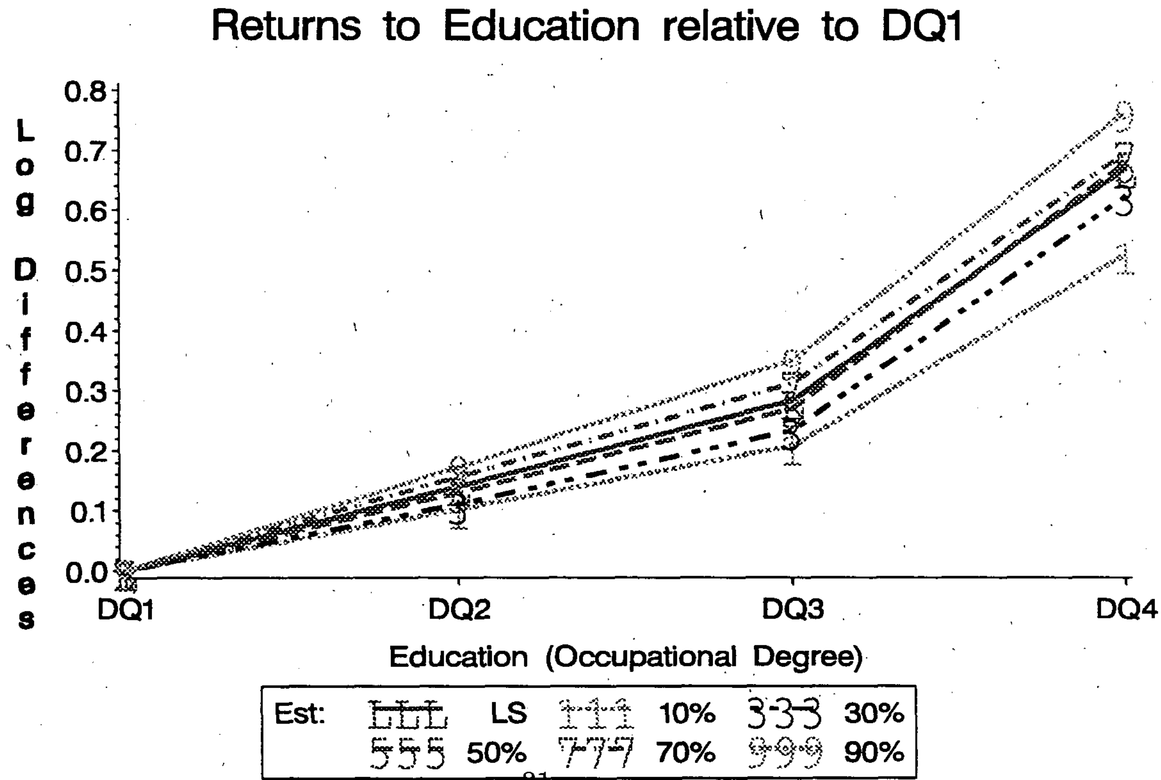


Figure 3: Estimated Returns to Experience for Least Squares and $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$

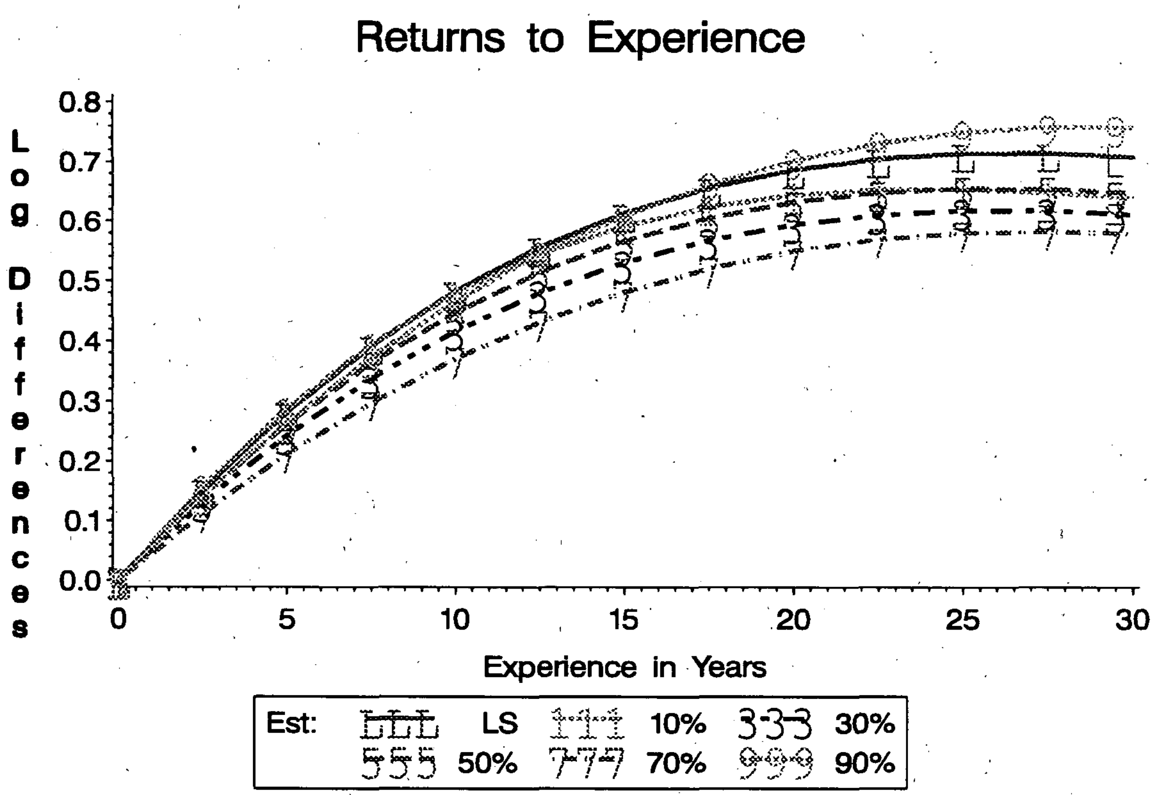
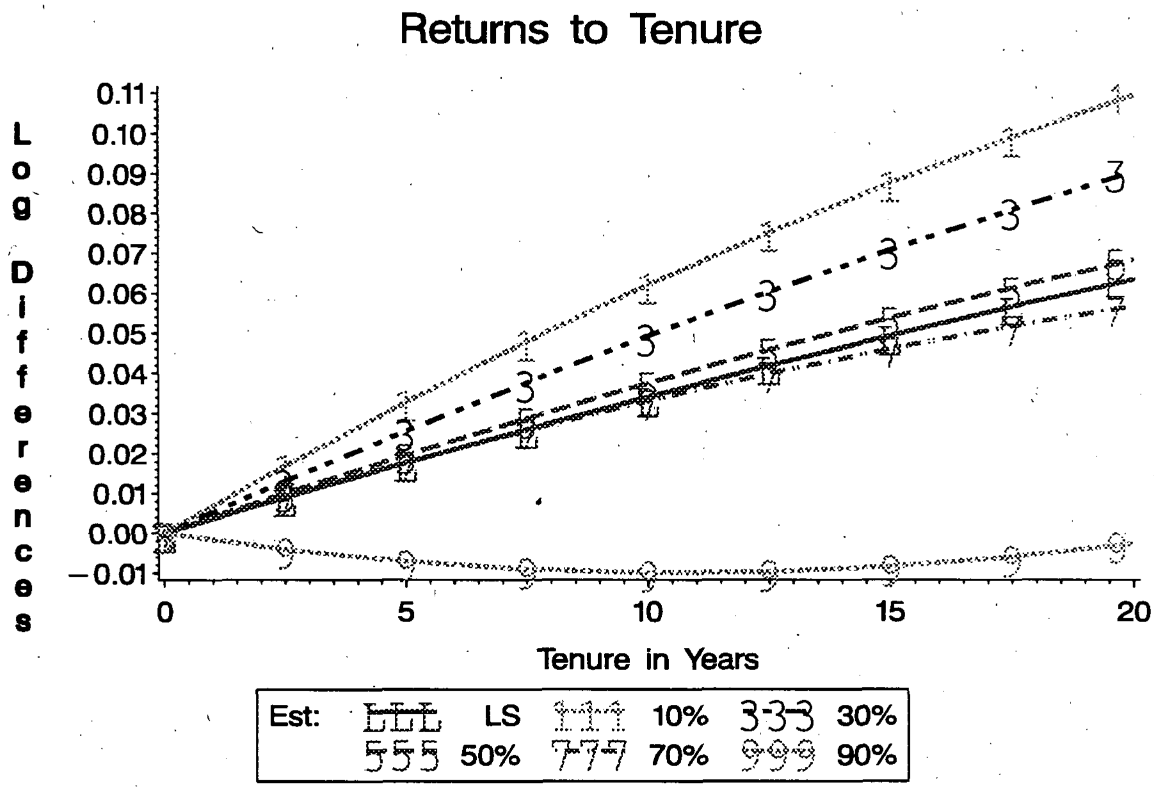



Figure 4: Estimated Returns to Tenure for Least Squares and $\theta = 0.1, 0.3, 0.5, 0.7, 0.9$



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