Ludsteck, Johannes und Haupt, Harry:

An Empirical Test of Reder Competition and Specific Human Capital Against Standard Wage Competition

An Empirical Test of Reder Competition and Specific Human Capital against Standard Wage Competition[*]

Johannes Ludsteck[†]and Harry Haupt[‡]

Revision : 6.0

August 24, 2007

Abstract

A firm that faces insufficient supply of labor can either increase the wage offer to attract more applicants, or reduce the hiring standard to enlarge the pool of potential employees, or do both. This simultaneous adjustment of wages and hiring standards has been emphasized in a classical contribution by Reder (1955) and implies that wage reactions to employment changes can be expected to be more pronounced for low wage workers than for high wage workers.

We test this hypothesis (together with a related hypothesis on firm-specific human capital) by applying a bootstrap-based quantile regression approach to censored panel data from the German employment register. Our findings suggest that market clearing is achieved by a combination of wage and hiring standards adjustment.

JEL codes: J31, J41, C24

1   Introduction

Reder's (1955) hiring standards adjustment hypothesis can be viewed as an extension and complement of the neoclassical wage competition framework.[1] It states that firms do not only adjust wages and take qualifications and ability as given in recruitment processes, but may change hiring standards too. Interestingly, what may seem to be a minor change of the institutional setting, can produce completely different labor market outcomes. Schlicht (2005) shows that the hiring standards mechanism can generate an efficiency wage effect and may therefore be a possible explanation for equilibrium unemployment, wage discrimination and overqualification.   Reder develops the hiring standards mechanism to explain occupational wage differentials and the response of the wage structure to labor demand changes. The main conclusion of the theory (which is tested empirically below) is that the lower part of the wage distribution for a homogenous group of workers responds more to labor demand changes than the upper part. For a brief exposition of the argument consider the demand for workers with identical formal qualification but differing ability and sort them with respect to ability. For sake of simplicity assume that ability takes on only three different values — low, medium and high — and that ability is used as a criterion to assign workers to three jobs or tasks, e.g. an instructor, a standard worker and a helper. Assume furthermore that the production technology of the firm requires all types of workers in a fixed relation (at least in the short run). How will wages respond if the firm wants to extend its production and requires one additional worker of each type?

---

[1]Similar theories can be found in Reynolds (1951) and Hall (1974). We refer to Reder, since his contribution emphasizes and explains the relation between labor market conditions and the wage distribution.

In the Reder framework[2] firms may respond to shortage of high ability workers by promoting medium ability workers to fill the open slots. This dampens upward pressure from wages of the high ability workers. Promotions create additional open slots for medium ability workers, leaving the firm with even more open slots for medium ability workers. These can either be filled by promoting low ability workers or by poaching workers from other firms. Hence we expect wages to respond stronger when moving down the ability ladder since the gaps become larger at each step. This domino-effect breaks down only if open slots can be filled from unemployed workers as can be expected at the bottom of the wage distribution. If the Reder hypothesis is a good approximation of employer behavior, the response of wages to unemployment changes should increase (in absolute value) as we move from the upper to the lower part of the wage distribution, i.e. lower quantiles of the (conditional) wage distribution should respond more strongly to employment changes.

Under the identifying assumption that additional labor demand is distributed evenly over the ability groups we test this hypothesis empirically by running regressions for different quantiles of wages on unemployment and control variables for a homogenous group of workers. As in most applied work, the relation between theory and the empirical model is not one-to-one here. Higher sensitivity of lower wage quantiles with respect to labor demand changes is also compatible with a firm-specific human capital model as developed in Devereux (2000): if high ability workers have accumulated more firm-specific human capital than their colleagues, firms will retain them in downturns and adjust labor demand by hiring and firing mainly low ability workers. As a consequence, the relation between labor demand of high ability workers and cyclical fluctuations is weaker than for the other groups, causing less pronounced wage responses.[3] Thus our empirical model

---

[2]In contrast, in a standard neoclassical model wages of the high ability workers would respond more than wages of the other groups to labor demand shifts *if unemployment is smallest for high ability workers*. Then competition drives up the wages of high ability workers since their supply is fixed in the short run. On the other hand, open slots for medium and especially low ability workers can be filled by formerly unemployment workers. Therefore their wages are expected to respond less strongly in this framework.

[3]Furthermore wages for the high ability workers may be sticky due to implicit contracts.

tests a composite hypothesis 'Reder competition or firm-specific human capital' against pure neoclassical wage competition. Given that the main purpose of the empirical analysis is to search for evidence for the existence of efficiency wage effects, the difference between a pure hiring standards setting and the specific human capital interpretation is not of great importance, however. Specific human capital is very likely to generate efficiency wage effects too.

The method of quantile regression enables a direct attack on this problem as follows. Under the identifying assumption that additional labor demand is distributed evenly over the ability groups we can test Reder competition and specific human capital against standard wage competition by running regressions for different quantiles of wages on unemployment and control variables for a homogenous group of workers. A methodological problem occurs as quantile regression analysis of fixed effects panel data models cannot be solved along the lines of classical mean estimation methods, that is, using a differencing approach to avoid the estimation of a possibly large number of fixed effects. In the present contribution we propose a solution to this problem by applying a bootstrap-based fixed effect quantile regression approach to censored panel data from the German employment register.

The paper is organized as follows. In Section 2 we provide a short review of related literature. Then, in Section 3, we derive our empirical model based on guidelines from theory and introduce scope and potential limitations of our data set. In Section 4 we provide a detailed analysis of the quantile regression methods employed in this paper. Section 5 follows with a short discussion of our empirical results and some conclusions in Section 6. Additional details on data preprocessing, Monte Carlo, bootstrap simulations, and estimation results, can be found in Appendices A, B, C, D, and E respectively.

2 A short review of related literature

The hypothesis in question is related to three strands of empirical literature: studies investigating business cycle effects on the level and structure of wages, wage curve empirics and empirical studies on wage rigidity.

While the relations between cyclical fluctuations and income or wage *levels* have been studied extensively (see e.g. Solon, Barsky, & Parker, 1994), only a few contributions focus on the corresponding relations with the *structure* of income and wages. The obvious reason for this selective interest seems to be that cyclicality of income and wage *levels* plays an important role for business cycle theory. Cyclicality of the wage *distribution* appeared to be less relevant or interesting due to the lack of a structured theoretical framework. Empirical studies on the relation between earnings *distributions* and unemployment stress the argument that low income earners face higher unemployment risks or are urged to reduce working hours more than other groups in downswings. This implies a reduction of their income shares and generates correlations between income inequality and (cyclical) unemployment. Most empirical work on the relation between earnings or income inequality and unemployment is based on simple linear regression models explaining income shares of wage distribution quintiles or overall inequality measures (e.g. the Gini coefficient) by regional or country-wide unemployment and control variables. Parker (1999) surveys 12 studies of each type. For the income share approach most of the studies report a significant negative effect of unemployment on the lowest quintile and a significant positive on the highest. The results from the composite inequality measure approach indicate positive (but not always significant) relations between income inequality and unemployment. These studies are of limited relevance in our context as they analyze a composite effect of variations in wages, working hours and the number of employed workers.

A second strand of empirical literature focusses on the estimation of the relation between wages and regional unemployment (dubbed the 'wage curve').[4] Most of these studies, however, are based on models for the conditional mean and therefore contain no information with regard to the Reder hypothesis. To the best of our knowledge the only studies more closely related to our approach (but delivering different results) are Büttner & Fitzenberger (2003) and Ammermüller, Lucifora, Origa, & Zwick (2007). Büttner and Fitzenberger analyze the effect of centralized wage setting in a union bargaining model. Their model predicts that lower quantiles of the wage distribution respond *less* to regional unemployment than higher ones. The essence of the argument is that union wage contracts set de-facto minimum wages for the low wage groups. Consequently their wages are more likely to be paid according to the centralized contract and should respond less to regional labor demand fluctuations compared to wages at higher quantiles of the wage distribution. High wages are frequently determined in individual bargaining and thus are more prone to regional labor demand shifts. The empirical implications of the centralized bargaining model sharply contrast those of the Reder hypothesis. Büttner & Fitzenberger (2003) use a two-step (minimum distance) quantile regression procedure to test their hypothesis and find it (weakly) confirmed by the data. Their estimation procedure may be biased, however, for two reasons. Firstly, their model does not include fixed district effects, and secondly, their regression procedure is based on aggregated data and therefore does not allow to control for composition bias (explained below). Composition bias seems to be present also in the study of Ammermüller et al. (2007), who apply a two-stage estimation technique similar to the models advanced in Bell, Nickell, & Quintini (2002).[5]

---

[4]See Blanchflower & Oswald (1995), Card (1995) and Blanchflower & Oswald (2005) for surveys

[5]The first stage consists of cross-section quantile regressions of wages on control variables and district fixed effects for every year. The fixed effects estimates are then regressed on the local unemployment rate and fixed district effects. Composition bias arises here since the fixed effects coefficients from the first stage are prone to district level quantile shifts due do composition changes of the workforce. Furthermore wage information is imprecise in their data base (the German 'Mikrozensus'). Income information is coded as interval data, i.e. respondents report only whether their income falls in relatively large intervals (e.g. 920 to 1 125 Euro, 1 125 to 1 278 Euro ...).

Some papers focussing on wage rigidity show the strongest relations to our work. Devereux (2000) develops a theory of specific human capital where more senior workers have accumulated more firm-specific human capital. In this environment firms respond to output demand shocks by hiring and firing workers in the lowest positions and assigning the remaining workers partially (and temporarily) to lower positions. The last implication — workers are assigned to tasks that require less skills in bad times — can be tested empirically. Devereux does this by regressing several proxies of task quality on state and national unemployment rates and control variables (worker-characteristics and match-specific fixed effects) and finds it confirmed. Devereux contrasts his firm specific human capital model with what he dubbes the Reynolds-Reder-Hall (RRH) hypothesis (Reynolds, 1951; Reder, 1955; Hall, 1974). According to Devereux (2000, p. 113), the central assumption maintained by these authors is that "wages within job titles are unresponsive to demand conditions faced by firms." Instead firms respond to output demand changes by transferring workers between job titles. A testable empirical implication based on this argument is that the main part of cyclical wage variations result from workers changing job titles rather than from wage changes *within* job titles.[6] Devereux suggests a test that compares the response of log wage changes on the change of state unemployment for the sample of workers switching job titles with workers remaining in their positions. He finds no significant difference and concludes that the data do not support the RRH hypothesis. This conclusion is, however, weakened by the fact that (a) unemployment response of wages is insignificant or marginally significant in all these regressions, and (b) information on job title changes in the PSID is imprecise. In complementary investigations Devereux (2002) stresses that Reder's theory implies dependence between occupational upgrading (quality adjustment) and the business cycle. This implication is tested (and confirmed)

---

[6]Note that our interpretation of the Reder hypotesis and our empirical test *allow* for wage changes within job titles, though wage quantiles show *different* responsiveness to labor demand conditions.

by regressing (a) shares of the high qualified in occupation cells, and (b) ocupation quality proxies for occupation cells on unemployment rates (and control variables).[7]

3   Model and data

3.1   The empirical model

As stated above, the Reder hypothesis implies that higher quantiles of the conditional regional wage distribution respond less strongly to regional labor demand changes than lower ones. Our test is based on the empirical model

$$w_{i,r,t}^* = u_{r,t}\, b(\tau) + x_{i,r,t}\, g(\tau) + \theta_s(\tau) + \gamma_r(\tau) + \xi_t(\tau) + \epsilon_{i,r,t} \tag{1}$$

with indexes $i = 1,\ldots,N$ for individuals, $r = 1,\ldots,326$ for regions (districts), $s = 1,\ldots,22$ for sectors and $t = 1984,\ldots,2001$ for time. Here, w^* denotes the natural logarithm of the real wage[8] u is the natural logarithm of the unemployment rate, θ, γ and ξ are fixed effects for sectors, districts and years, respectively, and x contains further control variables (a foreigner dummy, age, age squared, establishment size, establishment size squared, and tenure and tenure squared together with an interaction term taking on value 1 if tenure is greater than 8, since tenure is censored at 9 years in our data set[9]).

The specific choice given by this specification deserves several comments. First, the model is estimated at the individual (worker) level to avoid potential workforce composition bias. If workers at lower quantiles of the wage distribution face higher risks of becoming unemployed in recessions, this group will shrink more than the rest of the sample

---

[7]The studies are based on the Current Popuation Survey (CPS) 1983–1999 and the Panel Study of Income Dynamics (PSID) 1976–1992.

[8]More precisely, w^* is the latent uncensored wage. Further details are explained below.

[9]Tenure is not reported directly in our data set but can be computed by counting how long an employee worked in the same establishment. Since our data set dates back to 1975 and the estimation period starts in 1984, tenure is censored for all workers with tenure ≥ 9.

during recessions.[10] This composition shift generates wage compression in a mechanical way even if wages of the workers remaining employed respond uniformly to demand shifts. Composition effects are highly important especially for quantile regression analysis since their impact varies with quantiles. The idea can be demonstrated exemplarily by considering a uniform distribution of wages over the unit interval $[0, 1]$ (though the argument is valid in general). If all workers with wages below the median become unemployed, the minimum of the distribution increases by 0.5 whereas the median increases only by 0.25. Thus an increase in unemployment affecting essentially workers in the lower part of the wage distribution, generates a higher response of the lower quantiles in regression models based on aggregate data. To eliminate this composition effect our fixed effects quantile regressions are run at the individual level.

Second, though the number of control variables appears to be limited at a glance, our model is quite flexible. The included fixed effects capture *all* time-invariant heterogeneity between districts, sectors, and years.

Third, all fixed effects $\theta_s(\tau), \gamma_r(\tau)$, and $\xi_t(\tau)$ depend on the quantile τ. The introduction of a large number of fixed effects may inflate the variance of the estimated coefficients considerably. To avoid this, Koenker (2004) and Lamarche (2006) propose penalized quantile regression estimators which restrict the fixed effects coefficients to a common value for all quantiles. We do not follow this approach here since this form of restriction could invalidate our interpretation of the results in the Reder framework. Furthermore the number of observations is quite large in our data set and the unemployment coefficient remains significant despite the large number of consumed degrees of freedom.

Fourth, unemployment might be endogenous in our model. To account for this in a rather rough way, we repeated estimation of the specification above with lags one and two

---

[10]Solon et al. (1994) contains a description of the composition bias problem in the context of cyclicality of wages.

(together) instead of the contemporaneous unemployment rate.[11] Since the results differ only slightly, results from the models including lags are not reported below.

3.2 Data description

All data sets used here relate to the period 1984–2001[12] and are based on the employment register of the German National Agency for Labor. These data contain precise and reliable information on earnings and several other demographic variables of all workers covered by the German social security system. The social security system covers nearly 80 percent of the German workforce, excluding only the self-employed, civil servants, individuals in (compulsory) military services, and individuals in so-called 'marginal jobs' (jobs with at most 15 hours per week or temporary jobs that last no longer than 6 weeks).

Though earnings information is highly reliable (mis-reporting is subject to severe penalties), working time is reported only in three classes, full time, part time with at least 50 percent of full time working hours, and part time with less than 50 percent. Because of missing information on overtime work it is possible that overtime hours are remunerated directly for workers at lower quantiles of the wage distribution whereas this is an exception for workers at higher quantiles. The more pronounced response of lower wage quantiles to unemployment could then result as an artifact due to missing hours information. To avoid bias due to an imprecise denominator in hourly wage computations, we restrict our sample to prime-age (20-60 years) full time working men, since weekly and monthly working hours are quite stable for this group. Furthermore we exclude East-

---

[11]Proper treatment of the endogeneity problem requires instrumental variable techniques. We did not pursue this approach since good instruments are hard to find and wage curve studies applying IV estimators often exhibit rather small and economically insignificant differences between OLS and IV results.

[12]Our data set contains data from 1975–2001. Earnings reporting is subject to a significant structural break, however: Bonus payments are included in earnings from 1984 onwards. This could bias our quantile regressions since bonus payments play an important role only for earnings above the median. A surefire (but brute force) solution to the problem is to drop all years before 1984. This is innocuous since the dimension of the data set in the time and cross section dimension remains large enough.

German workers from our sample to avoid bias due to the economic adjustment process after re-unification in 1990 (with a chaotic touch at least in the beginning). A further restriction of our data base can be seen in the censoring of wages. Wages are right-censored if they exceed the social security threshold. For the whole sample, censoring is moderate (about 10-15 percent). For the high qualified male (college and technical college graduates), however, more than 50 percent are censored, making this group practically useless for the quantile regression analysis. Thus this group is dropped from our data sets. A further shortcoming of our data set regards imprecise or missing information on the qualification level. Qualification is missing or implausible for about 10% of all spells. To avoid this we use the qualification variable $IP2a$ from Fitzenberger, Osikominu, & Volter (2006) which is imputed from the orginal IABS qualification variable and improved by extensive checking procedures.

As will be explained in more detail below, it would be practically infeasible, to employ the whole employment register data sample in our regressions. Therefore we obtain wages and other demographic variables from the IABS, a representative 2 percent subsample. Only district level unemployment (which would be imprecise otherwise) is computed from the complete register data set. Several other data restrictions and problems require special treatment.

The empirical implications of the Reder effect are derived for a homogenous group of workers (at least homogenous with respect to formal qualification). To mimic this situation with real data, we either can select a group as homogenous as possible from our sample, or hope to construct it with help of multivariate models by using as many control variables as possible. Here we combine both approaches. First, we keep only prime age (20-60 years) full time working males since attachment of the other groups (female, part-time) to the labor market is less strong. Second, formal remuneration and recruitment regulations in public services leave less discretion to adjust wages to labor

market conditions – at least in the short and medium run. To ensure that our results are not biased because of public sector regulations, we exclude it from our estimation sample. Third, the effects of labor demand changes on wages may differ considerably between qualification groups. Therefore we estimate the model *separately* for two qualification groups: (a) unskilled workers (without completed apprenticeship training), and (b) skilled workers (with completed apprenticeship). After all these selections, we have 470 569 observations from 74 429 unskilled and 2 147 175 observations from 248 231 skilled workers. The effect of various selections on the sample size is documented together with basic descriptive statistics in Appendix A.

4 Bootstrap-based quantile estimation

The response in equation (1) is subject to censoring. As a consequence we observe $w_{i,r,t}^*$ only if it is smaller than the corresponding censoring point in time period t — say C_t, where we assume that the latter depends on t in a non-stochastic manner (and hence is observable for all, even uncensored observations in the sample). What we observe is the dependent variable

$$w_{i,r,t} = \min\left\{C_t, u_{r,t}b(\tau) + x_{i,r,t}g(\tau) + \theta_s(\tau) + \gamma_r(\tau) + \xi_t(\tau) + \epsilon_{i,r,t}\right\} \qquad (2)$$

The τ in parentheses denotes the dependence on the corresponding quantile with $0 < \tau < 1$. Because of censoring we estimate equation (2) only for quantiles $\tau \in \{0.05, 0.15, \ldots, 0.65, 0.75\}$.

Censored quantile regression has been introduced in two seminal papers by Powell (1984, 1986). Based on the model $Q_\tau(y_i|z_i) = \min\{C_i, z_i\,\beta(\tau)\}$ Powell suggested to mini-

mize the objective function

$$\sum_i \rho_\tau \left(y_i - \min\{C_i, z_i\, \beta(\tau)\} \right) \tag{3}$$

where $\rho_\tau(\epsilon) = (\tau - 1(\epsilon \leq 0))$. Under weak regularity conditions, Powell's estimator has desirable large sample properties, but exhibits undesirable properties in small samples. In addition numerical optimization based on (3) is extremely cumbersome, even with powerful modern computers. To avoid these problems, several two-step (e.g., Buchinsky & Hahn, 1998 and Khan & Powell, 2001) estimators were proposed in the literature. It is straightforward to show that the Powell estimator uses only observations with uncensored prediction. The two-step estimators exploit this fact by selecting observations with uncensored prediction using binary choice models. Here we adapt an ingenious suggestion Chernouzhukov & Hong (2002), and extend it to censored panel data regressions. Chernouzhukov & Hong (2002), building among others on the work of Buchinsky & Hahn (1998) and Khan & Powell (2001), propose a three-step estimation procedure which avoids the difficulties of Powell's estimator while reaching its asymptotic efficiency. A brief outline of our procedure will be given in the following (further details can be found in Chernouzhukov & Hong, 2002)

For expositional brevity we subsume all regressors (unemployment, control variates and fixed effect dummies) in z and drop region and time indices. Then the first step (logit) regression explaining not-censoring has the form

$$\delta_i = \dot{z}_i\, \gamma + \zeta_i \tag{4}$$

where δ_i is the indicator of not-censoring. The logit regressions do not include fixed individual effects. Instead we try to explain censoring as accurate as possible by including

a large set of regressors (time dummies, 22 sector dummies, 8 region type dummies, a cubic polynomial in age, a quadratic polynomial in establishment size, shares of high skilled workers in establishment, and a foreigner dummy).

From this first step we generate the quantile regression estimation sample J_0 by sorting the predicted values (propensity scores) $\dot{z}_i \hat{\gamma}$ from the logit model and dropping the 20 percent with lowest propensity score. This appears to be a surefire choice since only about ten percent of the original sample are censored. Then, the second step consists of solving the *uncensored* quantile regression minimization problem

$$\sum_{i \in J_0} \rho_\tau (y_i - z_i \beta(\tau)) \tag{5}$$

The linear prediction $z_i \hat{\beta}(\tau)$ is used to compute a second (and final) quantile regression sample $J_1 = \{i | z_i \hat{\beta}(\tau) < C_i\}$, containing all observations with uncensored prediction. Chernozhukov & Hong show that quantile regression coefficients based on J_1 reach the asymtotic efficiency of Powell's one step estimator.

Even our 2 percent sample of the register data (IABS) is large. Since simple transformations applied in OLS estimation (differencing or within-transformation) are not viable for quantile regression — in contrast to conditional expectations, conditional quantiles are not linear operators — all fixed effects have to be estimated directly. Direct inclusion of many fixed effects may generate two complications. First, coefficient estimates of the other regressors may become imprecise, and second, approximations for asymptotic distributions may be invalid. Therefore Koenker (2005) suggests to obtain standard errors using bootstrap procedures. Since the dimension of the estimation problem (more than 350 coefficients and more that 2 million observations for the skilled worker sample) is too large to be processed on a Pentium PC with 2 GB RAM, we apply the m out of n bootstrap surveyed by Bickel, Götze, & van Zwet (1997). The basic idea is to draw only

14

m observations (with replacement) from the whole sample of size n in every bootstrap replication, where m is small compared to n. Bootstrap variances obtained from the size m samples are then re-scaled (exploiting $\sqrt{n}$-consistency of the estimator) to infer standard errors for the base population. A disadvantage of the approach is that we have to rely on $\sqrt{n}$-consistency of the estimator and the implicit assumption of normality for the re-scaling of variances. We have checked the first assumption in a small simulation experiment and found it confirmed (see Appendix B). In addition, the bootstrap allows us to check also the second assumption by comparing kernel density estimates of the bootstrapped $m-$sample coefficients with the normal density. This is done in Appendix D.

As is well known, the standard (i.i.d.) bootstrap gives biased standard errors if the residuals of the regression model are correlated. In our analysis, such correlations are likely to be caused by regional demand or productivity shocks. To obtain consistent standard errors in this case, we use a block bootstrap procedure.[13] A bootstrap sample is generated by first drawing (with replacement) a district. Then we draw a sample of size $0.05 \times n_C$ from the workers in this district and all its direct neighbour districts (again, with replacement).[14] Here n_C denotes the number of workers in the cluster C. This sampling step is repeated until 10 000 workers are obtained for the skilled and unskilled workers group, respectively. To avoid possible collinearity problems and additional computational burden, we drop districts ending up with less than 10 observations from the bootstrap samples.[15] A more formal description of the bootstrap procedure is given in Appendix C.

A final word of caution. Not too much is known about censored panel quantile regres-

---

[13]See Fitzenberger (1997) for an exposition of the procedure and its properties.

[14]It would be desirable to sample *all* individuals from a cluster of neighbouring districts. This is not possible here since m is small compared to n. Then, the bootstrap samples would contain only a small number of districts, making identification of the unemployment coefficient infeasible.

[15]If all of 10 observations from a district are censored, the district and the corresponding district dummy are dropped from the sample before estimation. With sparse matrix objects the computation of predicted censoring for the third step of the Chernozhoukov & Hong procedure would then become cumbersome.

sion models such as (2), since until now only a limited number of papers simultaneously addressed quantile regression, censoring, and panel data. Recent works of Koenker (2004) and Lamarche (2006) deal with quantile regression analysis of fixed effect panel data models. Though from quite different perspectives, Honore (1992) and Hu (2002) are, to the best of our knowledge, the only papers providing hints on LAD regression of censored panel data models based on the results of Powell (1984) discussed before. Necessary and sufficient assumptions for favourable large sample properties of the procedure applied in this paper remain to be investigated in detail. However, our Monte Carlo simulations are encouraging and suggest that our estimators are well-behaved even for moderate sample size.

5   Estimation Results

The empirical model is estimated for unskilled and skilled workers separately.[16] Since censoring (below 2 percent) appears to be negligible for the unskilled workers, censoring is handled by simply dropping the censored observations for this group. The first step logit estimates used to predict censoring for the skilled workers are not reported here but available from the corresponding author upon request. The coefficients of the control variables are displayed in Appendix D. All results are based on 200 bootstrap replications with bootstrap sample size = 10 000 persons (corresponding to about 100 000 observations).

Table 1 contains estimates and bootstrapped standard errors of regression model (2). The table shows the point estimates (computed as means of the 200 bootstrap coefficients) of the effects of unemployment on wages together with their (sample size adjusted) standard errors and the corresponding measures for differences between the conditional

---

[16]Since interior point linear programming and sparse arrays are not available in Stata, the quantile regressions are programmed in *Mathematica* which implements both in an efficient and user friendly way. Similar procedures (developed by Roger Koenker) are available for the R programming environment. All programs developed by the corresponding author are available on request.

Table 1: Effects of log unemployment on log wage quantiles from quantile regressions including fixed effects for districts, sectors, and years. dependent variable: log real daily wage

| quantile | unskilled workers | | | skilled workers | |
τ	$b(\tau)$	$b(\tau)-b(0.05)$		$b(\tau)$	$b(\tau)-b(0.05)$
0.05	-0.018			-0.018	
	(0.008)			(0.004)	
0.15	-0.008	0.010		-0.008	0.010
	(0.005)	(0.006)		(0.003)	(0.003)
0.25	-0.008	0.010		-0.004	0.014
	(0.004)	(0.008)		(0.002)	(0.003)
0.35	-0.005	0.012		-0.002	0.015
	(0.004)	(0.008)		(0.002)	(0.004)
0.45	-0.003	0.015		-0.001	0.017
	(0.004)	(0.008)		(0.002)	(0.003)
0.55	-0.000	0.017		0.001	0.019
	(0.004)	(0.008)		(0.002)	(0.003)
0.65	0.002	0.020		0.003	0.021
	(0.004)	(0.009)		(0.002)	(0.004)
0.75	0.002	0.020		0.004	0.022
	(0.004)	(0.009)		(0.003)	(0.004)

Legend: τ denotes the quantile, $b(\tau)$ the coefficient of the unemployment rate and $b(\tau) - b(0.05)$ the difference between the coefficients for quantile τ and quantile 0.05. Small numbers in parentheses are standard errors.
All results are based on 200 bootstrap replications with sample size 10 000 workers. The regressions include fixed effects for districts, sectors and years. Additional control variables: a dummy for foreigners and linear and quadratic terms of age, establishment size and tenure. Since tenure is censored at 9 years (from above), an interaction dummy for tenure ≥ 9 is included too.

quantiles.[17]

To start with, consider the panel showing the results for the unskilled workers. The unemployment elasticity is -0.018 for quantile 0.05 but shrinks (in absolute size) to zero for the highest quantiles. Though coefficients are significant only for quantile 0.05, the differences between responses at lower and higher quantiles are highly significant.[18] The pattern is similar but estimated more precisely for the skilled workers. This means that

---

[17]To check whether the convergence rule for standard errors is valid also for small samples and our fixed effects design, we run a small simulation study. Design and results are described in Appendix B.

[18]Standard errors of the differences are computed by first generating the difference $b(\tau) - b(0.05)$ for every bootstrap replication. Then we compute the variances of these differences and re-scale them to account for sampling fewer than n observations.

lower quantiles respond more strongly to regional unemployment than the higher ones for both qualification groups, i.e. confirms Reder's hypothesis.

Though correspondence with conditional mean models from the wage curve literature cannot be exact, our estimates appear rather small at a glance, if compared with elasticities from the wage curve literature. A comparison with the recent study of Baltagi, Blien, & Wolf (2007) based on the same data set shows, however, quite similar results. The authors estimate dynamic two-step models using the same data set but a slightly different period (1980-2004) and different samples (male, female, low qualification and high qualification, but not low qualified male etc.). Their short and long-run elasticities for the male sample are -0.014 and -0.029, respectively. Taking into account that coefficients from static fixed effects models are biased towards the short run effects from dynamic panel data models, our unemployment coefficients are roughly compatible with theirs.[19]

6 Conclusions

This paper uses censored panel data based on the employment register of the German National Agency for Labor, covering a time span from 1984-2001 and containing rich regional and sectoral information. We apply a novel approach using a bootstrap-based procedure to estimate fixed-effects panel quantile regressions. In summary, our regressions show that lower quantiles of the wage distribution respond more strongly to regional unemployment changes than the upper part for skilled and unskilled workers. Whereas a strong interpretation of our results in favor of the Reder effect rests on the additional identifying assumption of a Leontieff type production technology (i.e. relative inputs of worker types are fixed in the short run), our results are quite suggestive for the presence of efficiency wage effects (possibly generated by firm specific human capital).

---

[19]See Baltagi & Griffin (1984) and Egger & Pfaffermayr (2004) for explanations of this relation.

References

Ammermüller, Andreas, Lucifora, Claudio, Origa, Federica, & Zwick, Thomas (2007). *Still Searching for the Wage Curve: Evidence from Germany and Italy* (Discussion Paper). ZEW Mannheim.

Baltagi, Badi, Blien, Uwe, & Wolf, Katja (2007). *Phillips Curve or Wage Curve? Evidence from West Germany: 1980–2004* (IAB Discussion Paper No. 14/2007). IAB Nuremberg and Syracuse University.

Baltagi, Badi, & Griffin, James (1984). Short and Long Run Effects in Pooled Models. *International Economic Review, 25(3)*, 631–645.

Bell, Brian, Nickell, Stephen, & Quintini, Glenda (2002). Wage Equations, Wage Curves and all that. *Labour Economics, 9*, 341–360.

Bickel, Peter, Götze, Friedrich, & van Zwet, Willem (1997). Resampling fewer than n observations: Gains, Losses, and Remedies for Losses. *Statistica Sinica, 7*, 1–31.

Blanchflower, David, & Oswald, Andrew (1995). *The wage curve.* MIT Press.

Blanchflower, David, & Oswald, Andrew (2005). *The Wage Curve Reloaded* (working paper). NBER.

Buchinsky, Moshe, & Hahn, Jinyong (1998). An Alternative Estimator for the Censored Quantile Regression Model. *Econometrica, 66(3)*, 653–671.

Büttner, Thiess, & Fitzenberger, Bernd (2003). *Central Wage Bargaining and Wage Flexibility: Evidence from the Entire Wage Distribution* (Tech. Rep.). ZEW Mannheim and University of Mannheim.

Card, David (1995). The Wage Curve: A Review. *Journal of Economic Literature, 33*, 785–799.

Chernouzhukov, Victor, & Hong, Han (2002). Three-Step Censored Quantile Regression and Extramarital Affairs. *Journal of the American Statistical Association, 97(459)*, 872–882.

Devereux, Paul (2000). Task Assignment over the Business Cycle. *Journal of Labor Economics, 18(1)*, 98–124.

Devereux, Paul (2002). Occupational Upgrading and the Business Cycle. *Labour, 13(2)*, 423–452.

Egger, Peter, & Pfaffermayr, Michael (2004). Estimating Long and Short Run Effects in Static Panel Models. *Econometric Reviews, 23(3)*, 199–214.

Fitzenberger, Bernd (1997). The Moving Blocks Bootstrap and Robust Inference for Linear Least Squares and Quantile Regression. *Journal of Econometrics*, 235–287.

Fitzenberger, Bernd, Osikominu, Aderonke, & Volter, Robert (2006). Imputation Rules to Improve the Education Variable in the IAB Employment Subsample. *Schmollers Jahrbuch, 126(3)*, 405–436.

Hall, Robert (1974). The Process of Inflation in the Labor Market. *Brookings Papers on Economic Activity, 2*, 343–393.

Honore, Bo (1992). Trimmed LAD and Least Squares Estimation of Truncated and Censored Regression Models with Fixed Effects. *Econometrica, 60(3)*, 533–565.

Hu, Luojia (2002). Estimation of a Censored Dynamic Panel Data Model. *Econometrica, 70(6)*, 2499–2517.

Khan, Shakeeb, & Powell, James (2001). Two-step Estimation of Semiparametric Censored Regression Models. *Journal of Econometrics*, *103*, 73–110.

Koenker, Roger (2004). Quantile Regression for Longitudinal Data. *Journal of Multivariate Analysis*, *91*, 74–89.

Koenker, Roger (2005). *Quantile regression.* Cambridge: Cambridge University Press.

Lamarche, Carlos (2006). *Robust Penalized Quantile Regression Estimation for Panel Data* (Tech. Rep.). University of Oklahoma.

Parker, Simon (1999). Income Inequality and the Business Cycle: A Survey of the Evidence and Some new Results. *Journal of Post Keynesian Economics*, *21(2)*, 201–225.

Powell, James (1984). Least Absolute Deviations Estimation for the Censored Regression Model. *Journal of Econometrics*, *25*, 303–325.

Powell, James (1986). Censored Regression Quantiles. *Journal of Econometrics*, *32(1)*, 143–155.

Reder, Melvin (1955). The Theory of Occupational Wage Differentials. *American Economic Review*, *45(5)*, 833–852.

Reynolds, Lloyd (1951). *The Structure of Labor Markets.* New York: Harpers Bros.

Schlicht, Ekkehart (2005). Hiring Standards and Market Clearing. *Metroeconomica*, *56(2)*, 263–279.

Solon, Gary, Barsky, Robert, & Parker, Jonathan (1994). Measuring the Cyclicality of Real Wages: How Important is Composition Bias? *Quarterly Journal of Economics*, *109(1)*, 1–25.

A Descriptive statistics

The following table shows the sample size after various steps of data preprocessing. The final sample used in the quantile regressions contains 470 569 observations from 74 429 unskilled and 2 147 175 observations from 248 231 skilled workers. Information on qualification is missing or inconsistent for about 10% of all spells in the original register data. Therefore we use the imputed and corrected variable IP2a from Fitzenberger et al. (2006).

Table 2: Evolution of Sample Size

sample	sample size	
all male, west germany, 1984-2001	3 976 577	
	unqualified	med. qual.
this qualification group only	550 204	2 954 563
drop public services sectors	502 477	2 685 035
drop left censored (extremely low wages)	501 172	2 682 279
drop spells shorter than 31 days	499 129	2 677 817
keep $20 \leq$ age ≤ 60	477 003	2 614 640
drop obs with missing establ. size info	476 439	2 609 951
drop cens. obs / obs with cens. prediction	470 569	2 147 175

Table 3: Means medians and quartiles of control variables

variable	Unskilled workers				Skilled workers			
	mean	25%	50%	75%	mean	25%	50%	75%
age	39.3	29	39	49	38.9	30	38	48
estab size	2316	42	212	1040	1813	21	106	596
$D(ten \geq 9)$	0.41				0.36			
$ten\|ten < 9$	2.81	0	2	5	2.88	1	2	5
$D(foreign)$	0.32				0.06			

Legend: $D(ten \geq 9)$: dummy for tenure greater or equal 9 years, $ten|ten < 9$: tenure for uncensored obs (tenure less than 9 years). $D(foreign)$: dummy for foreigners.

Figure 1: Distribution of log (real) wages by skill group
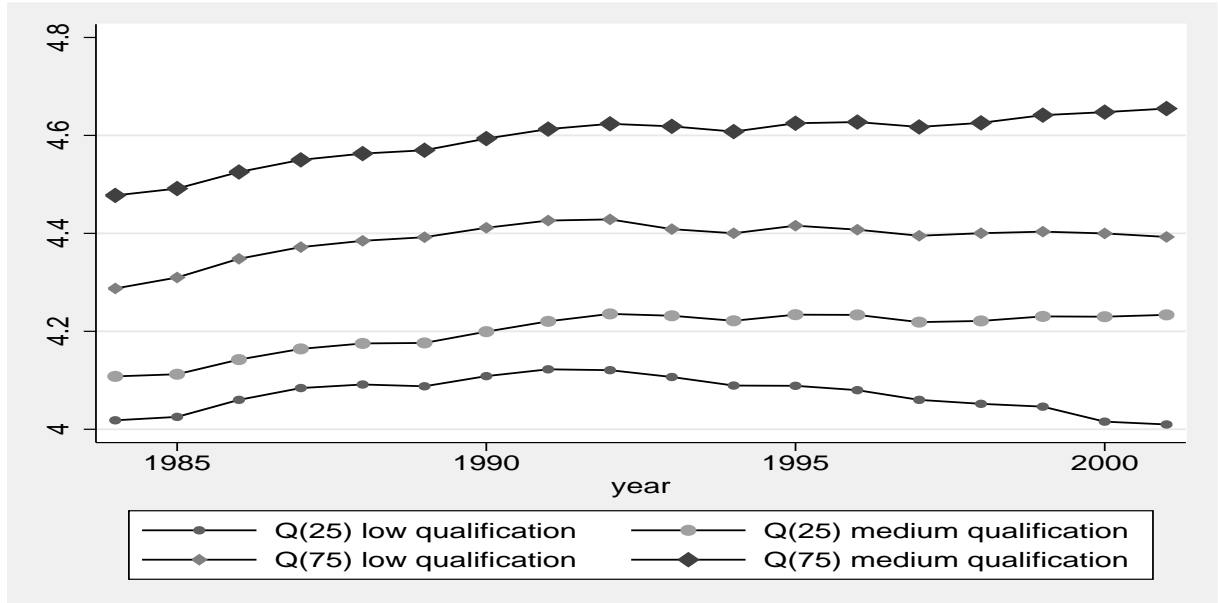
B Monte Carlo simulation to check $\sqrt{n}$- consistency of fixed effects quantile regressions

The m out of n bootstrap technique is based on the idea to draw bootstrap samples $m \ll n$ and to infer variances of the *base* sample coefficients from the bootstrap distributions using $\sqrt{n}$-consistency of the applied estimator. To check whether $\sqrt{n}$-consistency applies in the case of quantile regression with a large number of fixed effects, we conducted a small Monte Carlo study.[20] We generate a simple model of the form

$$y_{i,r,t} = x^1_{i,r,t} + x^2_{i,r,t} + x^3_{r,t} + \eta_r + u_{i,t}$$

with dimensions $i = 1, \ldots, 500$, $t = 1, \ldots, 10$, and $r = 1, \ldots, 10$. The data set contains $I \times t = 500 \times 10 = 5000$ observations. To mimic realistic situations we generate correlated

---

[20]The simulation programs (written in Stata to maximize transparency and ease replication) are available from the authors on request.

regressors:

$$u \sim N(0, 1)$$

$$x^1 \sim N(0, 1), \ x^2 \sim N(0, 1) + 0.5 \, x^1$$

$$x^3 \sim N(0, 1) + 0.5 \, (\bar{x}^1_{r,t} + \bar{x}^2_{r,t})$$

$$\eta_r \sim N(0, 1) + 0.5 \, (\bar{x}^1_r + \bar{x}^2_r)$$

The coefficients (for regression quantiles 0.25, 0.5 and 0.75) are bootstrapped (with 500 replications) using $m = 500$ observations from 50 individuals. Then the empirical variances of the m-size bootstrap are compared with the corresponding variances from a bootstrap using all $n = 5000$ observations from 500 persons. For a $\sqrt{n}$-consistent estimator, we expect variance ratios 10/1 for all coefficients. The resulting empirical variance ratios are given in the following table. They are good approximations for the expected theoretical values even for this extremely small sample size.

Table 4: Empirical variance ratios

regressor	Quantile 25	Quantile 50	Quantile 75
x^1	8.38	8.99	10.28
x^2	10.05	12.36	12.01
x^3	11.36	12.59	11.46

C   Formal description of the blocks bootstrap

This appendix provides a formal desription of the m out of n bootstrap using pseudo-code.

for $k := 1$ to R do

    initialize the estimation sample $S_k := \emptyset$

    $s := 0$; while $s < m$

        draw (with replacement) a district r

        build the set C of all workers in district r and all direct neighbours.

draw (with replacement) five percent from all workers in C.

add all observations of every selected worker to S_k

increment s by the number of selected workers.

run regressions using all observations in S_k and save the coefficients.

Here k is the bootstrap replication counter, R denotes the number of replications, m denotes the bootstrap sample size (number of workers), and s keeps track of the number of workers sampled.

D   Comparison of bootstrapped coefficient distributions with normal distribution

In figure 2 we compare the bootstrapped distributions of the unemployment rate coefficients with their asymptotic distributions (normal distribution). Note that the kernel density plots are based on the $m-$sample bootstrap coefficients (i.e. before sample size adjustement). The plots show only moderate deviations between the empirical and the asymptotic distributions.

Figure 2: Kernel density estimates of bootstrapped coefficient distributions with normal densities
a) Unskilled workers
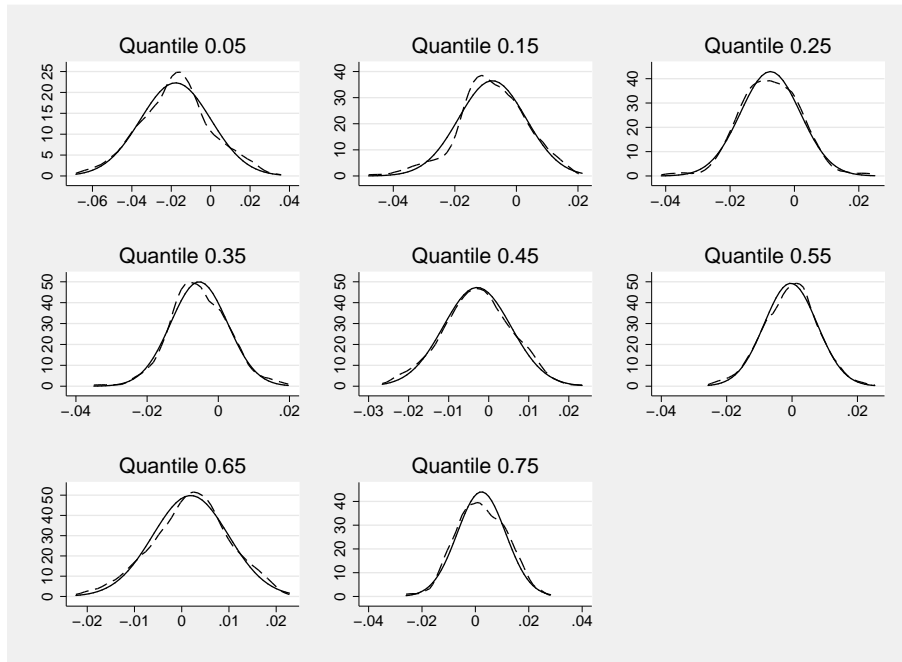
b) Skilled workers
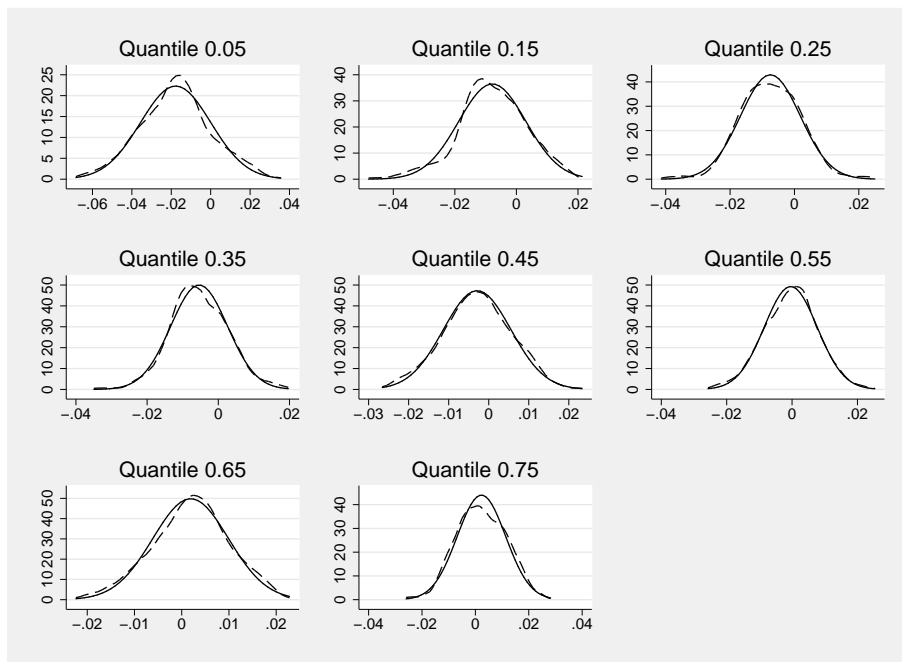
E Coefficient estimates of control variables

a) Unskilled workers

τ	u	age	age^2	es	es^2	ten	ten^2	$ten \geq 9$	foreign
0.05	-0.018	0.024	-0.0003	0.024	-0.0005	0.068	-0.0049	0.26	0.01
0.05	(0.009)	(0.001)	(0.0000)	(0.002)	(0.0001)	(0.002)	(0.0002)	(0.01)	(0.00)
0.15	-0.008	0.019	-0.0002	0.019	-0.0004	0.054	-0.0041	0.21	0.00
0.15	(0.006)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.001)	(0.0001)	(0.00)	(0.00)
0.25	-0.007	0.018	-0.0002	0.016	-0.0003	0.048	-0.0037	0.18	-0.00
0.25	(0.005)	(0.001)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)
0.35	-0.005	0.017	-0.0002	0.015	-0.0003	0.043	-0.0033	0.17	-0.00
0.35	(0.004)	(0.001)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)
0.45	-0.003	0.017	-0.0002	0.014	-0.0002	0.039	-0.0030	0.15	-0.01
0.45	(0.004)	(0.001)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)
0.55	-0.000	0.017	-0.0002	0.013	-0.0002	0.035	-0.0027	0.14	-0.01
0.55	(0.004)	(0.001)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)
0.65	0.002	0.017	-0.0002	0.012	-0.0002	0.031	-0.0023	0.13	-0.01
0.65	(0.004)	(0.001)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)
0.75	0.002	0.018	-0.0002	0.011	-0.0002	0.027	-0.0020	0.12	-0.01
0.75	(0.005)	(0.001)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)

b) Skilled workers

τ	u	age	age^2	es	es^2	ten	ten^2	$ten \geq 9$	foreign
0.05	-0.018	0.041	-0.0005	0.022	-0.0004	0.060	-0.0039	0.27	-0.09
0.05	(0.004)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.001)	(0.0001)	(0.00)	(0.00)
0.15	-0.008	0.036	-0.0004	0.019	-0.0004	0.042	-0.0029	0.19	-0.08
0.15	(0.003)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0001)	(0.00)	(0.00)
0.25	-0.004	0.036	-0.0004	0.018	-0.0003	0.036	-0.0025	0.16	-0.08
0.25	(0.002)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0000)	(0.00)	(0.00)
0.35	-0.002	0.037	-0.0004	0.017	-0.0003	0.032	-0.0023	0.15	-0.08
0.35	(0.002)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0000)	(0.00)	(0.00)
0.45	-0.001	0.039	-0.0004	0.017	-0.0003	0.029	-0.0021	0.13	-0.09
0.45	(0.002)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0000)	(0.00)	(0.00)
0.55	0.001	0.041	-0.0004	0.017	-0.0003	0.027	-0.0020	0.12	-0.09
0.55	(0.002)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0000)	(0.00)	(0.00)
0.65	0.003	0.043	-0.0004	0.017	-0.0003	0.025	-0.0018	0.10	-0.09
0.65	(0.002)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0000)	(0.00)	(0.00)
0.75	0.004	0.045	-0.0005	0.016	-0.0003	0.022	-0.0017	0.09	-0.10
0.75	(0.003)	(0.000)	(0.0000)	(0.001)	(0.0000)	(0.000)	(0.0000)	(0.00)	(0.00)

Legend: The first and second row contain (for every quantile τ) the point estimates and the standard error, respectively. Regressors: u: unemployment response (repeated from section results above), age: age in years, es: establishment size divided by 1000, ten: tenure (censored at 8 years), $ten \geq 9$: dummy for tenure greater or equal 9 years, $foreign$: dummy for foreigners.