Central Wage Bargaining and Local Wage Flexibility: Evidence from the Entire Wage Distribution

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Abstract:

The paper argues that in labor markets with central wage bargaining wage flexibility varies systematically across the wage distribution: local wage flexibility is more relevant for the upper part of the wage distribution, and flexibility of wages negotiated under central wage bargaining is particularly important at the lower part of the wage distribution. This hypothesis is tested empirically using a large random sample of German social-security accounts, where wage flexibility is analyzed across the wage distribution by means of quantile regressions. The results are supportive, as on the one hand, employees with low wages show significantly lower wage flexibility with respect to regional unemployment than high wage employees. This effect is particularly relevant for employees with low education. On the other hand, employees with low wages exhibit higher wage flexibility with respect to national unemployment.

Keywords: Central wage bargaining, Wage flexibility, Quantile regression

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1 Introduction

When economists are questioned about the reasons for the European unemployment problem they often point to labor market rigidities. In particular, the rigidity or insufficient responsiveness of wages to unemployment brought about by the industrial relations systems, is considered to lie at the roots of unemployment (e.g. Siebert, 1997). Yet, there are difficulties with this argument. First, many empirical studies fail to show that wage flexibility is lower in the European countries when compared with North America (cf. Nickell, 1997). Despite large and persistent differences in the regional unemployment rates in Europe (cf. OECD, 1989) but quick convergence in regional unemployment rates in the US (cf. Blanchard / Katz, 1992), Blanchflower / Oswald (1994a) among others establish a "wage curve" in European countries similar to that of the US. Second, the literature on collective bargaining suggests to take account of the specific characteristics of the industrial relations systems (e.g., Flanagan, 1999). With respect to wage flexibility, it seems important to distinguish different levels of wage formation, since the extent and nature of wage flexibility will depend on the degree of centralization of collective bargaining (cf. Calmfors / Driffill, 1988). On the one hand, a higher degree of centralization reduces the wage flexibility at the level of the region or the firm. On the other hand, centralization of wage bargaining may bring about a responsiveness of wages to the national performance of the labor market. Thus, the failure of empirical studies to find international differences in wage flexibility may very well be related to the neglect of labor market institutions.

In order to contribute to the understanding of the role of labor market institutions in shaping wage flexibility, this paper is concerned about the interaction of collective wage bargaining and local wage formation. It shows that, on the one hand, there are theoretical reasons to expect wage bargaining at industry-level to affect mainly the lower end of the (conditional) wage distribution, i.e. workers receiving low wage payments given their known characteristics. On the other hand, local wage formation at the level of the firm or the region is expected to affect mainly the upper tail of the wage distribution. Consequently, two kinds of wage flexibility need to be distinguished: wages may respond directly to local or regional unemployment, and, due to centralized wage bargaining they may also respond to national unemployment even with low interregional mobility. Following our theoretical considerations, the empirical investigation employs a quantile regression approach, which allows for a comprehensive study of the association between unemployment and pay across the wage distribution. Using quantile regression techniques seems straightforward in the current setting, since the theory suggests that coefficients of local and national unemployment vary systematically across the wage distribution, and, thus, it is potentially misleading to focus on the mean of the wage distribution as done in standard regression analysis.

As the empirical analysis is concerned with the influence of local unemployment on individual wages, inference needs to take into account unobserved characteristics affecting all observations within a region. Moulton (1986,1990) emphasized that conventional inference procedures are severely biased in the presence of unobserved common group effects. As a methodological novelty, this paper uses a flexible Block Bootstrap procedure for inference taking account of correlation in the error term both within regions and between neighboring regions. Our results reveal the importance of these effects for standard error estimates.

The main dataset used is the regional file of the "IAB-Beschäftigtenstichprobe" (IABS-REG), a 1% random sample from the German social security accounts, reporting wages, age, education, and other characteristics of employed workers as well as unemployed workers (as far as applicable) in West Germany's districts. This yields a large number of observations for individuals in 259 regions for 15 consecutive years in Germany.

When considering central wage bargaining, the German case is of particular interest. Similar to other European countries the German system of labor relations entails different stages of wage formation. Wage bargaining takes place at the level of industries between the employers' federation and the union. Even if there are separate regional agreements, the conditions of the agreements are almost identical across regions for major industries (cf. Buettner, 1999). However, wages actually paid are generally higher than centrally negotiated wages. Available studies estimate the difference between actual and negotiated wages to lie around 7-12 % on average (cf. Schnabel, 1994, and Meyer, 1995). In accordance with the literature (e.g., Schlicht, 1992), the stylized theoretical model put forward in this paper assumes that payments above the negotiated level are caused by efficiency wage effects. Yet, we show that the gap between actual and negotiated wages will vary over the wage distribution. Put differently, the lower the wage paid the more likely the wage floor - defined by the contract wage - is binding. Consequently, wage flexibility varies across the wage distribution. By considering the entire wage distribution this paper contributes to the general discussion on wage flexibility in the presence of collective bargaining and to the controversial discussion in Germany, for which empirical studies report significant local flexibility (e.g., Baltagi / Blien, 1998), while at the same time the collective wage bargaining system is criticized for the resulting wage rigidity (see Siebert, 1997).

The next section develops the theoretical implications on wage flexibility when both local and central wage formation is present. It provides the basis for the empirical analysis presented in section 3. A final section summarizes the findings. The appendix contains a description of data sources and details of the estimation results.

2 Wage flexibility with local and collective wage formation

The theoretical analysis of wage flexibility combines collective wage bargaining centralized at the industry level and wage formation at the local level. Various hypotheses have been entertained in the literature in order to capture the impact of local labor market conditions on the wage rate, in particular firm-level wage bargaining and incentive wages (e.g., Blanchflower / Oswald, 1994a). Also, there exists a large body of literature discussing the determinants of wage bargaining (e.g. Pencavel, 1991), which might also be used to model centralized wage bargaining. However, for our purpose to derive empirical implications it suffices to assume two very stylized wage equations, one determining the collectively negotiated *contract wage*, and the other determining the *local wage*. Consider a worker i, who is paid either according to the terms of the central wage agreement or who receives the local wage, formally

$$W_i \quad = \quad \max\left(W_i^L\,,\,W_i^C\right), \tag{1}$$

where W_i^L denotes the local wage paid to worker i and W_i^C denotes the contract wage according to the wage agreement of the considered industry given the individual characteristics of worker i. According to the maximum operation in equation (1) wages contracted in central wage agreements define the floor of the wage actually paid. The justification in the German setting is that firms pay the contract wage to all employees – not only to union members (cf. Franz, 1996).[1] Following Blanchflower / Oswald (1994a,1994b) we purport a wage curve such that the local wage is affected by the local or regional rate of unemployment (u_r).

$$w_i^L \equiv \log W_i^L = \alpha_1 - \beta_1 u_r + \epsilon_i^L. \tag{2}$$

In contrast to the local wage, the contract wage is independent of regional unemployment, since agreements do not allow for regional differentiation. But, as negotiations in the considered industry take place at the national level, it is set conditional on the national rate of unemployment.

$$w_i^C \equiv \log W_i^C = \alpha_2 - \beta_2 u + \epsilon_i^C. \tag{3}$$

If the industry is an important employer, there might be a possible feed-back effect of the industry's contract wage on national unemployment. But, in the current setting each industry is assumed to be small relative to the national labor market.

At this stage, we have a simple model of wage determination with two regimes, a local-wage regime and a contract-wage regime depending upon which of the two wage functions determines the actual wage according to equation (1). The basic difficulty of an application of this setting to the case of Germany is that we do not know to which regime a wage observation belongs, i.e., in statistical terms, we do not know the sample separation between the two regimes. Because agreements

[1]As a legal enforcement of contract wages ("Allgemeinverbindlicherklärung") is the exception rather than the rule, the reason might be that when paying non-union members less, employers would create an incentive for their workers to become union members. However, the notion of contract wages as the floor for paid wages assumes that employers are members of the employers' federation. Although this is generally the case in West-Germany during the time period considered here, the developments in East-Germany have shown that under strong labor market pressures employers may exit the associations (cf. Scheremet, 1995).

determine many specific payments and working conditions it is almost impossible to compute the relevant contract wage of an employee on the basis of publicly available statistical data. Therefore, we cannot compare the wage flexibility of contract and local wages directly, as done for instance by Elliot / Hemmings (1991) in the case of Britain. Nevertheless, under reasonable distributional assumptions this model of wage determination exhibits empirical implications on wage flexibility in the two regimes. In particular, we assume the conditional variance of (logarithmic) contract wages to be lower than that of the local-wage

$$\mathrm{Var}\left(w_i^C \mid u\right) \quad < \quad \mathrm{Var}\left(w_i^L \mid u_r\right).$$

This assumption seems reasonable, since wage agreements fix the wage of certain classified occupations. Also, the lower residual variance in the union sector is a common empirical finding (see Freeman, 1980, and Chamberlain, 1994). Furthermore, the observation of a non-negative gap between wages paid and wages contracted in the German case (see above) is consistent with a more dispersed distribution of local wages at least in the right tail of the wage distribution.

Then, with lower dispersion of residuals in the contract-wage regime, what are the consequences of industry-level wage bargaining on the responsiveness of wages to unemployment? The answer to this question is that it depends on the level of wages: the wage flexibility at higher wages is *systematically* different from that at lower wages. To make this point precise, and to show the direction of the differences in the responsiveness of wages, we pick different points of the wage distribution and analyze the impact of unemployment. In statistical terms, we consider the impact of unemployment at different quantiles of the wage distribution. Given u and u_r, let the probability to observe a wage below a certain threshold c be θ, formally:

$$\theta = F_w\left(c \mid u, u_r\right) \qquad \Rightarrow c = q_\theta\left(w \mid u, u_r\right), \tag{4}$$

where F_w denotes the cumulative distribution function of wages. Then, c is just the θ-quantile of the conditional wage distribution $q_\theta\left(w \mid u, u_r\right)$. Investigating regional wage flexibility, we inspect the impact of the regional rate of unemployment on this quantile by total differentiation of equation (4) while holding constant national unemployment and the probability at θ:

$$\begin{aligned} 0 &= \frac{\partial F_w\left(c \mid u, u_r\right)}{\partial u_r} du_r + \frac{\partial F_w\left(c \mid u, u_r\right)}{\partial c} dq_\theta \\ \Leftrightarrow \quad \frac{dq_\theta}{du_r} &= -\frac{\partial F_w\left(c \mid u, u_r\right)}{\partial u_r} \Big/ \frac{\partial F_w\left(c \mid u, u_r\right)}{\partial c}. \end{aligned} \tag{5}$$

According to the basic wage-determination model, the probability to observe a wage below the level c is the probability that the wages in both regimes are jointly below that level, i.e. formally:

$$\mathrm{P}\left(w_i \leq c\right) \quad = \quad \mathrm{P}\left(\left\{w_i^L \leq c\right\} \cap \left\{w_i^C \leq c\right\}\right)$$

If we assume a continuous joint distribution of the residuals in the two wage regimes, this can be formalized as

$$F_w\left(c|u, u_r\right) = \int_{-\infty}^{c-\alpha_2+\beta_2 u} \int_{-\infty}^{c-\alpha_1+\beta_1 u_r} f\left(\epsilon_i^L, \epsilon_i^C\right) d\epsilon_i^L \, d\epsilon_i^C, \tag{6}$$

where f denotes the continuous joint density of the residuals. Partial differentiation of equation (6) with respect to c and u_r and insertion into equation (5) yields an expression for the impact of regional unemployment onto the conditional θ-quantile of the wage distribution

$$\frac{dq_\theta}{du_r} = -\beta_1 \left(1 + \frac{f_{w^C}\left(c|u\right) F_{w^L}\left(c|u_r\right)}{f_{w^L}\left(c|u_r\right) F_{w^C}\left(c|u\right)}\right)^{-1}. \tag{7}$$

This expression indicates that the impact of regional unemployment on the θ-quantile of the observed wages is equal to $-\beta_1$ times a factor between 0 and 1. This factor can be interpreted as the weighted probability that a local-wage regime is observed at c. $f_{w^C}\left(c|u\right)$ is the (marginal) density of the wage in the contract wage regime at a given national rate of unemployment and $F_{w^L}\left(c|u_r\right)$ denotes the probability to observe a contract-wage regime at the wage level c. Accordingly, $f_{w^L}\left(c|u_r\right)$ is the density of the wage in the local-wage regime at a given regional rate of unemployment and $F_{w^C}\left(c|u\right)$ denotes the probability to observe that regime at the given wage level.

Under certain distributional assumptions, in particular, if the above variance assumption holds and the distribution of wages under the local-wage regime is more dispersed, it follows:

Proposition 1: *The observed response of the logarithmic wage to an increase in regional unemployment tends to zero at lower quantiles of the wage distribution, decreases over the wage distribution, and approaches $-\beta_1$ at upper quantiles.*

While a derivation of this proposition for a simple distribution is given in the appendix the intuition behind it is straightforward: If the observed wage is in the lower tail of the distribution, one can expect that the local wage is small relative to the contract wage. Therefore, the respective worker is more likely to be paid according to the contract-wage regime, and regional unemployment is expected to be irrelevant at the observed quantile. In the upper tail of the wage distribution the local wage is probably large relative to the contract wage. Thus, we can expect the respective worker to be paid according to the local-wage regime, and the impact of regional unemployment on the local wage governs the observed responsiveness of the wage.

Based on similar reasoning the impact of the national unemployment rate at a given level of the regional rate of unemployment can be characterized as follows:

Proposition 2: *The observed response of the wage to an increase in the national rate of unemployment is $-\beta_2$ at lower quantiles of the wage distribution, increases across the wage distribution, and approaches zero at upper quantiles.*

Again the appendix contains the details of the proof. The intuition is similar to that of Proposition 1: At lower quantiles of the observed wage distribution, the local wage is probably small relative to the contract wage. Hence, the worker is expected to be paid according to the contract-wage regime. An increase in national unemployment thus shows effects on the observed wage. At upper quantiles of the wage distribution, the local-wage regime is probably relevant, and thus no direct impact of the national unemployment rate is observed.

In a more general setting workers are mobile across regions and the equilibrium wage and equation (2) will also contain a negative impact of the unemployment rate in the neighborhood or of the national rate of unemployment. However, as is shown in the appendix, this additional impact will not alter the proposition that the impact of national unemployment declines in absolute terms across the wage distribution under the condition that the impact of the national rate of unemployment on the local wage rate at given regional unemployment is weaker than the impact on the industry-level contract wage.

3 Investigation approach

According to the theoretical discussion so far, the empirical study should consider differences of the observed effects of unemployment across the wage distribution. On the one hand, due to the joint presence of industry-level wage bargaining and local wage formation, the wage depressing impact of local unemployment might vanish when considering workers, who receive low wage payments given their characteristics. On the other hand, these workers might be more strongly affected by the national unemployment if this is taken into account in the industry-level wage bargaining. Therefore, it is potentially misleading to focus on the (conditional) mean of the wage distribution as in standard regression analysis. Rather, the question of whether the central-wage bargaining results in wage rigidity should be investigated by means of a quantile regression approach.

A second requirement from the theoretical discussion is to distinguish between regional and national wage flexibility, because there are direct effects of both regional and national unemployment. However, the theoretical discussion has focused on a set of employees with sufficient similarities to be equally affected by unemployment. As this seems quite restrictive, the empirical investigation allows for several differences across both employees and unemployed. In addition to the locality, employees are classified by age, education, sex, industry, full-time, and part-time employment. A union membership variable is used in order to identify employment in industries where contract wages might be higher because of higher union density. Furthermore, unemployed individuals are characterized by age, education, duration of unemployment, and participation in training programs.

Before presenting the results, a brief overview of the dataset and a description of the estimation approach are given in the following next subsections.

3.1 Dataset

The main database used in this paper is the regional file of the "IAB-Beschäftigtenstichprobe" (IABS-REG), which has only recently been made available to the scientific public (see Hilzendegen, 1996). This dataset is a 1% random sample from the German social security accounts merged with information on the timing of transfer payments from the Federal Employment Service during periods of unemployment. The dataset contains information on 259 districts in West Germany for the time period 1975 to 1990. The industry information in the IABS-REG is restricted to nine one-digit industries (see Table 4 in the appendix) and there is no information on firm size. In addition to the IABS-REG, we make also use of the standard file of the "IAB-Beschäftigtenstichprobe" (IABS) and the German Microcensus, an annual population survey (see appendix). The IABS, which provides detailed information on firm size and industry, is used in order to construct a union density measure across industries. The aggregate education specific unemployment rates obtained from German Microcensus are used to correct the non- employment rates constructed from the IABS-REG such that the national education specific unemployment rates correspond to their aggregate counterparts.

The empirical investigation is based on wage, employment, and unemployment information on 259 districts in West Germany during the time period 1976 to 1990. We omit West Berlin, since it provides a special case for political and geographical reasons. Also the year 1975 is not used, since the disaggregated unemployment information based on the IABS-REG is not reliable for the first year (see appendix). We restrict attention to workers in the age interval 20 to 59 years, because a large fraction of younger workers are in vocational training receiving low earnings, and the German pension system involves incentives for early retirement by workers above age 59 such that the employment rate in this group is fairly low.

The quantile regression approach considered in more detail in the following subsection is based on grouped data. Namely, we collect all individuals belonging to the same district, age interval, education class, and year into a group. Then, we analyze the determinants of the wage distribution within the cells by means of quantiles, i.e. for each cell we compute a certain quantile and then study the impact of cell characteristics, for instance, the cell-specific risk of unemployment. We group the data into cells defined by three skill groups, four age intervals, 259 districts, and 15 years (1976-1990), yielding at most 46620 cells.

The wage information in the IABS-REG is censored from above at the social security threshold. The threshold level is the same for all workers and changes by year. If the wage lies above the threshold then the dataset reports the level of the threshold instead. The empirical analysis in this paper only considers uncensored cell quantiles. This is innocuous since the threshold level is the same across observations for a given year. Table 1 provides the remaining number of uncensored cells for each quantile considered. The number decreases for higher quantiles, however, for the

Table 1: Number of Uncensored Cells

Quantile (θ=)	0.1	0.3	0.5	0.7	0.9
Uncensored Cells	43811	43441	42797	41814	39822

Number of education-age-district-year cells among 46620 possible cells for which the respective empirical quantile of the wage distribution is below the social security threshold.

90%-quantile, we still have 85% of all cells available. As known from other studies (e.g. Fitzenberger / Franz, 1998), censoring is most severe for high-educated workers and elder workers, thus, we cannot put a lot of confidence in the results obtained for these groups at high quantiles.

3.2 Quantile regression approach

In order to investigate the flexibility of the entire wage distribution, we estimate quantile regressions (Koenker / Bassett, 1978) of wages in response to different unemployment rates at various quantiles. The use of quantile regression techniques is a direct consequence of the theoretical analysis in section 2, since the interaction of central wage bargaining and local wage formation implies systematic changes in coefficient estimates at different quantiles. Furthermore, distinguishing between different education groups and other characteristics associated with the wage level, it seems likely that the wage floors defined by the central wage bargaining bind at different points in the within-cell wage distribution for different types of workers.

Due to the large number of observations and due to the large number of regressors, we implement the estimation of quantile regressions in a two-step-procedure rather than having to estimate censored quantile regressions directly (see Fitzenberger, 1997, for a survey on censored quantile regressions). The following two-step-procedure (Minimum-Distance) for discrete regressors has been suggested among others by Chamberlain (1994). First, the empirical wage quantiles are determined for each cell, where the cells are defined by the grouping of all regressor variables. Second, the uncensored cell quantiles are regressed using a weighted least squares approach on the respective determinants of wages, which are constant for each cell. Using only uncensored cells is asymptotically innocuous in the presence of fixed censoring, i.e. censoring where, as in our case, the threshold levels are known for each observation irrespective as to whether the observation is actually censored.

The second step of the estimation procedure automatically takes account of the sampling variability in the cell quantiles. Formally, it involves weighted least squares regressions of the type

$$\hat{q}_\theta(w_i|k) = x_k\beta_\theta + \epsilon_k^\theta, \tag{8}$$

where k denotes the cell, $\hat{q}_\theta(w_i|k)$ the empirical θ-quantile of (log) wages in cell k, x_k the regressor, which is constant within cells, ϵ_k^θ the cell and quantile specific error term, and β_θ the quantile specific coefficient vector. In our empirical application, the average cell size is about 58 observations which is above the minimum of 30 recommended by Chamberlain (1994) for the application of the Minimum-Distance method for quantile regression.[2] Here, cells are defined by education and age of the worker, by the district, where employment is based, and by the year of observation.

3.3 Block Bootstrap procedure for inference

Robust estimation of the variance-covariance matrix of the coefficient estimates has to take account of heteroscedasticity and of the dependency in the error term across observations. Facing these difficulties, we use a flexible Block Bootstrap approach (cf. Fitzenberger, 1998, for the treatment in the time series context). However, it should be mentioned first that there exists another great advantage of any Bootstrap approach in the quantile regression context. Namely, basing the resample estimates for all quantiles on the same set of resamples also automatically provides an estimate of the covariance of coefficient estimates at different quantiles (see Fitzenberger, 1997). The Block Bootstrap approach employed here extends the standard Bootstrap procedure by drawing blocks of observations to form the resamples and thus retains the dependencies between observations. For each observation in a block, the entire vector comprising the endogenous variable and the regressors is used, i.e., we do not draw from the estimated residuals. When forming the blocks, we use two versions:

BB1: Blocks of observations contain all education-age-district-year cells for a given district across time.

BB2: In addition to BB1, blocks contain all education-age-district-year cells for the given education-age-year combination in the neighboring districts.

Version BB1 takes account of the correlation of the error term across educations, age, and time in a given district, due to common unobservable district attributes. This is of particular importance since the estimation does not employ regional characteristics explicitly. In addition, version BB2 takes also account of the possible correlations (spillover effects) in the error term between neighboring districts. The advantage of these Bootstrap methods is that even if the associated dependency structure is not present in the data, inference based on these methods remains valid. Put differently, contrasting different standard error estimates allows one to infer heuristically, whether the assumed underlying dependency structure is important for inference. Previewing

[2] Because the number of workers with medium education level is disproportionately large, 49.7% of all cells exhibit less than 30 observations. Based on the simulation results in Fitzenberger (1997, section 4), this is innocuous for two reasons. First, we do not attempt to implement fully efficient GLS estimation (see next paragraph) requiring a reliable estimate of the variance of the empirical cell quantiles. And second, we weight each cell in the second step by the cells size effectively downweighting small cells.

the next section, our results show that correlation within the same district (BB1) proves important resulting in considerably higher standard error estimates compared to conventional heteroscedasticity-consistent estimates. However, standard error estimates change only slightly when switching from BB1 to BB2, i.e. dependency between neighboring districts does not seem to be of importance for inference.

4 Empirical results

4.1 Basic specification

Table 2 presents estimates from a basic regression at the median. Recall that we order the observations into groups or cells by year, education, age, and district. Then, we compute the 50%-quantile, i.e. the median, for all cells and, finally, we estimate a weighted regression of all cell-medians on various cell characteristics.

For each explanatory variable, the coefficient and alternative standard errors are reported (see appendix B for a detailed description of variables). The column denoted by HC contains conventional heteroscedasticity-consistent standard errors, whereas columns BB1 and BB2 contain robust standard errors obtained from Block Bootstrap estimation as discussed above. Because BB1-standard errors take account of correlation within districts and across time, and because they are almost twice as large as the conventional (HC) standard errors, autocorrelation in time or correlation within a given district and year are revealed to be present in the data. As BB2-standard errors are rarely larger than BB1, there is no indication for additional dependency between neighboring districts. However, in the following, inference is based on the BB2 standard errors, since they are robust in a more general sense.

The coefficients of the education variables show the expected positive effect, as both medium (MS) and higher education (HS) raises the level of pay at the median. A higher share of females (FEMR) and a higher share of part-time employees (PARTR) in the cell is associated with a lower wage rate. The age dummies (AGE30,AGE40,AGE50) reveal that elder workers earn higher wages, since the reference category is 20 to 29 years of age. Yet, the age between 30 and 39 (AGE30) shows quite a large relative wage at the median. It should be emphasized at this point that, since the unemployment rates are age-specific, the coefficients do not necessarily show the conventional age-earnings profile. The union density variable (UD) shows no significance at the median, i.e. industries with higher union membership are not associated with higher median wages. This might reflect spillover effects of contract wages to other employees.

To capture the effect of unemployment we consider three different variables. LUR denotes the local or cell-specific rate of unemployment corresponding to year, education, age, and district. We also employ regional rates of unemployment (RUR), where unemployment in the specific district and its neighbors for the given year, education, and age group is taken into account. Additionally, national rates of un-

Table 2: Median Regression Estimates (1976–1990)

		standard errors					standard errors		
Variable	Coeff.	HC	BB1	BB2	Variable	Coeff.	HC	BB1	BB2
Intercept	4.891	.373	.601	.593	DY82	.032	.008	.008	.009
MS	.120	.007	.009	.009	DY83	.111	.011	.012	.012
HS	.471	.010	.013	.013	DY84	.126	.013	.015	.015
FEMR	-.586	.043	.104	.093	DY85	.034	.011	.013	.013
PARTR	-.571	.085	.207	.188	DY86	.026	.015	.021	.021
AGE30	.101	.003	.004	.004	DY87	.041	.019	.027	.028
AGE40	.027	.004	.007	.007	DY88	.034	.027	.041	.041
AGE50	.044	.005	.008	.008	DY89	.029	.033	.051	.051
UD	-.016	.019	.030	.030	DY90	.057	.031	.058	.047
LUR	-.097	.059	.083	.082	ERS04	.349	.367	.590	.548
RUR	-.817	.096	.169	.163	ERS46	-.684	.084	.202	.183
NUR	-1.992	.145	.205	.208	ERS50	.245	.102	.212	.199
DY77	.024	.006	.008	.009	ERS53	.904	.405	.653	.644
DY78	.038	.005	.005	.006	ERS59	.539	.129	.324	.289
DY79	.050	.007	.009	.010	ERS63	.095	.133	.246	.239
DY80	.051	.006	.005	.006	ERS70	-.487	.197	.358	.346
DY81	.047	.006	.005	.006	ERS73	.627	.161	.317	.301

Notes: Coefficient estimates obtained from weighted least squares regressions of empirical cell quantiles on the set of regressors varying by 42799 year–education–age–district cells. HC: Heteroscedasticity–consistent standard error estimates. BB1: Block Bootstrap standard error estimates taking account of the dependency across all observations within a given district within a year and over time (based on 1000 resamples). BB2: Block Bootstrap standard error estimates additionally taking account of the dependency between the district and all its first order neighbors within a given year (based on 1000 resamples).

employment (NUR) corresponding to the year, education and age group of the cell are employed. Whereas the local rate of unemployment is insignificant, the regional rate of unemployment and the national rate of unemployment corresponding to the age-education-year cell shows a significant negative effect at the median. The insignificance of local unemployment is in line with Buettner (1999), who finds that districts are too small to be considered as (functional) regional labor markets. Also, simultaneity problems may matter more for unemployment solely in the district than for unemployment in the region, consisting of the considered district and its neighbors.

Table 3 contains the results of regressions for five quantiles, namely for the 10%-, 30%-, 50%-, 70%-, and 90%-quantile. Across quantiles, we find some remarkable differences. For instance, medium level education (MS) shows a similar effect across quantiles, but the effect of higher education (HS) is largest at the 10%-quantile and

Table 3: Quantile Regression Estimates (1976–1990)

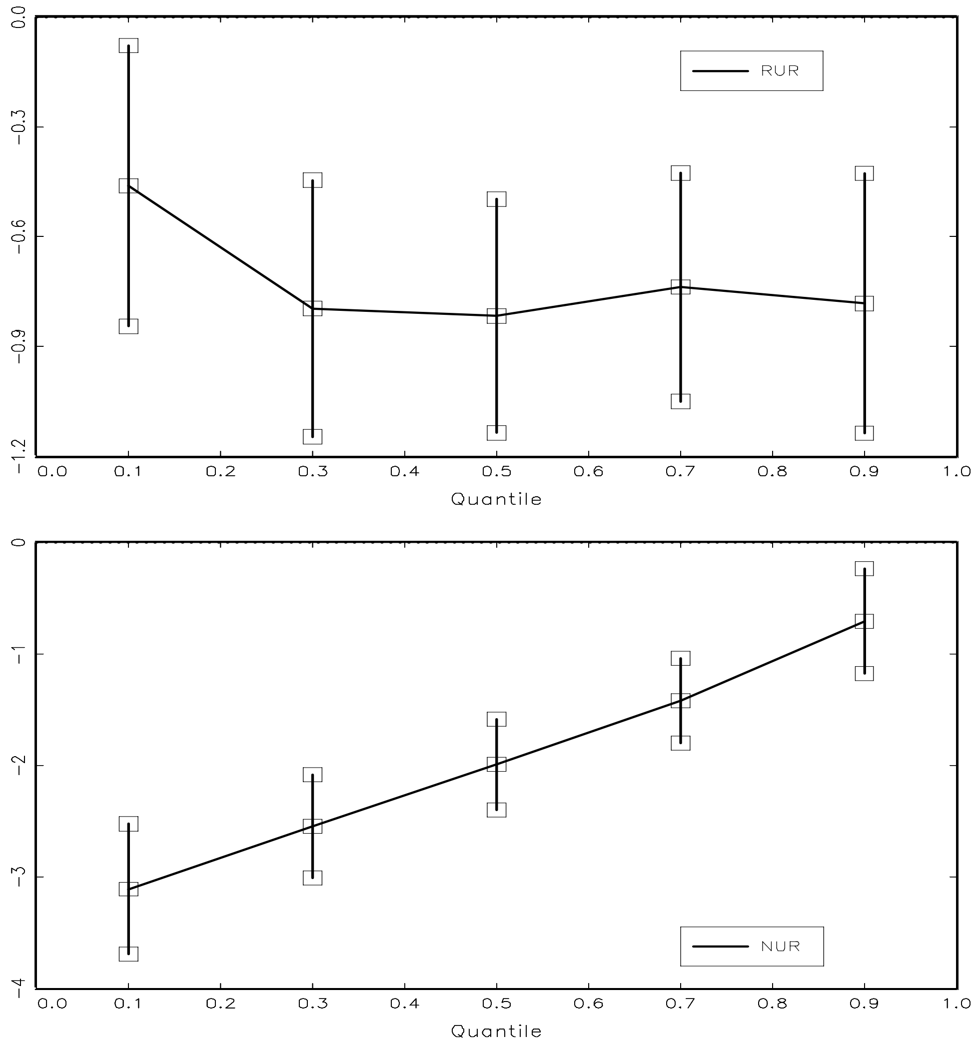
	$\theta = 0.1$	$\theta = 0.3$	$\theta = 0.5$	$\theta = 0.7$	$\theta = 0.9$
Variable	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)
Intercept	2.848 (.895)	3.630(.720)	4.891(.593)	5.754(.461)	6.177(.647)
MS	-.031 (.017)	.075(.012)	.120(.009)	.158(.007)	.215(.009)
HS	.565 (.025)	.520(.017)	.471(.013)	.418(.011)	.324(.013)
FEMR	-.315 (.122)	-.487(.110)	-.586(.093)	-.622(.093)	-.615(.103)
PARTR	-.833 (.227)	-.874(.224)	-.571(.188)	-.446(.188)	-.417(.207)
AGE30	-.083 (.007)	.030(.006)	.101(.004)	.148(.005)	.171(.006)
AGE40	-.150 (.011)	-.062(.009)	.027(.007)	.103(.007)	.144(.009)
AGE50	-.068 (.013)	-.018(.010)	.044(.008)	.096(.007)	.109(.009)
UD	.058 (.045)	.042(.036)	-.016(.030)	-.056(.023)	-.075(.033)
LUR	-.046 (.107)	-.081(.091)	-.097(.082)	-.037(.071)	.020(.080)
RUR	-.461 (.196)	-.796(.179)	-.817(.163)	-.738(.159)	-.782(.181)
NUR	-3.108 (.298)	-2.546(.236)	-1.992(.208)	-1.419(.194)	-.704(.240)
ERS04	-.922 (.866)	-.731(.700)	.349(.575)	1.093(.459)	1.473(.643)
ERS46	-.074 (.233)	-.485(.205)	-.684(.183)	-.877(.171)	-1.008(.191)
ERS50	.357 (.256)	.382(.226)	.245(.199)	.160(.171)	.238(.206)
ERS53	-.834(1.000)	-.317(.788)	.904(.644)	1.640(.541)	2.311(.781)
ERS59	1.142 (.368)	1.088(.328)	.539(.289)	.543(.279)	.681(.334)
ERS63	.639 (.333)	.478(.281)	.095(.239)	-.112(.206)	-.075(.266)
ERS70	-1.008 (.469)	-1.105(.410)	-.487(.346)	-.105(.296)	-.037(.376)
ERS73	1.080 (.420)	.831(.330)	.627(.301)	.035(.296)	-.405(.387)

Notes: Coefficient estimates obtained from weighted least squares regressions of empirical cell quantiles on the set of regressors varying by 43813 to 39824 year–education–age–district cells depending on the quantile (see text). A full set of time dummies is included. Block Bootstrap standard error estimates (BB2) in parentheses take account of the dependency across all observations within a given district within a year and over time and between the district and all its neighbors in the given year (based on 1000 resamples).

decreasing monotonically across the quantiles. This might reflect the censoring of earnings at the social security threshold, since for more highly educated workers censoring is most severe. The effects of the share of females (FEMR) and of parttime employees (PARTR) vary considerably across the wage distribution.

Turning to coefficients of unemployment, we may note first, that the local rate of unemployment (LUR) is insignificant not only at the median but also at the other quantiles. But, the regional (RUR) and national rates of unemployment (NUR) are significant at all quantiles. Figure 1 plots the estimated coefficients for regional and national unemployment. Taken literally, the theory of the previous section suggests that the impact of regional unemployment will vanish at the lower quantiles of the

Figure 1: Impact of Regional and National Unemployment



Notes: Horizontal axis reports the quantiles, vertical axis measures the coefficient estimates as reported in Table 3. Horizontal lines connect the point estimates of the coefficients, vertical lines depict the 95% confidence intervals. Using the bootstrap estimate of the variance-covariance matrix Wald statistics for equality of coefficients across quantiles are computed:

Significance of Differences:	RUR	NUR
P-value:	.165	.000

wage distribution, because for institutional reasons central wage determination may matter most strongly in this part of the distribution. In fact, the estimated impact of the regional rate of unemployment (RUR) is found to be lowest at the 10%-quantile. Based on the bootstrap estimate of the variance-covariance matrix we can also test whether the differences in the coefficients across quantiles are significant.[3] As displayed below Figure 1 the joint test fails to show significant differences. However, the difference between the 10% quantile and the 30%-quantile proves to be significant (t-statistic: -2.23). On the other hand, the theory predicts a negative impact of national unemployment at the lower quantiles which is decreasing in absolute value over the wage distribution. The data support this view, as the strongest negative impact of national unemployment is found at the 10%-quantile, and the absolute size of the coefficient decreases at higher quantiles. In this case, also the joint test supports differences across the quantiles.

The time dummies are of importance for the finding of a decreasing impact of national unemployment across the quantiles. An alternative regression (results are available upon request), where the set of time dummies was replaced by a cubic trend, did not show this effect. Whereas that regression deals with the variation of unemployment for a specific age and skill group around its long run movement, in the regression with time dummies the national unemployment variable captures the deviation of age- and education-specific unemployment from the average for a given year. In the present context the specification with time dummies is relevant, since we are interested in the impact of unemployment on the relative position in the cross-sectional wage distribution.

The joint inclusion of regional and national unemployment of the considered age-skill-year group requires that there is sufficient region-specific variation in order to avoid problems of multicollinearity. This requirement seems reasonable in the German case, which displays large disparities in regional labor market developments. But, to be certain that multicollinearity is not a problem, we checked the correlation structure between local, regional, and national unemployment rates conditional on the remaining set of explanatory variables. It turned out that in all cases no more than 50 % of the conditional variation of the respective unemployment rate can be explained by that of the other unemployment rates (results are available upon request).

According to the results in Table 3, the union density (UD) shows an interesting effect on the wage distribution raising the wage at lower quantiles but lowering the wage at higher quantiles. If we assume that union membership improves the bargaining position of the union in an industry's wage negotiations it will shift the contract wage (in terms of the above model α_2 will rise). This is in line with higher wages at the lower quantiles. However, at the higher quantiles we would expect no significant effect as the negotiated wage is less relevant. Overall, the results show that higher

[3]When evaluating the significance level note that we estimate robust standard errors which tend to be larger than conventional standard errors, see Table 2.

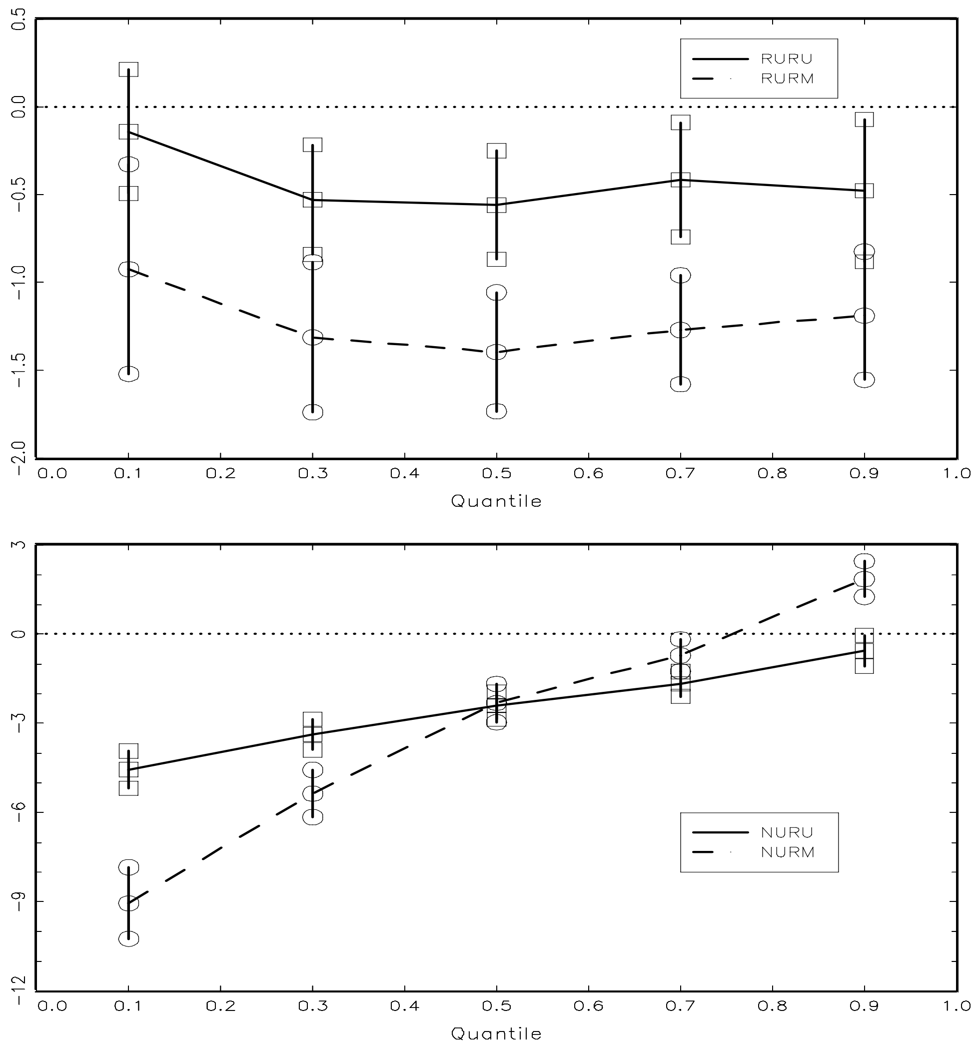
union density (UD) compresses the within-cell wage dispersion. Following the hypothesis of an asymmetric impact of unemployment, we should further expect less wage flexibility with respect to regional unemployment and higher flexibility with respect to national unemployment when union density is high (in particular at the lower quantiles). However, when interacting union density (UD) with the unemployment rates no support was found as the corresponding terms proved insignificant (results are available upon request).

4.2 Differences across education groups

In the basic specification in section 4.1, the impact of cell-specific unemployment on wages is implicitly assumed to be the same across education groups. For various reasons, this might be too strong an assumption. First, since more highly qualified employees exhibit higher interregional mobility, second, since unemployment varies strongly with the educational level (see Figure 3 in the appendix), and, third, since the wages of the highly skilled are less likely to be determined according to the central wage agreements. Finally, the observations of the highly skilled are much more affected by the censoring problem in the dataset due to top coding. Therefore, we allow both regional and national unemployment coefficients to differ with respect to the level of education. However, we omit the local unemployment rate as it proves insignificant.

Figure 2 focuses on the estimated coefficients (see also Table 5 in the appendix) for the unemployment rate of the unskilled and medium skilled, since the coefficients of the highly skilled are considered less reliable due to the censoring issue. The coefficients for the regional rates of unemployment are significantly negative. (RURU) denotes the unemployment rate corresponding to unskilled labor and (RURM) refers to the medium skill level. As in the basic specification the impact of regional unemployment is smaller at the lower quantiles. However, the results are more pronounced for the low education cells (RURU): whereas at the 30%-quantile a small but significant negative coefficient is reported, at the 10%-quantile no significant effect is found. In case of the unskilled even the joint test supports differences across quantiles. For medium education (RURM), the differences are less pronounced, but the absolute size of the coefficient of regional unemployment is lowest at the 10%-quantile and it differs significantly from the 30%-quantile (t-statistic: -1.85). Turning to national unemployment the estimation again shows a negative impact of national unemployment at the lower quantiles which gets weaker over the wage distribution. As compared to the results without eduction-specific coefficients the size of the coefficients is increased. However, again, multicollinearity does not appear to be a problem, since for all education groups less than 10 % of the variation in regional unemployment rates conditional on the remaining set of explanatory variables can be explained by the conditional variation of the national unemployment rate (results are available upon request).

Figure 2: Skill Specific Impact of Unemployment



Notes: Horizontal axis reports the quantiles, vertical axis measures the coefficient estimates as reported in Table 5 in the appendix. Horizontal lines connect the point estimates of the coefficients, vertical lines depict the 95% confidence intervals. Using the bootstrap estimate of the variance-covariance matrix Wald statistics for equality of coefficients across quantiles are computed:

Significance of Differences (P-value):

RURU	RURM	NURU	NURM
.011	.207	.000	.000

In order to make the findings of our semi-elastic specification comparable to the literature it seems interesting to express the results in terms of the implied unemployment elasticity of pay (cf., Blanchflower / Oswald, 1994a). For that purpose, we evaluate the elasticities at cell specific averages of regional and national unemployment rates over time. According to Table (6) in the appendix the results for the regional unemployment rate at the median are lower than the number of about -0.1 as typically found by Blanchflower and Oswald (1994a) for a series of countries. With estimates between -.055 and -.075 for the medium skill level depending on the age group they are roughly in line with the figure of -.07 obtained by Baltagi / Blien (1998). However, the elasticity varies across the wage distribution. In particular, for the lower skill groups the elasticity with respect to the regional rate of unemployment in absolute terms is much lower at the 10 % quantile.

5 Summary

Even though wage rigidity has a prominent position in the debate about the causes of the European unemployment problem, empirical studies often fail to show that wage flexibility in Europe is significantly lower than elsewhere. This paper argues that central wage bargaining as an institutional aspect of wage formation needs to be taken into account, in order to improve the theoretical understanding as well as the empirical results on wage flexibility.

Based on the German institutional setting, we show theoretically that due to the interaction of central wage bargaining and local wage formation (due to firm-level wage bargaining or incentive wages) wage flexibility varies systematically across the wage distribution. Wages in the lower part of the wage distribution are determined mainly by central wage bargaining, whereas for higher wages, local wage formation is more relevant. On the one hand, this implies that local wage flexibility, measured by the response of wages to regional unemployment, is more relevant for the upper part of the wage distribution. On the other hand, if wages negotiated under central wage bargaining respond to national unemployment, its effects are strongest in the lower part of the wage distribution.

Using the regional file of the "IAB-Beschäftigtenstichprobe", a 1% random sample from the German social security accounts, we estimate the response of wages to unemployment across the wage distribution by means of quantile regressions. To estimate standard errors, we use a Block Bootstrap procedure, which is robust against correlation in time, against correlation within groups, and against spatial correlation. The empirical results on wage flexibility conform with our hypothesis. Employees with low wages given their characteristics have a significantly lower regional wage flexibility than those with relatively high wages. This effect is particularly relevant for the unskilled, as the negative impact of unemployment vanishes at the 10%-quantile of the wage distribution. We also find a negative and asymmetric impact of national unemployment on wages, which is stronger at lower quantiles of the wage distribution.

As a conclusion, our study implies that central wage bargaining matters for regional wage flexibility. In the lower part of the wage distribution, we find empirical support for suppressed local wage flexibility in the German case. This effect is particularly relevant for less educated labor. In so far as the incidence of the German unemployment problem differs strongly between the regions, the suppressed local wage flexibility may have contributed to the unemployment problem. However, our results suggest that an assessment of central wage bargaining should also take into account the flexibility of wages with respect to national unemployment. In particular, central wage bargaining can involve a higher wage flexibility for less competitive groups of the labor market. However, it has to be acknowledged that this type of wage flexibility has not prevented the severe unemployment problem of the unskilled in Germany.

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Appendix A

A.1 Derivation of equation (7)

Partial differentiation of equation (6) with respect to u_r gives:

$$\frac{\partial F}{\partial u_r} = \beta_1 \int_{-\infty}^{c-\alpha_2+\beta_2 u} f\left(c-\alpha_1+\beta_1 u_r\,,\, \epsilon_i^C\right) d\epsilon_i^C .$$

This can be expressed as a product of a marginal density and a conditional probability:

$$\frac{\partial F}{\partial u_r} = \beta_1 f_{\epsilon^L}\left(c-\alpha_1+\beta_1 u_r\right) \int_{-\infty}^{c-\alpha_2+\beta_2 u} f\left(\epsilon_i^C | \epsilon_i^L = c-\alpha_1+\beta_1 u_r\right) d\epsilon_i^C .$$

Accordingly, the impact of u_r on the probability to observe a wage below c is equal to β_1 times the probability to observe a local-wage regime at a given level of the local wage weighted by the density of that specific local wage. Partial differentiation of equation (6) with respect to c gives:

$$\begin{aligned}\frac{\partial F}{\partial c} &= \int_{-\infty}^{c-\alpha_1+\beta_1 u_r} f\left(\epsilon_i^L\,,\, c-\alpha_2+\beta_2 u\right) d\epsilon_i^L \\ &+ \int_{-\infty}^{c-\alpha_2+\beta_2 u} f\left(c-\alpha_1+\beta_1 u_r\,,\, \epsilon_i^C\right) d\epsilon_i^C .\end{aligned}$$

Again, each of these terms can be expressed as a product of a marginal density with a conditional probability:

$$\begin{aligned}\frac{\partial F}{\partial c} &= f_{\epsilon^C}\left(c-\alpha_2+\beta_2 u\right) \int_{-\infty}^{c-\alpha_1+\beta_1 u_r} f\left(\epsilon_i^L | \epsilon_i^C = c-\alpha_2+\beta_2 u\right) d\epsilon_i^L \qquad (9) \\ &+ f_{\epsilon^L}\left(c-\alpha_1+\beta_1 u_r\right) \int_{-\infty}^{c-\alpha_2+\beta_2 u} f\left(\epsilon_i^C | \epsilon_i^L = c-\alpha_1+\beta_1 u_r\right) d\epsilon_i^C ,\end{aligned}$$

where f_{ϵ^L} and f_{ϵ^C} are the marginal densities of ϵ_i^L and ϵ_i^C, respectively. The expression for the differential of the wage quantile follows by inserting the two partial derivatives into equation (5), and after replacing the marginal densities of the residuals with the corresponding marginal densities of the conditional wage distribution.

A.2 Proof of Proposition 1

In order to prove Proposition 1 it is helpful to reformulate equation (7) yielding:

$$\frac{dq_\theta}{du_r} = -\beta_1 \left(1 + h\left(c\right)\right)^{-1}, \quad \text{where} \quad h\left(c\right) = \frac{f_{w^C}\left(c|u\right) F_{w^L}\left(c|u_r\right)}{f_{w^L}\left(c|u_r\right) F_{w^C}\left(c|u\right)}.$$

In terms of the distribution of the residuals, $h\left(c\right)$ can be rewritten using the derivations in appendix (A.1) above:

$$h\left(c\right) = \left(\frac{f_{\epsilon^C}\left(c - \alpha_2 + \beta_2 u\right)}{\int_{-\infty}^{c-\alpha_2+\beta_2 u} f\left(\epsilon_i^C | w_i^L = c\right) d\epsilon_i^C}\right) / \left(\frac{f_{\epsilon^L}\left(c - \alpha_1 + \beta_1 u_r\right)}{\int_{-\infty}^{c-\alpha_1+\beta_1 u_r} f\left(\epsilon_i^L | w_i^C = c\right) d\epsilon_i^L}\right). \tag{10}$$

The above proposition holds, if $h(c)$ decreases monotonously from infinite values to zero, when c increases. $h\left(c\right)$ is a ratio of two rates of changes in probability for small increases of the considered wage. In fact, it is the ratio of the rate of change in the probability of a local-wage regime to the rate of change in the probability of a contract wage regime. Intuitively, this ratio will fall as c increases, if the probability of a local-wage regime increases faster than the probability of a contract wage regime. For several distributions it suffices that the marginal density of contract wage residuals f_{ϵ^c} is below the marginal density of local-wage residuals f_{ϵ^L} at the bottom and at the top of the distribution, such that the marginal densities intersect twice.

In order to give a rigorous but simple proof consider the case of the uniform distribution when local and central wage residuals are independent. The two marginal densities are defined as follows:

$$\begin{aligned} f_{\epsilon^C}\left(c\right) &= \frac{1}{b-a}, \quad \text{where} \quad a < c \le b, \\ f_{\epsilon^L}\left(c\right) &= \frac{1}{b + d_u - \left(a - d_l\right)}, \quad \text{where} \quad a - d_l < c \le b + d_u. \end{aligned}$$

By introducing a lower increment $d_l > 0$ and an upper increment $d_u > 0$ the distribution of the local-wage residuals covers a larger interval. Consequently its variance is smaller than that of the local-wage residuals:

$$Var_{\epsilon^C}\left(c\right) \equiv \frac{\left(b-a\right)^2}{12} < Var_{\epsilon^L}\left(c\right) \equiv \frac{\left(b + d_u - a + d_l\right)^2}{12}.$$

However, the means of the two distributions need not be equal, as d_u may differ from d_l. The corresponding cumulative densities are:

$$\begin{aligned} F_{\epsilon^C}\left(c\right) &= \frac{c-a}{b-a}, \quad \text{where} \quad a < c \le b, \\ F_{\epsilon^L}\left(c\right) &= \frac{c - a + d_l}{b-a}, \quad \text{where} \quad a - d_l < c \le b + d_u. \end{aligned}$$

The proposition can easily be shown by deriving h as:

$$h\left(c\right) = \frac{c - a + d_l}{c - a} \quad \text{for} \quad a < c \leq b.$$

On the one hand, with contract wages defining wage floors, the distribution of observed wages is censored at a, i.e. wages can only be observed above a. Thus,

$$\lim_{c \to a} h\left(c\right) = \infty,$$

which describes h at the lower end of the observed wage distribution. On the other hand, for values of c above b the marginal density of the contract wage regime is zero and the probability that the contract wage is below the observed wage is unity. Thus,

$$h\left(c\right) = 0 \quad \text{for} \quad b < c \leq b + d_l,$$

which describes the top part of the observed wage distribution. Between these two extreme cases, $h(c)$ declines monotonically with c since

$$\frac{\partial h}{\partial c} = -\frac{d_l}{\left(c - a\right)^2} \quad < 0, \quad \text{where:} \quad a < c \leq b.$$

This proves Proposition 1 in the case of independent uniform distributions.

A.3 Proof of Proposition 2

Similar to the above analysis of the impact of regional unemployment, total differentiation of equation (4) holding constant regional unemployment and fixing the probability at θ gives:

$$\frac{dq_\theta}{du} = -\frac{\partial F_w\left(\, c \,|\, u \,,\, u_r\right) \,/\, \partial u}{\partial F_w\left(\, c \,|\, u \,,\, u_r\right) \,/\, \partial c} \tag{11}$$

Partial differentiation of equation (6) with respect to u gives:

$$\frac{\partial F_w}{\partial u} = \beta_2 f_{\epsilon^C}\left(c - \alpha_2 + \beta_2 u\right) \int_{-\infty}^{c - \alpha_1 + \beta_1 u_r} f\left(\epsilon_i^L | \epsilon_i^C = c - \alpha_2 + \beta_2 u\right) d\epsilon_i^C$$

Accordingly, the impact of u on the probability to observe a wage below c is equal to β_2 times the probability to observe a contract wage regime at a given level of the contract wage weighted by the density of that specific contract wage. Inserting into equation (11) together with equation (9) yields:

$$\frac{dq_\theta}{du} \quad = \quad -\beta_2 \frac{1}{1 + \left(h\left(c\right)\right)^{-1}}$$

where $h(c)$ is defined as above. The proposition follows by recalling that $h(c)$ is increasing with c.

A more general specification of the local wage regime allows for a direct impact of national unemployment. Then, equation (2) is modified to

$$w_i^L \equiv \log W_i^L = \alpha_1 - \beta_1 u_r - \beta_3 u + \epsilon_i^L.$$

As a consequence, the derivative for the θ-quantil of observed wages with respect to u becomes

$$\frac{dq_\theta}{du} = -\beta_2 \left(\frac{h(c) + \frac{\beta_3}{\beta_2}}{h(c) + 1} \right).$$

If $\beta_3 < \beta_2$ this expression declines as $h(c)$ increases. Therefore, proposition 2 holds also in the presence of an additional impact of national unemployment on the local wage at given local unemployment, as long as the impact of national unemployment on the industry's contract wage is stronger.

Appendix B: variables, data sources, and definitions

The two main data sources are the regional file of the "IAB-Beschäftigtenstichprobe" (IABS-REG) and the standard file IABS. Both datasets are independent 1% random samples from social security accounts in West Germany in the period from 1975 to 1990 including information on unemployment spells of workers receiving transfer payments from the Employment Service ("Leistungsempfängerdatei"). Main features of both datasets and a users' guide for IABS can be found in Bender et al. (1996). Specifics of IABS-REG are described in Hilzendegen (1996). The data appendix starts with a brief description of variables (symbols in parentheses).

B.1 Variables

Quantiles of wages: Quantiles of the within-cell distribution of logarithms of real daily wages (deflated by the aggregate consumer price index).

(FEMR): Proportion of female employees among all employees in the cell.

(PARTR): Proportion of parttime employees among all employees in the cell.

(ERSi): Proportion of employees in industry i among all employees in the cell (see Table 4 for the classification of industries).

(AGE20),(AGE30),(AGE40),(AGE50) Dummies for cell specific age in 10-year-intervals: [20 − 29 years],[30 − 39 years],[40 − 49 years],[50 − 59 years].

(US),(MS),(HS) Dummies for cell specific education: (US): unskilled, i.e. without a vocational training degree. (MS): medium skilled, i.e. with a vocational training degree. (HS): high skilled, i.e. with a technical college ("Fachhochschule") or university degree.

(LURU),(LURM),(LURH): District or local unemployment rates in the respective education-age-year class, i.e. (LURU): unskilled, (LURM): medium educated, and (LURH): highly educated. Unemployment rates are computed as non-employment rates from the data of the IABS-REG, and are corrected by means of aggregate figures, see below.

(RURU),(RURM),(RURH): Regional unemployment rates defined as a weighted average of unemployment rates for the education-age-year class in the respective cell in the respective district and in all neighboring districts (neighbors) for the same education-age-year class. The weights are the total number of persons in each district for the given education-age-year class.

(NURU),(NURM),(NURH): National unemployment rates defined as a weighted average of unemployment rates for the education-age-year class in the respective cell in all districts. The weights are analogous to regional unemployment rates.

(UD): Predicted union density among all employees in the cell, computed as the average of the aggregate industry specific predicted union densities in each year, weighted with industries' employment shares (ERSi) in each cell. See appendix B.4 for the prediction of union densities.

B.2 Features of IABS-REG and IABS

Social security contributions are mandatory for employees who earn more than a minimum threshold and who are working regularly. The main exemption are civil servants who do not pay social security contributions at all. Further exclusions from the mandatory contributions are students who work less than 20 hours a week on a regular basis or less than 6 weeks full-time. About 80 percent of the German employees are covered by this mandatory pension system.

The basic information in the IABS datasets consists of social security insurance (employment) spells and unemployment spells. The employment information comprises the starting and the end point of an employment spell and the average daily gross wage (excluding employers' contributions). The daily gross wage is censored from above and truncated from below. If the wage is above the upper social security threshold ("Beitragsbemessungsgrenze"), the daily social security threshold is reported instead. If the wage is below the lower social security threshold, the employee does not have to pay social security contribution and therefore, does not appear in the dataset. An annual wage observation is calculated as the weighted average of the wage observation of the individual for all spells within one year where the spell length is used as the weight. For the subsequent calculations, the annual wage observation is weighted by the total employment spell length within the year relative to the length of the year. These weights are used to calculate median wages and raw employment weights for all individuals in one education group and industry. Total employment in a cell defined by various workers' characteristics is obtained by adding up the length of all employment spells within cells. With multiple spells (jobs) at the same time (cf. Bender et al., 1996, p.74), we take the sum of the daily wages across spells as the wage observation. In case of spells originating from different industries, this sum is assigned to each industry as the wage observation together with an employment weight that is the product of the ratio between the respective daily wage and the sum of daily wages times the spell length in years. The latter procedure is based on the assumption that the respective wage share is a good estimate of the relative time spent in the different jobs and that the hourly wage is the same across jobs.

Over time, the earnings components being subject to the social security tax were extended (cf. Bender et al., 1996, p. 15). In particular, starting in 1984 one-time payments to the employee had to be taxed. Steiner / Wagner (1996) note that this results in a considerable spurious increase in earnings inequality due to the structural break in the data. Because of this structural break in the data, we corrected the wage observations before 1983 in a heuristic way. The correction is based on the assumption that only quantiles above the median need to be corrected upwards before 1983. This is operationalized for the IABS by a linear regression of wage growth between 1983 and 1984 for the 19 quantiles from 5% to 95%, where wage growth up to the median is assumed to be constant and on top of this uniform growth for the lower half of the distribution wage growth for the quantiles above the median is specified as a linear function in the percentage point difference between the respective quantile and the median. We interprete the linear function in the percentage difference as "excessive" (spurious) wage growth due to the structural break. For both datasets, wages above the median before 1983 are corrected upwards by this spurious wage growth. Further details of this correction can be found in Fitzenberger / Franz (1998, appendix).

Regarding spells of unemployment, the two datasets provide information on the time periods during which a person in the dataset receives transfer payments from the Federal Employment Service ("Bundesanstalt für Arbeit") while not working. There exist three types of transfer payments with different eligibility requirements: regular unemployment benefits ("Arbeitslosengeld"), unemployment assistance ("Arbeitslosenhilfe") and income maintenance during participation in a publicly sponsored training program. The datasets do not provide information on the size of the transfer payments. Analogous to the calculation of employment as described above, we obtain measures for the incidence of each transfer states. Based on the information for the spell length in a given year, we aggregate the time periods in each of the three transfer states for groups of workers with certain characteristics. For our empirical application, we define total unemployment as the sum of the three transfer states. Below, we will discuss some of the problems with the raw incidence measure described

Table 4: Industry Classification in IABS-REG

No.	Industry (in German)	Industry (in English)
01	Land- und Forstwirtschaft, Tierhaltung und Fischerei	Agriculture, Forestry, Animals and Fisheries
04	Energiewirtschaft, Wasserversorgung, Bergbau und Verarbeitendes Gewerbe	Energy, Water, Mining and Manufacturing
46	Baugewerbe	Construction
50	Handel	Trade
53	Verkehr und Nachrichtenübermittlung	Transport and Communication
59	Kreditinstitute und Versicherungsgewerbe	Banking and Insurance
63	Dienstleistungen, soweit n. anderw. genannt	Other Services
70	Gebietskörperschaften und Sozialversicherungen	Government
73	Organisationen ohne Erwerbscharakter und Private Haushalte	Non-Profit Organizations and Private Households

No. refers to the National Accounts classification of the Federal Statistical Office ("Statistisches Bundesamt", FS 18, R 1.3).

here and present a correction for these deficiencies.

The IABS-REG dataset contains locational information for 260 consolidated districts in West Germany and West Berlin. Due to data security requirements, certain districts among the original 327 districts ("Kreise") are combined with neighboring districts. For our empirical analysis, we omit West Berlin leaving us with 259 districts and, for each of these districts, we determine the group of neighboring districts (first order neighbors). The IABS-REG has no information on firm size and only one-digit industries can be distinguished, see the classification in Table 4.

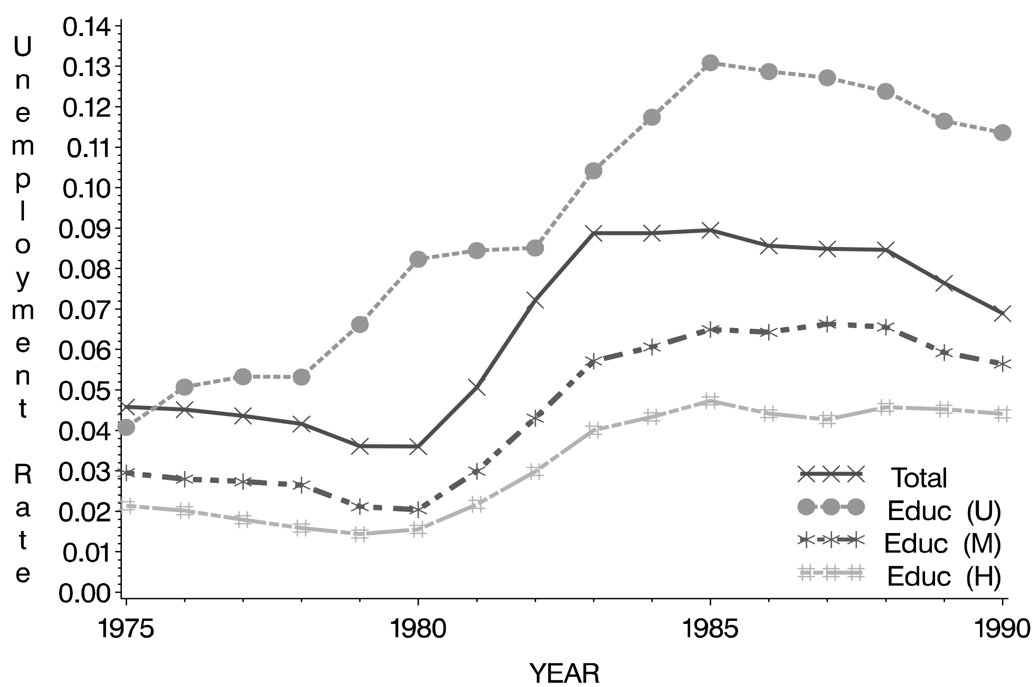
B.3 Computation of unemployment rates

Given that the IAB-Beschäftigtenstichprobe is drawn randomly from the population of social security accounts, unemployment is underrepresented. A further problem with the district data consists of the fact that the regional information is first provided by the first employment spell and that the location information in unemployment spells is taken from previous employment spells. Therefore, we calibrate the raw unemployment rates such that after aggregating the entire sample the annual education-specific unemployment rates correspond to the rates depicted in Figure 3.

When explicitly aggregating the raw unemployment rate from the IABS-REG for the three education groups (US,MS,HS), the estimate is extremely poor for the year 1975 where the aggregate rate in Figure 3 is between 30 and 86 times higher compared to the rate from the IABS-REG. However, after 1975 this factor decreases considerably and lies between 3 and 0.75. Thus, we omit the year 1975 in our further analysis, since it is unlikely that we can construct reliable unemployment rates for specific socioeconomic groups in that year and, for each of the years 1976 to 1990, we correct all unemployment rates by multiplying the rates for each socioeconomic group with the year and education-specific factor by which the education-specific unemployment rate is underestimated after aggregation.

German Microcensus data on education-specific employment and unemployment are taken from "Bevölkerung und Erwerbstätigkeit", Fachserie 1, Reihe 4.1.2 by the Federal Statistical Office (Statistisches Bundesamt). These data are available for the years 1976, 1978, 1980, 1982, 1985, 1988, and 1990. When calculating education-specific unemployment rates for the missing years, we interpolate the data using a regression approach where the aggregate unemployment rate is used to predict the period specific movement. The Microcensus distinguishes between three labor market states: Employed ("Erwerbstätig"), Unemployed ("Erwerbslos"), and Non-participating ("Nichterwerbsperson"). The state Unemployed does not necessarily correspond to the notion of "registered Unemployment" used by the Federal Employment Service ("Bundesanstalt für Arbeit"). Whereas the conventional aggregate unemployment rate refers to registered unemployment and employees during the entire year, the Microcensus only provides data on employment and unemployment for one point of time in the month of April. In addition, the definitions of unemployment and employment differ slightly. Therefore, the aggregate unemployment rate depicted in Figure 3 does not necessarily correspond to a weighted average of education-specific unemployment rates.

Figure 3: Trends in Education Specific Unemployment Rates



B.4 Using the IABS to predict union density

In West Germany, conventional industry specific measures of union density (ratio of union members to employment) typically cannot distinguish between working and non-working members (cf. Franz, 1996, chapter 7.2). Also the industry affiliation of the unions does not necessarily correspond to standard industry classifications and some unions cover large groups of industries. The recent study Fitzenberger / Haggeney / Ernst (1999) estimates union membership based on individual data from the German Socioeconomic Panel (GSOEP). The GSOEP provides the membership information for the years 1985, 1989, and 1993. The study shows that the econometric specification of union membership is stable across the three available years. One specification of these estimates for the unbalanced panel of observations in the GSOEP contains only variables, which are available in the IABS (the significant influence of political preferences is neglected). This specification is used to predict union membership rates among all employed workers in 46 industries for the years 1975 to 1990. Given the estimated probit membership function, it proves important to base the prediction on detailed industry and firm size information, which is provided in the IABS but not in the IABS-REG. The firm size information is only available after 1976. For the years 1975 and 1976, we take the same size class for each firm as provided for the first observation on the same firm after 1976. If there is no observation for a firm after 1976, we take the lowest firm size class, since firm attrition is likely to be negatively correlated with firm size. The industry classification differs slightly from the one used in the national account data. The IABS comprises 95 industries which, in most cases, is finer than the national account classification used for the prediction (see Fitzenberger / Franz, 1998 how to merge the two). It proceeds as follows: First, the IABS data for each year is grouped in cells defined by the explanatory variables of the membership functions except for firm size[4] and earnings. Second, for each cell the median wage and the average shares of each firm size category is calculated. Third, based on the cell attributes and the variables calculated in the second step, we predict the union density in the cell by the associated fitted membership probability. Fourth, the union densities across cells are aggregated for each industry in the IABS-REG (see Table 4) and for each year by calculating the weighted average across the respective cells where the weights correspond to the employment in each cell. In light of the German wage bargaining institutions, it seems reasonable to refer to industry-specific union density rates at the national level when predicting the cell specific union density, since despite a possible regional variation in union density, there exists almost no regional variation in bargained wages which are the result of central wage bargaining for a given industry.

[4] For two of the eight categories in the IABS (see Bender et al., 1996, p. 114), there exists no unique correspondence in the GSOEP. These are the categories 6 (100-499 employees) and 8 (1000 and more employees). For both categories, we assume that the respective employees spent 50% of their employment spell in each of the two categories in the GSOEP with overlap with the respective category in the IABS, cf. Fitzenberger / Haggeney / Ernst (1999, appendix) for details.

Appendix C: tables

Table 5: Quantile Regression Estimates (1976–1990)

Variable	$\theta = 0.1$ Coeff. (s.e.)	$\theta = 0.3$ Coeff. (s.e.)	$\theta = 0.5$ Coeff. (s.e.)	$\theta = 0.7$ Coeff. (s.e.)	$\theta = 0.9$ Coeff. (s.e.)
Intercept	2.643(.892)	3.503(.713)	4.811(.570)	5.707(.459)	6.146(.657)
MS	.140(.018)	.168(.014)	.148(.010)	.156(.009)	.160(.010)
HS	.686(.035)	.474(.026)	.340(.022)	.222(.019)	.116(.021)
FEMR	-.313(.120)	-.491(.110)	-.595(.091)	-.632(.091)	-.626(.103)
PARTR	-.831(.227)	-.864(.224)	-.553(.188)	-.425(.182)	-.398(.206)
AGE30	-.105(.007)	.017(.006)	.095(.005)	.145(.005)	.175(.005)
AGE40	-.231(.012)	-.102(.010)	.017(.009)	.106(.007)	.172(.008)
AGE50	-.111(.013)	-.038(.010)	.039(.009)	.098(.007)	.123(.008)
UD	.072(.045)	.050(.036)	-.011(.029)	-.053(.023)	-.074(.033)
RURU	-.141(.180)	-.528(.159)	-.559(.158)	-.415(.166)	-.477(.207)
RURM	-.924(.305)	-1.312(.218)	-1.395(.173)	-1.270(.158)	-1.189(.186)
RURH	-1.009(.451)	-1.268(.248)	-1.232(.222)	-1.153(.207)	-1.141(.200)
NURU	-4.564(.319)	-3.380(.265)	-2.404(.234)	-1.679(.212)	-.563(.265)
NURM	-9.053(.614)	-5.367(.403)	-2.321(.327)	-.716(.276)	1.853(.308)
NURH	-10.006(.858)	-2.773(.517)	1.513(.477)	4.273(.419)	6.493(.488)

Notes: The coefficients for the employment proportion in the different industries are not displayed. For further notes see table 3.

Table 6: Unemployment Elasticities of Wage Quantiles

Level of Education	Quantile θ	Regional unempl. (RUR) AGE20	AGE30	AGE40	AGE50
US	0.1	-.015	-.013	-.010	-.013
US	0.3	-.056	-.050	-.038	-.049
US	0.5	-.059	-.053	-.040	-.052
US	0.7	-.044	-.039	-.030	-.038
US	0.9	-.050	-.045	-.034	-.044
MS	0.1	-.049	-.045	-.036	-.044
MS	0.3	-.070	-.064	-.051	-.062
MS	0.5	-.075	-.068	-.055	-.066
MS	0.7	-.068	-.062	-.050	-.060
MS	0.9	-.064	-.058	-.047	-.057
HS	0.1	-.036	-.049	-.032	-.033
HS	0.3	-.045	-.061	-.040	-.042
HS	0.5	-.044	-.059	-.039	-.041
HS	0.7	-.041	-.056	-.037	-.038
HS	0.9	-.040	-.055	-.036	-.038

Level of Education	Quantile θ	National unempl. (NUR) AGE20	AGE30	AGE40	AGE50
US	0.1	-.481	-.432	-.325	-.423
US	0.3	-.356	-.320	-.241	-.313
US	0.5	-.253	-.227	-.171	-.223
US	0.7	-.177	-.159	-.120	-.156
US	0.9	-.059	-.053	-.040	-.052
MS	0.1	-.484	-.443	-.355	-.430
MS	0.3	-.287	-.263	-.211	-.255
MS	0.5	-.124	-.114	-.091	-.110
MS	0.7	-.038	-.035	-.028	-.034
MS	0.9	.099	.091	.073	.088
HS	0.1	-.354	-.483	-.318	-.331
HS	0.3	-.098	-.134	-.088	-.092
HS	0.5	.053	.073	.048	.050
HS	0.7	.151	.206	.136	.141
HS	0.9	.230	.314	.206	.215

Notes: Elasticities of wage quantiles with respect to changes in regional and national unemployment rates based on specification in Table 5 of the paper (evaluated at cell specific averages of national unemployment rates over time).