

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

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## Nontechnical Summary

This paper deals with the interaction of central wage bargaining and local wage formation with regard to wage flexibility. We show, that there are theoretical reasons to expect central wage bargaining to affect disproportionately the lower part of the wage distribution, i.e. workers receiving low wage payments given their known characteristics. On the other hand, local wage formation, representing firm-specific wage bargaining or incentive wages, may affect disproportionately the upper part of the wage distribution. Consequently, two kinds of wage flexibility need to be distinguished: wages may not only respond directly to local unemployment, but, even without interregional mobility, they may also respond to national unemployment when there is centralized wage bargaining.

Following our theoretical considerations, the empirical investigation employs a quantile regression approach, which allows for a comprehensive study of the impact of unemployment along the entire wage distribution. Using quantile regression techniques proves natural since the theoretical setting suggests that coefficients of local and national unemployment vary systematically across the wage distribution, and thus, it is potentially misleading to focus on the conditional mean of the wage distribution as done in standard regression analysis.

The main dataset used is the regional file of the “IAB-Beschäftigtenstichprobe”, a 1% random sample from the German social security accounts, reporting characteristics of employed and unemployed workers in West Germany’s districts. The results support our hypothesis, as employees with relatively low wages have a significantly lower regional wage flexibility than those with relatively high wages. We also find a negative and asymmetric impact of national unemployment on wages, which is stronger for employees with low wages. Both, the lower wage flexibility of low wage earners with respect to regional unemployment and the higher wage flexibility of low wage earners with respect to national unemployment are particularly relevant for the unskilled.

When distinguishing short- and long-term unemployment, regional long-term unemployment is found to have a much weaker impact on wages than short-term unemployment. Regarding short-term unemployment, there is again an increase of wage flexibility over the wage distribution. On the other hand, national long-term unemployment has a significant negative impact on wages which is especially relevant in the lower part of the wage distribution.

As a conclusion, our study implies that central wage bargaining matters for regional wage flexibility in the German case. In the lower part of the wage distribution, we find empirical support for suppressed local wage flexibility. This effect is particularly relevant for less educated labor. Our results also suggest that an assessment of central wage bargaining should take into account the flexibility of wages with respect to national unemployment. In particular, central wage bargaining may involve a higher wage flexibility for less competitive groups of the labor market.

## **Abstract:**

We argue 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 affects the lower part of the wage distribution. Using a random sample of German social–security accounts, we estimate wage flexibility across the wage distribution by means of quantile regressions. The results support our hypothesis, as employees with low wages have significantly lower local wage flexibility than high wage employees. This effect is particularly relevant for the lower educational groups. On the other hand, employees with low wages tend to have a 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 asked 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, are 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). Even with regional data, Blanchflower / Oswald (1994) among others managed to establish a “wage curve” in European countries similar to that of the US. With the background of large and persistent differences in the regional unemployment rates in Europe (cf. OECD, 1989) but convergence in regional unemployment rates in the US (cf. Blanchard / Katz, 1992) the similarity of the “wage curve” is somewhat puzzling. It seems to imply that the large concentration of unemployment in some European regions is not caused by insufficient wage flexibility.

Second, following a large body of literature on wage formation wage flexibility should be regarded as endogenous in the economics of the labor market. This means that knowledge of the determinants of wage flexibility is required before any policy recommendations can be given. This might be of particular relevance in the case of collective wage bargaining, where the degree of centralization can have ambiguous effects on wage flexibility (cf. Calmfors / Driffill (1988)). On the one hand, centralization of wage bargaining reduces the wage flexibility at the level of the industry, the region, and the firm. On the other hand, central wage bargaining may directly take into account the national performance of the labor market. The consequence is that a removal of collective wage bargaining institutions in order to raise wage flexibility could potentially exchange one form of wage rigidity for another.

The two problems concerning the lack of wage flexibility as a cause of unemployment are related. As long as labor market institutions are not introduced into the analysis of wage flexibility, one can hardly expect to identify causes of unemployment. Put differently, the failure of empirical studies to find international differences in wage flexibility may well be caused by the neglect of labor market institutions. In this paper, we are concerned about the interaction of central wage bargaining and local wage formation with regard to wage flexibility. We will show that there are theoretical reasons to expect central wage bargaining 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, representing firm-specific wage bargaining or incentive wages, is expected to affect mainly the upper tail of the wage distribution. Consequently, two kinds of wage flexibility need to be distinguished: wages may not only respond directly to local unemployment, but, even without interregional mobility, they may respond to national unemployment when there is centralized

wage bargaining. Following our theoretical considerations, the empirical investigation employs a quantile regression approach, which allows for a comprehensive study of the impact of unemployment across the wage distribution. Using quantile regression techniques proves natural since the theoretical setting suggests that coefficients of local and national unemployment vary systematically across the wage distribution, and thus, it is potentially misleading to focus on the (conditional) mean of the wage distribution as done in standard regression analysis.

As the empirical analysis is concerned with the impact of local unemployment on individual wages, inference needs to take into account unobserved characteristics affecting all observations within the location or the region including adjacent locations. Moulton (1986,1990) emphasized that conventional inference procedures are severely biased in the presence of unobserved but 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 characteristics of unemployed in West Germany’s districts. This yields a large set of observations for individuals in 259 contiguous regions for 15 consecutive years in Germany. When considering central wage bargaining, the German case is of particular interest. Similar to Scandinavian 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 representing the industry’s workers. Until recently this bargaining system proved fairly stable, but due to prolonged labor market problems, particularly in East Germany, the system is criticized for not providing sufficient flexibility. Although in some industries there are separate agreements in the regions, the conditions of the agreements show almost no differences across regions for major industries (cf. Büttner, 1998). However, because agreements determine all aspects of working conditions, such as working time and holidays, and specific payments, such as bonuses and overtime payments, it is almost impossible to compute the relevant contract wage of an employee on the basis of publicly available statistical data. Therefore, the level of negotiated wages for observed individual workers is generally not known in German labor market studies. Yet, some studies using unique datasets estimate the difference between actual wages and negotiated wages to be on average about 7-12 % (cf. Schnabel, 1994, see also Meyer, 1995). To explain the positive gap between actual wages and negotiated wages the literature puts forward efficiency wages and firm–level wage bargaining (e.g. Schlicht, 1992). This is in line with the application of the “wage–curve” hypothesis to the German case. However, even when negotiated wages are endogenous, it can be shown that the gap between actual and negotiated wages varies over the wage distribution and vanishes at the lower

end of the wage distribution (see Büttner, 1998). Put differently, the lower the wage paid the more likely is the specific wage floor set by contract wages binding. This paper takes a broad view on the implication for the wage flexibility across the entire wage distribution. Hence, in taking the institutional aspect of central wage bargaining into account we contribute to the controversial discussion on wage rigidity in Germany, for which empirical studies following the “wage–curve” hypothesis report significant local flexibility (see Blien, 1995, Bellmann / Blien, 1996, and Büttner, 1999), but the central wage bargaining system is criticized for its rigidity.

The following section shows theoretically the implications on wage flexibility when both local and central wage formation is present. It provides the basis for the empirical analysis, which is presented in section 3. A final section summarizes the findings.

## 2 Wage Flexibility with Local and Central Wage Formation

In this section the theoretical analysis of wage flexibility combines central wage bargaining at the supra–firm level and firm–specific wage formation at the local level. Various hypothesis have been applied in order to formulate the impact of local labor market conditions on the wage rate (see Blanchflower / Oswald, 1994). 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 central wage bargaining. However, for the present purpose it suffices to assume two very simplified reduced–form wage equations, one determining the collectively negotiated *contract wage*, and the other determining the firm–specific *local wage*. Consider a worker  $i$  with occupation in region  $r$ . The worker is paid either according to the terms of the central wage agreement or receives the local wage, formally:

$$W_{r,i} = \max (W_{r,i}^L, W_i^C), \quad (1)$$

where  $W_{r,i}^L$  denotes the local wage paid to a worker employed in the considered industry at location  $r$  and  $W_i^C$  denotes the contract wage according to the wage agreement given the individual characteristics of worker  $i$ . According to the maximum operator 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 tend to pay the contract wage not only to union members but to all employees (cf. Franz, 1996).<sup>1</sup> As the analysis deals with industry–level wage bargaining, the contract wage is not

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<sup>1</sup>As 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 view of contract wages as the floor for paid wages requires employers to be members of the employers’ federation. Thus, employers have an exit option as shown by the failure of the collective labor institutions in East–Germany (cf. Scheremet, 1995).

indexed by the region – reflecting the view that agreements do not allow for regional differentiation.

Following Blanchflower / Oswald (1994), the local wage is affected by the regional rate of unemployment of workers ( $u_r$ ) because of efficiency wages or firm-specific wage bargaining, formally:

$$w_{r,i}^L \equiv \log W_{r,i}^L = \alpha_1 - \beta_1 u_r + \epsilon_i^L. \quad (2)$$

It is assumed that, despite individual differences in payment, all workers are affected equally by the regional rate of unemployment. Without going into the details of the theoretical foundation for the “wage curve”, it is obvious that this specification relates to workers with similar labor supply behaviour. In contrast to the local wage, the contract wage does not react to the regional unemployment. But, as it is negotiated at the national level, it reacts to the overall or national rate of unemployment ( $u$ ):

$$w_i^C \equiv \log W_i^C = \alpha_2 - \beta_2 u + \epsilon_i^C. \quad (3)$$

At this stage, we have a simple wage determination model with two regimes, a local-wage regime and a contract-wage regime depending on which of the two wages determine the actual wage according to equation (1). The basic difficulty of the application of this setting to the observed wages is that we do not know to which regime an observed wage belongs, i.e., in statistical terms, we do not know the sample separation. This is a consequence of the above mentioned difficulties in measuring the contract wage. Nevertheless, under reasonable assumptions this model of wage determination exhibits empirical implications on the distribution of wages in the two regimes, in particular, when the conditional variance of (logarithmic) wages in the contract-wage regime is lower than in the local-wage regime:

$$\text{Var}(w_i^C | u) < \text{Var}(w_{r,i}^L | u_r)$$

As wage agreements fix the wage of certain classified occupations, it would require an implausibly large number of job categories for industry-level bargaining to violate this requirement. Also, the lower residual variance in the union sector in other countries 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 at the right-hand side of the wage distribution.

Then, with lower dispersion of residuals contract-wage regime, what is the consequence of industry-level wage bargaining for 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 whether the impact of

unemployment varies. 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  $\theta$ , formally:

$$\theta = F_w(c | u, u_r) \quad \Rightarrow \quad c = q_\theta(w | u, u_r), \quad (4)$$

where  $F_w$  denotes the cumulative distribution function of wages. Then,  $c$  is just the  $\theta$ -quantile of the conditional wage distribution  $q_\theta(w | u, u_r)$ . 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  $\theta$ :

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

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:

$$\begin{aligned} P(w_{r,i} \leq c) &= P(\{w_{r,i}^L \leq c\} \cap \{w_i^C \leq c\}) \\ &= P(\{\epsilon_i^L \leq c - \alpha_1 - \beta_1 u_r\} \cap \{\epsilon_i^C \leq c - \alpha_2 - \beta_2 u\}). \end{aligned}$$

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

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

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  $\theta$ -quantile of the wage distribution (cf. appendix for the details of this derivation).

$$\frac{dq_\theta}{du_r} = -\beta_1 \left( 1 + \frac{f_{w^C}(c | u) P(w_{r,i}^L \leq c | w_i^C = c, u_r)}{f_{w^L}(c | u_r) P(w_i^C \leq c | w_{r,i}^L = c, u)} \right)^{-1}, \quad (7)$$

where  $f_{w^L}(w_{r,i}^L | u_r)$  is the (marginal) density of the wage in the local-wage regime at a given regional rate of unemployment. Correspondingly,  $f_{w^C}(w_i^C | u)$  is the density of the wage in the contract wage regime at a given national rate of unemployment.  $P(w_i^C \leq c | w_{r,i}^L = c, u)$  denotes the probability to observe a local-wage regime at a given level  $c$  of the local wage. Finally,  $P(w_{r,i}^L \leq c | w_i^C = c, u_r)$  denotes the probability



to observe a contract–wage regime at a given level  $c$  of the contract wage. According to equation (7) the impact of regional unemployment on the  $\theta$ –quantile of the observed wages is equal to  $-\beta_1$  times a factor between 0 and 1, which can be interpreted as a weighted probability that a local–wage regime is observed at  $c$ .

If the above distributional assumption is fulfilled, i.e. if the distribution of wages under the local–wage regime is more dispersed, one can show the following proposition:

**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 higher quantiles.*

While a derivation of this proposition for a special case is given in the appendix the intuition of this proposition 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 worker is more likely to be paid according to the contract–wage regime, and the impact of local unemployment on the local wage is irrelevant for the observed quantile. Correspondingly, in the upper tail of the wage distribution the local wage is probably large relative to the contract wage. Thus, we can expect the 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 determined. Because, by assumption, the national rate of unemployment affects the contract wage but not the local wage, the following proposition holds:

**Proposition 2:** *The observed response of the wage to an increase in the national rate of unemployment tends to zero at higher quantiles of the wage distribution, but approaches  $-\beta_2$  at lower quantiles.*

Again the appendix contains the details of the proof. The intuition is similar to that of Proposition 1: At low 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 affects the observed wage. At high quantiles of the wage distribution, however, the local–wage regime is probably relevant, and thus no direct impact of the national unemployment rate is observed.

### 3 Empirical Investigation

According to the theoretical discussion of the previous section, the empirical study must take into account differences of the observed effects of unemployment across

the wage distribution: 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 central wage bargaining. Therefore, it is potentially misleading to focus on the (conditional) mean of the wage distribution as in standard regression analysis. Rather, the effect of central-wage bargaining on the 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 of 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. A detailed description of the datasets and the manipulations involved can be found in the appendix.

### 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 2 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 coun-

Table 1: Number of Uncensored Cells<sup>a</sup>

Quantile ( $\theta=$ )	0.1	0.3	0.5	0.7	0.9
Uncensored Cells	43813	43443	42799	41816	39824

a: 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.

terparts.

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 cannot be used, since the disaggregated unemployment information based on the IABS–REG does not appear reliable for this 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, educational 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. Since the wage information in the IABS–REG is censored from above at the social security threshold, the empirical analysis only considers uncensored cell quantiles. Table 1 provides the remaining number of uncensored cells for each quantile considered. The number decreases for higher quantiles, however, for the 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. It is shown in section 2 that the interaction of central wage bargaining, which results in different wage floors for different types of workers,

and firm-specific wage formation can imply changes in coefficient estimates at different quantiles. Distinguishing between different educational groups and other characteristics, which are associated with the wage level, it seems likely that the wage floors due to 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 random censoring, i.e. censoring that is independent of the regressor variables. The second step automatically takes account of the sampling variability in the cell quantiles. Formally, it involves weighted least squares regressions of the type

$$\hat{q}_\theta(w_{r,i}|k) = x_k \beta_\theta + \epsilon_k^\theta, \quad (8)$$

where  $k$  denotes the cell,  $\hat{q}_\theta(w_{r,i}|k)$  the empirical  $\theta$ -quantile of (log) wages in cell  $k$ ,  $x_k$  the regressor which is constant within cells,  $\epsilon_k^\theta$  the cell and quantile specific error term, and  $\beta_\theta$  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.<sup>2</sup> Here, cells are defined by education and age of the worker, by the district, where employment is based, and by the year of observation.

The variance-covariance matrix of the coefficient estimates involves heteroscedasticity due to different cell sizes and due to differences in the within wage distribution. In fact, even when assuming i.i.d. errors within cells, the variance of  $\epsilon_k^\theta$  is inversely proportional to the cell size (analogous to the case of cell means). To account for different cell sizes, in the second step each cell is weighted by the associated total employment in the cell. However, we do not try to implement a fully efficient GLS procedure, since it depends critically on the density estimates at the particular cell quantiles (which is notoriously hard to estimate unless one assumes an i.i.d. within-cell-distribution and cell sizes are sufficiently large). In addition, one has to take account of dependencies of the

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<sup>2</sup>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.

error terms across cells. Due to the estimation based on cell quantities, conventional inference procedures (heteroscedasticity-consistent standard errors in our subsequent application) already take account of dependencies within cells (see Moulton, 1986 and 1990). The regional econometrics literature emphasizes possible dependencies within a given district (over time and across workers with different characteristics) possibly due to common district effects and also between cells in neighboring districts possibly due to unobservable spillover effects. In the next subsection, we suggest a flexible Block Bootstrap procedure allowing for inference which is robust against heteroscedasticity and all mentioned forms of dependencies within districts and across neighboring districts. Thus, our approach also provides an alternative to deal with the problem of aggregate regressor variables when used in regressions based on more disaggregated data (see Moulton, 1990). Presumably, the use of aggregate regressor variables can result in correlation of the error term across neighboring districts, which robust inference procedures can take account of. This is also more flexible than the alternatives proposed by Moulton (1986, 1990) since we do not have to impose an equicorrelation property for the error terms within and across districts.

### 3.3 Block Bootstrap Procedure for Inference

Robust estimation of the variance-covariance matrix of the two-step 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 containing all education-age-district-year cells for a given district across time.

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

The Block Bootstrap version (BB1) takes account of the correlation of the error term across educations, age, and time in a given district, which might be due to common

unobservable district attributes affecting all observations in the district. 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 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.

### 3.4 Results

Before turning to the interpretation of all quantiles, it is useful to consider the median regression. Table 3 in the appendix presents estimates from a basic regression. 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 the columns BB1 and BB2 contain robust standard errors obtained from Block Bootstrap estimation as discussed in the previous section. 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 (Moulton, 1986) effects present in the data. However, as BB2-standard errors are rarely larger than BB1, there is no indication for additional dependency between neighboring districts. 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,

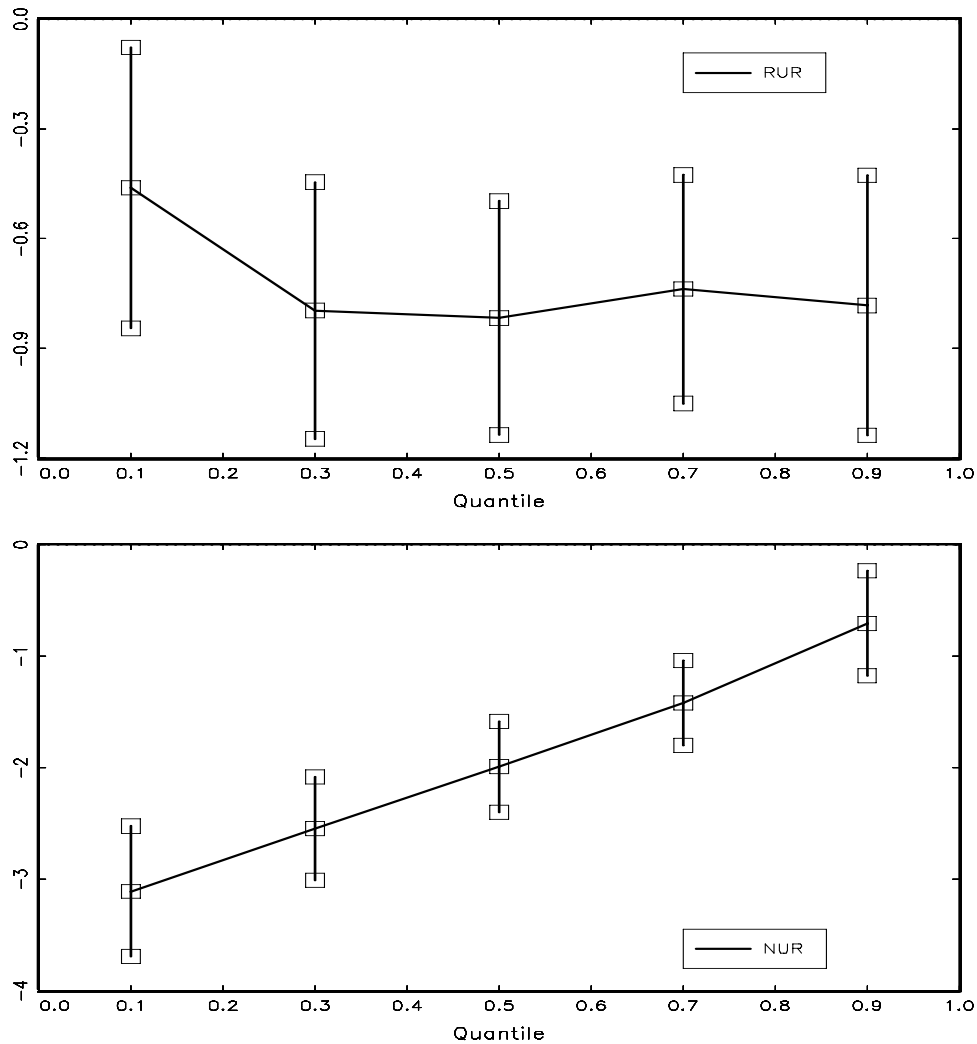
i.e. industries with higher union membership are not associated with higher median wages. This might be related to spillover effects of contract wages to other employees.

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 for the given year, education, and age (cell-specific) unemployment in both the district and its neighbors is taken into account. Additionally, national rates of unemployment (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. Quantitatively, the estimates imply that an increase in the regional rate of unemployment for a given age-education-year group by one percentage point *ceteris paribus* involves a wage decrease of less than one percent ( $= -.817\%$ ), and an increase of the national unemployment for this group by one percentage point involves a wage decrease of about 2 percent. Yet, since the estimated coefficients are semi-elasticities, the coefficients of regional and national unemployment are difficult to compare. Even when the elasticities are equal the estimated coefficients varies with the level of unemployment of the considered age-education group at regional and national level. The insignificance of local unemployment is in line with Büttner (1998), who finds that districts are too small to be considered as (functional) regional labor markets. And, finally, one might expect endogeneity to matter less for the unemployment in the region consisting of the considered district and its neighbors than for unemployment solely in the district.

Table 4 in the appendix contains the regressions not only for the median but 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 decreasing monotonically across the quantiles. This might be due to the censoring of earnings at the social security threshold, since for higher educated censoring is most severe. The effects of the shares 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 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

Figure 1: Impact of Regional and National Unemployment



Notes: Horizontal axis reports the quantiles, vertical axis measures the coefficient estimates as reported in Table 4 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:

RUR	NUR
.165	.000



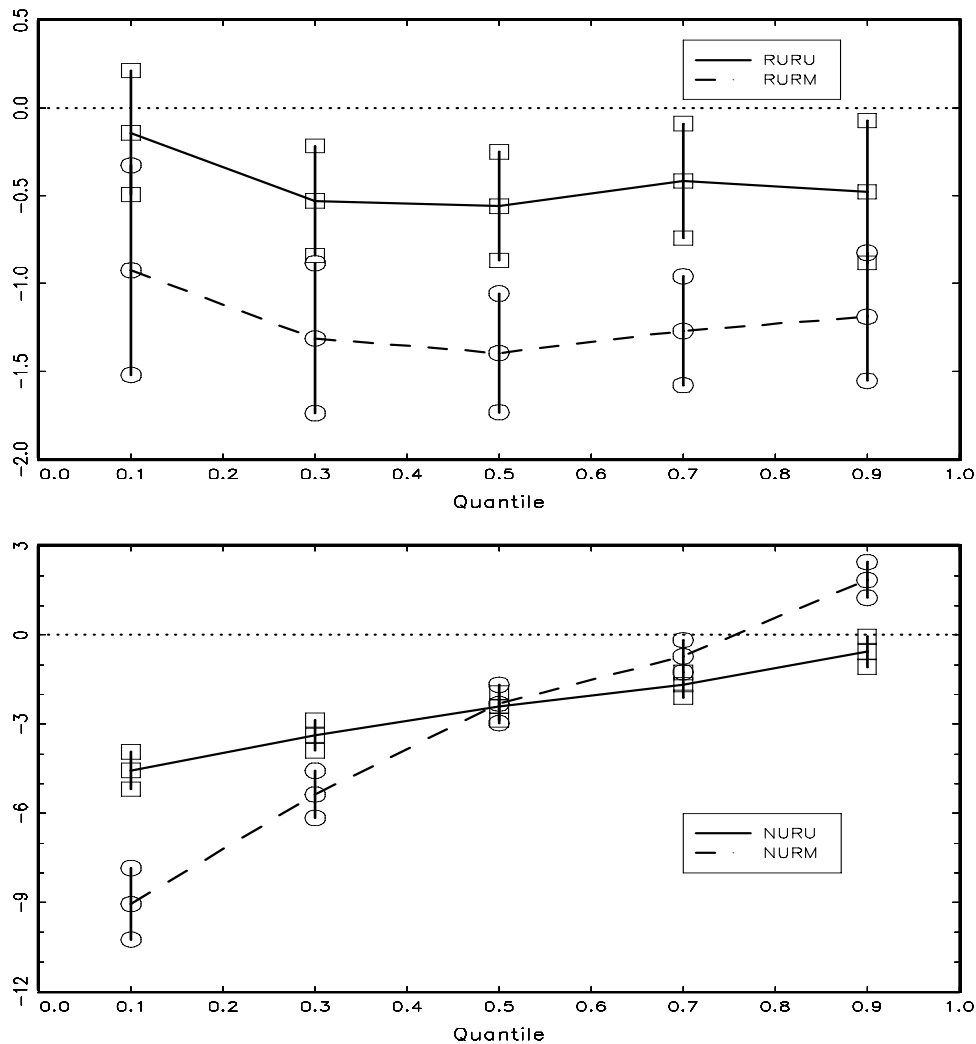
test whether the differences in the coefficients across quantiles are significant. As displayed below Figure 1 the joint test fails to show significant differences. However, the difference between the 10% quantile and the 30% quantile proves to be significant (t-statistic: -2.23). On the other hand, 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. Here the regression reflects the variation of unemployment for labor with certain education and age characteristics around its long run movement, whereas with time dummies the national unemployment variable captures deviations of unemployment for labor with certain education and age characteristics from the average unemployment 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 wage position within a given year.

To avoid problems of multicollinearity the joint inclusion of regional and national unemployment of the considered age-skill-year group requires that there is sufficient region-specific variation. One might assume this requirement to be fulfilled in the German case, which displays large disparities in regional labor market developments. But, this point can be made more precise by running regressions of the regional unemployment rates on the national unemployment rates. It turns out (results are available upon request) that even when considering specific education groups not more than 50 % of the variation of regional unemployment is explained by the national unemployment rate.

In the basic specification, the impact of cell-specific unemployment on wages was implicitly assumed to be the same across educational levels. This might be too strong an assumption, since higher qualified employees exhibit higher interregional mobility, since unemployment varies strongly with the educational level (see Figure 4 in the appendix), and since the wages of the highly skilled are less likely to be determined according to the central wage agreements. And, furthermore, the observations of the highly skilled are much more affected by the censoring in the dataset due to top coding. Therefore, we allow both regional and national unemployment coefficients to differ with respect to education level. However, we omit the local unemployment rate as it proved 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 because of the censoring issue. The coefficients for the regional rates of unemployment are significantly

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):**

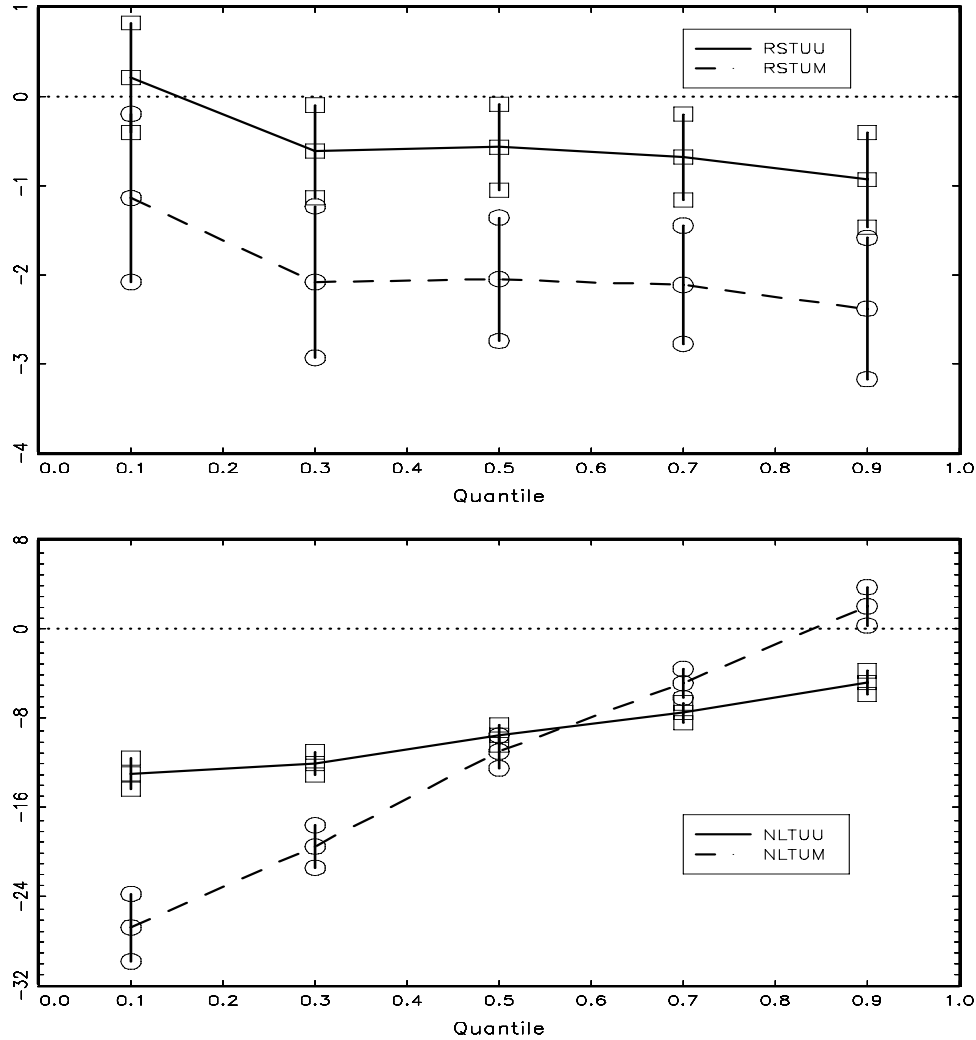
RURU	RURM	NURU	NURM
.011	.207	.000	.000

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 is weakening over the wage distribution.

According to the results in Table 4 to 6, the union density (UD) shows an interesting effect on the wage distribution raising the wage at the lower quantile but lowering the wage at the higher quantile. 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 model  $\alpha_2$  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 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 terms proved insignificant (results are available upon request).

Since the opportunity wage of employed individuals is affected differently depending on whether unemployment is short-term or long-term and whether unemployed individuals participate in publicly sponsored training programs, all of these components of unemployment could exhibit different impacts on wages. As described above, the IABS-REG dataset allows to distinguish between what can be considered as short-term and as long-term unemployment and, furthermore, to identify those unemployed individuals who obtain income maintenance while in continuous training. Under firm-specific wage formation, short-term unemployment will exert a stronger impact on wages than long-term unemployment because the long-term unemployed are less competitive in the labor market (cf. Layard / Nickell / Jackman, 1991). With central wage negotiations this argument is less convincing, since unions might also represent the long-term unemployed and thus reduce pressure in negotiations. However, the share of unemployed receiving income maintenance is expected to have a positive effect on the contract wages, as part of the cost of unemployment is shifted onto the public. The results when decomposing unemployment are presented in Table 6 in the appendix. The main findings relate to the impact of regional short-term and national long-term unemployment, which are presented in Figure 3. Whereas regional

Figure 3: Impacts of Short- and Long-Term 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):**

RSTUU	RSTUM	NLTUU	NLTUM
.006	.116	.000	.000

long-term unemployment essentially has insignificant effects on wages, short-term unemployment exerts the predicted influence. Wage flexibility with respect to short-term unemployment is smallest at the 10-% quantile, even vanishing for the unskilled (RSTUU). This is in line with the theoretical presumption that local wage formation matters most at the upper part of the wage distribution. As in the case of regional unemployment the differences across quantiles are more pronounced for the unskilled than for the medium skilled. Turning to the effects of national unemployment, the coefficients of national short-term unemployment are mainly insignificant, but national long-term unemployment exhibits significant negative effects at the lower quantiles. Also a positive effect of income maintenance is confirmed at the national level. If we assume that unions do, in fact, care for those with long term-unemployment, this finding conforms with the view that central wage formation matters most in the lower part of the wage distribution.

## 4 Summary

Although wage rigidity has a prominent position as one of the possible 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 with the interaction of central wage bargaining and local wage formation (due to firm-level wage bargaining or incentive wages) wage flexibility varies across the wage distribution. Wages in the lower part of the wage distribution are determined mainly by central wage bargaining, whereas at higher wages, local wage formation is more relevant. This implies that local wage flexibility, measured by the response of wages to regional unemployment, is more relevant for the higher part of the wage distribution. On the other hand, if wages negotiated under central wage bargaining respond to national unemployment, its effects may be found in particular at 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 dependencies within groups, and against spatial dependencies. 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. When distinguishing short- and long-term unemployment, we find that regional long-term unemployment has a much weaker impact on wages than short-term unemployment. Regarding short-term unemployment, there is again an increase of wage flexibility over the quantiles except for those with higher education. We also find a negative and asymmetric impact of national unemployment on wages, which is stronger at lower quantiles of the wage distribution. Even national long-term unemployment is found to have a significant negative impact especially on wages at the lower part 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 lower educated labor. 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 may involve a higher wage flexibility for less competitive groups of the labor market.

## A.1 Derivation of Equation (7)

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

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

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

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

. Accordingly, the impact of  $u_r$  on the probability to observe a wage below  $c$  is equal to  $\beta_1$  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:

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

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

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

where  $f_{\epsilon^L}$  and  $f_{\epsilon^C}$  are the marginal densities of  $\epsilon_i^L$  and  $\epsilon_i^C$ , 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:

$$\frac{dq_\theta}{du_r} = -\beta_1 (1 + h(c))^{-1}, \quad \text{where} \quad h(c) = \frac{f_{w^C}(c|u) \text{P}(w_{r,i}^L \leq c | w_i^C = c, u_r)}{f_{w^L}(c|u_r) \text{P}(w_i^C \leq c | w_{r,i}^L = c, u)}.$$

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

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

The above proposition holds, if  $h(c)$  decreases monotonously from infinite values to zero, when  $c$  increases.  $h(c)$  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 most distributions it suffices that the marginal density of contract wage residuals  $f_{\epsilon^C}$  is below the marginal density of local-wage residuals  $f_{\epsilon^L}$  at the bottom and at the top of the distribution, such that the marginal densities intersect twice. For distributions defined over  $] -\infty, +\infty[$  this requirement is implied by a smaller variance of the contract wage distribution compared to the local wage distribution.

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:

$$f_{\epsilon^C}(c) = \frac{1}{b - a}, \quad \text{where} \quad a < c \leq b,$$

$$f_{\epsilon^L}(c) = \frac{1}{b + d_u - (a - d_l)}, \quad \text{where} \quad a - d_l < c \leq b + d_u.$$

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:

$$\text{Var}_{\epsilon^C}(c) \equiv \frac{(b - a)^2}{12} < \text{Var}_{\epsilon^L}(c) \equiv \frac{(b + d_u - a + d_l)^2}{12}.$$

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

$$F_{\epsilon^C}(c) = \frac{c - a}{b - a}, \quad \text{where} \quad a < c \leq b,$$

$$F_{\epsilon^L}(c) = \frac{c - a + d_l}{b - a}, \quad \text{where} \quad a - d_l < c \leq b + d_u.$$



The proposition can easily be shown by deriving  $h$  as:

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

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

$$\lim_{c \rightarrow a} h(c) = \infty,$$

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,

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

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

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

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  $\theta$  gives:

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

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

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

Accordingly, the impact of  $u$  on the probability to observe a wage below  $c$  is equal to  $\beta_2$  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:

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

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

## B Variables, Data Sources, and Definitions

The analysis in this paper is based on two main data sources for West Germany: The regional file of the “IAB–Beschäftigtenstichprobe” (IABS–REG) and the standard file IABS. Both datasets are independent 1% random samples from German social security accounts during the period from 1975 to 1990 which have only recently been made available by the research institute of the Federal Employment Service (“Institut für Arbeitsmarkt– und Berufsforschung”) in Nürnberg. The data are augmented by information on unemployment spells of those workers receiving transfer payments from the Employment Service (“Leistungsempfängerdatei”). The main features of both datasets and a users’ guide for the IABS can be found in Bender et al. (1996). Specifics of the IABS–REG are described in Hilzendegen (1996). Due to data security requirements, the datasets are independent samples and differ in terms of the availability of variables. In this data appendix, we first give a brief description of variables (symbols in parentheses). Then we describe the common features of the two main datasets and finally turn to some specifics.

### 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.

(ERS $i$ ): Proportion of employees in industry  $i$  among all employees in the cell (see Table 2 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. The 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 the total number of persons in each district for the given education–age–year class.
- (RSTUU),(RSTUM),(RSTUH): Regional rates of short term unemployed in the respective education–age–year class, constructed in the same way as the regional unemployment rates. Short term unemployment is identified by the number of unemployed receiving unemployment benefit (“Arbeitslosengeld”), because benefit payments are limited to one year.
- (RLTUU),(RLTUM),(RLTUGH): Regional rates of long term unemployed in the respective education–age–year class, constructed in the same way as the regional unemployment rates. Long term unemployment is identified by the number of unemployed receiving transfer payments (“Arbeitslosenhilfe”) but no unemployment benefits, anymore.
- (RUIMU),(RUIMM),(RUIMH): Regional rates of unemployed with income maintenance in the respective education–age–year class, constructed in the same way as the regional unemployment rates. Unemployed with income maintenance are those participating in continuous training and receiving income maintenance.
- (UD): Predicted union density among all employees in the cell, computed as the weighted average of the aggregate industry specific predicted union density in each year, where the weights are the industry employment shares (ERS<sub>i</sub>) in each cell. Appendix B.4 describes, how the aggregate industry specific union density is predicted.

## 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 educational 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 interpret 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 the 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:

(STU): regular unemployment benefits (“Arbeitslosengeld”) which a worker receives for a certain time length (typically one year) after becoming unemployed, which depend on the previous net earnings and which are not means tested

(LTU): unemployment assistance (“Arbeitslosenhilfe”) which a worker receives after the maximum time length for receiving regular unemployment benefits is exhausted (typically after one year) and which are means tested

(UIM): 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 STU, LTU, and UIM for groups of workers with certain characteristics. A first raw measure of the STU-, the LTU-, and the UIM-rate is given by the ratio of the incidence measure and the total number of person years in a group. We take the incidence of LTU as a proxy for long-term unemployment and the incidence of UIM as a proxy for active labor market policy. 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 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”) had to be combined with neighboring districts to avoid districts with less than 100000 inhabitants. For our empirical analysis, we omit West Berlin leaving us with 259 districts and, for each of these districts, we determine the group of neighbor 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 2.

### B.3 Computation of Unemployment Rates

Given that the IAB-Beschäftigtenstichprobe is drawn randomly from the population of social security accounts, unemployment is underrepresented in the dataset. 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

Table 2: Industry Classification in IABS-REG<sup>a</sup>

No.	Industry German	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 anderweitig nicht genannt	Other Services
70	Gebietskörperschaften und Sozialversicherungen	Government
73	Organisationen ohne Erwerbscharakter und Private Haushalte	Non-Profit Organizations and Private Households

a: The industry classification used in this paper uses the classification given by the IABS-REG dataset. The numbers refer to the classification numbers used in the National Accounts of the German Statistical Office (“Statistisches Bundesamt”, FS 18, R 1.3).

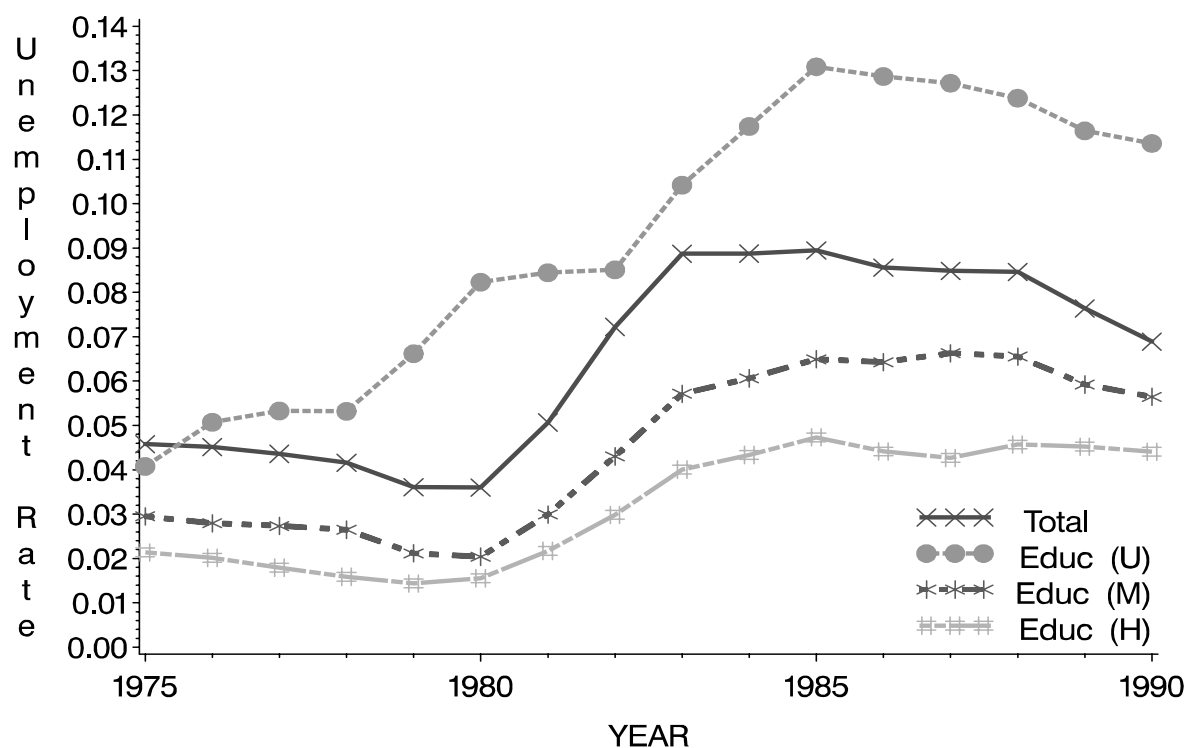
the raw unemployment rates such that after aggregating the entire sample the annual education-specific unemployment rates correspond to the rates depicted in Figure 4.

When explicitly aggregating the raw unemployment rate from the IABS-REG for the three educational groups (US,MS,HS), the estimate is extremely poor for the year 1975 where the aggregate rate in Figure 4 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 (unemployment, STU, LTU, and UIM) 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 4 does not necessarily correspond to a weighted average of education-specific unemployment rates.

Figure 4: 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 / Haggenev / Ernst (1998) 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 results of the study show 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 (we only neglect the significant influence of political preferences). This specification is used to predict union membership rates among all employed workers in 46 industries for the years 1975 to 1990 (for further details see Fitzenberger / Haggenev / Ernst, 1998). Given the estimated probit membership function, it proves very 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<sup>3</sup> 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 2) 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.

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<sup>3</sup>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 / Haggenev / Ernst (1998, appendix) for details.



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## D Tables

Table 3: Median Regression Estimates (1976–1990)

Variable	Coeff.	standard errors			Variable	Coeff.	standard errors		
		HC	BB1	BB2			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).

Table 4: Quantile Regression Estimates (1976–1990)

Variable	$\theta = 0.1$		$\theta = 0.3$		$\theta = 0.5$		$\theta = 0.7$		$\theta = 0.9$	
	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)

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	$\theta = 0.1$	$\theta = 0.3$	$\theta = 0.5$	$\theta = 0.7$	$\theta = 0.9$
Variable	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)	Coeff. (s.e.)
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 first order neighbors in the given year (based on 1000 resamples).

Table 5: 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	2.643(.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)

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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.)
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 4.

Table 6: 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	2.434 (.881)	3.397 (.716)	4.770 (.573)	5.733 (.457)	6.232 (.644)
MS	.209 (.026)	.248 (.019)	.228 (.015)	.237 (.015)	.229 (.015)
HS	.860 (.048)	.641 (.030)	.453 (.025)	.292 (.022)	.115 (.021)
FEMR	-.306 (.119)	-.461 (.105)	-.568 (.087)	-.600 (.085)	-.582 (.094)
PARTR	-.813 (.225)	-.877 (.221)	-.564 (.187)	-.442 (.178)	-.429 (.199)
AGE30	.078 (.011)	.154 (.008)	.168 (.006)	.162 (.005)	.139 (.005)
AGE40	.067 (.017)	.126 (.011)	.147 (.009)	.141 (.007)	.125 (.007)
AGE50	.245 (.017)	.256 (.011)	.226 (.009)	.172 (.008)	.107 (.008)
UD	.059 (.044)	.036 (.036)	-.021 (.029)	-.061 (.023)	-.079 (.033)
RSTUU	.212 (.313)	-.614 (.265)	-.568 (.245)	-.678 (.245)	-.933 (.270)
RSTUM	-1.136 (.481)	-2.081 (.433)	-2.050 (.353)	-2.113 (.339)	-2.379 (.405)
RSTUH	-1.396 (.531)	-1.854 (.407)	-1.866 (.417)	-1.406 (.324)	-1.170 (.316)
RLTUU	-.281 (.312)	-.445 (.270)	-.474 (.255)	-.099 (.278)	.036 (.322)
RLTUM	-.018 (.706)	-.391 (.563)	-.664 (.442)	-.573 (.410)	-.298 (.488)
RLTUH	-.738 (.645)	-1.069 (.417)	-.984 (.401)	-1.370 (.345)	-1.393 (.309)
RUIMU	.432(1.204)	3.623 (.927)	2.607 (.798)	1.921 (.750)	1.004 (.843)
RUIMM	-6.090(1.689)	-2.127(1.216)	-2.008 (.946)	-.390 (.795)	.598 (.929)
RUIMH	-1.496(1.644)	-.773 (.927)	-.425 (.714)	.299 (.586)	.123 (.728)
NSTUU	.518 (.718)	.945 (.540)	.316 (.451)	.286 (.401)	.021 (.434)
NSTUM	.305(1.142)	.867 (.874)	-.280 (.736)	-1.269 (.672)	-1.499 (.861)
NSTUH	1.545(2.317)	1.568(1.566)	4.352(1.363)	4.165(1.087)	4.558(1.233)
NLTUU	-12.988 (.713)	-12.090 (.528)	-9.516 (.445)	-7.516 (.459)	-4.796 (.544)
NLTUM	-26.810(1.545)	-19.523 (.981)	-11.013 (.752)	-4.871 (.658)	2.027 (.879)
NLTUH	-28.260(1.858)	-21.120(1.449)	-14.139(1.314)	-7.752(1.063)	-1.283(1.078)
NUIMU	24.820(2.139)	27.746(1.758)	24.513(1.579)	17.886(1.316)	14.387(1.379)
NUIMM	21.570(3.803)	16.766(2.717)	12.250(2.145)	1.902(1.702)	-2.539(2.011)
NUIMH	-10.100(6.765)	25.586(5.459)	27.534(3.572)	29.900(3.782)	29.921(3.618)

Notes: The coefficients for the employment proportion in the different industries are not displayed. For further notes see table 4.