SFB 649 Discussion Paper 2008-041

Unionization, Stochastic Dominance, and Compression of the Wage Distribution: Evidence from Germany

Michael C. Burda*
Bernd Fitzenberger**
Alexander Lembcke***
Thorsten Vogel*

* Humboldt-Universität zu Berlin, Germany
** Albert Ludwigs-Universität Freiburg
*** London School of Economics and Political Science, UK, and Albert-Ludwigs-University Freiburg.

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

http://sfb649.wiwi.hu-berlin.de
ISSN 1860-5664

SFB 649, Humboldt-Universität zu Berlin
Spandauer Straße 1, D-10178 Berlin

Unionization, Stochastic Dominance, and Compression of the Wage Distribution: Evidence from Germany*

Michael Burda†, Bernd Fitzenberger‡, Alexander Lembcke§, Thorsten Vogel†

6 March 2008

Abstract

This paper establishes theoretical and empirical linkages between union wage setting and the structure of the wage distribution. Theoretically, we identify conditions under which a right-to-manage model implies compression of the wage distribution in the union sector relative to the nonunion sector as well as first-order stochastic dominance. These implications are investigated using quantile regressions on the 2001 GSES, a large German linked employer–employee data set which contains explicit information on coverage by collective agreements. The empirical results confirm that, in case of industry-wide collective agreements, log union wage effects decline in quantiles, implying union wage compression. This finding, however, cannot be corroborated for wages determined at the firm level. Stochastic dominance is confirmed, as predicted by the theoretical model, for both types of collective agreements.

Keywords: Union wage effect, stochastic dominance, wage compression, quantile regressions, Machado-Mata decomposition

JEL: J31, J51, J52.

---

*This paper was written as part of the research project "Collective Bargaining and the Distribution of Wages: Theory and Empirical Evidence" under the DFG research program "Flexibility in Heterogenous Labor Markets" (FSP 1169). Financial support from the German Science Foundation (DFG) is gratefully acknowledged. Michael Burda and Thorsten Vogel also acknowledge support through the SFB 649 "Economic Risk". We thank the Research Data Center (FDZ) of the Hessian Statistical Office and, especially Hans-Peter Hafner for support with the data used in this study; all errors are our own.

†School of Business and Economics, Humboldt-Universität zu Berlin, Spandauer Str. 1, 10178 Berlin, Germany

‡Department of Economics, Albert Ludwigs-University Freiburg, 79085 Freiburg, Germany, Email: bernd.fitzenberger@vwl.uni-freiburg.de

§London School of Economics and Political Science, UK, and Albert-Ludwigs-University Freiburg.

1 Introduction

The impact of labor market institutions on economic performance in general, and on wage setting in particular, remains subject to intense scrutiny and debate (OECD 2006). Among the most prominent institutions under discussion is collective bargaining and its effect on the structure of earnings. It is widely held that collective bargaining raises wages and reduces wage inequality, possibly at the cost of reduced employment at the lower end of the wage distribution. While a large literature has concluded that the first outcome is robust (e.g., Lewis 1986, Blau and Kahn 1996, Card, Lemieux, and Riddell 2003), the notion that collective bargaining directly affects the wage distribution has virtually no explicit theoretical underpinning in the literature, and few if any tests have examined explicitly the effect of collective bargaining on the entire wage distribution.[1]

This paper shows that a leading model of wage setting under collective bargaining, the right–to–manage model (see Nickell and Andrews 1983, Cahuc and Zylberberg 2004), actually predicts such an effect on the quantiles of the wage distribution under certain conditions. We propose a simple right-to-manage model of wage determination in which there is a large number of segmented labor markets—implying a large number of different prevailing wage rates. In addition, we assume that labor demand is sufficiently elastic in the wage rate. This model, it is shown, implies compression of the support of the distribution of wages in the union sector compared to the nonunion sector which, in general, is associated with reduced dispersion of union wages. More specifically, our theoretical analysis thus suggests that log union wage markups decrease in quantiles of the wage distribution. Moreover, positive union wage markups in combination with the associated unemployment of some workers imply first-order stochastic dominance of the union wage distribution.

We employ quantile regression techniques to investigate the implications of the theory because it allows straightforward tests of the two predictions of our theoretical model: wage compression and stochastic dominance. To detect union wage compression, one can regress for a number of different quantiles (e.g., the 10th, the 50th, and the 90th percentile) log hourly wages on a dummy variable indicating whether wages are determined by a collective bargaining agreement. The coefficients of this variable capture the markups of log union wages at the respective quantiles. If these markups are declining in quantiles, union wages are compressed with respect to the log wage difference criterion. Moreover, if these markups are positive for the whole quantile regression process, union wages first-

[1] See also MaCurdy and Pencavel (1986), Brown and Ashenfelter (1986), Christofides (1990), Christofides and Oswald (1991). Fitzenberger and Kohn (2005) and Fitzenberger, Kohn, and Lembcke (2008) provide evidence that unionization compresses wages.

order stochastically dominate spot market wages.

Germany provides a particularly useful testing ground for studying the implications of union wage bargaining on the wage distribution. This is because, while the majority of workers is covered by union wage contracts, a large fraction of the workforce is not. Furthermore, union wage contracts may be industry–wide collective agreements, a dominant model of wage setting in corporatist economies, or firm–level agreements, which instead resemble the Anglo–Saxon approach to collective bargaining. The data used allow us to analyze differences in outcomes under both bargaining regimes. The dataset studied is the German Structure of Earnings Survey 2001 (GSES, or *Gehalt- und Lohnstrukturerhebung*), a large linked employer–employee file which contains detailed information on whether or not a worker is covered by a collective agreement and, if so, whether his contract falls under a industry–wide collective agreement or is determined at the firm–level. For each type of union coverage, the unconditional wage distribution is compared with that of uncovered workers. The empirical results show that for industry–wide bargaining the union wage effects are indeed higher in the lower part of the wage distribution compared to the upper part. Such a change across the wage distribution is however not found for firm–level bargaining. First–order stochastic dominance is confirmed under both industry-wide and firm-level collective bargaining.

The paper is structured as follows. Section 2 sketches a theoretical model which can account for the effects of unions on the wage distribution. Section 3 gives a brief review of collective bargaining in Germany, while section 4 describes the data. Section 5 discusses the econometric analysis and present the empirical results. Section 6 concludes. An appendix explains how clustered asymptotic standard errors are calculated for quantile regression and provides further information on the data and detailed empirical results.

2 The model

2.1 Structure and Technology

Consider an economy in which final output Y is produced by a representative, competitive firm which uses a large number of different intermediate inputs, indexed by $i \in \{1, ..., H\}$, with a constant returns production function $Y = G(Y_1, \ldots, Y_H) = \sum_{i=1}^{H} Y_i$. Each individual intermediate input is produced with a single type of labor L_i and physical capital K_i using a linear homogenous neoclassical production function $Y_i = \theta_i F(K_i, L_i)$, where θ_i is a productivity parameter which is a random variable drawn with support $[\underline{\theta}, \overline{\theta}]$ and cumulative distribution $\Theta(.)$. For simplicity, we assume a unit elasticity of substitution between labor and capital, which implies the Cobb-Douglas form $F(K, L) = K^{\alpha} L^{1-\alpha}$.[2] Each type of labor, defined by human capital attributes, qualifications and other indicators of productivity, is traded in a perfectly segmented market defined by immobility across those attributes. Intermediate producers are perfect competitors in both product and factor markets. Given K_i and θ_i, profit-maximizing behavior induces a demand for labor as a function of wages w_i in each segmented labor market given by $L^D(w_i | \theta_i, K_i)$, irrespective of how wages are determined. Since firm size is indeterminate, we let all firms be equally large to simplify the presentation.

In each labor market i, the supply of labor is denoted by $L_i^S(w_i)$. It is assumed to increase in the wage rate ($L_i^{S\prime} > 0$) and we denote the elasticity of labor supply as $\varepsilon_i(w_i)$. For convenience assume that $\varepsilon \geq 0$ is identical and constant for all i; i.e. $L_i^S = \Lambda_i w_i^{\epsilon}$ where Λ_i denotes the supply of type-i workers at unit wages.

An exogenous fraction c_i of workers each labor market i is represented by a labor union, which determines their wages in bargaining with firms. Firms subject to union wage determination are denoted as *covered firms* and workers employed there as *covered workers*. Hence, $(1 - c_i) L_{ui}^S = c_i L_{si}^S$ where subscripts u and s indicate labor in unionized (covered) firms and labor in firms that hire on the spot labor markets. Both covered and uncovered firms take the wage as given but are free to set employment to maximize profits. We ignore for the moment both the determination of union status of firms as well as selectivity of workers into unions; we will in fact impose conditions which ensure that workers never switch between covered and uncovered firms.[3]

We assume that the skill structure of covered and uncovered workers is symmetrical; i.e., that $c = c_i$ for all i. The important implication of this assumption is that for zero union wage mark-ups, the (unconditional) wage distribution of covered and uncovered workers is identical. Below, our empirical investigation will control for a large number of observable influences on wages and thereby for different skill compositions of the covered and uncovered labor force. For convenience we also assume that all labor markets are equally large, i.e., that $\Lambda_i = \Lambda$.

This paper abstracts from capital adjustments that are due to union wage structuring. Assuming symmetry of labor markets, we let capital intensities (defined as K/L) be identical in all labor markets and for any given wage.[4] From now on we therefore normalize and set $K_i = 1$ for all i such that covered and uncovered firms in labor market i utilize

[2]This assumption is made for simplicity. Vogel (2007) develops a more general version of this model assuming only that the elasticity of substitution does not exceed unity.

[3]Effectively we are assuming here that the "treatment" of workers with a union contract is exogenous. This assumption is, of course, highly problematic and will be discussed in the empirical section of the paper.

[4]See Vogel (2007) for an analysis of capital adjustments in a fully-fledged general equilibrium model.

respectively c and $1-c$ units of capital.

2.2 Uncovered workers

Wages in the uncovered sector are determined competitively. We now characterize the wage distribution that obtains for uncovered workers seeking employment in a typical spot labor market. Denote by $\overline{w}$ the wage-equivalent of the utility of an unemployed worker, which is assumed exogenous. Spot market wages for each labor type i are determined by a standard market clearing condition:

$$w_{si} = \theta_i F_L \left(1-c, L_s^S\left(w_{si}\right)\right) = \left(1-\alpha\right)\theta_i \left[1-c\right]^{\alpha} \left[L_s^S\left(w_{si}\right)\right]^{-\alpha} \tag{1}$$

Assume that even for the least productive workers the market clearing wage exceeds the reservation wage $\overline{w}$. It follows that spot market wages will increase monotonically in θ and are distributed on the support $[w_s^{\min}, w_s^{\max}]$ where $w^{\min} = \underline{\theta} F_L\left(1, L^S\left(w^{\min}\right)\right)$, $w^{\max} = \overline{\theta} F_L\left(1, L^S\left(w^{\max}\right)\right)$, and

$$\frac{\widehat{w_s}}{\widehat{\theta}} = \frac{dw_s/d\theta}{w_s/\theta} = \frac{1}{\alpha\varepsilon+1} \leq 1. \tag{2}$$

Figure 1 depicts labor supply and labor demand for three labor types, differentiated by their productivity θ_i.

Figure 1 about here

2.3 Covered workers

Wages in the covered sector are characterized by the solution of a *right-to-manage* problem, which is the Nash solution of a bargaining problem in which the fallback position for workers is to find employment in firms paying spot market wages w_{si}, while for firms the fallback is to hire workers at monopoly union wages w_{mi}. Then the union wage bargain solves

$$w_{ui} = \arg \max_{w \in [w_{si}, w_{mi}]} \left(w - w_{si}\right)^{\beta} \left(w_{mi} - w\right)^{1-\beta}$$

which implies the solution

$$w_{ui} = \left(1-\beta\right) w_{si} + \beta w_{mi} \tag{3}$$

where $\beta \in [0,1]$ parametrizes the union's bargaining power. One extreme case of such a right-to-manage model is the monopoly union model ($\beta = 1$), in which unions have the power to set wages unilaterally. In the other extreme ($\beta = 0$), wages of covered workers are identical to wages of uncovered workers at the spot wage. Depending on unions' bargaining power, the wage agreed on by firms and unions, w_{ui}, is located somewhere between these extremes.

To determine the wage under right-to-manage we have yet to find the monopoly union wage. The monopoly union chooses the wage w_{mi} so as to maximize expected utility of $L_u^S(w_{mi})$ covered workers (affiliated with covered firms),

$$\frac{L^D(w_{mi}|\theta_i, c)}{L_u^S(w_{mi})}u(w_{mi}) + \frac{L_u^S(w_{mi}) - L^D(w_{mi}|\theta_i, c)}{L_u^S(w_{mi})}u(\overline{w}),$$

where the union takes productivity θ_i and the capital stock $K_{ui} = c$ as given. Utility $u(\cdot)$ is concave, though not necessarily strictly concave function of the wage. Without loss of generality $u(\cdot)$ can be normalized such that $u(\overline{w}) = 0$.[5] So the monopoly union wage maximizes

$$\frac{L^D(w_{mi}|\theta_i, c)}{L_u^S(w_{mi})}u(w_{mi}).$$

It is standard that the interior solution to the maximization problem of the monopoly union can be characterized by the tangency condition of labor demand and union indifference curves, as depicted in Figure 1 (McDonald and Solow 1981, Oswald 1982, Farber 1986). Given the constant elasticity of the labor demand curve, the first-order condition of the union maximization problem yields

$$\frac{u'(w_{mi})\, w_{mi}}{u(w_{mi})} = \frac{1}{\alpha} + \varepsilon \tag{4}$$

as long as the solution satisfies $w_{mi} \geq w_{si}$.

Since $u'w/u$ is decreasing in w if $u'w/u > 1$ and because $1/\alpha > 1$ and $\varepsilon \geq 0$, the solution to condition (4) is unique. Note furthermore that it is independent of the productivity parameter θ_i. Thus, the monopoly union wage is the same for all labor types i as long as the solution of (4) is not smaller than w_{si} (see the thick solid upper curve in

[5] Maximization of a Benthamite utility function

$$L^D(w_{mi}|\theta_i, c)\, u(w_{mi})$$

yields almost identical results. In fact, the first-order condition then becomes identical to condition (4) with $\varepsilon(w_{mi})$ set to zero.

Figure 1 and notice that it is horizontal for small θ). By contrast, if the solution of (4) is below w_{si}, for these labor types i markets clear. Then $w_{si} = w_{mi}$ and hence both wages increase with total factor productivity according to (2).

Denote the specific total factor productivity for which labor markets just clear by θ^* such that $w_{si} < w_{mi}$ for all i with $\theta < \theta^*$ and $w_{si} = w_{mi}$ for all i with $\theta \geq \theta^*$. Although none of our results depend on this, it is convenient to assume that the latter labor types actually exists; i.e., that for some labor types productivity is sufficiently high such that both union wage mark-ups and unemployment vanish. Having obtained both spot market and monopoly union wages, wages under right-to-manage (w_{ui}) are easily determined from (3). Due to (2) the right-to-manage w_{ui} actually increases smoothly in θ (assuming $\beta < 1$), even though monopoly union wages are constant for all $\theta < \theta^*$.

Finally, notice that the model admits the co-existence of covered and uncovered firms in equilibrium, notwithstanding the fact that expected utility of covered and uncovered workers may differ. To see this denote expected utility of a type-i worker initially affiliated with a covered firm as v_{ui} and as v_{si} if initially affiliated with a uncovered firm. It is intuitive to conclude that $v_{ui} > v_{si}$ whenever $w_{ui} > w_{si}$. Under such conditions, positive wage differences persist for the same reason that different types of human capital co-exist even though they are remunerated at different rates: if switching costs from uncovered to covered firms are sufficiently high, workers will refrain from incurring them.[6]

2.4 Stochastic dominance

A distribution described by the cumulative distribution function $Y(x)$ is said to first-order stochastically dominate another distribution $Z(x)$ if $Y(x) \geq Z(x)$, with strict inequality holding for at least one x (Davidson 2008). We now argue that the wage distribution induced under right-to-manage will first-order stochastically dominate that paid on spot markets. In fact, the fraction of workers on spot markets earning more than any given $w \geq w^{\min}$ is *strictly* smaller than the respective fraction of workers employed in covered firms. Comparing wages paid on labor markets with different productivity θ, from now on we drop the subscripts i.

To generate intuition for this argument, it is useful to distinguish between two effects which both work in the same direction. First, consider the direct union effect of raising wages, abstracting from adverse effects on employment. If this wage increase is positive everywhere, the union wage distribution would be located to the right of the spot wage at

[6]If for some labor type i these costs (in utility terms) exceeded $v_{ui} - v_{si} > 0$, the wage difference $w_{ui} - w_{si} > 0$ could persist. In a dynamic setting a complementary explanation could also be based on one-time costs such as re-training or moving costs. Obviously, such one-time costs incurred at the initial period need to be the larger, the greater $v_{ui} - v_{si}$ and the smaller the rate of time preference.

each value of the cumulative distribution function (CDF). If the union wage is identical to the spot market above some critical wage w^*, the union wage distribution function is located below the spot wage distribution for all $w \in \left(w^{\min}, w^*\right)$ and coincides with the spot wage distribution for all $w \geq w^*$. This direct wage effect is shown in Figure 2 as the first, rightward shift of the CDF of the spot wage distribution.

Figure 2 about here

Yet a second employment effect can be seen to add to the direct wage effect because—comparing outcomes across labor markets with different θ—employment is positively correlated with wages. This implies that union wage setting crowds those (covered) workers out of employment which earn relatively low wages. Thus, the employment effect skews the wage distribution of covered workers towards higher wages. In the case of constant labor supply ($\varepsilon = 0$), the employment effect would follow simply from the observation that in all labor markets where $w_u > w_s$, it holds that $L_u < L_s$ and

$$\frac{d \log L_u}{d \log \theta} > 0 = \frac{d \log L_s}{d \log \theta}.$$

Similarly, if labor supply increases in the wage ($\varepsilon > 0$) and hence the right-hand side of the above expression is positive, we can show that if $w_m > w_s$

$$\frac{d \log L_u / d \log \theta}{d \log L_s / d \log \theta} > 1,$$

simply because the elasticity of spot wages (with respect to total factor productivity θ) is always higher than the respective elasticity of union wages under right-to-manage.[7] Then, ignoring the direct effect of unions on wages, the fraction of covered workers earning a

[7]In fact, total differentiation of (1) yields

$$\frac{d \log w_u}{d \log \theta} = 1 - \alpha \frac{d \log L_u}{d \log \theta}$$

and a similar expression for the elasticity of spot market wages w_s. From this it is easy to see that if $w_m > w_s$,

$$\frac{d \log L_u / d \log \theta}{d \log L_s / d \log \theta} = \frac{1 - d \log w_u / d \log \theta}{1 - d \log w_s / d \log \theta} > 1.$$

because differentiation of (3) yields

$$0 < \frac{d \log w_u}{d \log \theta} = (1 - \beta) \frac{w_s}{w_u} \frac{d \log w_s}{d \log \theta} < \frac{d \log w_s}{d \log \theta} < 1.$$

wage greater than some given $w > w^{\min}$ is always less than the respective fraction of uncovered workers. This implies that due to these negative employment effects, the union wage distribution is below the spot wage distribution for all $w \in \left[w^{\min}, w^{\max}\right)$—even for wages greater than w^*.

Because wage and employment effects work in the same direction, the union wage distribution is everywhere below the spot wage distribution (over the whole support of w_s, see Figure 2). Stated differently, consider the fraction of covered workers who are paid no more than some given $w \geq w^{\min}$. Then one observes that, first, this wage is paid in a smaller number of labor markets (direct wage effect) and, second, in each labor market, covered firms employ a smaller fraction of workers (employment effect). This result is summarized by the following proposition:

Proposition 1 *The union wage distribution first-order stochastically dominates the distribution of spot market wages. In fact, the fraction of covered workers who receive a wage* $w \in \left[w^{\min}, w^{\max}\right)$ *is strictly smaller than the respective fraction of uncovered workers.*

First-order stochastic dominance has the following implications:

Corollary 2 *At all quantiles* $\tau \in [0, 1)$ *monopoly union wages are strictly greater than spot market wages.*

Corollary 3 *Mean wages of workers determined by a monopoly union are higher than mean wages of workers on spot markets.*

The union wage literature usually focuses on confirmation of Corollary 3 and tries to quantify the actual gap in mean wages of the typical worker. Corollary 2, by contrast, allows for a more direct and hence more powerful test for first-order stochastic dominance.

2.5 Union wage compression

We now show that in the context of the present model, unions compress the wage distribution of covered workers, as measured by a standard wage dispersion measure such as for instance the $90 - 10$ log wage difference. More specifically, we next show that

$$\log \frac{w_u^{\tau''}}{w_u^{\tau'}} < \log \frac{w_s^{\tau''}}{w_s^{\tau'}}$$

for τ'' sufficiently close to one and τ' sufficiently close to zero, where τ'' and τ' (with $\tau'' > \tau'$) denote two quantiles of the respective wage distribution associated with wages $w^{\tau''}$ and $w^{\tau'}$.

This result is based on a simple continuity argument. Unions raise wages of low-paid workers but not of high-paid workers (distinguished by whether their total factor productivity θ being above or below θ^*). Hence, provided that union and spot market wages coincide in at least one labor market (i.e., $\theta^* \leq \overline{\theta}$), the upper bounds of the support of both union and spot market wage distributions are the same (i.e., $\max w_u = \max w_s$) but lower bounds are not.[8] In fact, due to the direct wage effect it holds that $\min w_u > \min w_s$. This implies that the union wage distribution has a smaller support than the spot market wage distribution:

$$\max w_u - \min w_u < \max w_s - \min w_s$$

We use the insight that wage determination under right-to-manage shrinks the support of the corresponding CDF to show union wage compression with respect to important log wage quantile differences. Notice that compression of the support of a wage distribution is identical to a reduction of the $100 - 0$ log wage difference, i.e. of $\log(w^1/w^0)$. Continuity of the log and the fact that a CDF is monotonously increasing then implies that log wage differences such as $\log w^{\tau''} - \log w^{\tau'}$ still reflect the compression of the support provided τ'' is sufficiently large and τ' sufficiently small. In our special case in which $\max w_u = \max w_s$ we can set τ'' to one. Compression of the support is then identical to a reduction of the difference $\log w^1 - \log w^{\tau'}$ for any $\tau' \in [0, 1)$. By continuity, we may now reduce τ'' while still preserving the result that the log wage difference is reduced, showing that wages are compressed. The following proposition summarizes these findings.

Proposition 4 *Let $w_{u/s}^{\tau''}$ and $w_{u/s}^{\tau'}$ denote the τ''th and τ'th quantile of the union wage and, respectively, spot wage distribution. Then for intervals of sufficient size, $\tau'' - \tau' > 0$ the union wage distribution is compressed when compared with the spot labor market; i.e.,* $\log\left(w_s^{\tau''}/w_s^{\tau'}\right) > \log\left(w_u^{\tau''}/w_u^{\tau'}\right)$.

3 Brief Review of Collective Bargaining in Germany

At this juncture, it is useful to contrast modes of wage determination in Germany with standard practice in the UK and the United States. Wages in Germany are set primarily in collective bargaining between a large labor union and an industrial confederation (employers' association), and less likely to be determined at level of the firm or the individual. Such industry–wide agreements (*Flächentarifvertrag*) then apply to firms which

[8] For conciseness we focus on the case where upper bounds of the support are identical but notice that the argument is more general and also holds if $\max w_u > \max w_s$.

are members of the employers' association who signed the contract in a specific region. In our sample, 52% of the employees are covered by such agreements (last column of Table I). If a firm is not member in an employers' association, the firm can directly negotiate pay and conditions with the union, resulting in a firm–level bargaining agreement (*Firmentarifvertrag* or *Haustarifvertrag*).[9] About 10% of the employees in our sample are paid according to firm–level agreements. Thus, while firm–level bargaining is the usual form of a collective bargaining agreement in the UK and the Unites States, in Germany the firm is not the level at which bargaining commonly takes place. Empirical evidence as well as theoretical considerations suggests that industry–wide and firm–level bargaining – while following similar patterns – exhibit differences that are pronounced enough to warrant separate evaluation.[10] The third category of wage agreements finally are described by bilateral or individual negotiations between an employer and an employee, including the mutually-agreed upon application of existing union contracts from other contexts or circumstances ("Anwendungstarifvertrag").

4 The GSES Dataset

Our empirical investigation is based on the 2001 cross-sectional sample of the German Structure of Earnings Survey (GSES, or *Gehalt- und Lohnstrukturerhebung*). The GSES is a linked employer-employee data set containing about 850,000 employees in roughly 22,000 firms from the private sector. It is conducted by the Federal Statistical Office with the express purpose of assaying the structure of earnings in the German private sector. The GSES is a stratified sample of firms with at least ten employees in a large number of industries. Each firm is asked to report basic information regarding the firm and in some more detail certain characteristics such as earnings, age, education, hours worked, tenure and the like of each employee (for firms employing more then 20 workers characteristics of a subsample of employees is reported). Besides being a large sample, this relatively new dataset has a number of distinctive and attractive features. First, it contains detailed and explicit information on union coverage, which is rarely observed in continental Europe. Second, wages are uncensored firm information and are thus more reliable than interview-based surveys (Jacobebbinghaus 2002). Third, hours worked are

[9]Instead of a union, the firm's works council might settle an agreement. We pool those two cases in our analysis and refer to them both as "firm–level bargaining" or "firm–level agreements".

[10]See Gürtzgen (2005, 2006) for empirical evidence as well as a discussion of possible causes for different outcomes of firm–level and industry–wide bargaining. Furthermore, Fitzenberger, Kohn, and Lembcke (2008), Kohn and Lembcke (2007), and Gerlach and Stephan (2006) estimate wage effects of coverage of an individual worker by a collective contract. For Spain, Card and de la Rica (2006) provide evidence on different wage outcomes when bargaining takes place at the firm–level or at the industry–wide.

directly observed. On the other hand, the GSES is not representative for all workers in Germany because it basically omits the public sector and small firms with less than 10 employees; in addition, only cross-sectional information is available.[11]

The focus in this study is on male employees in West Germany aged 25-55 years, who are working full time. We select this group of employees to minimize selection effects of education and early retirement schemes. Given the regional heterogeneity found by Kohn and Lembcke (2007), we focus on West Germany rather than Germany as a whole. After reducing the sample along these lines as well as some minor criteria mentioned in the Appendix, the sample contains approximately 330,000 white and blue collar employees.

As the most relevant variable for the present study, the GSES contains detailed information on union coverage. Coverage is defined as employment under a contract which has been determined in collective bargaining. The GSES report coverage separately for each worker and not just as a dummy variable for a firm.[12] It therefore occurs that within some firms a number of individuals are reported to be covered (by industry–wide or firm–level agreements), while others are not. In the subsequent analysis we focus on firm coverage instead of individual coverage because firm–level coverage is closest to our theoretical model and the estimates are better comparable to studies on Anglo-Saxon countries. There, at least in the private sector, basically all workers are covered or no worker is covered. A firm is considered covered if at least one worker is covered.[13] We recode coverage status of all individuals who are reported to be uncovered but work in a covered firm. After modification therefore within each firm either all workers are uncovered, covered by an industry–wide contract, or covered by a firm–level contract.

5 Econometric investigation

5.1 Econometric methodology

5.1.1 Conditional mean regression

The usual way to estimate trade union wage effects is to model the conditional mean of log hourly wages of employees as a linear function of union coverage and a set of other individual characteristics. As we distinguish for two types of union coverage (industry–

[11]A scientific–use–file (SUF) for the GSES has recently become available. Due to the higher level of aggregation of industries in the SUF, we choose the on-site version of the data at the research data center of the Hessian Statistical Office for our analysis.

[12]This is in contrast to the IAB establishment survey, which only provides a dummy variable on coverage for each firm. The IAB establishment survey is used by Gürtzgen (2005, 2006) and Schnabel (2005).

[13]Since in most firms either a large share of employees is covered or no worker is covered, this choice of threshold for firm coverage is not crucial.

wide and firm–level contracts, see the detailed description of the data above) a typical specification for the log hourly wage, $\log w$, would be

$$E\left[\log w\,|X\,\right] = Z'\beta^z + \beta^i D^i + \beta^f D^f \quad . \tag{5}$$

The base group being employees bargaining over their wages with firms at an individual bases, D^i and D^f indicate whether the firm of the respective worker is covered by a industry–level or a firm–level collective agreement. Z is a collection of other characters of the worker such as age, education, tenure, etc. (including also a constant). For brevity, define $X = \left\{Z, D^i, D^f\right\}$. OLS estimates of β^i and β^f then report the effect of industry–wide and firm–level bargaining on average log wages where, because the dependent variable is measure in logs and the coefficient are relatively close to zero, the coefficients are usually interpreted as a change of average wages in percentage points.

5.1.2 Conditional quantile regression

Least squares regressions focus on the wage level (average wage) only. Yet, in light of the theoretical model above, union wage effects are likely to differ across the distribution. To find evidence for the effect of unionization on the *entire wage distribution*, the empirical investigation will focus on using a set of quantile regression estimates. One the one hand this allows to describe and test union wage compression. On the other hand, it allows to directly test for first-order stochastic dominance.

Specify the τth quantile function of log hourly wages conditional on the set of covariates X as

$$q_{\log w}(\tau|X) = Z'\beta^z(\tau) + \beta^i\left(\tau\right)D^i + \beta^f\left(\tau\right)D^f \tag{6}$$

Quantile regression as introduced by Koenker and Bassett (1978) allows to estimate the coefficients $\beta\left(\tau\right) = \left[\beta^z\left(\tau\right), \beta^i\left(\tau\right), \beta^f\left(\tau\right)\right]$ by quantile τ considered. In our data, firms with more than 20 employees do not report information on all of their employees, but only on a sample of workers. While the computation of consistent regression quantiles is easy to achieve, obtaining consistent standard errors is slightly more complicated. In addition, usually reported standard errors may also be inconsistent in case of firm-specific wage effects (clustering). Standard errors of the quantile regression coefficients then should be adjusted appropriately. As at present standard software does not incorporate these adjustments, we show in the appendix how to consistently estimate the covariance matrix

$\widehat{VAR}(\hat{\beta}(\tau))$, while accounting for both sampling weights and cluster effects.[14]

5.1.3 Decomposition of unconditional quantile functions

For the rest of this subsection ignore the difference between industry–wide and firm–level collective bargaining. It is straightforward to decompose the difference of the unconditional sample quantile functions between covered and uncovered employees (denoted by $\hat{q}_{cov}(\tau)$ and $\hat{q}_{uncov}(\tau)$) as follows:

$$\hat{q}_{cov}(\tau) - \hat{q}_{uncov}(\tau) = [\hat{q}_{cov}(\tau) - \hat{q}_{uc}(\tau)] + [\hat{q}_{uc}(\tau) - \hat{q}_{uncov}(\tau)] \tag{7}$$

where $\hat{q}_{uc}(\tau)$ is the estimated counterfactual quantile function, i.e. the quantile function that would be generated for covered workers were they to be in work as uncovered employees. The first term on the right hand side gives the quantile treatment effect on the treated (QTET), where treatment refers to union coverage. The second term captures the effect of the workers' characteristics. In terms of our theoretical model this means that we evaluate the difference between covered and uncovered sector net of the difference induced by varying skills in the two sectors.[15] This method is an extension of the decomposition of average effects introduced by Blinder (1973) and Oaxaca (1973). For quantile treatment effects the method usually employed is derived by Machado and Mata (2005). In our analysis, we use the alternative approach proposed by Melly (2006) for greater ease in computation.

Given the quantile function (6), the QTET is given by the coefficient $\beta^{cov}(\tau)$. However, if the coefficients $\beta^{z}(\tau)$ are different for covered and uncovered workers (except for the coefficient of the constant), computations of counterfactual quantile functions and hence quantile treatment effects have to take account of this heterogeneity.[16] We estimate unconditional quantile functions for covered (separately for coverage at the industry and at the firm–level) and uncovered employees using their sample counterparts[17], which leaves the counterfactual distribution to be estimated. Following Melly (2006), we estimate the

[14]In principle, bootstrapping is always an alternative approach for estimating $VAR(\hat{\beta}(\tau))$. But due to computational constraints, as in our case, it may not always be feasible.

[15]We assumed in Section 2 that the skill structure in the covered and uncovered sector is the same.

[16]Variation of the coefficient on the constant is already captured by $\beta^{cov}(\tau)$.

[17]While Melly (2006) argues that estimating the unconditional quantile functions is more precise than taking the sample quantiles, robustness checks using the scientific use file exhibited only marginal differences. Since computational resources at the research data center are constrained and our sample size is very large, we choose to use sample quantiles.

counterfactual quantile function as

$$\hat{q}_{uc}(\tau) = \inf\left(q : \frac{1}{N_{cov}} \sum_{j:cov} \hat{F}_{uncov}(q|X_j) \geq \tau\right), \tag{8}$$

where N_{cov} is the number of covered employees in the sample $\{j : cov\}$ and $\hat{F}_{uncov}(q|X_j)$ is the conditional distribution function of wages in the uncovered sample evaluated at the characteristics X_j of the covered individual j. We obtain an estimate for the counterfactual conditional distribution function $F_{uncov}(q|X_j)$ by

$$\hat{F}_{uncov}(q|X_j) = \sum_{m=1}^{M}(\tau_m - \tau_{m-1})\mathbb{1}(X_j'\hat{\beta}_{uncov}(\tau_m) \leq q). \tag{9}$$

where $\mathbb{1}$ is an indicator function, $\hat{\beta}_{uncov}(\tau_m)$ is the sequence of $m = 1, ..., M$ piecewise constant quantile regression coefficient estimates, and $0 = \tau_0 < \tau_1 < \ldots < \tau_M = 1$. Instead of a computationally intensive iterative procedure, we simply arrange the predicted values for all quantiles and all individuals and seek the corresponding value at the τth sample quantile. As a further simplification, we follow the applications in the literature (Machado and Mata 2005, Melly 2006) and estimate 49 evenly spaced quantile regressions starting at the 2%–quantile.[18]

5.1.4 Wage compression and stochastic dominance

Stochastic dominance requires that holding workers' characteristics fixed, the share of covered workers receiving at most a given wage is never greater than the respective share of uncovered workers. This is to say that the wage distribution of covered workers is stochastically dominating at first order if and only if at all quantiles $\tau \in (0, 1)$ the coverage effect is non–negative. Both wage compressing effects of union coverage as well as first-order stochastic dominance can be directly inferred from our quantile regression estimates.

For conditional quantile regressions, our test for conditional stochastic dominance boils down to simple Wald–tests. For instance, in the case that $\beta^{z}(\tau)$ is identical for covered and uncovered workers, we test that for all quantile $\tau \in (0, 1)$ all coefficients $\beta^{cov}(\tau)$ are zero against the one–sided alternative that all coefficients $\beta^{cov}(\tau)$ are non–negative and some are strictly positive. Furthermore, the wage compression effect is investigated by testing whether $\beta^{cov}(\tau)$ are positive and decrease in τ. The latter implies a lower wage

[18]Instead of treating τ as a uniformly distributed random variable on $[0, 1]$, τ is treated as uniformly distributed on the 49 even percentiles. This way, we avoid estimation for all M possible cases, where M can be very large in applications like ours.

dispersion for covered workers compared to uncovered workers.[19] Such simple Wald–tests for stochastic dominance and wage compression become impractical when there is a lot of heterogeneity in the union wage effects depending upon worker and firm characteristics.

Analogous to the conditional quantile regression coefficients, the quantile treatment effects on the treated (QTET) are informative for our purposes and can be used for an unconditional investigation of stochastic dominance. The QTET contrasts the wage distribution in the covered sector with the estimate of what this wage distribution would have been in the hypothetical absence of coverage, holding workers' characteristics constant. The QTET can be analyzed easily even in the presence of heterogeneity where the union wage effects depend upon worker and firm characteristics. Analogous to the argument in footnote 19, the QTET at two given quantiles (τ'' and $\tau' < \tau''$) suggest union wage compression whenever the QTET at τ'' is below the QTET at τ'.

5.2 Descriptive Statistics

The dependent variable is a wage measure constructed as the logarithm of the actual hourly wage in October 2001 (the reference period for the GSES). This was constructed as the ratio of actual gross monthly wage or salary (excluding employer contributions to social insurances) to reported hours (including overtime) in October 2001.

Some summary statistics describing the wage distribution, the number of observations, and the coverage shares are provided in Table I. Further descriptive statistics on our covariates are reported in column 3 of Table II. Among the 330,000 employees about 61% are covered by an industry–wide or a firm–level bargaining agreement (upper panel of Table I). The share decreases by 8 percentage points when we consider coverage at the individual level, not at the firm–level (lower segment of Table I), indicating that there is a non-negligible share of employees who themselves work in covered firms and who are reported to be uncovered.[20]

Columns 2-5 of Table I report descriptive statistics on marginal wage distributions.

[19]For a worker with given characteristics Z_i, union wages are compressed if at two quantiles τ' and $\tau'' > \tau'$ it holds that

$$q_{cov}(\tau''|Z_i) - q_{cov}(\tau'|Z_i) \equiv \beta^{cov}(\tau'') - \beta^{cov}(\tau') + Z_i'[\beta^z(\tau'') - \beta^z(\tau')]$$
$$< q_{uncov}(\tau''|Z_i) - q_{uncov}(\tau'|Z_i) \equiv Z_i'[\beta^z(\tau'') - \beta^z(\tau')]) .$$

Simple rearranging of this inequality proves the claim. This implies in particular that union wages are everywhere compressed, i.e. at all τ' and τ'', if the QTET as a function of τ decreases monotonically.

[20]Furthermore, the shares in the upper panel do not add up to 100% because about 3,500 employees work in firms that pay some of their employees according to a firm–level contract and, at the same time, some of their employees according to a industry–level contract. Such a situation is typically ruled out by German legislation but may occur in practice due to individual agreements or by extension of contracts agreed upon in the past which are still binding for parts of the workforce.

Statistics on firm coverage on which we focus here are shown in the upper panel. We see that while average hourly wages do not differ by more than 3 log points between firm–level and industry–wide bargaining, there is a substantial wage gap between the average wage of workers employed in covered and uncovered firms. In fact, the difference of average wages of workers in uncovered firms and of workers in firms in which wages are determined at the industry–level amounts to about 13 log points. Moreover, wages of covered workers are higher at every quartile with the wage gap but this gap is decreasing as we move to the upper end of the wage distributions. Under industry–wide bargaining the marginal wage distribution hence is compressed with respect to the wage distribution of uncovered workers (individual-level bargaining). Similar conclusions can be drawn from the reported statistics on the marginal distribution of workers employed in firms where wages are contracted at the firm–level.

5.3 Empirical Specifications

We estimate three specifications of the model, involving different sets of covariates. As a baseline specification (specification I), we condition only on age, education, tenure, and professional status. Age is grouped into six 5-year intervals (25-29, 30-34, ...). We distinguish four education categories: low education, vocational training, university graduates, and those workers with missing information on educational attainment. As evidence in Fitzenberger, Garloff, and Kohn (2003) suggests different earnings profiles for different levels of education, age and education variables are interacted. Tenure denotes the number of years the worker is employed by the firm. Professional status reflects the employees' status within the firm, for instance whether an employee is a blue-collar or white-collar worker. In total, there are ten distinct categories, with unskilled laborers at the lower end and executive staff at the upper end.

Specification II differs from the baseline specification in that we also include dummy variables indicating whether the worker also works overtime or is on shift–work. Specification III further includes a set of industry dummies, distinguishing in total 30 industries (2-digit NACE categories). A more detailed description of variables can be found in Table II. Summarizing, our three definitions in this main part are:

(I) Age, Education, Age∗Education, Tenure and Professional Status Category.

(II) Age, Education, Age∗Education, Tenure, Professional Status Category, Night Work, Shift Work, Work on Weekends/Holidays and Overtime.

(III) Age, Education, Age∗Education, Tenure, Professional Status Category, Night Work, Shift Work, Work on Weekends/Holidays, Overtime and Industry.

5.4 Results

5.4.1 OLS estimates

Table III reports OLS estimates of equation (5) for each of the above three specifications. The estimate of β^i can be found in the line saying "industry–wide bargaining", the estimate of β^f in the line on "firm–level bargaining". We find that in all three specifications the union wage markup, as measured by β^i and β^f, is positive and significantly different from zero. In our baseline specification the estimated union wage markup amounts to 9 log points for industry–wide bargaining and to 10 log points for firm–level bargaining. As more covariates are added estimated markups decrease somewhat to 5.5 and 7 log points for industry–wide and firm–level bargaining, but still remain statistically significant.

5.4.2 QR estimates

As argued in Section 5.1.4, union wages are compressed over the whole support of the wage distribution if the quantile regression coefficient for coverage is decreasing over the distribution. Union wages stochastically dominate the wage distribution of uncovered workers if the coefficient is everywhere non–negative and positive for some quantiles. If coefficients on covariates other than the union status ($\beta^z(\tau)$) are identical for all employees, both union wage compression and stochastic dominance can thus be easily detected when plotting the respective coefficients $\beta^i(\tau)$ and $\beta^f(\tau)$ against quantiles τ. Consider for instance the wage distribution of workers covered by industry–wide bargaining agreements. If $\beta^i(\tau)$ is found to decrease monotonically in τ, the distribution of these covered workers is compressed everywhere with respect to the log wage difference inequality measure. More specifically, industry–wide bargaining is associated with a compressed wage distribution with respect to e.g. the 90-10 wage percentile ratio if $\beta^i(.9) < \beta^i(.1)$. If $\beta^i(\tau)$ is found to be non–negative for all quantiles and positive for some quantiles, the wage distribution of this type of covered workers stochastically dominates the wage distribution of uncovered workers.

Figure 3 shows the estimates $\hat{\beta}^i(\tau)$ and $\hat{\beta}^f(\tau)$ for 19 different quantiles ($\tau = .05,.10,.15,\ldots,.95$). Solid lines depict the union wage gap under industry–wide bargaining and dashed lines refer to firm–level bargaining. Thin lines indicate 95 percent (pointwise) confidence bands. In all three graphs we find both $\hat{\beta}^i(\tau)$ and $\hat{\beta}^f(\tau)$ everywhere positive, thus suggesting stochastic dominance of covered wage distributions. Moreover, confidence bands are almost everywhere above zero. In fact, only in specification (III) for the highest quantile can we not reject the hypothesis that the union wage markup is positive.

Considering the wage effects of industry–wide bargaining first (solid lines), we observe that in the baseline specification (I) $\hat{\beta}^i(\tau)$ is relatively flat for low quantiles, but decreases sharply at the upper 20 percent of the wage distribution. With respect to the 90-10 wage percentile ratio the wage distribution of this type of covered workers is hence compressed. Conditioning on other worker characteristics (specification II) and also on industries (specification III), $\hat{\beta}^i(\tau)$ is monotonically decreases over the whole zero-one interval. This indicates that under industry–wide bargaining wages are everywhere compressed.

When bargaining takes place at the firm–level, stochastic dominance holds but wages are not compressed. In fact, in our baseline specification (I) as well as in specification (II) the wage distribution widens at the upper end of the wage distribution. In specification (III), conditioning also on a detailed set of industries, $\hat{\beta}^f(\tau)$ remains almost flat. The data therefore do not support the hypothesis that unions compress the wage distribution if bargaining takes place at the firm–level and not on the industry–wide.

Comparing wages paid in firms covered by industry–wide and firm–level agreements, Figure 3 shows strong differences of union wage effects at the upper end of the wage distributions. While union wage markups are very similar for wages below the median wage, markups decrease for higher wages if industry–wide agreements are applied and increase for firm–level agreements.

Decomposition of unconditional quantile functions

Table IV reports the estimated quantile treatment effect on the treated (QTET). That is, in contrast to the previously discussed results we now allow covered workers to have different age-earnings profiles and also to differ with respect to the wage effects of other characteristics (such as, e.g., industry). Estimating the QTET this way is a sensitivity check of the previous results for conditional quantile effects and it shows explicitly the coverage effects on the unconditional wage distribution of the covered. Note that due to computational constraints at the research data center, we only estimate the QTET at the four quintiles (20%,40%,60%,80%) and we can not provide standard errors.

The marginal wage distributions described in Table I reemerge in the column labeled "total", reporting differences of unconditional quantile functions. The decomposition we present in the table tells us how strong is the effect that is attributable to actual union coverage ("QTET") and how strong is the effect that is due to differences in employees' characteristics ("Char."). Take for instance the first row in the upper panel of Table IV. The table shows that, comparing wages of uncovered workers (base group) and workers whose wages are bargained over at the firm–level, at the 20th percentile of the respective wage distributions wages of covered workers are 0.197 log points greater than wages of uncovered workers. Table IV now says that, considering specification (I) and holding characteristics of covered workers constant, 0.088 (≡QTET) log points of this difference are due to differences in the pay structure, i.e., due to different coefficients. That is, had these covered workers been paid as are uncovered workers, their unconditional wage would have been only 0.088 log points lower, not 0.197. The remaining difference of 0.110 log points is due to differences in the distribution of characteristics between covered and uncovered employees.

There are two important insights to be gained from inspection of Table IV. First, covered workers receive higher wages over the whole wage distribution. The QTET is always positive implying stochastic dominance of the union wage distribution. That is, if uncovered workers had the same distribution of covariates as the covered workers, the marginal wage distribution of covered workers would still dominate the marginal wage distribution of uncovered workers. This results holds true both when wages are determined at the firm or at the industry–level.

The second finding is that the union wage effects lead to a compression of the wage distribution. For both firm–level and industry–wide bargaining it holds quite generally that the greater τ, the lower the QTET. The decline of the estimated QTET in the quantile τ is comparable to the decline of the coefficients $\hat{\beta}^i(\tau)$ and $\hat{\beta}^f(\tau)$ depicted in Figure 3. Thus, also in this more general formulation of model (6)—after all, coefficients $\beta^z(\tau)$ are not assumed to be identical for covered and uncovered workers—we find that unions raise wages of covered workers and at the same time reduce the dispersion of wages, confirming our theoretical results summarized in propositions 1 and 4.

6 Conclusion

This paper develops and tests implications of a right–to–manage model for the distribution of wages. The theoretical analysis implies that the union wage effect decreases when moving up the wage distribution, implying that unions compress the union wage distribution. Moreover, the theoretical model predicts first-order stochastic dominance of union wages. The implications of the theory are testable and were investigated empirically using quantile regressions.

The analysis is based on the German Structure of Earnings Survey 2001, a large linked employer–employee data set which allows to identify coverage by industry–wide and firm–level collective agreement. We analyze both the effect of union coverage on the conditional and the unconditional wage distribution. This is implemented by estimating both the quantile regression coefficients for coverage dummies and the quantile treatment effect for the treated (QTET), i.e. the covered employees. The empirical results show that the union wage effects decline when moving up the wage distribution for industry–wide bargaining but not for firm–level bargaining. First-order stochastic dominance is also confirmed.

Future research should consider the endogeneity of the wage bargaining regime and the selectivity of the uncovered workers in covered firms. Based on more recent data, it will be possible to analyze whether the share of uncovered low wage workers in covered firms has increased over time given that the coverage rates have declined over time and there has been a trend towards higher wage dispersion in the lower part of the wage distribution.

References

Angrist, J., V. Chernozhukov, and I. Fernández-Val (2004): "Quantile Regression under Misspecification, with an Application to the U.S. Wage Structure," Working Paper 10428, NBER.

——— (2006): "Quantile Regression under Misspecification, with an Application to the U.S. Wage Structure," *Econometrica*, 74(2), 539–564.

Blau, F. D., and L. M. Kahn (1996): "International Differences in Male Wage Inequality: Institutions versus Market Forces," *Journal of Political Economy*, 104(4), 791–837.

Blinder, A. S. (1973): "Wage Discrimination: Reduced Form and Structural Estimates," *Journal of Human Resources*, 8(4), 436–455.

Brown, J. N., and O. Ashenfelter (1986): "Testing the Efficiency of Employment Contracts," *Journal of Political Economy*, 94(3), S40–S87.

Cahuc, P., and A. Zylberberg (2004): *Labor Economics*. MIT Press.

Card, D., and S. de la Rica (2006): "Firm-Level Contracting and the Structure of Wages in Spain," *Industrial and Labor Relations Review*, 59(4), 573–592.

Card, D., T. Lemieux, and W. C. Riddell (2003): "Unions and the Wage Structure," in *International Handbook of Trade Unions*, ed. by J. T. Addison, and C. Schnabel, chap. 8, pp. 246–92. Edward Elgar, Cheltenham, UK.

Christofides, L. N. (1990): "Non-Nested Tests of Efficient Bargain and Labour Demand Models," *Economic Letters*, 32, 91–96.

Christofides, L. N., and A. J. Oswald (1991): "Efficient and Inefficient Employment Outcomes: A Study Based on Canadian Contract Data," *Research in Labor Economics*, pp. 173–90.

Davidson, R. (2008): "Stochastic Dominance," in *The New Palgrave Dictionary of Economics*, ed. by S. Durlauf, and L. Blume. Palgrave Macmillan, 2nd edn.

Farber, H. S. (1986): "The Analysis of Union Behavior," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and R. Layard, vol. 2, chap. 18, pp. 1039–1089. Elsevier Science.

Fitzenberger, B., A. Garloff, and K. Kohn (2003): “Beschäftigung und Lohnstrukturen nach Qualifikationen und Altersgruppen: Eine empirische Analyse auf Basis der IAB-Beschäftigtenstichprobe,” *Mitteilungen aus der Arbeitsmarkt- und Berufsforschung*, 36(4), 509–524.

Fitzenberger, B., and K. Kohn (2005): “Gleicher Lohn für gleiche Arbeit? Zum Zusammenhang zwischen Gewerkschaftsmitgliedschaft und Lohnstruktur in Westdeutschland 1985-1997,” *Zeitschrift für Arbeitsmarktforschung*, 38(2/3).

Fitzenberger, B., K. Kohn, and A. C. Lembcke (2008): “Union Density and Varieties of Coverage: The Anatomy of Union Wage Effects in Germany,” Discussion Paper 08-012, ZEW Mannheim.

Froot, K. A. (1989): “Consistent Covariance Matrix Estimation with Cross-Sectional Dependence and Heteroscedasticity in Financial Data,” *Journal of Financial and Quantitative Analysis*, 24(3), 333–355.

Gerlach, K., and G. Stephan (2006): “Pay Policies of Firms and Collective Wage Contracts – An Uneasy Partnership?,” *Industrial Relations*, 45(1), 47–67.

Gürtzgen, N. (2005): “Rent-sharing: Does the bargaining regime make a difference? Theory and empirical evidence,” Discussion Paper 05-15, ZEW Mannheim.

——— (2006): “Rent-Sharing and Collective Bargaining Coverage – Evidence from Linked Employer-Employee Data,” Discussion Paper 05-90, ZEW Mannheim.

Hall, P., and S. J. Sheather (1988): “On the Distribution of a Studentized Quantile,” *Journal of the Royal Statistical Society, Series B*, 50(3), 381–391.

Hendricks, W., and R. Koenker (1992): “Hierarchical Spline Models for Conditional Quantiles and the Demand for Electricity,” *Journal of the American Statistical Association*, 87(417), 58–68.

Jacobebbinghaus, P. (2002): “Die Lohnverteilung in Haushaltsdatensätzen und in amtlich erhobenen Firmendaten,” *Wirtschaft und Statistik*, (3), 209–221.

Koenker, R. (1994): “Confidence Intervals for Regression Quantiles,” in *Asymptotic Statistics: Proceeding of the 5th Prague Symposium on Asymptotic Statistics*, ed. by P. Mandl, and M. Hušková. Physica, Heidelberg.

——— (2005): *Quantile Regression*. Cambridge University Press, Cambridge.

Koenker, R., and G. Bassett (1978): "Regression Quantiles," *Econometrica*, 46(1), 33–50.

Kohn, K., and A. C. Lembcke (2007): "Wage Distributions by Bargaining Regime: Linked Employer-Employee Data Evidence from Germany," Discussion Paper 0813, CEP.

Lewis, H. G. (1986): *Union Relative Wage Effects*. University of Chicago Press, Chicago.

Machado, J. A. F., and J. Mata (2005): "Counterfactual Decomposition of Changes in Wage Distributions using Quantile Regression," *Journal of Applied Econometrics*, 20(4), 445–465.

MaCurdy, T. E., and J. H. Pencavel (1986): "Testing Betwen Competing Models of Wages and Employment Determination in Unionized Markets," *Journal of Political Economy*, 94(3), S3–S39.

McDonald, I. M., and R. M. Solow (1981): "Wage Bargaining and Employment," *American Economic Review*, 71, 896–908.

Melly, B. (2006): "Estimation of counterfactual distributions using quantile regression," Discussion paper, unpublished manuscript, University of St. Gallen.

Moulton, B. R. (1990): "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units," *Review of Economics and Statistics*, 72(2), 334–338.

Nickell, S. J., and M. Andrews (1983): "Unions, Real Wages and Employment in Britain 1951-79," *Oxford Economic Papers*, 35(Supplement), 183–206.

Oaxaca, R. (1973): "Male-female wage differentials in urban labour markets," *International Economic Review*, 14, 693–709.

OECD (ed.) (2006): *OECD Employment Outlook – Boosting Jobs and Incomes*. Organisation for Economic Co-operation and Development, Paris.

Oswald, A. (1982): "The Microeconomic Theory of the Trade Union," *Economic Journal*, 92, 576–595.

Schnabel, C. (2005): "Gewerkschaften und Arbeitgeberverbände: Organisationsgrade, Tarifbindung und Einflüsse auf Löhne und Beschäftigung," *Zeitschrift für Arbeitsmarkt-tForschung*, 38(2/3), 181–196.

Silverman, B. W. (1986): *Density Estimation for Statistics and Data Analysis*. Chapman and Hall, London.

Vogel, T. (2007): "Union wage compression in a Right-to-Manage model," Discussion Paper 2007-009, SFB 649.

Williams, R. L. (2000): "A Note on Robust Variance Estimation for Cluster-Correlated Data," *Biometrics*, 56, 645–646.

Standard Errors for Quantile Regression with Sampling Weights and Clustering

When estimating M quantiles in a non-iid setting, the asymptotic distribution of $\hat{\beta}$, where $\hat{\beta}$ is a column vector with elements $\hat{\beta}(\tau)$ is given by

$$\sqrt{N}(\hat{\beta} - \beta) \sim N(0, VAR) \tag{10}$$

where VAR consists of M blocks given by:

$$VAR(\tau, \tau') = J(\tau)^{-1}\Sigma(\tau, \tau')J(\tau')^{-1} \tag{11}$$

with $VAR(\tau, \tau') = VAR(\hat{\beta}(\tau), \hat{\beta}(\tau'))$. The elements of this sandwich formula are defined as:

$$\Sigma(\tau, \tau') \equiv E[(\tau - \mathbb{1}\{Y < X'\beta(\tau)\})(\tau' - \mathbb{1}\{Y < X'\beta(\tau')\})XX'] \tag{12}$$

and

$$J(\tau) \equiv E[f_y(X'\beta(\tau)|X)XX'] = E[f_u(0|X)XX'], \tag{13}$$

which holds even if the true model is non-linear and the linear specification is only an approximation (Angrist, Chernozhukov, and Fernández-Val 2006). f_u denotes the density of the error term; compare Hendricks and Koenker (1992), Koenker (2005), and Melly (2006). We estimate $VAR(\tau, \tau')$ by

$$\widehat{VAR}(\hat{\beta}(\tau), \hat{\beta}(\tau')) = \frac{1}{N}\hat{J}(\tau)^{-1}\hat{\Sigma}(\tau, \tau')\hat{J}(\tau')^{-1} \tag{14}$$

where bread and butter are estimated as

$$\hat{\Sigma}(\tau, \tau') = \frac{1}{N}\sum_{i=1}^{N}(\tau - \mathbb{1}\{Y_i < X_i'\hat{\beta}(\tau)\})(\tau' - \mathbb{1}\{Y_i < X_i'\hat{\beta}(\tau')\})X_iX_i' \tag{15}$$

and

$$\hat{J}(\tau) = \frac{1}{N}\sum_{i=1}^{N}\hat{f}_iX_iX_i' \tag{16}$$

for the case without weights and without clustering. To estimate the density function we use the "Powell Sandwich"

$$\hat{J}(\tau) = \frac{1}{2Nc_N}\sum_{i=1}^{N}\mathbb{1}(|\hat{u}_i| < c_N)X_iX_i' \tag{17}$$

and define c_N as:

$$c_N = \min\{sd(\hat{u}), IQR(\hat{u})/1.34\}\{\hat{F}^{-1}(\tau + h_N) - \hat{F}^{-1}(\tau + h_N)\} \tag{18}$$

Where the first term on the right hand side is a robust estimate of scale (Silverman 1986) given by the minimum of the standard deviation of the residuals and the interquartile range of the residuals (divided by 1.34). In the second part of the product $\hat{F}^{-1}$, empirical quantile function (of the residuals), is evaluated at a range around the quantile of interest given by the bandwidth h_N. In analogy to Koenker (1994) the empirical quantile function is derived as is an interpolated piecewise linear function of the ordered residuals. To estimate the bandwidth h_N we employ Hall and Sheater's (1988) rule:

$$h_N = \frac{1}{N^{1/3}} z_\alpha^{2/3} [1.5 s(\tau)/s''(\tau)]^{1/3}, \tag{19}$$

where z_α satisfies $\Phi(z_\alpha) = 1 - \alpha/2$ for the construction of $1 - \alpha$ confidence intervals and $s(\tau)$ denotes the sparsity function.[21] As in Koenker (1994), we use the normal distribution to estimate

$$s(\tau)/s''(\tau) = \frac{f^2}{2(f'/f)^2 + [(f'/f)^2 - f''/f]} = \frac{\phi(\Phi(\tau)^{-1})^2}{2(\Phi(\tau)^{-1})^2 + 1}. \tag{20}$$

Analogously to Angrist, Chernozhukov, and Fernández-Val (2004), we take account of sampling weights by replacing (15) with

$$\hat{\Sigma}(\tau, \tau') = \frac{1}{N} \sum_{i=1}^{N} w_i^2 (\tau - \mathbb{1}\{Y_i < X_i'\hat{\beta}(\tau)\})(\tau' - \mathbb{1}\{Y_i < X_i'\hat{\beta}(\tau')\}) X_i X_i' \tag{21}$$

and (16) with

$$\hat{J}(\tau) = \frac{1}{N} \sum_{i=1}^{N} w_i \hat{f}_i X_i X_i'. \tag{22}$$

Clustering allows for dependence of observations within clusters (see Froot (1989), Moulton (1990), or Williams (2000) for the case of OLS). We take account of clustering at the firm level and use sampling weights that indicate the inverse sampling probability of an observation. We normalize by dividing the individual weight by the size of the represented population, $\sum_{i=1}^{N} w_i/N_{pop} = 1$. Acknowledging that the sampling weights in the GSES

[21] The sandwich formula is extensively described in Koenker (2005, pp. 79–80). Koenker also mentions the "Hendricks-Koenker sandwich", which is employed by e. g., Fitzenberger, Kohn, and Lembcke (2008).

are equal for all individuals $i = 1, ..., N_c$ within a cluster c, (21) and (22) generalize to

$$\hat{\Sigma}(\tau, \tau') = \frac{1}{N} \sum_{c=1}^{C} w_c^2 \sum_{i=1}^{N_c} \sum_{j=1}^{N_c} X_{ic}(\tau - \mathbb{1}\{Y_{ic} < X_{ic}'\hat{\beta}(\tau)\})(\tau' - \mathbb{1}\{Y_{jc} < X_{jc}\hat{\beta}(\tau')\})X_{jc}' \quad (23)$$

and

$$\hat{J}(\tau) = \frac{1}{N} \sum_{c=1}^{C} w_c \sum_{i=1}^{N_c} \hat{f}_{ic} X_{ic} X_{ic}'. \quad (24)$$

German Structure of Earnings Survey 2001

The German Structure of Earnings Survey (GSES, *Gehalts- und Lohnstrukturerhebung*) 2001 is a linked employer-employee data set administered by the German Statistical Office in accordance with European and German law (European Council Regulation (EC) No 530/1999, amended by EC 1916/2000; German Law on Wage Statistics, *LohnStatG*). It is a sample of all firms in manufacturing and private service sectors with at least ten employees. Sampling takes place at the firm or establishment level. At a first stage, firms are randomly drawn from every Federal State, where the sampling probability varies between 5.3% for the largest state (North Rhine-Westphalia) and 19.4% for the smallest (Bremen). At the second stage, employees are randomly chosen from the firms sampled at the first stage. The share of employees sampled depends upon the firm size and ranges between 6.25% for the largest firms and 100% for firms with less than 20 employees. The data set provides sampling weights. The GSES 2001 is available for on-site use at Research Centers of the Federal States' Statistical Offices (FDZ) since 2005. This study uses an anonymized use-file which includes all firms and employees from the original data except for one firm in Berlin (the only firm in Berlin falling into NACE section C). Regional information is condensed to 12 "states", and some industries have been aggregated at the two-digit level. Overall, the use-file consists of 22,040 sites with 846,156 sampled employees. We focus on prime-age (25–55-year-old) male full-time employees in West Germany (without Berlin), including both blue and white-collar workers. Employees in vocational training, interns, and employees subject to partial retirement schemes are left out because compensation for these groups does not follow the regular compensation schedule, but special regulations or even special collective bargaining agreements apply. Individuals who worked less than 90% of their contractual working hours in October 2001 and individuals paid subject to a collective contract with a missing identification number for the agreement are dropped. Part-time and full-time employees are distinguished based on the employer's assessment recorded in the GSES. For blue-collar workers, actual working time and not contractual working time is relevant for monthly payments. We exclude individuals with an actual working time of more than 390 hours in October 2001. We analyze gross hourly wages including premia. This measure is more appropriate than wages without premia if premia are paid on a regular basis. We impose a lower bound of one euro for hourly wages.

Tables and Figures

Table I: Sample Statistics

	Log Hourly Wage							
	Mean	S.d.	10%	50%	90%	90/10	#	Share
Individual negotiations	2.73	0.41	2.28	2.66	3.29	2.73	94,173	0.28
Industry-level bargaining	2.88	0.34	2.49	2.84	3.34	2.33	200,885	0.61
Firm-level bargaining	2.92	0.37	2.51	2.88	3.44	2.54	36,604	0.11

"90/10" refers to the ratio w_{90}/w_{10}.

Table II: Definition of Variables

Label	Description	Share/Mean
Specification (I)		
AGE1	Age bracket: 25–29.	0.108
AGE2	Age bracket: 30–34.	0.185
AGE3	Age bracket: 35–39.	0.218
AGE4	Age bracket: 40–44.	0.187
AGE5	Age bracket: 45–49.	0.153
AGE6	Age bracket: 50–55.	0.149
TENURE	Tenure in years/10.	0.925
NA_EDUC	Missing information on the level of education.	0.068
LOW_EDUC	Low level of education: no training beyond a school degree (or no school degree at all).	0.140
MED_EDUC	Intermediate level of education: vocational training.	0.671
HIGH_EDUC	High level of education: university or technical college degree.	0.122
BC_STAT1	Blue-collar worker, professional status category 1: vocationally trained or comparably experienced worker with special skills and highly involved tasks.	0.114
BC_STAT2	Blue-collar worker, professional status category 2: vocationally trained or comparably experienced worker.	0.218
BC_STAT3	Blue-collar worker, professional status category 3: worker trained on-the-job.	0.151
BC_STAT4	Blue-collar worker, professional status category 4: laborer.	0.081
WC_STAT1	White-collar worker, professional status category 1: executive employee.	0.035

Continued on next page...

... table II continued

Label	Description	Share/Mean
WC_STAT2	White-collar worker, professional status category 2: executive employee with limited procuration.	0.157
WC_STAT3	White-collar worker, professional status category 3: employee with special skills or experience who works on his own responsibility on highly involved or complex tasks.	0.099
WC_STAT4	White-collar worker, professional status category 4: vocationally trained or comparably experienced employee who works autonomously on involved tasks.	0.100
WC_STAT5	White-collar worker, professional status category 5: vocationally trained or comparably experienced employee working autonomously.	0.039
WC_STAT6	White-collar worker, professional status category 6: employee working on simple tasks.	0.007
Specification (II)		
NIGHT	Individual worked night shifts.	0.142
SUNDAY	Individual worked on Sundays or on holidays.	0.149
SHIFT	Individual worked shift.	0.221
OVERTIME	Individual worked overtime.	0.257
Specification (III)		
SECTOR1	Mining and quarrying (NACE: 10–14)	0.018
SECTOR2	Manufacture of food products, beverages and tobacco (NACE: 15–16)	0.025
SECTOR3	Manufacture of textiles and textile products; leather and leather products (NACE: 17–19)	0.012
SECTOR4	Manufacture of wood and wood products; pulp, paper and paper products (NACE: 20–21)	0.037
SECTOR5	Publishing, printing and reproduction of recorded media (NACE: 22)	0.029
SECTOR6	Manufacture of coke, refined petroleum products and nuclear fuel; chemicals and chemical products (NACE: 23–24)	0.036
SECTOR7	Manufacture of rubber and plastic products (NACE: 25)	0.039
SECTOR8	Manufacture of other non-metallic mineral products (NACE: 26)	0.031
SECTOR9	Manufacture of basic metals; fabricated metal products, except from machinery and equipment (NACE: 27–28)	0.071
SECTOR10	Manufacture of machinery and equipment n.e.c. (NACE: 29)	0.057
SECTOR11	Manufacture of electrical machinery and apparatus n.e.c. (NACE: 31)	0.028
SECTOR12	Manufacture of electrical and optical equipment; radio, television, and communication equipment and apparatus (NACE: 30 + 32)	0.028

Continued on next page...

... table II continued

Label	Description	Share/Mean
SECTOR13	Manufacture of medical, precision and optical instruments, watches and clocks (NACE: 33)	0.022
SECTOR14	Manufacture of transport equipment (NACE: 34–35)	0.067
SECTOR15	Manufacture n.e.c. (NACE: 36–37)	0.024
SECTOR16	Electricity, gas and water supply (NACE: 40–41)	0.032
SECTOR17	Construction (NACE: 45)	0.066
SECTOR18	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel (NACE: 50)	0.026
SECTOR19	Wholesale trade and commission trade except of motor vehicles and motorcycles (NACE: 51)	0.052
SECTOR20	Retail trade, except from motor vehicles and motorcycles; repair of personal and household goods (NACE: 52)	0.024
SECTOR21	Hotels and restaurants (NACE: 55)	0.010
SECTOR22	Land transport; transport via pipelines; air transport (NACE: 60 + 62)	0.036
SECTOR23	Water transport (NACE: 61)	0.007
SECTOR24	Supporting and auxiliary transport activities; activities of travel agencies (NACE: 63)	0.047
SECTOR25	Post and telecommunications (NACE: 64)	0.023
SECTOR26	Financial intermediation, except from insurance and pension funding; activities auxiliary to financial intermediation, except from insurance and pension funding (NACE: 65 + 67.1)	0.018
SECTOR27	Insurance and pension funding, except compulsory social security; activities auxiliary to insurance and pension funding (NACE: 66 + 67.2)	0.016
SECTOR28	Real estate activities; renting of machinery and equipment without operator and of personal and household goods (NACE: 70–71)	0.011
SECTOR29	Computer and related activities (NACE: 72)	0.029
SECTOR30	Research and development; other business activities (NACE: 73–74)	0.078

Table III: OLS Regression Results

	Specification					
	(I)		**(II)**		**(III)**	
Industry-level bargaining ($\hat{\beta}^i$)	0.089**	(0.005)	0.070**	(0.004)	0.055**	(0.004)
Firm-level bargaining ($\hat{\beta}^f$)	0.103**	(0.016)	0.080**	(0.016)	0.070**	(0.010)

Regressions account for sampling weights. Robust standard errors (accounting for sampling weights and clustering at the firm level) in parentheses. ** indicates significance at the 1% level.

Table IV: Decomposition of Unconditional Quantile Functions

		Specification					
		(I)		**(II)**		**(III)**	
Firm-level bargaining	**total**	QTET	Char.	QTET	Char.	QTET	Char.
$\tau = 0.2$	0.197	0.088	0.110	0.069	0.128	0.073	0.124
$\tau = 0.4$	0.173	0.091	0.082	0.066	0.107	0.072	0.101
$\tau = 0.6$	0.162	0.093	0.069	0.063	0.098	0.072	0.090
$\tau = 0.8$	0.114	0.067	0.047	0.043	0.071	0.048	0.066
Industry-level bargaining							
$\tau = 0.2$	0.189	0.108	0.081	0.090	0.099	0.083	0.106
$\tau = 0.4$	0.163	0.108	0.056	0.087	0.076	0.080	0.083
$\tau = 0.6$	0.138	0.103	0.035	0.080	0.057	0.070	0.068
$\tau = 0.8$	0.065	0.056	0.009	0.042	0.023	0.023	0.042

Decomposition of the sample quantile function difference of unionized (<u>cov</u>ered) and spot market (<u>uncov</u>ered); $\hat{q}_{cov}(\tau) - \hat{q}_{uncov}(\tau)$.
QTET: Quantile Treatment Effect on the Treated ($\hat{q}_{cov}(\tau) - \hat{q}_{uc}(\tau)$). Char.: Impact of employees' (observed) characteristics ($\hat{q}_{uc}(\tau) - \hat{q}_{uncov}(\tau)$).

Figure 1: Comparison of wage determination on spot labor markets and in a monopoly union model

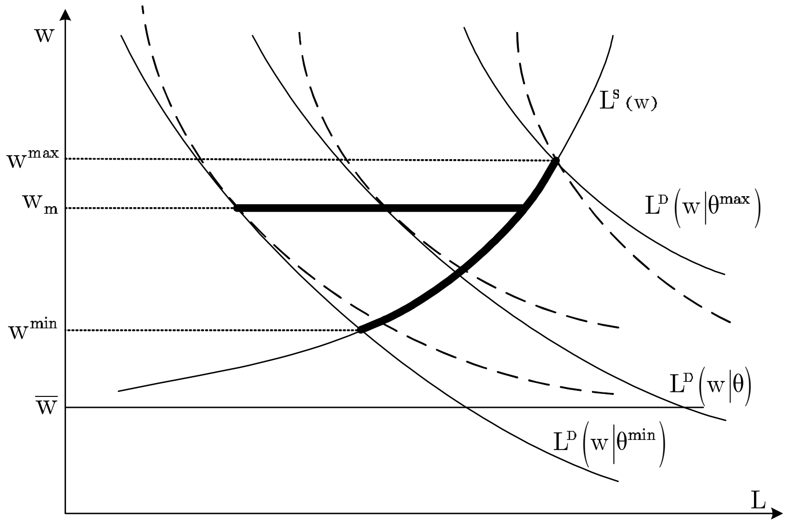


Figure 2: Stochastic Dominance of Wage Distributions

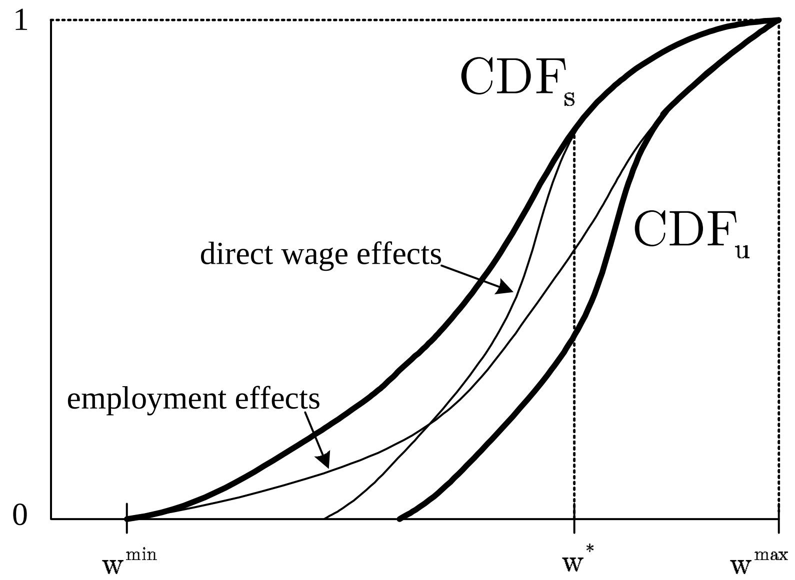
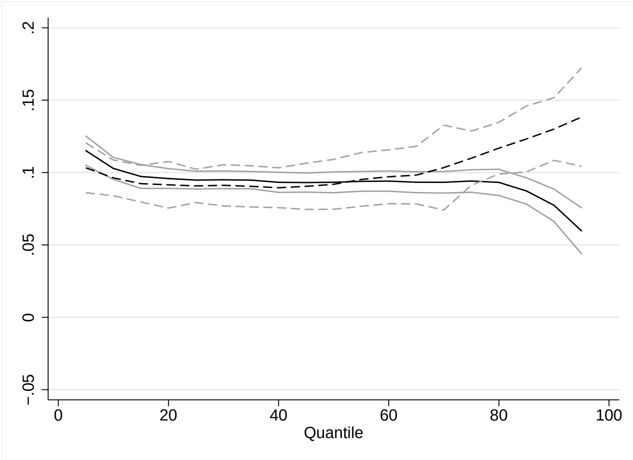
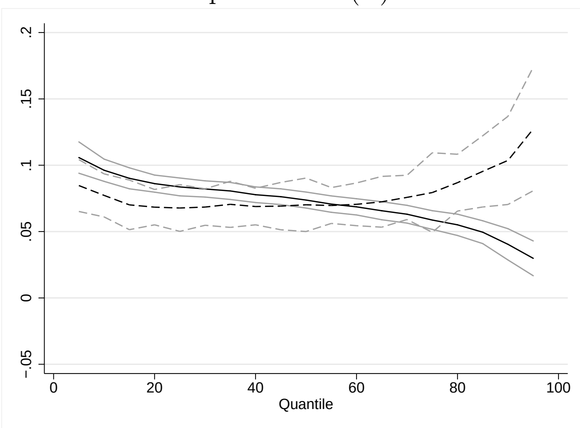


Figure 3: Quantile Regression Coefficients

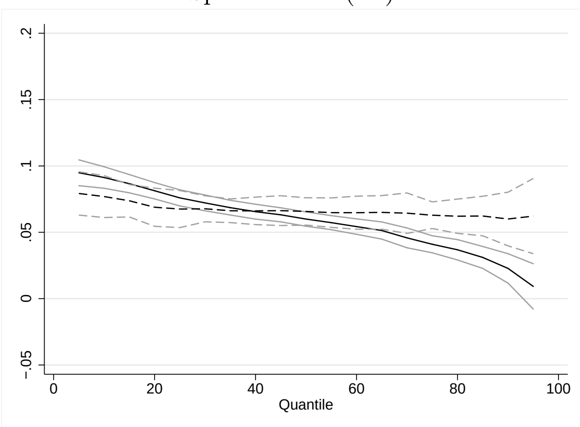
Specification (I)



Specification (II)



Specification (III)



Solid lines refer to industry-level bargaining (β^i), dashed lines to firm-level bargaining (β^f). Base category: Individual wage negotiation. Thin lines depict 95% confidence bands using standard errors that account for sampling weights and clustering at the firm level. See Section 5.3 and Table II for a description of specifications.

SFB 649 Discussion Paper Series 2008

For a complete list of Discussion Papers published by the SFB 649, please visit http://sfb649.wiwi.hu-berlin.de.

001 "Testing Monotonicity of Pricing Kernels" by Yuri Golubev, Wolfgang Härdle and Roman Timonfeev, January 2008.
002 "Adaptive pointwise estimation in time-inhomogeneous time-series models" by Pavel Cizek, Wolfgang Härdle and Vladimir Spokoiny, January 2008.
003 "The Bayesian Additive Classification Tree Applied to Credit Risk Modelling" by Junni L. Zhang and Wolfgang Härdle, January 2008.
004 "Independent Component Analysis Via Copula Techniques" by Ray-Bing Chen, Meihui Guo, Wolfgang Härdle and Shih-Feng Huang, January 2008.
005 "The Default Risk of Firms Examined with Smooth Support Vector Machines" by Wolfgang Härdle, Yuh-Jye Lee, Dorothea Schäfer and Yi-Ren Yeh, January 2008.
006 "Value-at-Risk and Expected Shortfall when there is long range dependence" by Wolfgang Härdle and Julius Mungo, Januray 2008.
007 "A Consistent Nonparametric Test for Causality in Quantile" by Kiho Jeong and Wolfgang Härdle, January 2008.
008 "Do Legal Standards Affect Ethical Concerns of Consumers?" by Dirk Engelmann and Dorothea Kübler, January 2008.
009 "Recursive Portfolio Selection with Decision Trees" by Anton Andriyashin, Wolfgang Härdle and Roman Timofeev, January 2008.
010 "Do Public Banks have a Competitive Advantage?" by Astrid Matthey, January 2008.
011 "Don't aim too high: the potential costs of high aspirations" by Astrid Matthey and Nadja Dwenger, January 2008.
012 "Visualizing exploratory factor analysis models" by Sigbert Klinke and Cornelia Wagner, January 2008.
013 "House Prices and Replacement Cost: A Micro-Level Analysis" by Rainer Schulz and Axel Werwatz, January 2008.
014 "Support Vector Regression Based GARCH Model with Application to Forecasting Volatility of Financial Returns" by Shiyi Chen, Kiho Jeong and Wolfgang Härdle, January 2008.
015 "Structural Constant Conditional Correlation" by Enzo Weber, January 2008.
016 "Estimating Investment Equations in Imperfect Capital Markets" by Silke Hüttel, Oliver Mußhoff, Martin Odening and Nataliya Zinych, January 2008.
017 "Adaptive Forecasting of the EURIBOR Swap Term Structure" by Oliver Blaskowitz and Helmut Herwatz, January 2008.
018 "Solving, Estimating and Selecting Nonlinear Dynamic Models without the Curse of Dimensionality" by Viktor Winschel and Markus Krätzig, February 2008.
019 "The Accuracy of Long-term Real Estate Valuations" by Rainer Schulz, Markus Staiber, Martin Wersing and Axel Werwatz, February 2008.
020 "The Impact of International Outsourcing on Labour Market Dynamics in Germany" by Ronald Bachmann and Sebastian Braun, February 2008.
021 "Preferences for Collective versus Individualised Wage Setting" by Tito Boeri and Michael C. Burda, February 2008.

SFB 649, Spandauer Straße 1, D-10178 Berlin
http://sfb649.wiwi.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".

022 "Lumpy Labor Adjustment as a Propagation Mechanism of Business Cycles" by Fang Yao, February 2008.
023 "Family Management, Family Ownership and Downsizing: Evidence from S&P 500 Firms" by Jörn Hendrich Block, February 2008.
024 "Skill Specific Unemployment with Imperfect Substitution of Skills" by Runli Xie, March 2008.
025 "Price Adjustment to News with Uncertain Precision" by Nikolaus Hautsch, Dieter Hess and Christoph Müller, March 2008.
026 "Information and Beliefs in a Repeated Normal-form Game" by Dietmar Fehr, Dorothea Kübler and David Danz, March 2008.
027 "The Stochastic Fluctuation of the Quantile Regression Curve" by Wolfgang Härdle and Song Song, March 2008.
028 "Are stewardship and valuation usefulness compatible or alternative objectives of financial accounting?" by Joachim Gassen, March 2008.
029 "Genetic Codes of Mergers, Post Merger Technology Evolution and Why Mergers Fail" by Alexander Cuntz, April 2008.
030 "Using R, LaTeX and Wiki for an Arabic e-learning platform" by Taleb Ahmad, Wolfgang Härdle, Sigbert Klinke and Shafeeqah Al Awadhi, April 2008.
031 "Beyond the business cycle – factors driving aggregate mortality rates" by Katja Hanewald, April 2008.
032 "Against All Odds? National Sentiment and Wagering on European Football" by Sebastian Braun and Michael Kvasnicka, April 2008.
033 "Are CEOs in Family Firms Paid Like Bureaucrats? Evidence from Bayesian and Frequentist Analyses" by Jörn Hendrich Block, April 2008.
034 "JBendge: An Object-Oriented System for Solving, Estimating and Selecting Nonlinear Dynamic Models" by Viktor Winschel and Markus Krätzig, April 2008.
035 "Stock Picking via Nonsymmetrically Pruned Binary Decision Trees" by Anton Andriyashin, May 2008.
036 "Expected Inflation, Expected Stock Returns, and Money Illusion: What can we learn from Survey Expectations?" by Maik Schmeling and Andreas Schrimpf, May 2008.
037 "The Impact of Individual Investment Behavior for Retirement Welfare: Evidence from the United States and Germany" by Thomas Post, Helmut Gründl, Joan T. Schmit and Anja Zimmer, May 2008.
038 "Dynamic Semiparametric Factor Models in Risk Neutral Density Estimation" by Enzo Giacomini, Wolfgang Härdle and Volker Krätschmer, May 2008.
039 "Can Education Save Europe From High Unemployment?" by Nicole Walter and Runli Xie, June 2008.
040 "Solow Residuals without Capital Stocks" by Michael C. Burda and Battista Severgnini, August 2008.
041 "Unionization, Stochastic Dominance, and Compression of the Wage Distribution: Evidence from Germany" by Michael C. Burda, Bernd Fitzenberger, Alexander Lembcke and Thorsten Vogel, March 2008

SFB 649, Spandauer Straße 1, D-10178 Berlin
http://sfb649.wiwi.hu-berlin.de

This research was supported by the Deutsche Forschungsgemeinschaft through the SFB 649 "Economic Risk".