# Employment effects of sectoral minimum wages in Germany

## Semi-parametric estimations from cross-sectional data

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**Preliminary version, please do not quote!**

**Abstract**

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# 1 Motivation

The debate about the introduction of a federal minimum wage in Germany has been going on for some time and figures to remain on the political agenda for the forseeable future (Müller (2009)). The most controversial issue is the likely effect of a statutory minimum on employment. Nearly all of the existing papers are ex ante simulations based on wage and employment data as well as aggregated labor demand elasticities.[1] Those studies provided rather rough estimates of average effects based on restrictive assumptions. The lone ex post analysis for the German construction sector was conducted by König and Möller (2008) and found negative employment effects for East Germany and insignificant estimates for the West. The study provoked a lot of controversy about the validity of the findings since working hours had to be imputed from another data set based on a probability model.

Empirical studies on minimum wages are commonly based either on time series or panel data. Alternatively, quasi-experimental settings (regional or sectoral variation in minimum wage levels) are utilized (Neumark and Wascher (2007)). In this paper we follow a different approach. The employment effects of the sectoral minimum wage are estimated with structural labor demand models which are based on a single cross-sectional distribution of individual hourly wages. The original labor demand model was derived by Meyer & Wise (Meyer and Wise (1983a); Meyer and Wise (1983b)). Dickens, Machin & Manning later discussed and extended the approach and applied it to data from the UK (Dickens, Machin, and Manning (1998)). In a nutshell the basic idea of these models is to parameterize the observable (censored) wage distribution under an existing minimum wage with covariates at hand and certain distributional assumptions. Then this distribution is compared it with an estimated counterfactual distribution which is not subject to a minimum wage. Employment effects are simulated from differences between the observed and counterfactual distributions. Critical assumptions concern the functional form of the (underlying) distribution and the selection of a censoring point for the estimation. Since individual wage information on the whole distribution is used, wage and employment effects can be modeled conditional on the distance to the minimum. More-

[1] Recent ex ante evaluation studies include Müller (2009), Bauer, Kluve, Schaffner, and Schmidt (2009), Kalina and Weinkopf (2009), Knabe and Schöb (2008), Müller and Steiner (2008), Ragnitz and Thum (2007), Ragnitz and Thum (2008).

over, potential spill-over effects on wages above the level of the minimum wage can be (at least informally) tested for in the extended model version of Dickens et al.

Currently there is no federal minimum wage in Germany; only certain industries (e.g. the construction sector, postal and cleaning services) are regulated by specific minima. We can therefore estimate the described models with the data at hand only for the construction sector since the sectoral minimum has already been established in 1997. Besides adding to the empirical literature on minimum wages in the German economy, especially to the hotly debated question about employment effects of the minimum wage in the construction sector, the paper contributes to the theoretical and methodological literature on estimating the employment effects of minimum wages from single cross sections. The restrictive functional form assumptions of the original models is relaxed. Other than estimating the models with maximum likelihood we employ semi-parametric estimators and estimate the observed wage distribution with a series of censored quantile regressions that do not rely on symmetry and normality of the residual distribution. We exploit a unique matched employer-employee data set 'Gehalts- und Lohnstrukturerhebung 2001' ('Verdienststrukturerhebung 2006') which has reliable and precise information about hourly wages and is large enough to conduct a semi-parametric estimations on the sectoral level.

We find a theoretically consistent patterns of employment effects for the parametric as well as the semi-parametric models. The sectoral minimum wage led to negative employment effects in East Germany whereas we estimate zero effects in the West where the minimum wage hardly bit. We also reveal robustness issues of the parametric models. The effect size differs between the parametric approaches and is sensitive with respect to the censoring point chosen for the respective model. We get more reasonable semi-parametric estimates. Negative employment effects of the minimum wage in the East German construction sector vary between 5 and 10% and are thus markedly larger then previously estimated. Finally we give an outlook how our extended model could be used to estimate employment effects of a federal minimum wage in Germany.

The remainder of the paper proceeds as follows: After briefly outlining the parametric models of Meyer & Wise and Dickens et al. we show how semi-parametric censored quantile regression estimators can be applied to estimate the structural labor demand model without relying on functional form assumptions. We then discuss in what way the sectoral minimum wage in the German construction sector creates a quasi-experimental situation that is comparable to the studies of reference. Since the relative level of the nominal minimum wage was markedly lower in the West German compared to the East German construction sector, the estimated effects should be much more pronounced in the East compared to the West. Moreover, the sectoral minimum wage was only implemented in the main construction trade ('Bauhauptgewerbe'). Therefore the effects should not be detectable in other branches of the construction sector (or other sectors of the German economy without a minimum wage). In the empirical section we first replicate both the models of Meyer & Wise as well as Dickens et al. and estimate them on our data set with maximum likelihood. We test the robustness of findings with regard to the ceonsoring point. Finally we estimate the employment effects with our semi-parametric estimator. The last section concludes.

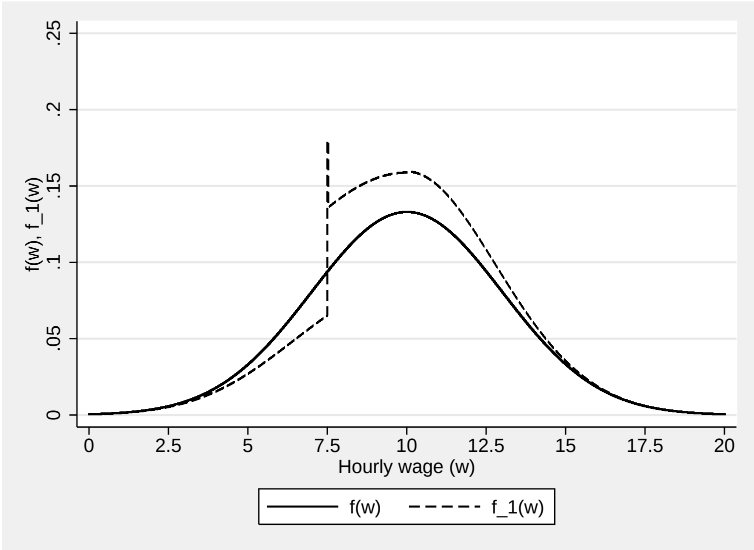
# 2 Theoretical and econometric framework

This section first outlines the parametric models of Meyer & Wise and Dickens et al. After that we show how the functional form assumptions of those parametric models can be relaxed with semi-parametric censored quantile reression models. Finally we discuss the application for the German construction sector.

## 2.1 The Meyer & Wise approach

Meyer and Wise (1983a,b) developed an approach to estimate wage and employment effects of the minimum wage from individual cross-sectional data when a federal minimum is already in existence. The one-equation version of their model starts from an 'underlying wage distribution' without a minimum wage which could be written as a latent variable $w^\star$: $f(w^\star)$. For a given minimum wage $M$, Meyer & Wise assume that because of non-coverage and non-compliance some workers with underlying wages $w^\star < M$ remain employed at wages $w < M$ with probability $P_1$. Moreover, they assume that a fraction of persons with $w^\star < M$ are now paid at $w = M$ with probability $P_2$. Therefore the probability of people with $w < M$ to be

Fig. 1: Underlying and observed wage distribution

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without work after the introduction of a minimum wage is $1 - P_1 - P_2 = 1 - P$ with $P = P_1 + P_2$. They rule out spill-over effects of the minimum on individuals with $w^\star > M$. The underlying (latent) distribution is specified as follows:

$$w_i^\star = X\beta + \epsilon_i \qquad \epsilon_i \sim N(0, \sigma^2) \tag{1}$$

where $X$ is a matrix containing individual and regional attributes and $\epsilon$ is a normally distributed error term with variance $\sigma^2$. The underlying distribution $f(w)$ and the observed wage distribution $f_1(w)$ are exemplarily displayed in Fig. 1 for hourly wages between zero and 20€/hour with the minimum wage being fixed at 7.50€/hour. The solid line marks the underlying, the dashed line the observed wage distribution. In this illustration the minimum wage induces spill-over effects in higher parts of the distribution up to about 15€/hour.

For $f_1(w)$ being the likelihood of observed wage rates, $w^\star$ or, e.g., $logw^\star$ normally distributed, and $\Phi$ the standardized normal distribution Meyer & Wise write the likelihood of observed hourly wages $w$ as:

$$f_1(w) = \begin{cases} \frac{f(w)\cdot(P_1)}{D} & if \quad w < M \\ \frac{\Phi[(M - X\beta)/\sigma]\cdot(P_2)}{D} & if \quad w = M \\ \frac{f(w)}{D} & if \quad w > M \end{cases} \tag{2}$$

where $D = 1 - Pr[w^\star < M](1 - P_1 - P_2) = 1 - \Phi[M - X\beta/\sigma] \cdot (1 - P)$ which is the probability that an individual who is employed without the minimum is also employed after its introduction. The distribution $f_1(w)$ is the conditional distribution of observed hourly wages in terms of the underlying distribution - given that wages are observed. The first part of the likelihood with $w < M$ are observed with probability $P_1$ times the likelihood for $w^\star = w$. The second part of the likelihood for observed wages $w = M$ is given by probability $P_2$ times the likelihood that $w^\star < M$ is raised by the minimum to $w = M$. The third part refers to observed wages above the minimum and is equal to the underlying distribution except from the fact that the share of people with $w > M$ might be higher than the share with $w^\star > M$ which is expressed in the denominator. Meyer & Wise use an interval around $M$ as in their data the pile-up of hourly wages varies around the nominal minimum due to measurement error and potential spill-over effects.

Note that this specification is quite similar to a standard Tobit model with censoring at $M$. In addition to common censored data there is also the case where wages below the 'censoring point' are observed which is mirrored in the first term of the likelihood as well as the denominator of all terms in the likelihood function. For $N$ persons with observed wage rates, among them $N_1$ with hourly wages below, $N_2$ at, and $N_3$ above $M$ the full log-likelihood is given as follows:

$$logL = \sum_{i=1}^{N_1} lnf_1(w_i) + \sum_{i=1}^{N_2} lnf_1(w_i) + \sum_{i=1}^{N_3} lnf_1(w_i) \tag{3}$$

The parameters in $\beta$ as well as $P_1$ and $P_2$ are estimated by maximizing (3) for the sample of observed people in employment. The employment effects are calculated by way of simulation. Intuitively, the number of employed people below $M$ without a minimum wage which is predicted on the basis of the underlying distribution is compared with the number of observed people with $w < M$. To be more precise, the employment effects of the minimum wage are simulated using the estimated parameters for (3). Remember that conditional on $X_i$ $D_i$ is the individual's probability to be still employed under the minimum given that he or she would be in employment under a minimum wage at $w_i < M$. Conversely the inverse $1/D_i$ is the expectation that a person would be in employment without a minimum wage. For a sample of $N$ persons the total expected number of employed people without the minimum amounts to

$$T = \sum_{i=1}^{N} \frac{1}{D_i} \tag{4}$$

The percent increase in employment is therefore $(T - N)/N$. Meyer & Wise focus their analysis on youth employment and find that about 30%-50% of the youths that would normally be employed in the absence of a minimum wage are without work because of the minimum. This figure represents 7% of all young men. They acknowledge that their estimation does depend upon a number of assumptions they have to make about the censoring point or the distribution of the error term, but claim that robustness tests show that their results are not overly sensitive to these assumptions. These critical points were carried forward by Dickens, Machin, and Manning (1998). We will discuss their model in the following sub-section.

## 2.2 Critique by Dickens, Machin, and Manning

Dickens, Machin, and Manning (1998) apply the Meyer & Wise approach to UK data to test its robustness with regard to the selection of the censoring point as well as the functional form assumption. They start from a simple version of the Meyer & Wise model with $P_1 = 0$ which means that people are not employed at $w < M$ with a minimum wage being in effect. Therefore only the probability $P_2 = P$ of remaining employed at $w = M$ under the minimum wage is part of the model. In order to point out the critical assumptions, Dickens et al. start from the following reformulation of the Meyer & Wise model. In the absence of the minimum employment $L_0$ is reached with the distribution of wages given by $f(w; \theta)$ with $\theta$ being a set of parameters to be estimated. When a minimum wage is introduced the density function changes to $f_1(w; \theta)$ which leads to employment $L_1$.

For $f_1$ to be estimated from observed wages, one has to assume that there is a wage $w_1$ above which wages are not affected by the minimum in order to infer on the underlying distribution $f$. Dickens et al. point out that Meyer & Wise assume $w_1$ to be very close to the minimum wage. They show that the choice of $w_1$ can be crucial for the estimated employment effect, if spill-over effects are present. Under the assumptions made the distribution of observed wages and the underlying wage distribution are related as follows:

$$\begin{aligned} f_1(w; \theta) &= \tfrac{L_0}{L_1} f(w; \theta) \\ &= \gamma f(w; \theta) \quad \text{for} \quad w > w_1 \end{aligned} \tag{5}$$

The ratio $\gamma$ of employment without and with the minimum serves as measure of the employment effect. Equation (5) states that for wages above the censoring point $w_1$ the observed and the underlying distribution are equal up to the scaling factor $\gamma$. Since they assume that employment above $w_1$ remains constant under the minimum it holds that

$$\begin{aligned} L_1(1 - F_1(w_1;\theta)) &= L_0(1 - F(w_1;\theta)) \\ F_1(w_1;\theta) &= 1 - \gamma(1 - F(w_1;\theta)) \end{aligned} \tag{6}$$

Specifying a tobit model for the wage equation with the censoring point at $w_1$ and plugging in (5) and (6) the log-likelihood becomes:

$$\begin{aligned} logL &= \textstyle\sum_{i=1}^{j} logf_1(w_i;\theta) + (L_1 - j) \cdot logF_1(w_1;\theta) \\ &= \textstyle\sum_{i=1}^{j} logf(w_i;\theta) + j \cdot log\gamma + (L_1 - j) \cdot log[1 - \gamma \cdot (1 - F(w_1;\theta))] \end{aligned} \tag{7}$$

Note that this tobit model is estimated only on those people who are observed to be employed with $N = L_1$ as the total number of observations. Moreover, $j$ denotes the number of persons with $w \geq w_1$ and $L_1 - j$ comprises those who are below the truncation point.[2] Parameters $\gamma$ and $\theta$ are estimated by maximizing (7) which yields the following Maximum Likelihood estimator of $\gamma$:

$$\gamma_{MLE} = \frac{j}{L_1 \cdot [1 - F(w_1;\theta)]} \tag{8}$$

The intuitive interpretation is that employment decreases (increases) under the minimum wage if the observed fraction of workers below $w_1$ is smaller (larger) than it is predicted on the basis of the distribution of those paid above $w_1$. Inserting this estimator in (7) yields the concentrated likelihood[3] which is equal to a likelihood from a sample of workers with observations truncated at $w_1$:

$$logL = \textstyle\sum_{i=1}^{j} logf(w_i;\theta) - j \cdot log[(1 - F(w_1;\theta))] + \text{constant} \tag{9}$$

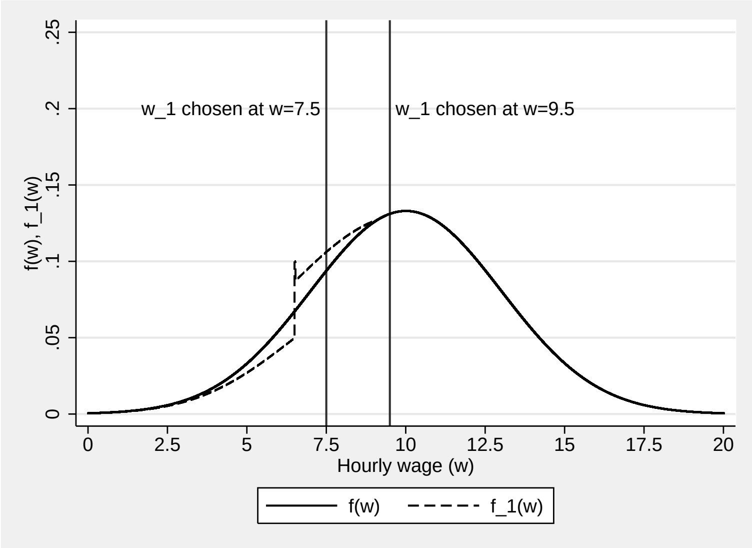
Having estimated $\theta$ from (9) $\gamma$ can be obtained from (8). Dickens et al. experiment with two different functional forms for $F(w_1;\theta)$: first they assume a log-normal wage distribution as have Meyer & Wise. Second, they specify the Singh-Maddala distribution ($F(w_1;\theta) = 1 - \left[1 + w_1/\theta_1)^{\theta_2}\right]^{\theta_3}$ with $\theta_1, \theta_2, \theta_3 > 0$).

Dickens et al. apply this model to UK Wage Council data between 1987-90 for the retail and wholesale sector and estimate it separately for men and women. They

[2]This must not be confused with a tobit model which is specified for all individuals who are observed to be employed (i.e. $L_1$) and those who are unvoluntarily (registered) unemployed.

[3]Note that this simplification to a concentrated likelihood does only work without parameterizing the distribution with respect to individual characteristics. [additional note on parameterization]

Fig. 2: Choosing different censoring points




Sources: own illustration

show that estimates of the employment effect are sensitive with respect to two critical assumptions. First, choosing different *censoring points* (at the 10th, 20th, 30th and 40th decile) yields vastly different results. It is obvious that setting $w_1$ too high results in inefficient estimates of $\gamma$ whereas setting it too low may yield inconsistent estimates. The latter might happen if the minimum affects higher parts of the wage distribution above the chosen censoring point (so-called 'spillover effects'). This clearly violates the assumption of (6) as is demonstrated in Fig. 2. Again the solid line marks the underlying and the dashed line the observed wage distribution. If the first censoring point at 7.50 €/hour was chosen, estimates would be biased as the observed distribution is influenced by the spill-over effects of the minimum. The second cut-off point at 9.50 €/hour does not suffer from this problem. Dickens et al. thus emphasize that the Meyer & Wise model could be inconsistent when spill-over effects of the minimum wage to higher parts of the wage distribution occur. Since Meyer & Wise only consider $w_1$ values close to the minimum, spill-over effects are rather likely.[4]We will test the robustness of our results specifying a range of different censoring points.

Second, Dickens et al. also show that with their data the choice of the *functional form* is crucial for the estimated employment effects. Intuitively, as soon

[4]One other difference between the Meyer & Wise approach and Dickens et al. is that the former estimate the probability $P$ to remain employed after the minimum whereas the latter specify the employment ratio $\gamma = L_0/L_1$. Dickens et al. discuss how both indicators are related ($P = (\gamma^{-1} - 1) \cdot F(W_1;\theta)^{-1}$) and what the advantage is to estimate $\gamma$ rather than $P$.

as one assumes a symmetric distribution and then infers from the right part of a left-truncated observed wage distribution (e.g. the log-normal distribution) to an underlying distribution, estimates become inconsistent if the underlying distribution is indeed asymmetric. In this instance results are driven by the non-truncated part of the distribution which might be fundamentally different from the truncated part which occurs regularly with income data. Dickens reject the symmetry assumption for their data and find markedly different results for the asymmetric Singh-Maddala compared to the log-normal distribution. Therefore we specify semi-parametric models that relax the functional form assumptions.

The main result of Dickens et al. is the potential sensitivity of the Meyer & Wise approach to its critical assumptions. Dickens et al.'s findings markedly differ from those of Meyer & Wise with their own employment effects being implausibly large for certain specifications. We will subsequently address both critical points. In the following section we relax the functional form assumption by specifying semi-parametric models for a truncated wage distribution. In section 2.4 we discuss the selection of the censoring point for the German case.

## 2.3 Semi-parametric estimators

The major criticism put forward by Dickens et al. which has already been addressed by Meyer & Wise refers to the functional form assumptions needed to infer from the observed on the underlying wage distribution and thereby simulating the employment effects of the minimum wage (i.e. $\epsilon \sim N(0, \sigma)$). If this assumption is not met by the data, the maximum likelihood estimator is inconsistent which means that the underlying distribution is not correctly estimated. Meyer and Wise (1983a) use a Box-Cox transformation whereas Dickens, Machin, and Manning (1998) reject the (log-)normality assumption on statistical grounds and specify an alternative model on the basis of the Singh-Maddala distribution.

We will take another route here by specifying semi-parametric models for censored (or truncated) distributions that relax the functional form assumptions. A number of those models have been suggested over the last few years (cf. Chay and Powell (2001)). The main idea of these models is to parameterize the regression function as usual without putting any parametric restrictions on the error term. In the following we focus on the *censored quantile regression* (CQReg) which is described extensively by Buchinsky (1994). Our estimation framework for the employment effects remains similar to the parametric version. Emplyoment effects are simulated based on the comparison of the observed with the estimated underlying wage distribution. We start again from a latent underlying distribution $w^\star = X\beta + \epsilon_i$ as in equation (1) above. The first step is thus to estimate a series of censored quantile regressions for a number of quantiles of this distribution. Then the conditional (underlying) distribution is estimated using the parameters from the first step and the employment effects are simulated by comparing the underyling with the observed distribution.

The idea of the quantile regression model is to model the $\tau$-th sample quantile $Q^{(\tau)}$ of the distribution of wages $w$ conditional on a set of $X$-variables.[5] Since $w$ is censored, for the CQR it depends if the $\tau$-th quantile lies below or above the censoring point. As long as the quantile is in the uncensored region of the distribution (less than a share of $\tau$ observations are below the cut-off point) it is unaffected by the censoring. If the quantile lies in the censored region it is equal to the censoring point (see Fig. 3). $Q^{(\tau)}(X, \beta_\tau) = max[w_1, X\beta_\tau]$ then denotes the conditional quantile function of the observed wages $w$ censored at $w_1$ and depends on the regressors $X$ and the parameter vector $\beta_\tau$. The CQR model implies the following assumptions:

$$\begin{aligned} Q^{(\tau)}(\epsilon_i|X) &= 0 \\ Q^{(\tau)}(w^\star|X) &= X\beta_\tau \end{aligned} \tag{10}$$

It is assumed that the conditional quantile of the error term is zero in which case the conditional quantile of the true underlying variable $w_i^\star$ would be equal to $x_i\beta$. The CQR neither requires distributional assumptions about $\epsilon_i$ nor homoscedasticity. The CQR estimator thus handles nonnormal, heteroscedastic and asymmetric errors which is important for the analysis of empirical wage distributions. The parameter vector $\beta_\tau$ is estimated by minimizing the weighted sum of the absolute deviations of $w_i$ from $max[w_1, X\beta]$ over all $\beta_\tau$ in the following objective function:

$$Q^{(\tau)}(\beta) = \sum_{w_i > X\beta} \tau |w_i - max[w_1, X\beta]| + \sum_{w_i < X\beta} (1-\tau)|w_i - max[w_1, X\beta]| \tag{11}$$

[5] $Q^{(\tau)}$ means a share of $\tau$ observations are smaller then $Q$ with $0 \leq \tau \leq 1$ Quantiles are defined as inverse of the c.d.f.: $Q^{(\tau)} = F^{-1}(\tau)$.

Fig. 3: Density of $w^\star = X\beta + \epsilon_i$ for $X\beta > w_1$ and $X\beta < w_1$


Sources: own illustration.

There is no closed-form solution to this problem. The model is estimated by solving the linear programming representation of the maximization problem. For the QCR Buchinsky suggested the Iterative Linear Programming Algorithm (ILPA) which alternates between two steps (Buchinsky (1994)): In the first step, the model applies the least absolute deviations estimator to all observations. In the second step, the data set is re-censored by excluding all those values for which the CQR-estimated values are smaller than the censoring point. Then, step one is repeated with the re-censored data. The steps are repeated until convergence is achieved and further re-censoring is no longer needed. The final CQR-estimation thus does not use all observations.[6] Alternatice semi-parametric approaches would be censored least squares estimators, namely the symmetrically censored least squares (SCLS) or the identically censored least squares (ICLS) estimator (cf. Powell (1986); Honore and Powell (1994)).[7]

We estimate a series of CQR models to calculate the underlying distribution conditional on the observed explanatory variables in a very flexible form at different quantiles. Similar procedures that estimate conditional distributions are, e.g., discussed in the literature on decomposition of distributions to analyze sources of wage

[6]If a certain number of observations is censored and the respective quantile lies in the censored region, the CQR-estimator will not converge. In this case we have to approximate this quantile by a higher quantile where convergence is achieved.

[7]SCLS is based on symmetric trimming combined with standard OLS analysis. ICLS does not rely on symmetry; the wage distribution is re-censored for pairs of observations such that the densities have the same shape for each pair. Both approaches iterate between the estimation of the regression function and a re-censoring step until convergence is achieved.

inequality (cf. Gosling, Machin, and Meghir (2000), Melly (2005), Melly (2006)) or the estimation of unconditional distributions and quantile treatment effects (cf. Firpo, Fortin, and Lemieux (2009), Firpo (2007)). In fact most of those papers also estimate CQR models since (wage) distributions are censored as well, mostly at the top. In our application the censoring is from below and the censored part of the distribution is approximated by the lowest estimable quantile. In this version we estimate the model at the following quantiles: 0.02 (0.02) 0.3; from there on we use a coarser grid: 0.3 (0.1) 0.9. We use Buchinsky's ILPA implemented in Stata (cf. Jolliffe, Krushelnytskyy, and Semykina (2000)) in a slightly modified version. Having estimated the underlying distribution the employment effects are simulated analogous to equation (4) or eqation (8). We compare the probability mass below the cut-off point with its counterpart under the density of the observed wages. The simplest way to do this is to compare the number of predicted observations below the chosen cut-off point with the number of observed observations:

$$\Delta E = (\hat{N}_{below} - N_{below})/L_1 \tag{12}$$

The difference between those two values standardized by the observed employment level is the percentage change of employment that would result if the minimum wage was not in effect.

## 2.4 Application for the German construction sector

The Meyer & Wise approach like the modified version suggested by Dickens et al. cannot be applied straightforwardly to the German economy, because no federal minimum wage currently exists. Over the last ten plus years sectoral minimum wages have been implemented in several industries (e.g. the construction sector and, more recently, also in postal and cleaning services). In the construction sector a sectoral minimum wage was introduced in 1997 and since then amended repeatedly (cf. Rattenuhber (2010)). The legislation covered only blue-collar workers (so-called 'gewerbliche Arbeitnehmer') in large parts of the main construction trade ('Bauhauptgewerbe'). Minimum wage levels were set differently for West (9.80 €) and East Germany (8.63 €). This situation is an ideal test case for the above-mentioned labor demand models for the following reasons:

1. The sectoral minimum wage created a situation like in the studies of reference mentioned above. We have only a single cross-section of wage data. The the minimum is binding for a sizeable proportion of the individuals observed, but not all of them. Therefore we can estimate the parametric models with the German data and see if their findings can be replicated for the sectoral minimum wage in the German construction sector.

2. Although the fixed minimum wage levels differed between the East and West, as we will show below, the minimum wage was more binding in East compared to West Germany. Acording to theory the effects should therefore be much more pronounced in the East. We can test this hypothesis by specifying separate models for East and West Germany with the West serving as a control group.

3. The sectoral minimum wage was only implemented in the main construction trade ('Bauhauptgewerbe'). Effects should neither be detectable in other branches of the construction sector (which can not be tested with the current data set but is possible in principle) nor in other sectors of the economy. We will not utilize this variation in the current version of the paper but will include the rest of the economy (or specific sectors) as additional control groups.

4. So far employment effects in the German construction sector have been tough to analyze with standard ex post evaluation methods and existing data. We briefly mentioned the controversial study by König and Möller (2008) in the introduction above and are able to relate our results to their findings.

We come back to those points in the discussion of the results. All findings should be taken with a grain of salt for the following reasons. First, we conduct a partial analysis of employment effects in the construction sector which is different from other studies where the minimum wage covered not only one sector but the whole economy. We cannot analyze substitutional or complementary employment effects with other sectors. Substitution effects, e.g. between covered blue and non-covered white collar workers, within the main construction trade are included in the analysis since we estimate the models on all employees in the sector. Second, capital-labor-substitution is likely to occur to some degree in the construction sector as the price of labor increases under the sectoral minimum wage which we do not estimate here. Third, we do not explicitly consider the output price elasticity for the construction sector. Increasing the price of one production factor likely reduces the demand for construction tasks to some degree. All those points suggest that we rather underestimate the employment effects of the sectoral minimum wage.

# 3 Data, sample, variables

The empirical analysis is based on *data* from the 'Gehalts- und Lohnstrukturerhebung 2001' (Salary and Wage Survey, GLS). In this version of the paper we use data from the scientific usefile for the year 2001. The GLS is a linked employer-employee data set provided by the German Federal Statistical Office (Hafner (2006)). The 2001 wave does not include employees in firms with less then 10 employees and several sectors of the economy (e.g. agriculture, public services, health care and social services).[8] The large sample size (about 1 million observations in total) enables precise estimations for sub-groups of employees. This is indispensable especially for the semi-parametric estimators and for sub-samples like the German construction sector. Another great advantage of the GLS data is that the hourly wage measures are more reliable than in household surveys like, e.g., the German Socioeconomic Panel (SOEP), since the information comes directly from the firm and is based on the employment contract. Measurement errors due to incomplete memory of the respondent, discrepancies between reported working hours and wage income are therefore less of a problem. On the other hand several drawbacks of the data have to be acknowledged. Firms with less than or equal to 10 employees and certain sectors (agriculture, the public sector and household services) are not included in the sample. Both gaps lead to a systematic under-representation of certain individuals. Marginally employed, e.g., work more often in small firms (see Müller (2009)). Furthermore, it lacks information on the household context (family status, children, etc.). That the GLS is not a panel data set is not important here.

The *sample* is restricted to the to main construction trade ('Bauhauptgewerbe') of the German construction sector in 2001 where a sectoral minimum wage was

[8]We will suplement the analysis with data from the latest wave of 2006 as soon as the scientific usefile will become available. The latest version of this dataset goes under the name 'Verdienststrukturerhebung 2006' (VSE) (see Bundesamt (2009)).

in place that was binding for a sizeable proportion of workers. In order to get a more homogeneous sample estimations are further constrained to male blue collar workers and employees who are not in vocational training since the minimum only covers blue-collar workers and males clearly dominate this industry. Note that in this sample there is non-coverage (blue-collar workers with non-constructions tasks) and there might also be some non-compliance which does not affect the results. In 2001 coverage amounted to about 39% in East and 35% of all workers in the West German construction sector (cf. Rattenuhber (2010) for detailed information about the minimum wage for the German construction sector). We will show below that for the majority of employees in the West this minimum was not binding. All models are therefore estimated separately for the West and East.

The *hourly wage measure* is based on reported gross income from work in the month of the survey. Any payments for additional (overtime) work in the observed month are subtracted from this amount. Hourly wages are calculated by dividing this number by reported monthly working hours also diminished by overtime if applicable. Wages used in the analysis thus refer to regular payments and actual working hours as opposed to contractual wages and hours. Given the reliability of the GLS data we are confident that this gives a precise wage measure which can be related to the legal minimum wage levels.

The selection of explanatory variables is dictated by the GLS data set. The specification of our models is theoretically motivated by the standard Mincerian wage equation which explains earned wages on the basis of human capital (Mincer (1974)). We therefore include polynomials for *age* and the *level of education* which should approximate human capital accumulation. We also distinguish different types of *employment contracts* (full-time, part-time, and marginal employment). Furthermore, as the literature on internal labor markets suggests, additional years of *tenure* in a firm lead to an increase in wages (Abraham and Medoff (1981)). As we have this information in the data we include tenure in our wage regressions. We have no information on the entire labor market career of the individuals, though, and cannot account for the potential depreciation of human capital over past periods of unemployment or inactivity. In addition to observable individual and job characteristics some factors on the labor demand side are also important for the wage. We therefore add firm attributes to our model: we include dummy variables for the *firm size* and the *industry* where the individual works as different forms pay different wages for equally skilled and productive people. We also have information on the type of *collective bargaining* agreement (sectoral, firm, or no agreement) which varies widely between East and West Germany. Lastly we control for the influence of the *public sector* in the firm.

The descriptive statistics of the log wage and all explanatory variables used are reported in Tab. 1. They reveal first the differences in the average wage level between West and East Germany. Second, an important institutional discrepancy which is crucial for the bargained wages as well as the agreed minimum wage levels (see also Rattenuhber (2010)) concerns the degree of unionization. In West Germany almost 80% of all individuals in the sample work under a collective bargaining agreement (CBA) whereas this share is only about half that size in the East. Since firm CBAs did not play a significant role in the German construction sector at that time the majority of East German workers is not directly covered by any CBA.

Tab. 1: Descriptive statistics: wages & explanatory variables

| | East Germany | | West Germany | |
|---|---|---|---|---|
| | mean | [s.d.] | mean | [s.d.] |
| Log wage | 2.3338 | [0.1722] | 2.6405 | [0.1755] |
| Age | 39.1049 | [9.5005] | 40.5143 | [10.7692] |
| Tenure | 81.5588 | [95.0811] | 115.2525 | [112.7403] |
| Dummy 'Abitur' | 0.0036 | [0.0600] | 0.0044 | [0.0665] |
| Dummy no CBA | 0.6188 | [0.4858] | 0.2008 | [0.4006] |
| Dummy firm CBA | 0.0233 | [0.1509] | 0.0110 | [0.1044] |
| Dummy sector CBA | 0.3579 | [0.4795] | 0.7882 | [0.4086] |
| Dummy no public | 0.9509 | [0.2161] | 0.9746 | [0.1574] |
| Dummy limited public | 0.0236 | [0.1518] | 0.0148 | [0.1207] |
| Dummy high public | 0.0255 | [0.1577] | 0.0106 | [0.1026] |
| Dummy firm size $< 20$ | 0.1615 | [0.3680] | 0.1553 | [0.3622] |
| Dummy firm size $20 - 50$ | 0.2209 | [0.4149] | 0.2514 | [0.4338] |
| Dummy firm size $50 - 100$ | 0.2630 | [0.4403] | 0.2114 | [0.4083] |
| Dummy firm size $100 - 250$ | 0.2372 | [0.4254] | 0.2500 | [0.4330] |
| Dummy firm size $250 - 500$ | 0.0824 | [0.2750] | 0.0835 | [0.2767] |
| Observations | 3,604 | | 10,343 | |

Source: GLS; own calculations.

With respect to other individual characteristics construction workers are slightly older in the West compared to the East. Their average tenure in the job is 35 weeks longer and the share of people with a higher school degree is slightly higher. Concerning firm characteristics the public sector has a slightly larger influence in

East German firms whereas firm sizes are rather similar between the West and East German construction firms. The sample comprises about 3,600 East German cosntruction workers whereas the sample size for the West is more than 10,300 employees.

# 4 Results

All wage regressions are estimated on log wages to reduce the asymmetry in the distributions. We do not report the results for the regression coefficients of the explanatory variables in the paper.[9] Apart from space restrictions parameter estimates for the explanatory variables are not the focus of our analysis, since we are mainly interested in the (underlying) conditional distribution. Direction and size of the coefficients are theoretically plausible.[10] First, we present descriptive evidence for East and West Germany. We then discuss the parametric estimates from the Models of Meyer & Wise as well as Dickens et al. Finally we present the semi-parametric censored quantile regression results and relate them to the previous evidence.

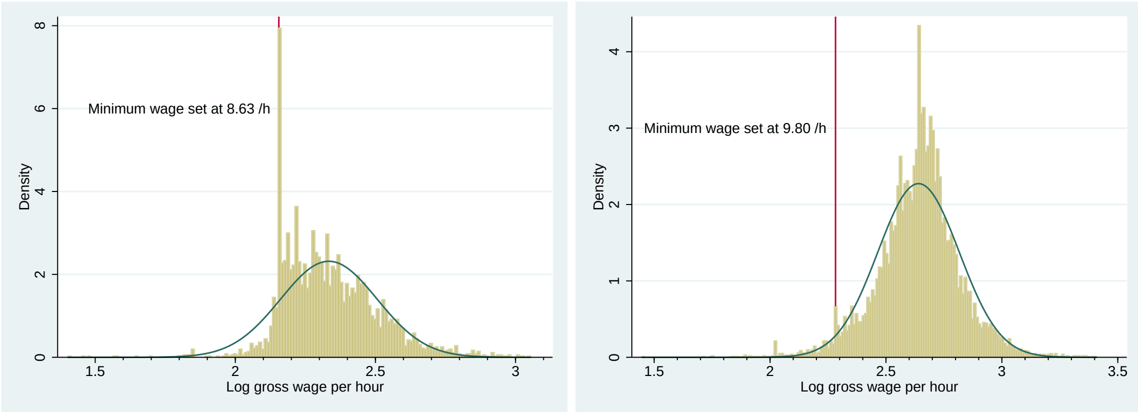
## 4.1 Descriptive evidence

After the minimum in the German construction sector was introduced in 1997 it was amended several times. We apply data gathered in September 2001 and use therefore minimum wage levels set in September 2001 at 8.63 €/hour in East and 9.80 €/hour in West Germany. The histograms of Fig. 4 show the empirical distributions of log hourly wages for the sample of the construction workers in 2001 separately for East (left panel) and West Germany (right panel). The respective minimum wage levels are also included in the graphs. For both regions the expected pattern for the wage distribution under a minimum wage arises (compare with Fig. 1 above). A clear spike of wages at the legal minimum wage level is visible, although much more pronounced in East Germany. One also observes hourly wages below the defined minimum indicating non-coverage (and potentially some non-compliance). There is

[9] Quite a large number of different models for sub-groups and several censoring points was estimated, especially for the censored quantile regressions. Complete estimation results are available from the author upon request.

[10] See Tab. 5 and 6 in the appendix.

Fig. 4: Distribution of log hourly wages (East & West Germany




Sources: GLS 2001; own calculations.

slight descriptive evidence for some spill-over effects directly above the minimum wage; this cannot be tested formally, though.

The main result of the descriptive analysis is that the minimum wage in the construction sector was much more binding in East compared to West Germany since the defined nominal minimum wage level is clearly closer to the median of the wage distribution. This is important for the interpretation of the model estimates. The chosen minimum wage level for East Germany was economically more relevant for East German firms. According to this descriptive evidence we would expect negative employment effects for the East German construction sector whereas the results should be much less clear for West Germany. Therefore the West may indeed serve as a control group. The differential effects should be mirrored in the estimates of the employment effects that are carried out separately for the East and the West.

## 4.2 Parametric estimates

We will first present estimation results for the two parametric models of Meyer & Wise and Dickens et al. (see Tab. 2). As mentioned the models are estimated separately for East and West Germany. The figures in Tab. 2 refer to a percentage change in employment that would result if there was no minimum wage at all, i.e. positive values indicate negative employment effects of the minimum and vice versa. Bootstrapped 95-percent-confidence-bands are reported in parentheses. We also analyze the sensitivity of the models with respect to the choice of different censoring points by estimating all models for the cut-off points given in the first column. The horizontal lines in the table mark the set minima for the East and West and separate cut-off points below and above the legally set minimum wage levels.

Tab. 2: Employment effects: parametric models

| | East Germany | | | |
|---|---|---|---|---|
| Cut-off (€/h) | Meyer & Wise | | Dickens et al. | |
| 8.5 | 0.15 | [0.07 ; 0.23] | 0.29 | [0.29 ; 0.29] |
| 8.6 | 0.09 | [0.04 ; 0.15] | 0.36 | [0.36 ; 0.37] |
| 8.7 | -0.01 | [-0.01 ; 0.00] | 0.19 | [0.19 ; 0.20] |
| 8.8 | -0.01 | [-0.02 ; -0.01] | 0.21 | [0.20 ; 0.22] |
| 8.9 | -0.02 | [-0.02 ; -0.01] | 0.22 | [0.21 ; 0.23] |
| 9.0 | -0.02 | [-0.03 ; -0.02] | 0.21 | [0.19 ; 0.22] |
| 9.1 | -0.03 | [-0.03 ; -0.02] | 0.24 | [0.22 ; 0.26] |
| 9.2 | -0.03 | [-0.04 ; -0.03] | 0.27 | [0.25 ; 0.30] |
| 9.3 | -0.03 | [-0.04 ; -0.03] | 0.20 | [0.15 ; 0.25] |
| 9.4 | -0.04 | [-0.05 ; -0.03] | 0.26 | [0.18 ; 0.32] |
| 9.5 | -0.06 | [-0.07 ; -0.05] | 0.30 | [0.22 ; 0.36] |
| | West Germany | | | |
| Cut-off (€/h) | Meyer & Wise | | Dickens et al. | |
| 9.7 | 0.00 | [0.00 ; 0.00] | -0.02 | [-0.02 ; -0.02] |
| 9.8 | 0.00 | [0.00 ; 0.00] | -0.02 | [-0.02 ; -0.02] |
| 9.9 | 0.00 | [0.00 ; 0.00] | -0.03 | [-0.03 ; -0.03] |
| 10.0 | 0.00 | [0.00 ; 0.00] | -0.03 | [-0.03 ; -0.03] |
| 10.1 | 0.00 | [0.00 ; 0.00] | -0.03 | [-0.03 ; -0.03] |
| 10.2 | 0.00 | [0.00 ; 0.00] | -0.03 | [-0.03 ; -0.03] |
| 10.3 | 0.00 | [0.00 ; 0.00] | -0.04 | [-0.04 ; -0.04] |
| 10.4 | 0.00 | [0.00 ; 0.00] | -0.04 | [-0.04 ; -0.04] |
| 10.5 | 0.00 | [0.00 ; 0.00] | -0.04 | [-0.04 ; -0.04] |

Notes: All models estimated for varying censoring points according to 1st column. Bootstrapped 95%-confidence bands in parentheses.

Source: GLS; own calculations.

The findings for *East Germany* are consistent with our theoretical expectations. We estimate negative employment effects for the East German construction sector in 2001 in the interpretable range of cut-off points for both parametric models. Yet those findings are sensitive to different model assumptions as well as the selection of the cut-off points. The interpretation of results crucially depends on those assumptions. Starting with the Meyer & Wise model it has to be made clear that estimates are only interpretable around the set minimum wage level of 8.63 €/hour, since the spike at the minimum (see Fig. 4 above) is explicitly modeled. We use an interval of 0.20 €/hour above the stated censoring point; therefore only the reported cut-off points 8.50 €/hour and 8.60 €/hour include the observed spike. We find indeed negative employment effects for those two cut-offs. According to these estimates employment would be 10-15% higher without the minimum wage which is a rather large effect. All other estimates should return inconsistent estimates since the theoretical spike is specified above the observed spike in the distribution. Those estimates are actually negative indicating theoretically implausible positive employment effects. This shows that the Meyer & Wise approach can only be estimated with a censoring point near the set minimum wage level which mirrors the critique of Dickens et al. Meyer & Wise's model overly hinges on a narrow region of censoring points which in addition makes this model potentially vulnerable to spill-over effects.

Therefore Dickens et al. constructed their model such that the sensitivity with respect to the choice of different censoring points is indirectly testable. Note that, since opposite to the Meyer & Wise their model is based on a truncated regression, only those estimates based on cut-off points above the legal minimum wage level (8.70 €/hour in our application for the East) are consistent. Moreover, the robustness of findings for different cut-off points serves as informal test for the influence of spill-over effects. We find negative employment effects for the interpretable range of estimates. Employment would be about 20% higher without a sectoral minimum wage which is even higher than for the Meyer & Wise model and hardly convincing. The estimates are robust between cut-off points of 8.7 €/hour-9.0 €/hour. For censoring points further above the distribution (where decreasingly less information of the observed distribution is used to estimate the underlying distribution) the effects become even larger. It is noteworthy that Dickens et al. report even higher estimates for the employment losses.

The parametric results for *West Germany* also mostly fit our hypotheses as we find no or even very small positive employment effects of the sectoral minimum wage in the construction sector. For the Meyer & Wise model the estimates are zero which would confirm the hypothesis that the minum was hardly binding in the West and therefore should have only minor implications for employment. The Dickens et al. model yields even slight positive effects. This is not very plausible and rather hints on a slightly inconsistent estimates for the West. Overall the findings of the parametric models replicated the result patterns of the studies of reference and are qualitatively consistent with theoretical expectations. We do find negative employment effects for the East German construction sector whereas estimates tend to zero for the West. On the other hand the problems of the parametric approaches become obvious. We could show that the models are sensitive with respect to the choice of a cut-off point. Moreover, the size of the employment effects raise the suspicion that the parametric assumptions (i.e. normality of error terms) are too restrictive and lead to inconsistent estimates. It is theoretically rather inconceivable that the still moderate sectoral minimum wage would lead to employment losses of 10-20% in the short term. It seems that the Dickens et al. model is more vulnerable with respect to violations of these assumptions as it relies on a smaller part of the observed distribution compared to Meyer & Wise's approach. We therefore turn to the semi-parametric models in the following sub-section.

## 4.3 Semi-parametric estimates

Do the findings change if we relax the functional form assumption? The results of the semi-parametric estimators are displayed in Tab. 3. The models are again estimated separately for East and West Germany and a range of cut-off choices. As in the Dickens et al. model the estimates are consistent starting with the cut-off point of 8.70 €/hour. Different cut-offs above this threshold serve as a robustness check for the existence of spill-over effects with the caveat being that identification rests on an increasingly smaller part of the distribution as in the parametric models with higher censoring points.

Overall the semi-parametric estimates are qualitatively consistent with the parametric model results and theoretical expectations. We find again negative employment effects for the East German construction sector whereas estimates are only slightly negative for West Germany. Regarding the size of the effect we estimate that employment would be about 5% higher in the East German construction sector if there had been no minimum wage. This seems to be a more reasonable figure compared to the 10-20% range for the parametric models and suggests that functional form assumptions might indeed bias those results. According to the Cqreg estimates employment in the West German construction sector would have been 2%

Tab. 3: Employment effects: semi-parametric models

| Cut-off (€/h) | East Germany | | Cut-off (€/h) | West Germany | |
|---|---|---|---|---|---|
| 8.5 | 0.08 | [0.06 ; 0.11] | 9.7 | 0.02 | [0.01 ; 0.03] |
| 8.7 | 0.07 | [0.05 ; 0.09] | 9.9 | 0.02 | [0.02 ; 0.03] |
| 8.9 | 0.06 | [0.04 ; 0.08] | 10.1 | 0.02 | [0.02 ; 0.03] |
| 9.1 | 0.06 | [0.04 ; 0.08] | 10.3 | 0.02 | [0.02 ; 0.03] |
| 9.3 | 0.05 | [0.02 ; 0.07] | 10.5 | 0.02 | [0.01 ; 0.02] |
| 9.5 | 0.04 | [0.02 ; 0.06] | | | |

Notes: All models estimated for varying censoring points according to 1st column. Bootstrapped 95%-confidence bands in parentheses.
Source: GLS; own calculations.

higher without the minimum wage. So we find minor employment losses for West Germany as well. The semi-parametric results are very robust with respect to the choice of a cut-off point. The censored quantile regression model seems to work better if it is based on a smaller part of the observable distribution compared to the parametric models. Since the observable distribution is modeled in a more flexible way the sensitivity of the estimates with respect to spill-over effects of the minimum wage to higher parts of the distribution seems to be much smaller.

How do our estimates relate to the previous findings? We could reproduce some of the patterns in the reference studies. Although the Meyer & Wise model is only consistent for a very small range of cut-off points it apparantly gives more reasonable estimates than the Dickens et al. approach. The reason could be that the later model utilizes a smaller amount of information from the distribution by choosing higher censoring points. Although for both models the parametric assumption for the error term leads to rather high estimates of the employment effect this seems to be more of a problem for the Dickens et al. model. Interestingly, the authors report still even higher negative employment effects in their paper. So we seemingly re-enact this problem with our data. The semi-parametric estimator gives more reasonable effects and we would argue that it helps to model the underlying distribution more adequately.

Are the findings in line with previous research for the German construction sector? To put the differences which are presented in Tab. 4 in perspective one has to keep in mind that König and Möller (2008) use a different methodology and data base. They estimate a difference-in-difference framework on an administrative data set which lacks crucial information about hours worked. Their construction of the treatment and control group rests on the imputation of working hours on the basis of a probability model.

Tab. 4: Comparison of employment effects

| | East Germany | | West Germany | |
|---|---|---|---|---|
| Koenig & Moeller - treated | 0.04 | [0.01 ; 0.07] | -0.02 | [-0.04 ; 0.00] |
| Koenig & Moeller - overall | 0.00 | [0.00 ; 0.01] | 0.00 | [0.00 ; 0.00] |
| Meyer & Wise model | 0.09 | [0.09 ; 0.10] | 0.00 | [0.00 ; 0.00] |
| Dickens et al. model | 0.19 | [0.19 ; 0.20] | -0.03 | [-0.03 ; -0.03] |
| Cqreg model | 0.07 | [0.05 ; 0.09] | 0.02 | [0.02 ; 0.03] |

Notes: Bootstrapped 95%-confidence bands in parentheses for own models. For König and Möller (2008) re-employment probabilities for treated compared to non-treated. Second line relates effect size to all employed. 95%-confidence bands.
Source: König and Möller (2008); GLS; own calculations.

Qualitatively we almost reproduce their findings, i.e. negative employment effects for East Germany and close to zero effects for the West. The first discrepancy is that our semi-parametric specification yields also slightly negative effects for West Germany whereas König and Möller (2008) even report positive employment effects of the minimum in some of their specifications. The second more important point is that the negative effects for East Germany are markedly higher in comparison with König and Möller (2008) (see Tab. 4). If their employment effects are translated to the whole construction sector they become smaller than 1%. We estimate an effect of nearly 5%. This adds information to the economic politicy debate about the effects of the minimum wage in the German construction sector and leads to a more pesimistic picture.

# 5 Conclusion

In this paper we applied different parametric and semi-parametric approaches to estimate the employment effects of a sectoral minimum wage in the German construction sector from a single cross-sectional wage distribution in 2001. The pattern of the employment effects is consistent throughout different models with clearly negative effects for East Germany and only slightly negative effects for West Germany.

This result confirms our theoretical expectations which were based on the economic influence of differential minimum wage levels that were set much higher in the East German construction sector.

Concerning the size of the effect the results for the parametric models range between 10-20% and are thus implausibly high. We conclude that parametric functional form assumptions are overly restrictive for the observed wage distributions and drive those estimates. This results confirms previous findings and reservations about this approach in the literature. We therefore suggest an innovative way to relax the parametric assumptions by estimating a series of semi-parametric censored quantile regression models. We find smaller and more reasonable estimates with this approach. According to the semi-parametric estimates employment levels would be 5-6% higher without the sectoral minimum wage in East Germany. Moreover, we also estimate slightly negative effects for the West of about 2%. We conclude that this model is a meaningful extension to existing approaches that allows to estimate underlying wage distributions more precisely.

The paper also contributes to the controversial debate about the employment effects of the sectoral minimum wage in the German main construction trade and the discussion about a federal minimum wage in Germany. We confirm previous findings for Germany and reiterate the negative employment effect of the sectoral minimum wage in East Germany. Especially the differential effects in West and East Germany should be taken into account for future amendments of the minimum wage and in current discussion about additional secotral minima in Germany.

The scope of results is obviously limited by the fact that we neither explicitly estimate substitution effects with other sectors nor account for capital-labor substitution and overall output adjustments in the construction sector. Future extensions should focus on robustness checks for further control groups without a sectoral minimum wage. In addition alternative functional form assumptions could be tested. Employment effects could also be broken down according to certain characteristics (age, qualification, tenure).

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# Appendix

Tab. 5: Estimation results: East Germany

| | Meyer &Wise | | Dickens et al. | | Cqreg | |
|---|---|---|---|---|---|---|
| Age | 0.263 | [ 0.027 ] | 0.035 | [ 0.004 ] | 0.018 | [ 0.003 ] |
| Age squared | -0.003 | [ 0.000 ] | 0.000 | [ 0.000 ] | 0.000 | [ 0.000 ] |
| Tenure (months) | 0.004 | [ 0.000 ] | 0.000 | [ 0.000 ] | 0.000 | [ 0.000 ] |
| Education high | 1.496 | [ 0.573 ] | 0.137 | [ 0.062 ] | 0.137 | [ 0.065 ] |
| No collective agreement | -0.876 | [ 0.084 ] | -0.099 | [ 0.011 ] | -0.072 | [ 0.007 ] |
| Firm collective agreement | -0.084 | [ 0.243 ] | -0.025 | [ 0.027 ] | -0.057 | [ 0.017 ] |
| No public influence | 0.245 | [ 0.234 ] | 0.011 | [ 0.027 ] | 0.012 | [ 0.016 ] |
| Limited public influence | -0.477 | [ 0.325 ] | -0.025 | [ 0.047 ] | -0.021 | [ 0.022 ] |
| Firm size: below 21 | -1.647 | [ 0.223 ] | -0.195 | [ 0.027 ] | -0.119 | [ 0.022 ] |
| Firm size: below 21-50 | -1.720 | [ 0.217 ] | -0.197 | [ 0.025 ] | -0.117 | [ 0.020 ] |
| Firm size: below 51-100 | -1.374 | [ 0.208 ] | -0.132 | [ 0.023 ] | -0.081 | [ 0.019 ] |
| Firm size: below 101-250 | -0.681 | [ 0.205 ] | -0.049 | [ 0.022 ] | -0.037 | [ 0.020 ] |
| Firm size: below 251-500 | 0.136 | [ 0.224 ] | 0.023 | [ 0.023 ] | 0.026 | [ 0.022 ] |
| Constant | 5.639 | [ 0.611 ] | 1.650 | [ 0.097 ] | 2.031 | [ 0.063 ] |
| p1 | 0.208 | [ 0.020 ] | | | | |
| p2 | 0.320 | [ 0.029 ] | | | | |
| sigma | 0.675 | [ 0.017 ] | 1.650 | [ 0.005 ] | | |
| Observations | 3,604 | | 3,052 | | 3,517 | |
| Log-likelihood | -7,242 | | 2,264 | | | |

Notes: All models estimated with specific censoring point. Standard errors in parentheses. Cqreg model for 0.5 quantile. Sample size changes as not all observations are used for estimation due to censoring.
Source: GLS; own calculations.

Tab. 6: Estimation results: West Germany

| | Meyer &Wise | | Dickens et al. | | Cqreg | |
|---|---|---|---|---|---|---|
| Age | 0.218 | [ 0.015 ] | 0.015 | [ 0.001 ] | 0.015 | [ 0.001 ] |
| Age squared | -0.002 | [ 0.000 ] | 0.000 | [ 0.000 ] | 0.000 | [ 0.000 ] |
| Tenure (months) | 0.006 | [ 0.000 ] | 0.000 | [ 0.000 ] | 0.000 | [ 0.000 ] |
| Education high | 0.292 | [ 0.348 ] | 0.021 | [ 0.023 ] | 0.027 | [ 0.029 ] |
| No collective agreement | -0.708 | [ 0.061 ] | -0.033 | [ 0.004 ] | -0.051 | [ 0.004 ] |
| Firm collective agreement | -3.130 | [ 0.230 ] | -0.178 | [ 0.018 ] | -0.210 | [ 0.022 ] |
| No public influence | -0.397 | [ 0.227 ] | -0.027 | [ 0.014 ] | -0.036 | [ 0.015 ] |
| Limited public influence | 0.702 | [ 0.294 ] | 0.031 | [ 0.019 ] | 0.024 | [ 0.021 ] |
| Firm size: below 21 | -0.319 | [ 0.122 ] | -0.027 | [ 0.008 ] | -0.018 | [ 0.011 ] |
| Firm size: below 21-50 | -0.581 | [ 0.116 ] | -0.041 | [ 0.008 ] | -0.034 | [ 0.011 ] |
| Firm size: below 51-100 | -0.319 | [ 0.117 ] | -0.017 | [ 0.008 ] | -0.021 | [ 0.011 ] |
| Firm size: below 101-250 | -0.065 | [ 0.115 ] | 0.000 | [ 0.007 ] | -0.004 | [ 0.011 ] |
| Firm size: below 251-500 | -0.344 | [ 0.133 ] | -0.018 | [ 0.009 ] | -0.023 | [ 0.012 ] |
| Constant | 9.692 | [ 0.399 ] | 2.337 | [ 0.026 ] | 2.354 | [ 0.024 ] |
| p1 | 0.595 | [ 0.049 ] | | | | |
| p2 | 0.231 | [ 0.026 ] | | | | |
| sigma | 0.847 | [ 0.008 ] | 0.147 | [ 0.001 ] | | |
| Observations | 10,343 | | 10,000 | | 10,123 | |
| Log-likelihood | -23,429 | | 5,422 | | | |

Notes: All models estimated with specific censoring point. Standard errors in parentheses. Cqreg model for 0.5 quantile. Sample size changes as not all observations are used for estimation due to censoring.
Source: GLS; own calculations.