THE CONTRIBUTION OF MINIMUM WAGES TO INCREASING WAGE INEQUALITY

Coen N. Teulings*
Tinbergen Institute/Erasmus University Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The NETHERLANDS
E-mail: Teulings@few.eur.nl

Abstract

Recent research has shown the reduction in the minimum wage to be the main cause of the rise in wage dispersion in the lower half of the wage distribution in the United States during the eighties. However, the return to human capital does not seem to have been much affected. This paper develops new methodology for estimating the effect on both the wage distribution and the return to human capital. The research confirms previous conclusions regarding the wage distribution, but shows that the return to human capital has also increased strongly by the fall in the minimum, for wage levels up to twice the minimum. This effect explains virtually the whole increase in inequality in the lower half of the distribution. A 10% reduction of the minimum wage causes the wage of worker earning before the reduction to fall by 8%. The results are interpreted as evidence in favor of a production function with a Distance-Dependent-Elasticity of Substitution (DIDES) structure.

JEL code: J3.

* The author thanks Chris Flinn, Joop Hartog, Arie Kapteijn, Larry Katz, Francis Kramarz, Alan Krueger, David Lee, Thomas Lemieux, Alan Manning, Steve Machin, Steve Nickell, and Jan van Ours for their comments on a previous version of the paper. David Lee, Pieter Gautier, and Wouter Buitenhuis provided assistance in additional data collection and in computer work respectively.

1 Introduction

Since 1970, there has been a massive increase in wage inequality in the United States. In particular, since 1980 the 10-50 and 50-90 log wage differential grew by 0.10 and 0.06 respectively. Economists have tried to put their finger on the causes of this phenomenon. Among the causes that they considered are globalisation, both in labor and commodity markets, technological progress, and institutions. Wood (1995) believes globalisation to be the main cause. However, most empirical research suggests that international trade is only a small part of the explanation, see Freeman (1995) for a survey. Others hold skill-biased technological progress responsible, for example Bound and Johnson (1992). However, technology is always a kind of residual item, for which appropriate variables are hardly available. Its impact is therefore difficult to pin down empirically. Autor, Katz, and Krueger (1998) have shown that the use of computers by industry is strongly correlated to the increase in the employment of college graduates.

DiNardo, Fortin and Lemieux (1996) called attention to the role of institutions, in particular, declining unionism and the fall in minimum wages during the 1980s. DiNardo et.al. hold minimum wages responsible for 25 percent of the increase in wage dispersion. Pictures of the estimated density functions for the period 1973-1990 show that minimum wages have had a large impact. In particular, there was a large spike around the minimum, when the real minimum reached its maximum around 1979. For the calculation of the effect of minimum wages, Dinardo et.al. assume a change in the minimum wage to have no effect on the shape of the wage distribution to the right of the minimum. At first glance, the wage distributions plotted in their paper suggest that this assumption is not supported by the data, implying that their estimate of 25 percent is a lower bound.

Indeed, applying a different methodology, Lee (1999) reached the conclusion that the decrease in minimum wages can explain virtually the whole increase in wage inequality. Lee simply takes 10-50 and 50-90 log wage differentials by year and state and regresses them on the relevant minimum wage, using state variation in minimum wages. Lee's results open the question as to what mechanism makes that minimum wages have so large an impact. There are two potential channels. Either, minimum wages cause low skilled workers to be eliminated from employment, leading to a reduction in wage dispersion. However, this runs counter to Card's and Krueger's (1994) results that the disemployment effects of minimum wages are small. Or, the general equilibrium effects of minimum wages lead to a compression of wage differentials. However, Lee's results seem to rule out this explanation. Standard wage regressions presented in his paper suggest the return to education to be not much affected by the level of the minimum wage. Hence, we are left with a puzzle.

Teulings (2000) takes an indirect approach to the issue. There, I discuss a production function exhibiting a DIstance-Dependent-Elasticity of Substitution (DIDES) structure. In this type of world, the general equilibrium effects of an increase in the minimum wage leads to a compression of relative wages. The parameters of the model are estimated for the United States, using changes in the assignment of workers to jobs. The estimation results are applied to simulate the effect of the reduction in the minimum during the eighties on employment and relative wages. My results were in line with the surprising conclusions of Lee (1999): the decrease of the minimum can explain most of the increase in inequality in the lower half of the wage distribution. However, the general equilibrium effects contribute most to this conclusion. Hence, these results make the resolution of the puzzle why Lee finds such a small effects on the return to education even more pressing.

Where Teulings (2000) took an indirect approach on the issue of minimum wages, here I address the impact of minimum wages directly. Variation in the minimum wage is applied to estimate its effect on the wage distribution and the return to human capital. First, the paper discusses a methodology which requires few a priori assumptions on how and where minimum wages affect the wage distribution. For this purpose, a two stage procedure is applied. The first stage characterizes the wage distribution for each economy by a small number of parameters. In the second stage, the differences in these parameters are related to the minimum wage in that economy. Tests based on these regressions reject DiNardo, Fortin, and Lemieux's (1996) assumption that the minimum wage had no effect on the shape of the wage distribution to right of the minimum. Furthermore, the results of this part are in line with the conclusion of Lee (1999) that the minimum wage is the main cause of the increase in wage dispersion during the eighties.

Next, I analyze the return to human capital. For this purpose, the single index assumption of Teulings (1995) is applied, which states that all components of human capital, including both years of schooling and experience and unobserved characteristics, can be aggregated in a single index. Like for the wage distribution, a two stage approach is applied: …rst, estimating a small number of parameters for a non-linear wage function for each economy, then, relating these parameters to the minimum wage in each economy. The increase in the minimum wage is shown to reduce the return to human capital in the wage interval from the minimum upto at least twice the minimum. A 10% reduction of the minimum wage causes the wage of a worker earning the minimum before the reduction to fall by 8%. The minimum wage can account for most of the increase in the return to human capital in the lower half of the distribution. This e¤ect is strongly non-linear. I show that this explains why Lee, using a linear wage equation, …nds much lower e¤ects. The single index assumption is an essential tool for the dealing with this non-linearity. The estimation results square surprisingly well with the simulation results presented in Teulings (2000).

The data used for the analysis cover the same time period as DiNardo et.al. I use data on only …ve selected years (1973, 1979, 1985, 1989, 1991). Entering more years to the regression does not add much variation, since between these years, the pattern in minimum wages is close to a time trend. One might wonder whether the minimum is not just a proxy for other factors explaining the rise in dispersion. This issue is relevant in particular because two alternative explanations –the decline in unionization and skill biased technological progress– are well covered by a time trend. As a partial remedy to this problem, regional variation is applied by distinguishing the four main regions, yielding in total 4 regions x 5 years = 20 separate economies. Though the (federal) nominal minimum wage is the same across regions, nominal wages in the south are 5-10 percent lower than in the rest of the country, so that the same nominal minimum wage has a much stronger impact on the wage distribution in the south than elsewhere. Moreover, these regional di¤erentials are not constant over time. The south is catching up, while the midwest is declining. A number of both statistical and plausibility tests show that the minimum wage variable is unlikely to pick up the e¤ect of skill biased technological progress or de-unionization.

The structure of the paper is as follows. Section 2 describes the underlying model and the estimation methodology. Data and estimation results for wage distributions and return to human capital for each of the 20 economies are presented in Section 3. In Section 4, the estimation results for the impact of minimum wages are discussed. Section 5 concludes by evaluating the evidence in relation to the DIDES model.

2 Methodology

2.1 The theoretical framework

The theoretical framework makes use of the idea that the human capital of a worker can be meaningfully summarized in a single index (Teulings, 1995; Card and Lemieux, 1996). Log wages w are an increasing function of this human capital index:

$$w = w_t(q) \tag{1}$$

with $w_t'(q) > 0$, where $w_t(q)$ is assumed to be differentiable. This wage function is allowed to differ between economies indexed by t. Let $f_t(q); F_t(q)$ be the density and distribution function of this human capital index; $f_t(q)$ is assumed to be differentiable. The density function of the log wage distribution satisfies:

$$d_t(w) = f_t[q_t(w)]\, q_t'(w) \tag{2}$$

where $q_t(w)$ is the inverse function of $w_t(q)$ (which exists, since $w_t'(q) > 0$). Given two functions of the triple $w_t(q)$, $f_t(q)$, and $d_t(w)$, the third can be calculated residually. In this paper, we focus on wages $w_t(q)$ and their density $d_t(w)$ and leave the distribution of human capital as a residual item.

Suppose that types of workers are not perfect substitutes. More specifically, suppose that the aggregate production function of the economy satisfies a DIstance-Dependent-Elasticity of Substitution (DIDES) structure: the substitutability of two types of workers q_1 and q_2 declines with the distance between their level of human capital, $|q_1 - q_2|$. Teulings (2000) shows that an economy with heterogeneous workers and jobs characterized by comparative advantage of high q workers in complex jobs exhibits this type of substitution structure.[1] What will happen to relative wages when the left tail of the human capital

[1] Next to comparative advantage, Teulings (2000) also assume absolute advantage. This assumption yields the result $w_t'(q) > 0$ for any distribution of human capital, see equation (1).

distribution in economy t, $q < qm_t$, is eliminated? The subsequent argument is a heuristic replication of the formal analysis in Teulings (2000). The human capital distribution in economy t satis…es:

$$F_t(q) = \frac{F_0(q) - F_0(qm_t)}{1 - F_0(qm_t)} \qquad (3)$$

for $q > qm_t$, where $t = 0$ refers to the economy without any truncation. Firms that were employing workers from the eliminated left tail substitute towards worker types that are the closest substitutes for the eliminated workers, that is, worker types with q slightly above qm_t, say type q^+. This raises the wages of q^+. Due to this wage increase, …rms that were employing these q^+ type workers …nd it pro…table to substitute towards workers with a slightly higher q, say $q^{++} > q^+$. This raise the wages of q^{++} in turn, but by slightly less than the wage increase for type q^+. This argument gets repeated for the …rms that employed q^{++} type workers before, which substitute to type $q^{+++} > q^{++}$. This yields a pattern wage of changes $\Delta w(q; qm_t)$ for type q as a function of the truncation point qm_t that is positive at the truncation point and declines (at a decreasing rate) for higher levels of q. The larger qm_t, the stronger these e¤ects:

$$\begin{aligned}
\Delta w(qm_t; qm_t) &> 0 \\
\Delta w_2(qm_t; qm_t) &> 0 \\
\Delta w_1(q; qm_t) &< 0 \\
\Delta w_{12}(q; qm_t) &< 0 \\
\Delta w_{11}(q; qm_t) &> 0
\end{aligned}$$

where the indexes refer to the partial derivatives with respect to the relevant argument.

The truncation of the human capital distribution has therefore two type of e¤ects. The direct e¤ect is the elimination of the left tail, which a¤ects the wage distribution, but not the return to human capital. Note that this e¤ect yields just a proportional increase in the density function for the non-truncated part of the wage distribution, analogous to the e¤ect on the human capital distribution, see equation (3). Any change in the shape of the wage distribution cannot be explained by truncation alone. The indirect, general equilibrium e¤ect leads to changes in relative wages. This affects both the wage distribution and the return to human capital. The return to human capital satisfies:

$$w_t'(q) = w_0'(q) + \Delta w_q(q; qm_t) < w_0'(q)$$

By equation (2), the effect on the return to human capital feeds back into the wage distribution, since $q_t'[w_t(q)] = [w_t'(q)]^{-1}$. It leads to higher density just above $w_t(qm_t)$.

A typical policy that tends to eliminate the left tail of the human capital distribution is an increase in the minimum wage. Consider an increase in the minimum from wm_1 to wm_2 which causes the truncation point of the skill distribution to go up from qm_1 to qm_2. Then:

$$wm_2 - wm_1 = w_0(qm_2) - w_0(qm_1) + \Delta w(qm_2; qm_2) - \Delta w(qm_2; qm_1)$$

The change in the minimum wage is equal to the sum of the direct truncation effect, $w_0(qm_2) - w_0(qm_1)$, and the indirect, general equilibrium effect for the worker at the new truncation point qm_2, that is, $\Delta w(qm_2; qm_2) - \Delta w(qm_2; qm_1)$. By $\Delta w_2(qm_t; qm_t) > 0$, this effect is positive. This paper sets out to estimate the share of the indirect, general equilibrium effect in the total increase of the minimum.

The nice feature of this pattern of general equilibrium effects is the strong prediction regarding its non-linear shape, which allows a clear test, both for the wage distribution and for the return to human capital: the largest effect is at the minimum itself, and it declines for higher wage levels, and does so at a decreasing rate. In the previous discussion, minimum wages were the only factor that was allowed to affect wage distribution and return to human capital. Empirically, other factors will also play a role, like skill biassed technological progress, de-unionisation, and changes in the distribution of human capital. However, these factors do not exhibit the specific pattern of shifts in relative wages that is induced by a change in the minimum wage. If the estimated impact of minimum wages fits this pattern while the estimation method is sufficiently flexible to pick up any conceivable non-linear pattern, then we feel reasonably save when assuming that the other factors are absorbed by the error term. As a further check of competing explanations, I shall run a number of additional tests.

The single index assumption for human capital is implemented in the following way:

$$q_{it} = x_{it}^{0}{}^{-} + \underline{q}_{it} \tag{4}$$

where x_{it} is a vector of characteristics of person i in economy t, like experience, education, etc., where $^{-}$ is a vector of parameters, and where $\underline{q}_{it}$ is a standard normally distributed random variable, capturing unobserved worker characteristics. Since we have not yet scaled the return q_{it}, there is no loss in generality in normalizing the variance of $\underline{q}_{it}$ to unity. The e¤ect of any other choice would have been o¤set by a counteracting variation in $w_t^0(:)$. The single index assumption states that the relation $w_t(:)$ may vary across t but not the contribution of the components of x_{it} to q_{it} as measured by $^{-}$. The single index assumption implies that the marginal return on each component varies proportionally. For example, there is a …xed ratio of the return to experience and education, which is measured by the respective elements of $^{-}$. These implications will be tested. However, the level of the return is determined by the derivative $w_t(:)$, and may therefore vary both within economies –due to the non-linearity of $w_t(:)$- and between economies– since $w_t(:)$ is speci…c for each economy t. Where wages are the only ingredient for the estimation of the wage distribution and where wages are directly observed, we do not have to bother about the e¤ect of minimum wages on the distribution of unobservables. This does not hold for the estimation of the return to human capital. There, $\underline{q}_{it}$ is unobserved. Hence, a minimum wage will selectively eliminate lower values $\underline{q}_{it}$. The estimation procedure has to account for this selectivity.

In summary, the analysis of the wage distribution, on the one hand, is fairly ‡exible, as it does not require many more assumptions than the di¤erentiability of the wage distribution. The potential damage of this assumption is further limited by allowing a separate treatment of the spike in the wage distribution at the minimum. However, the interpretation of the results is less clear cut as it mixes up the direct e¤ect of shifts in the distribution of human capital due to truncation and the indirect, general equilibrium e¤ect on the return to human capital. The analysis of the return to human capital, on the other hand, clearly separates out the general equilibrium e¤ect, by controlling for the level of human capital. However, it requires more assumptions than just di¤erentiability, in particular the single index assumption for human capital and the normality of the distribution of unobserved worker characteristics.

2.2 The estimation methodology

My approach for analyzing the impact of minimum wages on wage distribution and return to human capital is based on a two stage methodology. In the …rst stage, a ‡exible functional form is applied to both wage distribution and return to human capital in each of the 20 economies in my sample. In the second stage, the variation in the parameters of this ‡exible form between the 20 economies is related to the minimum wage. Let T be the number of economies (20 in this particular example) and let L be the number of parameters of the ‡exible functional form for the wage distribution. Basically, the functional form is described by a polynomial. So, L is the order of the polynomial and we can increase the ‡exibility of the functional form by raising L. In the …rst stage, wage distributions are estimated for each economy. This yields T observations on L parameters. Mutatis mutandis the same procedure applies to the return to human capital.

In the second stage, the variation in these L parameters between the T economies is regressed on an intercept and the minimum wage relative to the median wage in that economy. The median wage is the standard benchmark for comparison of minimum wages across economies in this literature, see DiNardo, Fortin, and Lemieux (1996), Dolado et.al. (1996), and Lee (1999). The mean is more sensitive to endogenous e¤ects than the median. In particular, when minimum wages raise the wages of workers earning slightly more than the minimum, an increase in the minimum will raise the mean. The median wage is less sensitive to this problem than the mean since spill-over e¤ects will probably be small at the median wage level. Hence, I line up with the literature in using the median wage. The estimation procedure for Stage 1 is set out for wage distribution and return to human capital in Subsections 2.3 and 2.4 respectively. Stage 2 is discussed in Subsection 2.5.

2.3 The wage distribution

Let w_{it} denote the log hourly wage of worker i and let wm_t denote the log hourly minimum wage in economy t, both relative to median wage in that economy. Furthermore, let $d_t(:)$ denote the density function of w_{it} in economy t. A ‡exible functional form for this density function reads:

$$d_t(w_{it}) = \exp\left[\Sigma_{l=0}^{L} d_{lt} w_{it}^{l}\right] \quad (5)$$

This specification takes account of the non-negativety constraint for density functions. It has two special cases. For $L = 1$, it is equivalent to the exponential distribution. For $L = 2$, it yields the normal distribution (provided that $d_{2t} < 0$). By adding higher order terms this specification encompasses more general families of density functions. By setting L high enough, many distributions can be covered up to an arbitrary small degree of misspecification. The parameters d_{lt} are estimated by maximum likelihood. The contribution to the likelihood of each observation is $\exp\left[\Sigma_{l=1}^{L} d_{lt} w_{it}^{l}\right] / \int \exp\left[\Sigma_{l=1}^{L} d_{lt} w^{l}\right] dw$, where the parameter d_{0t} drops out. It is important to realize that the parameters d_{lt} are estimated consistently even when only truncated data on $w_{it} > wm_t$ are available, provided that we adjust the domain of integration of denominator properly. The density of w_{it} in the data is in that case equal to $d_t(w_{it}) / [1 - D_t(wm_t)]$, where $D_t(.)$ is the distribution function that goes with $d_t(.)$. Hence, the limitation of the domain of integration of the denominator deals with the effect of truncation. We cannot establish the probality mass in the truncated tail, $D_t(wm_t)$, but that does not affect the estimation results for d_{lt} for the rest of the distribution up to a multiplicative constant that goes into d_{0t}.

2.4 The return to human capital

Since the derivative of the wage function $w_t(q)$ is strictly positive due to the absolute advantage assumption, it has a well defined inverse function. For maximum likelihood estimation, it turns out to be more convenient to use this inverse, since it yields an explicite expression for the unobserved skill component $\underline{q}_{it}$. A flexible specification of this inverse is again a polynomial:

$$q_{it} = x_{it}'\beta + \underline{q}_{it} = \Sigma_{k=0}^{K} a_{kt} w_{it}^{k} \quad (6)$$

The log likelihood of this class of models is given in Teulings (1995, Appendix 3). The standard linear Mincerian wage equation with economy specific returns to education is a special case of this model, namely $K = 1$. For that simple case, the return to human capital in economy t is simply equal to $1/a_{1t}$. Would we on top of that impose the restriction that a_{1t} =constant, then equation (6) is equivalent to a standard linear wage equation with dummies for each t. The more general, non-linear model can therefore be tested against the standard log normal wage function by a simple likelihood ratio test. Tests of this type are presented in Section 3.3. Where the parameters d_{lt} of equation (5) can be estimated independently for each t, the parameters a_{kt} are interrelated because β applies to all economies. Unlike the case of the wage distribution discussed in Section 2.3, truncation is a serious problem in this case. The elimination of the sub-minimum wage observations introduces selection bias in the distribution of the unobserved skill characteristics $\underline{q}_{it}$. I apply the assumption of the normality of the distribution of $\underline{q}_{it}$ to account for this truncation in the likelihood function, similar to Meyer and Wise (1983a,b). Since this correction procedure is sensitive to the distributional assumption on $\underline{q}_{it}$, I provide a plausibility test of these assumptions in Section 4.4.

2.5 Stage 2: the impact of the minimum wage

The methodology for estimating the impact of minimum wages is explained for the wage distribution. The methodology is similar for the return to human capital. Consider the following model:

$$d^e_{lt} = \delta_{0l} + wm_t \delta_{1l} + \underline{d}_{lt}$$

where d^e_{lt} is the estimate of d_{lt} derived from the maximum likelihood estimation discussed in Section 2.3, and where $\underline{d}_{lt}$ is a random variable. In matrix notation we have:

$$d^e = X\delta + \underline{d} \qquad (7)$$

where $d^e \equiv \{d^e_{lt}\}$ and $\underline{d} \equiv \{\underline{d}_{lt}\}$ are $(TL) \times 1$ vectors, where X is the $(TL) \times (2L)$ matrix of explanatory variables, and where δ is a $(2L) \times 1$ vector with elements δ_{0l} and δ_{1l}. The error term $\underline{d}$ is composed of two independent components. The first component is the estimation error $d^e - d$ of Stage 1 of the estimation procedure. An estimate of the covariance matrix V of this component is available from the maximum likelihood estimation discussed in Section 2.3. Accounting for the covariances $d^e - d$ is crucial since the estimation errors can be expected to be highly correlated, in paricular for higher values of L. The second component covers factors affecting the wage distribution other than the minimum wage, like unionization, the composition of labor supply and skill biased technological progress. Their covariance matrix is unknown. For the sake of convenience, this covariance is assumed to be proportional to V.

Hence: $\underline{d} \sim N(0; \sigma^2 V)$. When $\sigma^2 = 1$, $\underline{d}$ is fully due to the first component, the estimation error in d^e. When $\sigma^2 > 1$, part of the variation in d must be due to factors other than minimum wages. Using this assumption on the covariance matrix of $\underline{d}$, we estimate (7) by GLS.

In practice, (7) is estimated both for the parameter vector $d_t \equiv \{d_{lt}\}$ of the density of w_{it} and the parameter vector d_t^* of the density of $w_{it} - wm_t$. The only difference between both densities is a shift along the horizontal axes by wm_t. There is a simple linear relation between both parameter vectors: $d_t^* = D_t d_t$, where D_t is transformation matrix, which depends on wm_t in a non-linear way.[2] Hence, for the Stage 1 maximum likelihood estimation, this transformation does not make a difference. However, d_t^* fits equation (7) better as can be seen by comparing the R^2 statistic for both models that will be presented in Table 2 and 3 below. The reason for this phenomenon is that the non-linear transform D_t contributes to a proper description of the effect of wm_t on the density function $d_t(.)$. The intuition is that most of the non-linearity in the density is at the minimum wage, where the density function jumps upward. Contrary to d_t, the parameter d_t^* measures the first derivative at that point directly, because higher order terms cancel at $w_{it} - wm_t = 0$.

The restriction $\delta_{1l} = 0$ for all l can be used as null hypothesis for the case that minimum wages do not affect the shape of the wage distribution in the model for d. This restriction can be tested by means of an F-test. Furthermore, the null hypothesis is extended in three directions, by adding time dummies, region dummies and the unionization rate as explanatory variable. In the model for d^*, there is no suitable null hypothesis. The null hypothesis $d_{lt}^* = \delta_{0l} + \underline{d}_{lt}^*$ is logically inconsistent, since the coefficients d_{lt}^* measure the wage distribution with wm_t as a point of reference. By construction, a shift in wm_t must therefore have an impact on the wage distribution. Furthermore, the model for d with $\delta_{1l} = 0$ cannot be used as null for the model for d^*, since it is non-nested in

[2] This can be seen be realizing that the log density functions must be identically equal for all w_{it} in both specifications. Hence:

$$\Sigma_l d_{lt} w_{it}^l = \Sigma_l d_{lt}^* (w_{it} - wm_t)^l$$

For each t, the left and the right hand side are L-th degree polynomials in w_{it}. For identity, all coefficients of this polynomial must be equal to zero. This yields a system of L equations of the form:

$$d = \Delta(wm_t) d^*$$

where $\Delta(wm_t)$ is a $L \times L$ matrix that depends non-linearly on wm_t. $D_t = \Delta(wm_t)^{-1}$.

the unrestricted model for d^* (due to the non-linearity of the transformation $d_t^* = D_t d_t$ in wm_t). Hence, a strict statistical test is not available for the model based on d^*. However, we can compare a generalized R^2, measuring the increase in the explained part of the variance due to the minimum wage variables.[3]

Mutatis mutandis the same methodology is applied to the return to human capital, where we estimate:

$$a^e = X\beta + \underline{a} \tag{8}$$

again both for a and for a^*.

3 Estimation results for Stage 1

3.1 The data

The estimation results refer to the United States, except Alaska and Hawaii. They are based upon CPS data for 1973, 1979, 1985, 1989 and 1991. The four main regions are viewed as separate economies. Since the analysis is motivated by the potential effect of changes in the minimum on relative wages, due to substitution between types of labor, it is appropriate to have a sample that is representative of labor input in production. Therefore, a sample is used weighted not by person but by hours worked. This is done by deleting some of the part-timers in the sample. A full-timer is supposed to work 40 hours a week. A part-timer working 20 hours is deleted with a probability of one-half; a part-timer working 10 hours is deleted with a probability of 0.75. All self-employed persons are deleted. Following this selection and after deleting all observations

[3] The variance of the estimation error $\underline{d}$ satisfies: $E[(d^e - d)'V^{-1}(d^e - d)] = TL$. Hence, the R^2 of model (7) relative to a model with the explanatory variables X_0 (X_0 being a subset of X) reads:

$$R^2 = 1 - \frac{d^{e\prime}\left\{V^{-1} - V^{-1}X[X'V^{-1}X]^{-1}X'V^{-1}\right\}d^e - TL}{d^{e\prime}\left\{V^{-1} - V^{-1}X_0[X_0'V^{-1}X_0]^{-1}X_0'V^{-1}\right\}d^e - TL}$$

where the term TL is the correction for the measurement error in d^e. The significance of the additional variables in X can be tested by a standard F-test, derived from this R^2 statistic. For the model based on d^*, we use the following R^2 statistic:

$$R^2 = 1 - \frac{d^{e\prime}\left\{V^{-1} - V^{-1}D^{-1}X[X'D'^{-1}V^{-1}D^{-1}X]^{-1}X'D_0'^{-1}V^{-1}\right\}d^e - TL}{d^{e\prime}\left\{V^{-1} - V^{-1}X_0[X_0'V^{-1}X_0]^{-1}X_0'V^{-1}\right\}d^e - TL}$$

Since the null-hypothesis is not nested in the general model (since D_t depends non-linearly on wm_t), an F-test is not available.

for which information is missing, a sample of about 5,000 observations is drawn randomly for each of the 20 economies, yielding a dataset totalling about 100,000 observations. Table 1 gives some summary statistics for each of the 20 economies in the sample. The economies are listed according to their value of wm_t , as will be the standard procedure throughout the paper. Where this ordering has the disadvantage of making it less easy to trace down the effects by time or region, it has the advantage of facilitating the comparison for different levels of the minimum. All observations for which w_{it} is less than $wm_t - 1$ are deleted. These observations tend to be erratic. The number of observations that is deleted for this purpose is limited, as seen in Table 1. The contribution of regional variation in minimum wages stands out immediately. The 10-50 and 50-90 log wage differentials document the increase in wage dispersion from 1979 to 1989.

3.2 The wage distribution

Figure 1 plots the estimated log wage distributions for the 20 economies. The dotted lines refer to the distribution including the sub-minimum wage observations, using $L = 12$; the solid lines refer to the distribution excluding the spike and the subminimum observations, $w_{it} > wm_t$, using $L = 9$. The vertical line indicates the position of the minimum. The probability mass is normalized as such that both densities can be directly compared. Furthermore, the size of the spike is depicted in the figure. Compared to the Kernel methods used by DiNardo, Fortin and Lemieux (1996), the polynomial approximations applied here yield a smoother representation of the density function. Their pictures reveal spikes, not only at the minimum but also at some round numbers for the hourly wage like \$5 or \$10 per hour. Whether these spikes are a real phenomenon (a focal point in wage bargaining) or due to imperfect reporting is unclear. The impact of the minimum is clearly visible in Figure 1. In the South in 1979 (the highest minimum), the modus is at the minimum. In the Northeast, in 1989 (the lowest minimum), the distribution is nicely bell shaped with hardly any visible impact around the minimum.

The smoothing of the distribution around the spike makes it hard to tell from the estimation results including spike and the sub-minimum observations whether the supra-minimum wage distribution is really affected, or that it is just a statistical artefact of the smoothing of the spike. The estimation results using only the supra-minimum observations provide an answer on this issue, see Figure 1. The impact of the minimum remains clearly visible even when the spike itself is excluded from the data. The exclusion of the left tail of the distribution has no visible impact on the result as long as the spike is small, despite the fact that in some cases a substantial number of observations is deleted, see Table 1. Only when the spike is huge, like in the South in 1979, the estimation results di¤er in the interval just above the minimum due to the smoothing out of the spike. The results excluding the spike and the sub-minimum wage observations are therefore more reliable.

Table 2 lists the sum of the log likelihood for all 20 economies for a range of values of L. In each case, the procedure converges to an optimum quickly. Each further increase in L yields a signi…cant improvement (measured for 20 economies jointly), as can be concluded from likelihood ratio tests. Closer inspection of the detailed estimation results for the case where the sub-minimum observations are included reveals that increasing the order of the polynomial yields a more pronounced spike around the minimum. This …ts the observation that each increase in L yields a much smaller gain in terms of the log likelihood when the observations at or below the minimum are excluded. This is the motivation for setting L at a lower value for these estimations. The estimation results do not suggest a natural cut-o¤ point for the order of polynomials. The actual order applied for the analysis is therefore arbitrary, but the choice does not have a big impact on the conclusions of Stage 2 of the analysis.

The minimum wage can be expected to have a larger impact on the female than on the male wage distribution, since women earn on average lower wages than males. Moreover, the male-female wage gap has declined throughout the estimation period. The decline of the minimum relative to the median wage was therefore stronger for females, since the median went up for this group. For these reasons, separate distributions are estimated for males and females. Only the supra-minimum wage observations are applied in order to avoid problems with the spike which have been discussed previously.

The estimated distributions are depicted in Figure 2. The economies are ordered according to the value of wm_t, based on the median wage for both sexes. The visible impact of the minimum wage for females is enormous. Due to the upward trend in the female median relative to the male median, the di¤erence in wm_t for both sexes is much larger in 1973 than in 1991. This e¤ect can be clearly traced down in the figures. If the spike had been included in Figure 2, the effect would have been even stronger. A comparison of the shapes of the distribution for females in the South in 1979 and in the Northeast in 1989 offers an eyeball test of the size of the spill-over effects of changes in the minimum to the supra-minimum distribution. The Stage 2 estimation results presented in Section 4 will allow a formal test.

3.3 The return to human capital

The usual variables are included in the vector x_{it} for the estimation of equation (6). Following Murphy and Welch (1990), a third order term for experience is included. For education, the variable "highest grade attained" and four dummy variables are included: high school completed, and 2, 4 and 6 years of college completed.[4] Furthermore, there are dummies for marital status (single vs. married/divorced/widowed) for each sex and a dummy for blacks. Tenure is not included because of its endogenous nature. As in the case of the wage distribution, the procedure quickly converges to an optimum. Table 3 gives an overview of some key statistics. The relative magnitude of the contribution of each of the components to the human capital index q is in accordance with the results from ordinary wage regressions. Their absolute value can be appreciated by noticing that the standard deviation of the residuals is normalized to unity. As the root mean squared error in an ordinary wage regression is about 0.40, the coefficients have to be multiplied by this number to make these coefficients comparable to those of a standard wage regression.[5] The implied first derivative of the wage function $w_t(q)$ is indeed positive for all observations, as has been assumed in Section 2, except for a small number of observations in the extreme right tail in some economies.

A handsome way to present the estimation results is to depict the return to human capital for various wage levels w_{it} for each economy.[6] Since the standard

[4] I use this specification instead of the standard specification (years of education and its square and last grade completed) since it yields a better fit, as can be checked by running an OLS regression with dummies for all years crossed with grade completed. Note that this issue is independent of the non-linearity of the wage equation.

[5] Following this rule of thumb, the high school-4 years of college wage gap is (using the estimation results in the first column) $[4 \times .089 + .803 - .277] \times 0.40 = 0.352$. Obviously, this rule of thumb can only yield an average across economies, since the estimation result indicate this wage differential differs between economies.

[6] By equation (6) and the inverse function theorem: $w_t'[q_t(w_{it})] = q_t'(w_{it})^{-1} = [\sum_{k=1}^{K} k\, a_{kt} w_{it}^{k-1}]^{-1}$.

deviation of the residuals is normalized to unity while it is about 0.40 in standard wage regressions, the average return is around 0.40. I apply a normalization of the average return to unity, by dividing the calculated number by 0.40. This practice will be maintained throughout the paper. The returns are depicted in Figure 3. If the standard log linear wage equation were to apply, then the return would be ‡at, somewhere around unity. The pictures suggest therefore that there is substantial non-linearity in the wage function. This impression is con…rmed statistically by the substantial and highly signigicant improvements in the loglikelihood achieved by increasing K. As in Subsection 3.2, the dotted line refers to the estimation results using all observations, while the solid line is based on the observations exceeding the minimum only. For the former case, the return is depicted for the wage interval [-1,1] only, since outside that interval the results become highly unreliable due to the low number of observations. With this restriction, the return is quite high in the sub-minimum wage trajectory for the economies with high minimum wages. Though these results are also based on a relatively low number of observations, they re‡ect a real phenomenon. For high levels of the minimum, sub minimum wages workers are paid substantially below the minimum. By the smoothing of the wage function, this translates in a high return just below the minimum.

Table 3 also lists the log likelihood of the model for di¤erent values of K. The value of ¯ turns out to be insensitive to the choice of K. Increasing the order of the polynomial yields a substantial increase in the log likelihood. As in the distribution, there is no natural cut o¤, but again the actual choice of the polynomial does not matter much for the Stage 2 results. Subsequent results will be based on $K = 9$. The estimation results show the estimates for ¯ to be also not much a¤ected by the exclusion of the sub-minimum wage observations. The earnings schedule is ‡attened around the minimum, pushing the return to human capital to a much lower level than in the case where all observations are included, as can be seen from Figure 3. This result is related to the phenomenon that the return to human capital jumps downward when moving from just below to just above the minimum. By including data from both sides of the minimum, this jump is smoothed, leading to an overestimation in the interval just above the minimum. Hence, the estimation results excluding the sub-minimum observations yield the more reliable answer. Since the non-linearity in the return to human capital is much smaller we use a much lower value of $K = 4$ for the results excluding the sub-minimum observations.

3.4 Testing the single index assumption

The single index assumption for human capital implies β to be equal across t. In fact, though the general trend in the remuneration of all components is identical (including the unobserved component), Katz and Murphy (1992) and Juhn, Murphy and Pierce (1993) have documented differences in the timing of the rise in the return to education and experience. The single index assumption cannot be expected to hold literally. It can only be expected to cover a substantial share of the variation in the returns to human capital between economies. The assumption can be tested by dividing the sample of 20 economies in a number of subsets and estimating separate β for each subset. Two statistics of this type are calculated, first for each region separately, and secondly for each year. The sum of log likelihoods for each region and for each year are reported in Table 3. Although the restrictions of the β's being equal across regions or years are clearly rejected at conventional levels of significance, the results show the single index assumption to provide a reasonable description of the data. The increase in the log likelihood that can be obtained by raising the order of polynomial K by 2 on the one hand (introducing 2 x 20 = 40 additional parameters) and by allowing separate vectors for each region or year on the other hand (introducing 3 x 12 = 36 additional parameters) are of the same order of magnitude, even starting from $K = 9$, see Table 3. Hence, the single index assumption is less harmful than the standard linearity assumption in most earnings equations. Separate estimation for both sexes shows that the single index assumption does a better job for both sexes separately, although it is still not statistically acceptable. In all cases, the increase of the log likelihood per observation by dropping the single index assumption is about 0.005, translating in a reduction of the standard deviation of the residuals by 0.5 %. I feel therefore safe to apply the single index assumption as a reasonable approximation.

4 Stage 2: the effect of minimum wages

4.1 Estimation results

The variation in the parameters between the 20 economies will be used to estimate models (7) and (8), and to analyze the effect of changing the minimum on wage distribution and return to human capital. Table 2, panel II reports the $F_{L;(T-x)L}$-statistics for the null hypothesis that wm_t does not affect the wage distribution. We do that for six cases: a single intercept, year dummies, region dummies, an intercept plus union density (for all workers, males only, or females only, depending on the data used), year and region dummies simultaneously, and the latter plus union density (with x being 2, 6, 5, 3, 9, and 10 respectively). These test-statistics confirm the impressions from Figures 1 and 2 that minimum wages are an important determinant of the wage distribution. The null hypothesis is rejected at all conventional levels of significance in most cases, as long as we do not include year and region dummies simultaneously and except for males when we do not include year dummies. Apparently, both time and spatial variation contribute to estimation of the effect of wm_t. The tests using only the supra minimum wage observations are particularly relevant, since they provide a direct test of DiNardo, Fortin, and Lemieux's (1996) assumption that the above minimum part of the wage distribution is unaffected by the minimum. This assumption is rejected by the data. For males, including year dummies even improves the results. This suggests that the minimum wage is not a proxy for skill-biased technological progress. Controlling for the effects of skill-biased technological progress by adding year dummies improves the identification of the effect of minimum wages. The former affects the whole distribution, where the latter only affects the lower tail, as we shall see in Section 4.2. For females, a combination of year and region dummies explains virtually all the variance (as can be seen from the R^2 statistics), so that there is no way to establish the impact of minimum wages. However, an exclusion restriction for region effects is acceptable ($F(99;27) = 1.15$). Hence, the minimum can explain all the interregional variation in the wage distribution. Union density rate contributes substantially to the explanation in all cases except for females, judged from the increase in the R^2 statistic. However, next to this, minimum wages remain important.

A comparison of the R^2 statistics in Table 2, panel I, for the appropriate value of L and the R^2 statistics in panel II (the case with a single intercept only) gives insight in the explanatory power of a model based on d^* relative to a model based on d. In all three cases, the R^2 statistic is substantially higher in panel I, in some cases even 10 percentage points. For this reason, the simulations are based on the results for d^*.

Similar R^2 and F-statistics are calculated for the return to human capital. They reject the null hypothesis of no effect of wm_t even more strongly, for all cases and at all conventional levels of significance. Again, the significance of the minimum wage variable in the presence of year dummies is particularly important evidence for ruling out that the minimum wage is a proxy for skill biased technological progress. Again, union density rates contribute to the explanation, but next to the minimum wage.

4.2 Counterfactual distributions

A simple way to evaluate the impact of the minimum on distribution and return to human capital is to calculate counterfactuals using equations (7) and (8), i.e. how would wage distribution and return to human capital have looked like when the average value of $E[wm_t] = -0.818$ had applied in all economies. So for the wage distribution, we calculate: $d^{cf}_{lt} = d^{e}_{lt} + \delta_{1l}(E[wm_t] - wm_t)$. The estimated parameters d^{e}_{lt} and the counterfactual parameters d^{cf}_{lt} are then be applied to form a factual and a counterfactual distribution. Also, 10-50 and 50-90 log wage differentials and the standard deviation of log wages are calculated for these distributions, see Table 4.[7] I report these statistics for each economy seperately only for the estimation results using all observations. However, the standard deviation of these statistics across the 20 economies are listed for all versions. The minimum explains 28 percent $[= 1 - \frac{.022}{.026}^2]$ of the between-economy variation in the standard deviation of log wages. A comparison of the 10-50 and 50-90 differentials reveals that the main impact is in the lower half of the wage distribution, where the minimum explains 74 percent of the variation, while 50-90 differential is completely unrelated to the minimum. This fits the discussion in Section 2.1 perfectly. Note that nothing in the estimation procedure imposes this outcome a priori. The latter result is strong evidence that the estimated effect of minimum wages does not pick up skill biased technological progress. This process is supposed to raise in

[7] When using the estimation results for the distributions excluding the sub-minimum observations for the calculation of the 10-50 differentials, we need additional information on the factual and counterfactual probability mass in the spike and the left tail. These are calculated from the regressions reported in the upper panel of Table 5. The percentage of workers in the spike (defined as: wm_t -0.005 < w_{it} < wm_t +0.005) and below the minimum (w_{it} < wm_t -0.005) is regressed on an intercept, wm_t and its square. The lower R^2 for the spike is due to two outlier observations for 1973, related to state level minimum wage regulations exceeding the federal minimum in large states New York, New Jersey and California (Neumark and Wascher, 1992).

particular the demand for labor in the highest skill categories, see e.g. Juhn, Murphy, and Pierce (1993). The puzzle generated by Juhn's et.al. results is that wage dispersion went up along the whole distribution throughout the 1980s, and not only in the upper tail. The combination of the asymmetric technological progress and the decline in minimum wages might solve this puzzle. The period 1989-1991 provides a test for this hypothesis, since then the minimum was raised again. Indeed, the 50-90 differential has gone up throughout the whole period 1973-1991 almost monotonically in each region, from 0.574 to 0.759 in the West, or from 0.684 to 0.752 in the South, see Table 4. Were the minimum just a proxy for skill biased technological progress, the model would have attributed a substantial part of the variation in the 50-90 differential to the minimum wage. The results in Table 4 point in the opposite direction.

The minimum explains as much as 90 percent of the variation in 10-50 differential for females $[= 1 - \frac{.032}{.103}^2]$, but only 29 percent for males $[= 1 - \frac{.058}{.069}^2]$. Again, this provides strong evidence against the hypothesis that the minimum is a proxy for the decline in union density, for this decline affects almost exclusively the male wage distribution (DiNardo, Fortin, and Lemieux, 1996, p. 1024-1025). Factual and counterfactual distributions are plotted for the two economies with the extreme values of wm_t (South 1979 and Northeast 1989) in Figure 4. There is a strong convergence of the distributions when the average value of wm_t is applied. The impact of the minimum can be seen even more clearly when the highest minimum is applied in the economy with the lowest factual minimum wage and vice versa. Figure 5 provides similar results for males and females separately.

4.3 Counterfactual return to human capital

A similar approach of calculating counterfactuals is applied to the return to human capital. Here, wage differentials for fixed intervals of the human capital index are calculated: $w_t(qa) - w_t(qb)$, where qa and qb are two levels of q, e.g. no education versus high school completed, for a non-black unexperienced worker, where we set $\underline{q}_{it}$ equal to zero in both cases. Three statistics of this type are reported in Table 4. The minimum explains most of the variance in the first interval (no education versus high school completed for an unexperienced white male, 67 percent of the between-economy variance). When comparing the results of various versions of the model, the general theme that emerges from the statistics in Table 4 is that the effects of minimum wages are heavily concentrated in the trajectory just above the minimum and that males are less affected than females. Again, these results are consistent with predictions discussed in Section 2.1. Factual and counterfactual returns to human capital are plotted in Figure 6. Again, the results are depicted for the economies with the highest and the lowest minimum. The figures show the strong convergence of the return to human capital when the average value of wm_t is applied.

4.4 Evaluating the effect of selection bias

As is set out in Subsection 2.4, truncation of the unobserved worker characteristics $\underline{q}_{it}$ plays a role in the estimation of the return to human capital. The higher the minimum wage, the larger will be this truncation. I correct for this truncation by using the assumed standard normality of the distribution of $\underline{q}_{it}$. However, the validity of this approach depends crucially on this assumption. In order to evaluate the effect of selection bias, I calculate for each economy t the number of observations that has been truncated (as implied by the estimation results on Stage 1) as a share of the number observations in the estimation, using the results based on supra minimum wage observations.[8] Part of these truncated observations will either be in the spike or will earn wages below the minimum. This share can be calculated from the regression in the upper panel of Table 5. Both the number of truncated observations as a share of the number of observations above the spike and the shares at or below the spike are regressed on the log minimum wage, see the lower panel of Table 5. The difference between both shares (and hence: the difference between both regression coefficients) is an estimator of the disemployment effect of the minimum wage. The elastiticy of employment with respect to minimum wages varies from approximately 0.20 (for both sexes together) to 0.50 (for females only). These numbers are much higher than elasticities that are usually reported in the literature.[9] If anything, the selection effect is therefore overestimated by the Stage 1 regression. This would yield an overestimation of the human capital of workers just above the minimum, which would lead to an overestimation of the return to human capi-

[8] This ratio is equal: $\frac{\sum_i \Phi(qm_t - q_{it})}{\sum_i [1 - \Phi(qm_t - q_{it})]}$.

[9] The high values of these elasticities might be due to the fact that an increase in the minimum wage, leading to an increase in qm_t, is likely to yield substitution from workers with q_{it} just below the new qm_t to workers with q_{it} just above qm_t. The supply of the latter group is likely to go up due their higher pay.

tal for these workers. Hence, the fall in the return to human capital cannot be attributed to an underestimation of the selection bias due to the truncation of low productivity workers out of employment.

4.5 The elasticity of wages to changes in the minimum

The estimation results for the return to human capital can be used to calculate the elasticity of wages with respect to the minimum wage, keeping constant the level of the human capital of the individual, $dw_{it}=dwm_t jq_{it}$.[10] The calculations are based on the estimation results including only the supra-minimum wages observations for both males and females, using the mean of $a^{\text{¤}e}_{kt}$ and wm_t over t. By using only the supra-minimum observations, we avoid the bias introduced by the smoothing of the spike. The calculated elasticities are shown in Figure 7. The band around the continuous line represents the one standard error reliability interval. The horizontal axis represents the initial wage level w_{it}; wm_t is depicted by the vertical line. The general pattern in the compression e¤ects …ts the predictions discussed in Section 2.1: the largest e¤ect at the minimum, gradually declining when moving to the upper tail of the wage distribution.

When evaluated at the minimum wage, $w_{it} = wm_t$, the elasticity measures the wage reduction due to a decrease the minimum wage for a worker who currently receives the minimum. This elasticity is 0.85. Hence, a 10 % reduction in the minimum wage reduces this worker 's wage by 8.5 %. This is remarkably close to the simulations with the DIDES model in Teulings (2000, Table 5), which suggest a wage reduction of 8.2 % for 1985. Changes in the minimum wage have therefore strong e¤ects on wage inequality. In general, the e¤ect of

[10] The elasticities are derived from the estimation results for $a^{\text{¤}}$. Equation (6) and (8) can be combined to yield a model of the form:

$$Q \,\text{i}\, w_{it} \;\text{¡}\; wm_t; wm_t; \underline{a}_t \,\text{¢} = q_{it}$$

Taking the total di¤erential and setting $d\underline{a}_t$ and dq_{it} equal to zero yields:

$$dw_{it}=dwm_t jq_{it} = \text{¡}\frac{Q_{wm}}{Q_{w\,\text{¡}\,wm}} \;\text{¡}\; 1 = \text{¡}\frac{\text{§}_k \text{®}_{1k}\,(w_{it} \;\text{¡}\; wm_t)^k}{\text{§}_k k a^{\text{¤}e}_{1k}\,(w_{it} \;\text{¡}\; wm_t)^{k\,\text{¡}\,1}} \;\text{¡}\; 1$$

The calculation of the full standard error of this statistic is cumbersome, since estimated coe¢cients show up both in the numerator (®_{1k}) and in the denominator ($a^{\text{¤}e}_{kt}$). However, the error in $a^{\text{¤}e}_{kt}$ is of minor importance relative to that in ®_{1k}, as follows from the estimation results for equation (8), where ¾^2 is much larger than unity, so that the estimation error in $a^{\text{¤}e}_{kt}$ is small relative to other random disturbances. I therefore ignore the randomness of the coe¢cients in denominator. The standard error of the nominator can be calculated straightforwardly from the covariance matrix of the GLS estimator of ®_{1k}, since the nominator is a linear combination of these coe¢cients.

a decrease in the minimum on the wages for various levels of human capital is highly non-linear. Relative wages are strongly affected just above the minimum, while there is hardly any effect at wage levels above the median. Hence, allowing for the non-linearity in the wage function and for the discrete drop in the return to human capital at the minimum is crucial for the conclusions obtained.[11]

Figure 7 implies that the effect of a change in the minimum on log wage differentials for all workers is heavily concentrated in the lower percentiles of the log wage distribution. A 10 % reduction of the minimum wage causes the 25-50 log wage differential to increase by 2.2 % (0.09 % per percentile), while the 10-25 differential by 3.5 % (0.23 % per percentile). This holds a fortiori for males separately. This explains why it is hard to detect any impact of the minimum beyond the 10-th percentile, in particular for males.

4.6 Minimum wages and the widening of the wage distribution

How much did minimum wages contribute to the rise in wage inequality during the 1980s? I calculate a counterfactual for 1989 by a procedure similar to that set out in Subsection 4.2 and 4.3. The mean decrease in wm_t across 4 regions from 1979 to 1989 is 0.335. The counterfactual for 1989 is calculated by deducting this number from wm_t for each region. Table 6 reports the same statistics as have been reported in Table 4 but now for the comparison of the mean across regions for 1979 and 1989. The results are remarkable. The decline in wm_t explains 80 percent of the 5 percentage point increase in the standard deviation of log wages. A break down in the 10-50 and the 50-90 log wage differential shows that impact of minimum is concentrated in the lower half of the distribution, where it explains more than the actual increase in dispersion. Had there not been a reduction in the minimum wage, wage dispersion in the lower half of the distribution would have gone down. The results on the return to human capital tell a similar story. In particular the differential of high school versus no education at all for unexperienced males is heavily affected by the reduction in minimum wages.

[11] When we would not have allowed for the discrete drop by applying the estimation results based on all observations, then the elasticity at the minimum wage would not have been 0.85 but 0.52.

4.7 Comparison with Lee's results

The results reported in Table 4 and Figure 7 suggest larger spill-over e¤ects of the minimum wage on the return to human capital for wage levels above the minimum than has been reported by Lee (1999, Table VI) for the return to education. Why is this the case? My claim is that it is the non-linearity of the problem (see Figure 7) that distorts Lee's conclusions. The general equilibrium e¤ects of an increase in the minimum wage are the largest just above the minimum. Then, regression coe¢ cients on one variable, years of education in this case, are a bad variable to explain in a Stage 2 regression, for four reasons. First, where the college-high school di¤erential might be close to the minimum at the beginning of somebody's labour market career, it might be far above the minimum at higher levels of experience. Hence, the estimated e¤ect will a be mixture of strong e¤ect just above the minimum and an e¤ect that is basically zero at higher levels of experience. Unobserved worker characteristics aggravate this problem, by mixing workers at various points in the wage distribution. Secondly, the e¤ects of the minimum wage are expected to be much larger for lower years of education, since these worker types earn wages much closer to the minimum. Thirdly, the lowest education levels might even earn wages below the minimum. Since the return to human capital has been shown to be exceptionally high in the subminimum part of the distribution, this obscures the wage compression just above the minimum. Finally, the position of the minimum varies between economies. Again, this dilutes the measurement of the e¤ect just above the minimum. Where in the one economy worker qa is just above the minimum, in the other economy that might be worker qb.

Table 7 presents some simple evidence documenting the relevance of the …rst three mechanims. Line 1 reproduces the regression presented by Lee (1999). First, separate regressions for each economy are run to obtain the return to education, using data on all males. Next, these returns are regressed on the minimum wage and an intercept. I report the R^2 of the regression and a counterfactual for the return in 1979 would the minimum wage 1989 have applied. The results are almost exactly similar to Lee's. Line 2, 3, and 4 checks the …rst three arguments presented above, by excluding, …rst all workers with 10 or more years of experience, second all workers with more than 14 years of education, and …nally, less than 6 years of education.[12] The R^2 creeps up in each step, and

[12] The raw probability of earning a wage below the minimum is a factor 5 higher for some-

the counterfactual return for 1979 using the minimum of 1989 becomes closer and closer to the return for 1989. This evidence shows the importance of accounting for the non-linearity of the wage function. The methodology applied in this paper does so.

5 Conclusion

The increase in wage dispersion has been a broad phenomenon in the recent economic history of the United States. It is therefore not surprising that economists have spent a great deal of e¤ort to understand its causes. Where there has been a lot of debate on whether either trade or technological progress is the main cause, minimum wages were considered to have contributed little until recently. In this respect, the conclusions of this paper are surprising: minimum wages can explain the whole increase in wage inequality in the lower half of the wage distribution during the 1980s. The 0.335 reduction of the log minimum wage relative to the median wage has increased the 10-50 log wage di¤erential by at least 10 percentage points. The impact of the minimum goes beyond the spike on the wage distribution, contrary to what has been assumed in previous work (e.g. Meyer and Wise, 1983a,b; DiNardo, Fortin, and Lemieux, 1996). The null hypotheses that the return to human capital and the shape of the distribution for the supra-minimum wage observations are independent of the minimum are stongly rejected.

There is an alternative way to interpret the contribution of this paper. The reduction in minimum wages in the United States during the eighties can be viewed as an excellent natural experiment to test various aggregate production functions and their implications for the response of relative wages to a change in the composition of labour supply. The results provide strong support for a DIstance-Dependent-Elasticity of Substitution (DIDES) structure, in which elastiticies of substitution between worker categories depend on their skill distance. Variation in minimum wages is the most attractive instrument for analyzing this issue, since it a¤ects labour supply at the lowest level of human capital, that is at the maximum conceivable distance. The strong non-linearity in the model's predictions for the e¤ect of a change in the minimum on relative wages provides a much better opportunity for testing than e.g. variations

body with less than 5 years of education than for the average worker.

in school enrollment rates shifting small fractions of workers between various grades.

At the same time, imperfect substitution between workers with various levels of human capital cannot fully explain the evidence. The emergence of a spike in the wage distribution strongly suggests the existence of frictions in the labour market. With frictions, workers and …rms have to set wages somewhere in between their outside options. A minimum wage in between both outside options then yields a spike. Flinn (2001) shows that this type of model can also yield spill over e¤ects to higher wage levels. A binding minimum wage in low paying jobs stengthens the bargaining power of these workers in better paying jobs. One can therefore interprete the evidence presented in this paper as supporting either imperfect substitution conform a DIDES-type model, or the relevance of frictions, or of a combination of the two (as in Teulings and Gautier, 2001). However, this paper shows that any realistic model should come up with some explanation for substantial spill-over e¤ects of the minimum.

6 REFERENCES

Amemiya, T. (1985), "Advanced econometrics", Oxford: Basil Blackwell.

Autor, D.H., L.F. Katz, and A.B. Krueger (1998), "Computing inequality: have computers changed the labor market?", Quarterly Journal of Economics, p. 1169-1213.

Bound, J. and G. Johnson (1992), "Changes in the structure of wages in the 1980s. An Evaluation of Alternative Explanations", American Economic Review, No. 3, Vol. 82: 371-392.

Card, D. and A. Krueger (1994), "Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania", The American Economic Review, No. 4, Vol. 84: 772-793.

Card, D. and A. Krueger (1995), Myth and measurement, The new economics of the minimum wage, Princeton: Princeton University Press.

Card, D. and T. Lemieux (1996), "Wage dispersion, returns to skill, and black-white wage di¤erentials", Journal of Econometrics, No. 2, Vol. 74: 319-361.

DiNardo, J., N.M. Fortin, and T. Lemieux (1996), "Labor market institutions and the distribution of wages, 1973-1992", Econometrica, No. 5, Vol. 64:

1001-1044.

Dolado, J., F. Kramarz, S. Machin, A. Manning, D. Margolis and C. Teulings (1996), "The economic impact of minimum wages in Europe", Economic Policy, Vol. 23: 317-372.

Flinn, C. (2001), "Interpreting minimum wage e¤ects on wage distributions: A cautionary tale", Les Annales d'Economie et de Statistique (forthcoming).

Fortin, N.M., and T. Lemieux (1999), "Rank regressions, wage distributions, and the gender gap", Journal of Human Recources, Vol. 33, no. 3: 610-643.

Freeman, R.B. (1995), "Are your wages set in Beijing?", Journal of Economic Perspectives, No. 3, Vol. 9: 15-32.

Grossman, J.B. (1983), "The impact of the minimum wage on other wages", Journal of Human Resources, vol. 18, no. 3: 359-378.

Juhn, C., K.M. Murphy, and B. Pierce (1993), "Wage inequality and the rise in the returns to skill", Journal of Political Economy, No. 3, Vol. 101: 410-442.

Katz, L.F. and K. Murphy (1992), "Changes in relative wages, 1963-1987: supply and demand factors", Quarterly Journal of Economics, No. 1, Vol. CVII: 35-78.

Lee, D.S. (1999), "Wage Inequality in the U.S. during the 1980s: Rising Dispersion or Falling Minimum Wage?", Quarterly Journal of Economics, No. 3, Vol. 114: 941-1023).

Meyer, R.H. and D.A. Wise (1983a), "Discontinuous distributions and missing persons: the minimum wage and unemployed youth", Econometrica, No. 6, Vol. 51: 1677-1698.

Meyer, R.H. and D.A. Wise (1983b), "The e¤ects of the minimum wage on the employment and earnings of youth", Journal of Labor Economics, No. 1, Vol. 1: 66-100.

Murphy, K.M. and F. Welch (1990), "Empirical Age-Earning Pro…les", Journal of Labor Economics, No. 2, Vol. 8: 202-229.

Neumark, D. and W. Wascher (1992), "Employment E¤ects of Minimum and Subminimum Wages: Panet Data on State Minimum Wage Laws", Industrial and Labor Relations Review, No. 1, Vol. 46: 55-81.

Teulings, C.N. (1995), "The wage distribution in a model of the assignment of skills to jobs", Journal of Political Economy, No. 2, Vol. 103: 280-315.

Teulings, C.N. (1999), "Substitution and complementarigy under comparative and the accumulation of human capital", Tinbergen Institure, discussion paper 99-049/3, Amsterdam/Rotterdam.

Teulings, C.N. (2000), "Estimation bias in elasticities of substitution and the minimum wage paradox", International Economic Review, 359-398.

Teulings, C.N. and P.A. Gautier (2001), "The right man for the job ", Discussion Paper TI2000-38/3.

Wood, A. (1995) "How trade hurt unskilled workers", Journal of EconomicPerspectives, No. 3, Vol. 9: 57-80.

Table 1: Summary statistics for the economies in the sample

		# obs.	# obs. > wmin-1			# obs. > spike			-log min .wage			% < spike	% in spike	log wage diff. (data)					
														10-50			50-90		
year	region	all	all	male	female	all	male	female	all	male	female	all	all	all	male	female	all	male	female
1979	South	4776	4759	2814	1945	4233	2618	1615	0.545	0.727	0.312	0.059	0.051	0.545	0.693	0.312	0.693	0.611	0.608
1973	South	4962	4938	2917	2021	4492	2759	1733	0.629	0.811	0.414	0.068	0.023	0.598	0.613	0.478	0.693	0.665	0.592
1979	Northeast	4823	4803	2867	1936	4452	2750	1702	0.640	0.822	0.387	0.045	0.028	0.606	0.663	0.387	0.618	0.598	0.590
1979	Midwest	5003	4979	3002	1977	4591	2855	1736	0.651	0.878	0.352	0.045	0.033	0.617	0.706	0.352	0.613	0.542	0.598
1991	South	5000	4989	2580	2409	4624	2438	2186	0.708	0.856	0.572	0.038	0.035	0.651	0.693	0.549	0.753	0.742	0.722
1979	West	5073	5049	3044	2005	4695	2919	1776	0.727	0.909	0.439	0.043	0.027	0.693	0.721	0.439	0.629	0.552	0.575
1985	South	4781	4773	2645	2128	4425	2526	1899	0.737	0.887	0.583	0.031	0.042	0.665	0.709	0.583	0.762	0.727	0.644
1991	Midwest	5000	4985	2670	2315	4670	2554	2116	0.791	0.951	0.607	0.034	0.029	0.680	0.788	0.573	0.719	0.670	0.683
1985	Midwest	4804	4792	2761	2031	4490	2649	1841	0.842	1.023	0.601	0.030	0.033	0.729	0.797	0.572	0.657	0.580	0.664
1973	Northeast	5047	5034	3232	1802	4895	3190	1705	0.852	0.989	0.589	0.022	0.005	0.629	0.559	0.444	0.627	0.621	0.550
1973	Midwest	5011	4991	3202	1789	4753	3124	1629	0.852	1.012	0.560	0.035	0.012	0.629	0.623	0.519	0.575	0.533	0.529
1991	West	5000	4992	2769	2223	4734	2670	2064	0.856	0.951	0.722	0.024	0.027	0.693	0.788	0.658	0.741	0.741	0.710
1989	South	5000	4988	2609	2379	4783	2536	2247	0.864	1.002	0.737	0.020	0.021	0.687	0.707	0.624	0.730	0.733	0.675
1985	Northeast	4758	4746	2679	2067	4546	2591	1955	0.871	1.053	0.714	0.023	0.019	0.693	0.758	0.601	0.709	0.640	0.603
1973	West	5004	4987	3179	1808	4823	3110	1713	0.911	1.061	0.629	0.025	0.007	0.688	0.721	0.539	0.572	0.548	0.531
1985	West	4969	4957	2872	2085	4721	2773	1948	0.911	1.094	0.737	0.022	0.025	0.734	0.856	0.630	0.692	0.603	0.608
1991	Northeast	5000	4988	2740	2248	4809	2662	2147	0.936	1.073	0.804	0.025	0.011	0.704	0.728	0.642	0.708	0.699	0.670
1989	Midwest	5000	4989	2697	2292	4803	2634	2169	0.957	1.094	0.775	0.020	0.018	0.739	0.693	0.610	0.693	0.693	0.643
1989	West	5000	4989	2800	2189	4862	2747	2115	0.988	1.147	0.806	0.014	0.011	0.742	0.842	0.604	0.726	0.650	0.693
1989	Northeast	5000	4992	2747	2245	4898	2715	2183	1.094	1.189	0.916	0.014	0.005	0.693	0.671	0.621	0.693	0.709	0.678

Economies ordered by the level of the minimum wage relative to the median (all observations).

Table 2: Estimation results for the distribution, various values of L

	L	all obs. Log L.	all obs. R2[1]	obs. > wmin Log L.	obs. > wmin R2	obs. > wmin (males) Log L.	obs. > wmin (males) R2	obs. > wmin (females) Log L.	obs. > wmin (females) R2
	4	-783,832.37	0.15	-749,735.10	0.27	-413,278.51	0.03	-274,324.54	0.48
	5	-783,674.07	0.14	-749,689.41	0.24	-413,214.52	0.06	-274,301.94	0.52
	6	-783,283.46	0.17	-749,631.50	0.19	-413,159.16	0.05	-274,287.34	0.50
	7	-783,123.59	0.33	-749,588.25	0.18	-413,089.31	0.04	-274,267.48	0.49
I	8	-782,962.54	0.30	-749,540.41	0.18	-413,062.75	0.04	-274,239.15	0.47
	9	-782,681.99	0.22	-749,496.20	0.19	-413,040.27	0.07	-274,220.45	0.46
	10	-782,618.24	0.35						
	11	-782,534.72	0.33						
	12	-782,352.42	0.27						

		all obs. L = 12			obs. > wmin L = 9			obs. > wmin (males) L = 9			obs. > wmin (females) L = 9		
		F-test[2]	(p)[3]	R2	F-test	(p)	R2	F-test	(p)	R2	F-test	(p)	R2
	F_L	3.99	(5)	0.20	1.79	(1)	0.10	0.64		0.04	6.79	(5)	0.35
II	F_L,year	5.91	(5)	0.71	4.14	(5)	0.73	5.77	(5)	0.76	1.34		0.87
	F_L, region	4.08	(5)	0.50	2.36	(4)	0.37	1.65	(4)	0.35	8.60	(5)	0.53
	F_L, union	5.77	(5)	0.40	2.46	(3)	0.35	1.25		0.49	8.19	(5)	0.44
	F_L, year region	1.30		0.87	2.10	(2)	0.88	3.17	(5)	0.93	0.67		0.97
	F_L, all	0.74		0.88	1.30		0.89	1.91	(1)	0.93	0.42		0.99

Notes:

[1] The R^2 statistics in panel I refer to models where d is used as the endogenous variable, where the R^2 and F-statistics in panel II use d^2.

[2] The H_0 for the first F-statistic is a model with L dummies, the second with 5L dummies (for each year), the third with 4L dummies (for each region), the fourth with 2L dummies (intercept and union density), the fifth with 8L dummies (years and regions), and the ninth with 9L dummies (also including union density). The alternative hypothesis includes the minimum wage.

[3] Significance levels of the F-tests: (1) = .10-.05; (2) = .05-.025; (3) = .025-.010; (4) = .10-.005; (5) < .005.

Table 3: Estimation results for the return to human capital, various values of K

		all obs.			obs. > wmin			obs. > wmin (males)			obs. > wmin (females)		
	K	Log L.		R2	Log L.		R2	Log L.		R2	Log L.		R2
	3	37,200.34		0.39	43,670.57		0.60	23,680.86		0.36	21,188.80		0.83
	4	37,307.32		0.36	44,802.11		0.51	24,190.20		0.35	21,757.82		0.76
	5	37,428.45		0.35	46,113.08		0.72	24,834.28		0.48	22,456.14		0.84
I	6	37,489.79		0.35	46,565.05		0.73	24,999.83		0.51	22,704.26		0.87
	7	37,993.14		0.32	47,091.76		0.74	25,263.63		0.53	23,026.73		0.84
	8	38,182.75		0.35	47,298.97		0.75	25,336.29		0.55	23,146.21		0.87
	9	38,295.38		0.43	47,734.22		0.71	25,549.83		0.50	23,400.54		0.84
		K = 9			K = 4			K = 4			K = 4		
	Years separate	38,755.20			45,237.63			24,334.76			21,852.78		
	Regions separate	38,531.00			45,016.89			24,306.10			21,844.86		
		F-test	(p)	R2	F-test	(p)	R2	F-test	(p)	R2	F-test	(p)	R2
	F_K	9.33	(5)	0.36	16.32	(5)	0.48	9.15	(5)	0.35	43.65	(5)	0.72
II	F_K,year	16.67	(5)	0.83	24.07	(5)	0.84	33.72	(5)	0.75	19.77	(5)	0.90
	F_K,region	5.78	(5)	0.56	13.51	(5)	0.64	5.99	(5)	0.30	46.10	(5)	0.80
	F_K, union	11.26	(5)	0.50	19.58	(5)	0.58	14.14	(5)	0.56	44.89	(5)	0.75
	F_K,year region	3.57	(5)	0.95	6.04	(5)	0.92	9.63	(5)	0.96	4.00	(5)	0.93
	F_K,all	2.76	(5)	0.96	5.55	(5)	0.93	7.41	(5)	0.97	4.06	(5)	0.94
	Beta	coeff.		std. err.	coeff.		std. err.	coeff.		std. err.	coeff.		std. err.
	e/100	10.107		0.163	10.261		0.170	11.650		0.238	10.264		0.251
	(e/100)2	-27.089		0.758	-28.999		0.800	-30.116		1.067	-34.005		1.241
	(e/100)3	19.601		1.007	24.073		1.079	22.154		1.406	33.873		1.711
	grade	0.089		0.003	0.087		0.003	0.097		0.004	0.079		0.005
	high sco	0.277		0.012	0.256		0.013	0.219		0.016	0.351		0.021
III	2 y coll	0.467		0.019	0.457		0.020	0.320		0.025	0.665		0.032
	4 y coll	0.803		0.023	0.791		0.024	0.645		0.030	1.015		0.039
	6 y coll	0.957		0.030	0.983		0.030	0.752		0.037	1.376		0.051
	fem/sing	-0.933		0.009	-0.907		0.009				-0.064		0.012
	mal/sing	-0.494		0.011	-0.463		0.011	-0.318		0.013			
	fem/mar	-0.795		0.009	-0.760		0.009						
	black	-0.147		0.012	-0.155		0.012	-0.282		0.017	-0.040		0.017

[5] see Table 2, but replace L by K and d by a.

Table 4: Summary statistics for the effect of minimum wages for 20 economies, factual and counterfactual for the mean minimum wage

		std. dev. (w)		10-50% diff. (w)		50-90% diff.(w)		qb-qa		qc-qb		qd-qe	
year	region	fact.	c.f.	fact.	c.f.	fact.	c.f.	fact.	c.f.	fact.	c.f.	fact.	c.f.
1979	South	0.492	0.513	0.527	0.667	0.702	0.681	0.419	0.509	0.527	0.561	0.439	0.436
1973	South	0.518	0.532	0.587	0.625	0.684	0.716	0.510	0.536	0.489	0.509	0.484	0.513
1979	Northeast	0.490	0.502	0.592	0.638	0.638	0.660	0.466	0.517	0.482	0.486	0.425	0.442
1979	Midwest	0.488	0.495	0.619	0.662	0.617	0.623	0.463	0.521	0.517	0.508	0.390	0.401
1991	South	0.532	0.540	0.613	0.656	0.752	0.746	0.462	0.489	0.567	0.590	0.482	0.478
1979	West	0.507	0.512	0.649	0.684	0.654	0.646	0.462	0.495	0.540	0.537	0.400	0.403
1985	South	0.535	0.542	0.644	0.680	0.748	0.747	0.502	0.526	0.564	0.575	0.471	0.462
1991	Midwest	0.537	0.541	0.673	0.684	0.714	0.714	0.492	0.501	0.573	0.575	0.459	0.459
1985	Midwest	0.535	0.522	0.718	0.703	0.657	0.651	0.544	0.536	0.565	0.566	0.407	0.409
1973	Northeast	0.475	0.474	0.588	0.587	0.627	0.621	0.480	0.478	0.451	0.449	0.424	0.421
1973	Midwest	0.480	0.477	0.658	0.658	0.568	0.562	0.547	0.545	0.436	0.438	0.391	0.387
1991	West	0.563	0.555	0.701	0.677	0.759	0.762	0.481	0.465	0.599	0.597	0.482	0.479
1989	South	0.538	0.532	0.658	0.641	0.740	0.741	0.512	0.499	0.558	0.553	0.480	0.481
1985	Northeast	0.523	0.528	0.683	0.674	0.696	0.703	0.556	0.547	0.514	0.512	0.442	0.444
1973	West	0.498	0.492	0.699	0.683	0.574	0.568	0.552	0.535	0.462	0.470	0.392	0.382
1985	West	0.534	0.539	0.735	0.700	0.686	0.716	0.556	0.522	0.573	0.577	0.419	0.432
1991	Northeast	0.536	0.529	0.686	0.668	0.701	0.691	0.543	0.520	0.539	0.535	0.456	0.450
1989	Midwest	0.544	0.529	0.711	0.674	0.704	0.696	0.558	0.524	0.546	0.543	0.463	0.464
1989	West	0.554	0.536	0.724	0.626	0.714	0.741	0.529	0.469	0.589	0.588	0.459	0.467
1989	Northeast	0.530	0.515	0.669	0.639	0.702	0.672	0.551	0.528	0.519	0.500	0.459	0.465
std. dev.	all obs.	0.026	0.022	0.055	0.028	0.055	0.058	0.042	0.024	0.046	0.048	0.033	0.035
	obs. > wmin			0.056	0.039	0.056	0.058	0.041	0.013	0.048	0.045	0.039	0.043
	obs. > wmin (males)			0.069	0.058	0.071	0.072	0.044	0.027	0.052	0.045	0.054	0.055
	obs. > wmin (females)			0.103	0.032	0.060	0.054	0.043	0.018	0.066	0.036	0.028	0.050

fact. = factual minimum wage
c.f. = counter factual minimum wage

qa = white without education and experience
qb = white with high school
qc = white with six years of college
qd = white with six year of college and twenty years experience

Table 5: Regressions of share of observations in spike and below spike and of implied number of truncated observations

	share of observations in spike						share observations below spike					
	all		male		female		all		male		female	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
intercept	0.182	0.035	0.204	0.057	0.155	0.024	0.085	0.052	0.034	0.079	0.101	0.036
wmin	-0.282	0.089	-0.315	0.120	-0.234	0.082	-0.082	0.131	-0.001	0.166	-0.136	0.126
wmin^2	0.117	0.055	0.128	0.062	0.093	0.068	0.008	0.080	-0.019	0.086	0.042	0.104
R2	0.853		0.788		0.847		0.583		0.346		0.538	

	spike plus below spike as a share of above spike observations						implied number of truncated observations as a share of above spike observations					
	all		male		female		all		male		female	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
wmin	0.184	0.015	0.115	0.015	0.255	0.024	0.407	0.074	0.459	0.156	0.794	0.130

Table 6: Minimum wages and the rise of income dispersion 1979-1989

year(y. wmin)	std. dev.(w)	log wage diff. 10-50	log wage diff. 50-90	log wage diff. by skill qa - qb	qb - qc	qc - qd
all obs.						
1979(1979)	0.494	0.597	0.653	0.453	0.516	0.414
1989(1989)	0.542	0.691	0.715	0.537	0.553	0.465
1989(1979)	0.504	0.554	0.701	0.458	0.537	0.472
obs. > wmin						
1979(1979)		0.596	0.646	0.329	0.498	0.441
1989(1989)		0.693	0.713	0.426	0.563	0.485
1989(1979)		0.579	0.702	0.311	0.543	0.518
males						
1979(1979)		0.675	0.573	0.364	0.419	0.515
1989(1989)		0.741	0.686	0.439	0.491	0.600
1989(1979)		0.630	0.684	0.329	0.439	0.614
females						
1979(1979)		0.364	0.580	0.208	0.457	0.415
1989(1989)		0.606	0.666	0.322	0.608	0.420
1989(1979)		0.362	0.596	0.196	0.449	0.546

qa = white without education and experience
qb = white with high school
qc = white with six years of college
qd = white with six year of college and twenty years experience

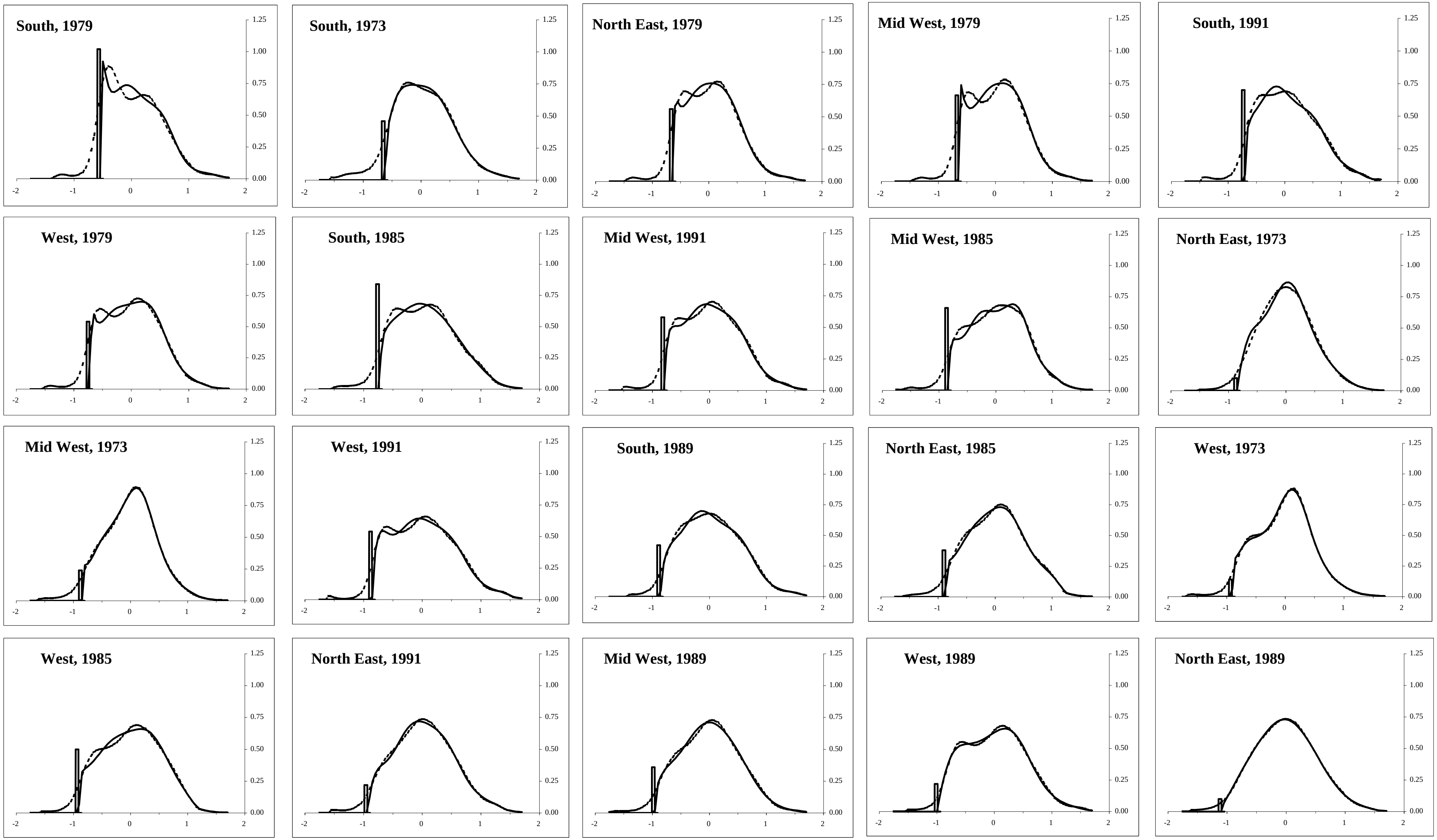
Table 7: The effect of the minimum wage on the return to education in various subsamples

Subsample	R^2 min.wage 20 economies [1)]	return[2)] in 1979	return[2)] in 1989	return in 1979 (min. wage 1989)
1. all men	0.057	0.0559	0.0815	0.0632
2. like 1., but excl. experience ≥ 10	0.141	0.0582	0.0988	0.0736
3. like 2., but excl. years of education >14	0.456	0.0640	0.0909	0.0853
4. like 3., but excl. years of education <6	0.479	0.0640	0.0917	0.0861

[1)] R^2 from a regression of the return to education on an intercept and the real minimum wage; the returns to education are taken from 20 regressions (one for each economy) with a cubic in experience and dummies for black and family status.

[2)] mean value across 4 regions.

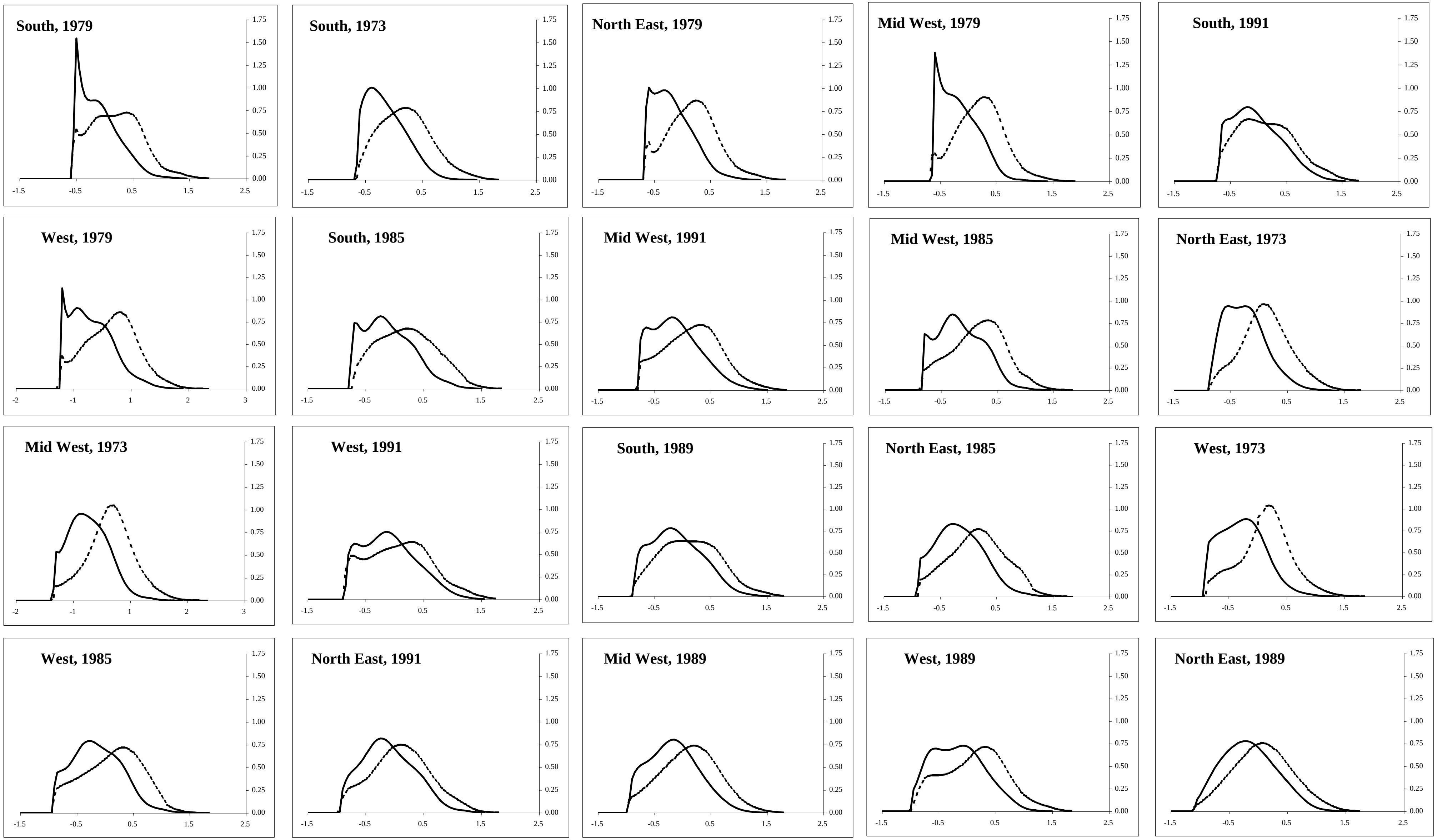
Figure 1: Log wage distribution, estimation results



Solid line: exclusive wage observations in the spike and below.

Dotted line: including observations below the spike.

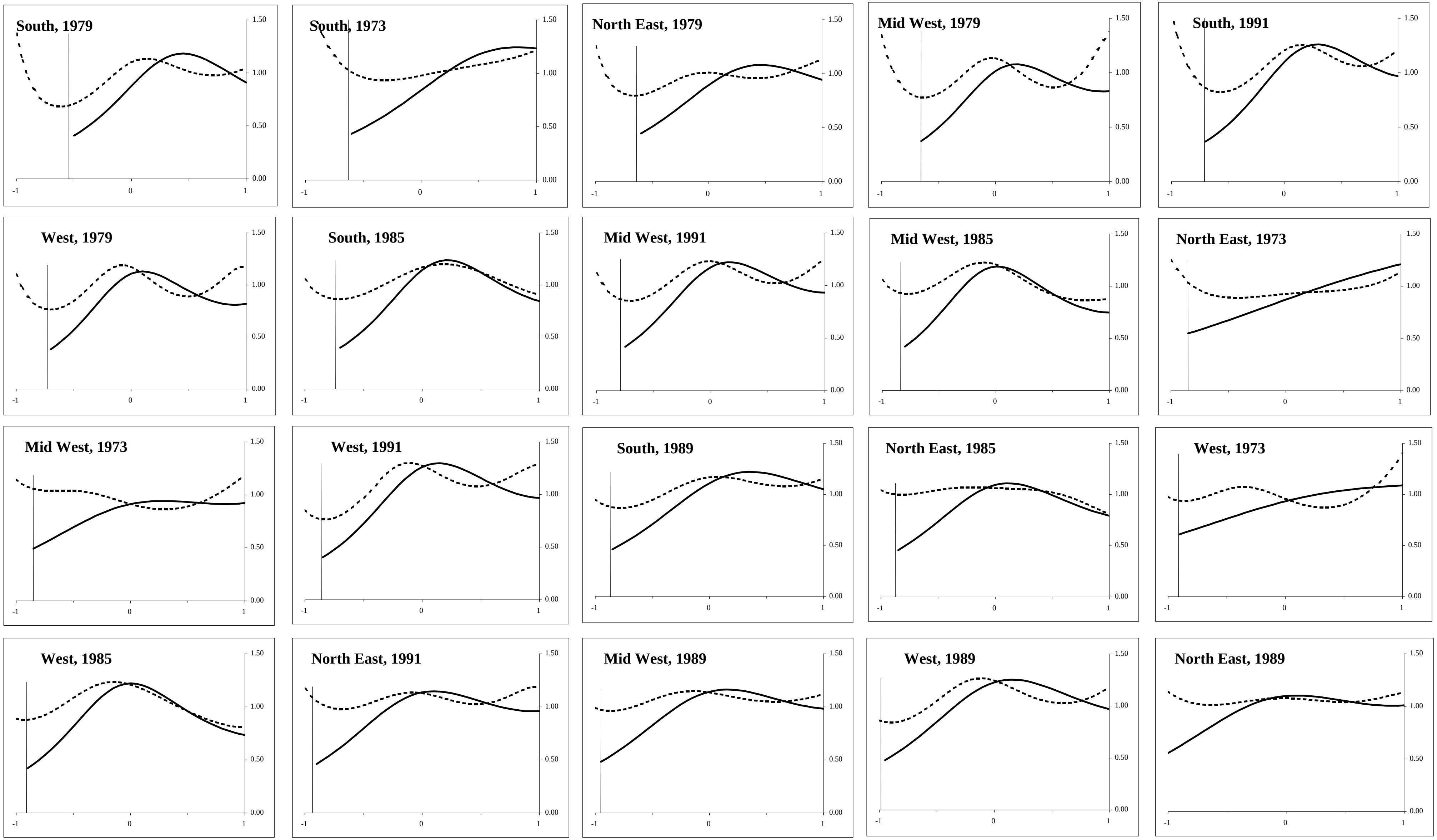
Figure 2: Log wage distributions for males and females separately, estimation results



Solid line: females

Dotted line: males

Figure 3: Return on human capital by log wage level, estimation results

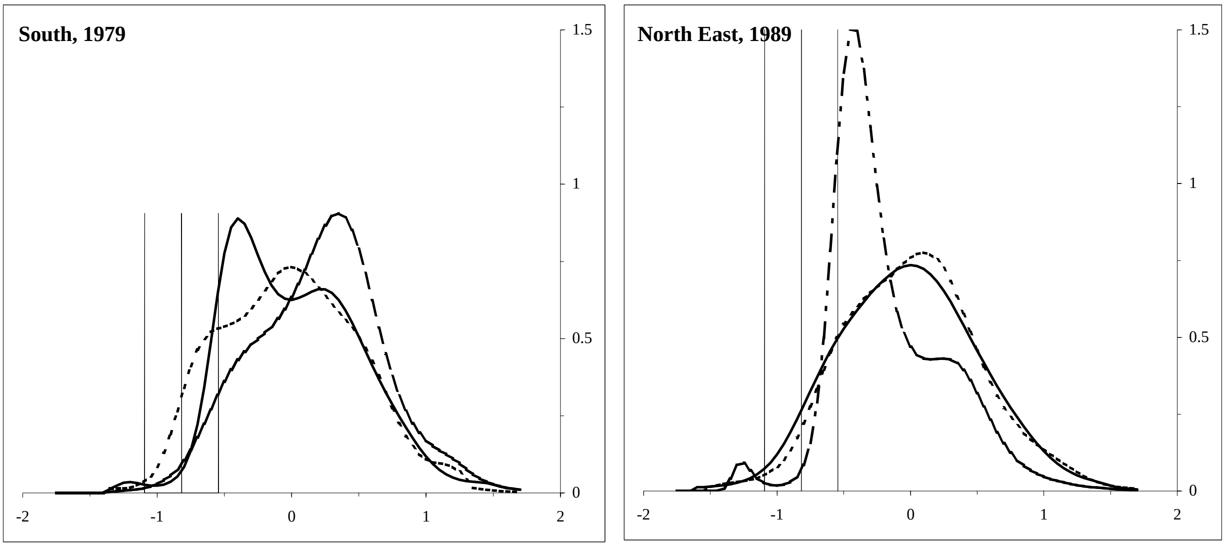


Solid line: excluding wage observations in the spike and below.

Dotted line: inclusive observations below the spike.

The vertical line indicates the minimum wage.

Figure 4: Log wage distributions, factual and counter factual estimation results include all observations

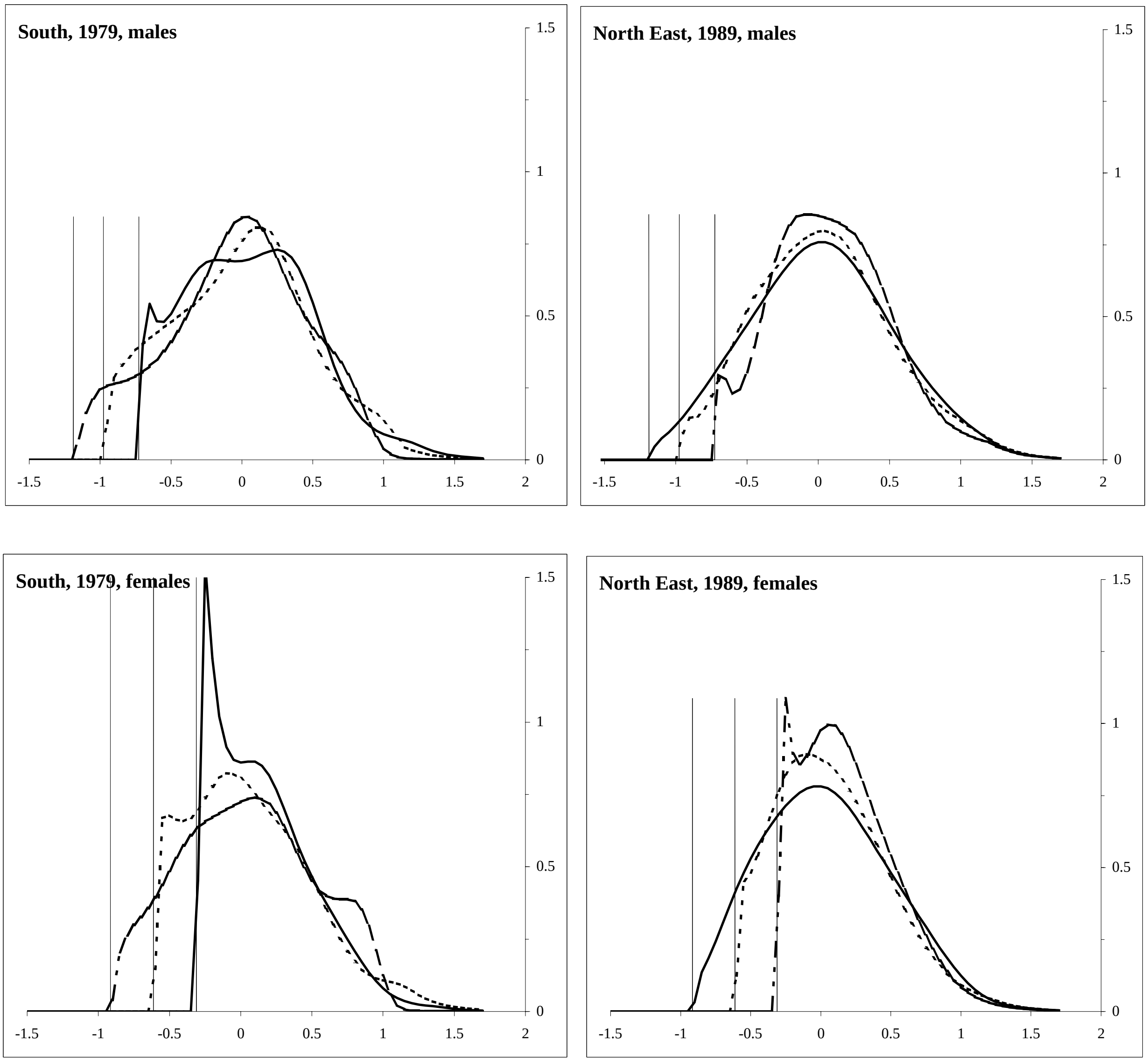


Solid line: factual density.

Regular dotted line: counter factual with the average minimum wage.

Dotted line with long and short stripes: counter factual with the lowest and highest minimum wage.

Figure 5: Log wage distributions, factual and counter factual for males and females separately

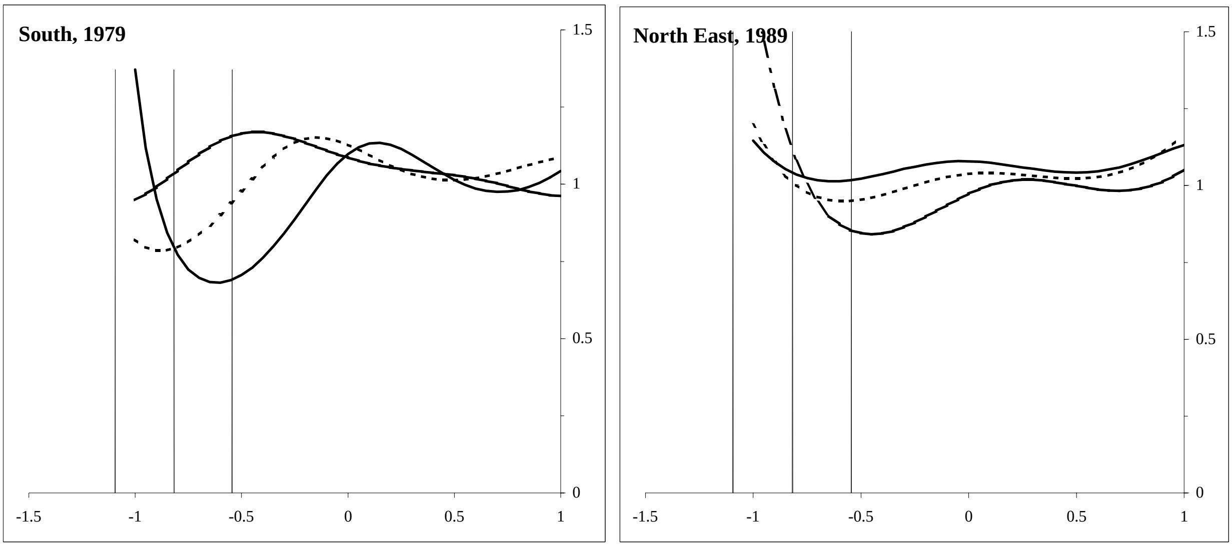


Solid line: factual density.

Regular dotted line: counter factual with the average minimum wage.

Dotted line with long and short stripes: counter factual with the lowest and highest minimum wage.

Figure 6: Return on human capital by log wage level, factual and counterfactuals.
Estimation results include all observations.

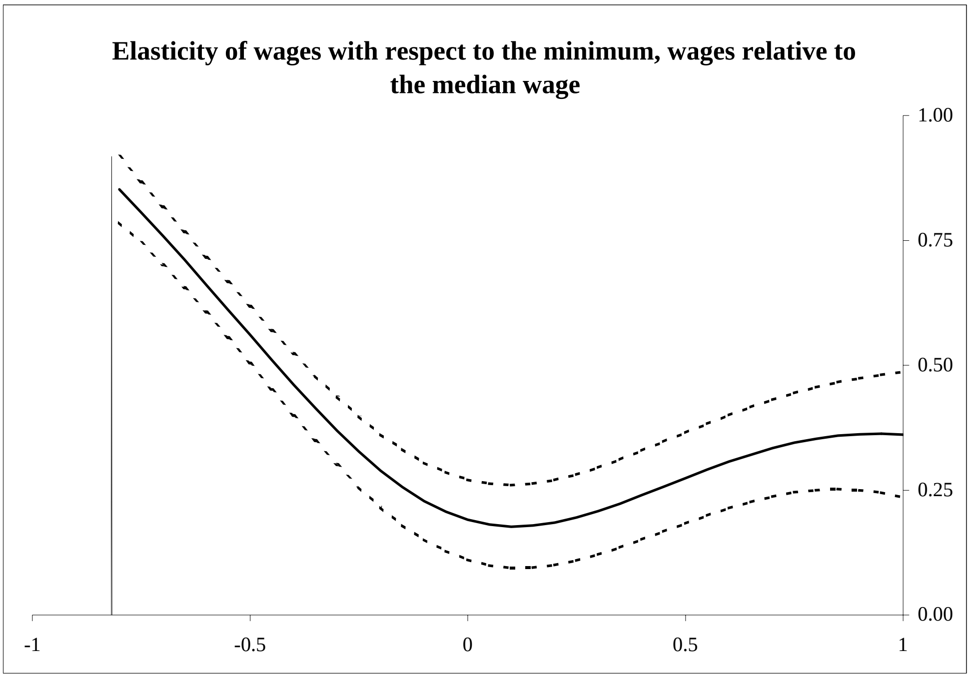


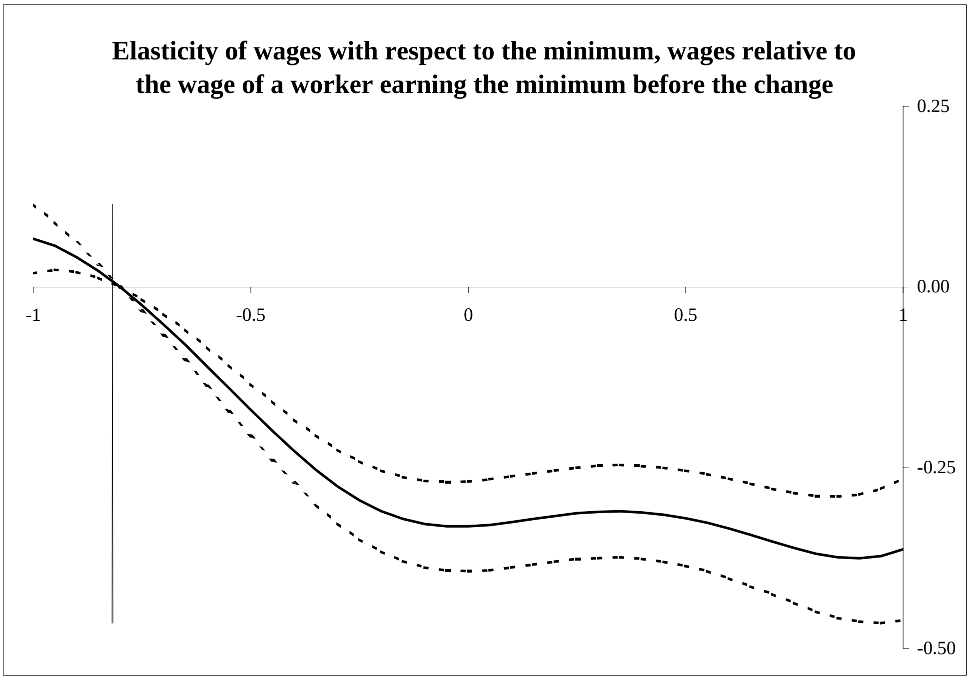
Solid line: factual density.

Regular dotted line: counter factual with the average minimum wage.

Dotted line with long and short stripes: counter factual with the lowest and highest minimum wage.

Figure 7: Effect of a change in minimum on wages by the log wage level of the worker before the change. Estimation results include all observations.





The vertical line indicates the minimum wage.