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THE CONTRIBUTION OF MINIMUM WAGES TO INCREASING WAGE INEQUALITY

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Abstract

DiNardo, Fortin, and Lemieux (1996) estimated the contribution of minimum wages to the reduction in wage dispersion in the United States to be 25 percent. However, their method requires strong assumptions and does not allow testing. This paper uses a new methodology requiring no assumptions on how minimum wages affect wage distribution and return to human capital. Estimation results for the period 1973-1991 show that the rise in wage inequality in the lower half of the distribution during the 1980s can be largely explained by the decrease in minimum wages. The compressing effect of increasing minimum wages is felt at wage levels up to twice the minimum. These results provide strong evidence against CES models and in favor elasticities of substitution that decline by the skill distance between worker types.

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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. However, it is not immediately clear how to relate this evidence to the increase in wage dispersion. 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 contributed greatly to the explanation of rising inequality. DiNardo et.al. hold minimum wages responsible for 25 percent of the increase in wage dispersion.

The methodology of DiNardo, Fortin and Lemieux (1996) is based on a comparison of wage distributions at different points in time. They apply non-parametric Kernel methods to estimate the density function of log wages. Pictures of the estimated density functions for the period 1973-1990 show that minimum wages have had a large impact.

In particular, when the real minimum reached its maximum around 1979, there was a large spike around the minimum. The log wage distribution was highly asymmetric at that point in time. In 1990, when real minimum wages were at their minimum, there was hardly any spike and the log wage distribution was almost symmetric.

For the calculation of the effect of minimum wages, Dinardo et.al. invoke the results of Card and Krueger (1994) to justify the assumption that the minimum wage had no effect on employment. Furthermore, they assume that a change in the minimum wage has no effect on the shape of the wage distribution to the right of the minimum. For the sub-minimum wage part of the distribution, they assume that a change of the minimum would lead to a proportional change in the distribution leaving its shape unaffected. At first glance the wage distributions plotted in their paper suggests that the assumption that wages above the minimum are uneffected is not supported by the data. Their approach is merely an accounting exercise. They were unable to work out a methodology for directly estimating the effect of minimum wages. Though their plots of the density functions are suggestive, the reader gets neither an idea of the statistical significance nor the explanatory power of these assumptions.

This paper develops a methodology which depends neither on Card's and Krueger's conclusions on the employment effects of minimum wages, nor on a priori assumptions on how and where minimum wages affect the distribution. Data will decide. For this purpose, a two stage procedure is applied. The first stage characterizes the wage distribution for each year (and region) by a small number of parameters. In the second stage, the differences in these parameters are related to the level of the minimum wage. The generality of using a non-parametric approach to estimating the density function

in DiNardo et.al. is traded for having to impose more structure on the functional form of the density function, but then being able to directly infer the effect of minimum wages. Moreover, this methodology allows the calculation of confidence intervals of the estimated effect. The results presented in this paper clearly reject DiNardo, Fortin, and Lemieux (1996) assumption that minimum wage had no effect on the shape of the wage distribution to right of the minimum.

The conclusion from this part of the analysis leaves open the issue of the mechanism that is generating this effect. At least two explanations are available. First, a minimum wage might simply discard the left tail of the wage distribution. The truncation of low-wage workers yields a relation between the minimum and wage dispersion. I shall refer to this mechanism as the truncation effect. Secondly, an increase in the minimum wage might cause the wage structure to be compressed by spill-over effects to wage levels way above the minimum. For example, an increase in the minimum wage might yield a reduction of the wage differential between two unexperienced white males, one having completed high school and the other having no education at all. I shall refer to this mechanism as the compression effect.

In order to evaluate both explanations, the analysis is extended. The single index assumption of Teulings (1995) is applied, which states that all components of human capital can be aggregated in a single index of human capital, made up of observable characteristics, like education and experience, and of unobservable characteristics. In principle empirical evidence on the relationship between the return to this index on the

one hand, and the level of the legal minimum wage on the other hand allows us to distinguish between truncation and compression effects. A practical problem is that we have to deal with unobserved skill characteristics and therefore run the risk of selection bias. I shall present plausibility checks on this issue. An increase in the minimum wage will be shown to reduce the return to this human capital index in the wage interval from the minimum upto at least twice the minimum, consistent with the compression effect.

The data used for the analysis cover the same time period as DiNardo et.al. However, unlike DiNardo et.al., I use data on only five selected years (1973, 1979, 1985, 1989, 1991). Entering more years to the regression is not going to add much variation in the minimum, since between these years, the pattern in minimum wages is close to a time trend. More generally, 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 asymmetric technological progress-- are well covered by a time trend. However, the correlation between minimum wages and time is far from perfect. Minimum wages did increase from 1973 to 1979 and from 1989 to 1991. As further 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 in the rest of the country.[1]

[1]This idea is similar that in Castillo-Freeman and Freeman (1992), who analyze the impact of the US minimum on the low wage area Puerto Rico.

Furthermore, these regional differentials are not constant over time. The south is catching up, while the midwest is declining. This variation helps to distinguish the impact of minimum wages from the effect of unionization and skill biased technological progress. Futhermore, I shall discuss a substantial amount of circumstantial evidence that the reported effects are indeed due to the minimum wage. Finally, I shall test whether the impact of minimum wages is robust to the inclusion of either year or region dummies, to account for fixed year and region effects. In particular, year dummies are important as they can account for the impact of skill biased technological progress. The variation in the data does not allow the inclusion of year and region dummies simultaneously.

In a recent paper, Lee (1999) reached very much similar conclusions regarding the contribution of the minimum to increasing wage inequality. However, Lee's results on the return to human capital are much more moderate than the results that will be reported here. This invokes the question as how to square a large impact on wage dispersion with a small impact on relative wages. His research strategy is different from the one applied here in two aspects. First, he uses a finer regional disaggregation. This allows him to benefit from state level variation in the nominal minimum, where I have to apply the federal minimum. Furthermore, this finer disaggregation provides sufficient variation to enter both year and state dummies, where I can include only one of two sets of dummies at a time. Instead, I extend the time span of the analysis back to 1973, thereby adding the variation due to increase in the minimum from 1973 to 1979. Secondly, Lee uses 10-50 log wage differentials as variables, instead of using a flexible functional form, as is done in this paper. A drawback of this approach is that

it does not allow one to establish exactly the location of the minimum in the log wage distribution. Since changes in the minimum have their maximum impact on the distribution and the return to human capital specifically at wage levels just above the minimum, his approach tends to understate their effect. This problem is probably less important for the log wage distribution, where we reach similar results. However, I shall argue that it might explain Lee's low estimate of the compression effect on the return to human capital. The single index assumption will proof to be an essential tool for the dealing with this problem.

The application of the estimated parameters for the calculation of a counterfactual wage distribution in 1989 would the minimum of 1979 have applied yields a surprising conclusion. The reduction in real minimum wages can explain the full increase in lower half the distribution. When asking the monocausal question "trade or technological progress?" on the main cause of increasing dispersion, the simple answer for the lower half of the distribution seems to be "minimum wages".

This leaves open the interpretation of these results. DiNardo, Fortin, and Lemieux (1996) take their results as evidence in supporting the impact of institutions on relative wages. My interpretation is entirely different. Teulings (2000) shows how a standard supply and demand framework can yield exactly the outcome that is documented in this paper, provided that one uses a DIStance-Dependent-Elasticity-of-Substitution (DIDES) production structure instead of the standard CES model, of which Katz and Murphy (1992) is the canonical example. Minimum wages tend to eliminate the least skilled workers from employment, thereby raising the wages of slightly better skilled

workers. The huge variation in the minimum wage between 1973 and 1991 provide therefore an excellent natural experiment. The DIDES is shown to outperform the CES model.

The structure of the paper is as follows. Section 2 describes the 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 The estimation method

2.1 Basic 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 first stage, a flexible 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 flexible form between the 20 economies is related to the level of the legal minimum wage. The general discussion in this subsection will be concentrated on the wage distribution. Mutatis mutandis the same procedure applies to the return to human capital. Let T be the number of economies (20 in this particular example) and let L be the number of parameters of the flexible 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 flexibility of the functional form

by raising L. In the first stage, wage distributions are estimated for each economy. This yields T observations on L parameters. In the second stage, the variation in these L parameters between the T observations is regressed on an intercept and a minimum wage variable.

For the second stage, the level of the minimum wage in each of the 20 economies is used as an explanatory variable. Obviously, one cannot simply compare the nominal level of the minimum wage across economies. Some kind of a benchmark is needed to which to compare the level of the minimum wage. The problem with any benchmark is that it is likely to be endogenous. In fact, most variation in real minimum wages is not due to variation in the nominal minimum itself, but in the benchmark, see for example the decline in real minimum wages during the eighties. One possibility is to use the CPI as a deflator. However, we think that the same minimum wage will have a much larger impact in Puerto Rico than in the rest of the United States, see Castillo-Freeman and Freeman (1992), which is largely due to the lower level of productivity in Puerto Rico. Hence, it is more natural to use a wage level, like the median or mean as a benchmark. The median is applied most frequently in the literature, see DiNardo, Fortin, and Lemieux (1996), Dolado et.al. (1996), and Lee (1999). Using the mean instead has the disadvantage that it is even more endogenous than the median. 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 effects will probably be small at the median wage level. Hence, I shall line up with the literature in the field and use median as the benchmark.

The estimation procedure for Stage 1 will be set out for wage distribution and return to human capital in Subsections 2.2 and 2.3 respectively. Stage 2 will be discussed in Subsection 2.4.

2.2 The specification of the wage distribution

Let w_{it} denote the log hourly wage of worker i minus the log median wage, and let $wmin_t$ denote the log hourly minimum wage minus the log median, both in economy t. Furthermore, let $d_t(.)$ denote the density function of w_{it}-$wmin_t$ in economy t. A flexible functional form for this density function reads:

$$d_t(wm_{it}) = \exp[\ \Sigma_{l=0}^{L}\ d_{lt} wm_{it}^{\ l}\ ] \qquad (1)$$

where:

$wm_{it} \equiv w_{it} - wmin_t$. 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. Hence, equation (1) is a simple flexible parameterization of a density function that can serve as an alternative for the non-parametric Kernel estimators applied by DiNardo et.al.

The parameters d_{lt} are estimated by maximum likelihood. The contribution to the likelihood of each observation is $\exp[\ \Sigma_{l=0}^{L}\ d_{lt} wm_{it}^{\ l}\ ]$, subject to the constraint:

$\int \exp[\ \Sigma_{l=0}^{L}\ d_{lt} wm^{l}\ ]\ \mathrm{d}wm = 1.$

Alternatively, the contribution to the likelihood can be written as:

$\exp[\ \Sigma_{l=1}^{L}\ d_{lt} wm_{it}^{\ l}\ ]\ /\ \int \exp[\ \Sigma_{l=1}^{L}\ d_{lt} wm^{l}\ ]\ \mathrm{d}wm.$

where the parameter d_{0t} drops out. The calculation of the first and second derivative of the log likelihood is straightforward. It is important to realize that the parameters d_{lt} will be estimated consistently even when only truncated data on wm_{it} are available, provided that the support of the integral in the denominator is adjusted properly. Suppose for example that wm_{it} is distributed normally, but that we do not observe the observations i for $wm_{it} < 0$ (or: $w_{it} < wmin_t$). This type of densities will indeed be estimated. The estimation procedure will be able to recover the parameters of the underlying untruncated distribution, similar to Meyer and Wise (1983a,b). Numerical simulations confirm this conclusion. Obviously, the estimation results on the unobserved left tail will be unreliable, but that is not a problem since the analysis in Stage 2 refers to the observed part of the distribution. Hence, truncation is not a problem here.

For future reference, it is useful to define the density $d_t^*(.)$ of w_{it}. This density satisfies:

$d_t^*(w_{it}) = \exp[\ \Sigma_{l=0}^{L}\ d_{lt}^{\ *} w_{it}^{\ l}\ ].$

The only difference between both densities is a shift along the horizontal axes by $wmin_t$. The log likelihood for the estimation of both densities has exactly the same value. There is a simple linear relation between the both parameter vectors:

$d_t^* = \mathbf{D}_t\ d_t,$

where d_t and d_t^* are the vectors of d_{lt} and d_{lt}^*, and where $\mathbf{D}_t$ is LxL matrix, which

depends on $wmin_t$ in a non-linear way.[2]

2.3 The specification of the return to human capital

The analysis of the return to human capital requires somewhat more structure. Human capital is made up of many components. It is impossible to separately analyze the non-linear relationship between wages and each component, for the non-linearity implies that the impact of a marginal change of one component depends on the value of the other components. I therefore apply the single index assumption on human capital (Teulings, 1995; Card and Lemieux, 1996). Suppose that there is a relation between personal characteristics of worker *i* (years of education, experience etc.) in economy *t* and a latent variable q_{it}:

$$q_{it} = x_{it}'\beta + \underline{q}_{it} \qquad (2)$$

where:

x_{it}: a vector of characteristics of person *i*, excluding a constant;

β: a vector of parameters of corresponding dimension;

$\underline{q}_{it}$: a random variable, distributed as N(0,1), which is independent of x_{it}.

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[2]This matrix can be derived from the equality $\Sigma_{l=0}^{L} d_{lt}^{*} w_{it}^{l} = \Sigma_{l=0}^{L} d_{lt}(w_{it}-wmin_t)^l$. This equation has to apply identically for all w_{it}. For each *t*, both sides of the equation are *L* th degree polynomials in w_{it}. For identity, the coefficients of the corresponding terms of these polynomials have to be the equal, yielding a system of *L*+1 equations with d_{lt}^{*} on the left hand side and expressions in d_{lt} and $wmin_t$ on the right hand side. These expressions are linear in d_{lt} but non-linear in $wmin_t$. The equation for the zero order term can be dropped, yielding a *L*x*L* matrix, which depends non-linearly on $wmin_t$.

and that this latent variable is related to wages:

$$wm_{it} = w_t(q_{it}) \tag{3}$$

where $w_t(.)$ is a flexible functional form: $w_t'(.) > 0$.

The single index assumption states that the relation $w_t(.)$ may vary across economies t but that the contribution of each component of x_{it} to q_{it} is constant, i.e. β does not vary across economies. The variable q_{it} will be referred to as the human capital index. The single index assumption implies that the marginal return on each human capital component varies proportionally, both within and between economies. For example, there is a fixed *ratio* of the return to experience and education, which is measured by the respective elements of β. 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 specific for each economy t. The non-linearity of $w_t(.)$ will be crucial in establishing the impact of minimum wages, because a minimum wage compresses the return to human capital $w_t'(.)$ most significantly in the wage interval just above the minimum.

The single index assumption can be tested against a more general structure where the returns of different human capital components may vary between economies independently, by specifying a separate β for each economy. Such tests will be reported in Section 3.

The model (2) and (3) is underidentified. Since q_{it} is not observed directly, any

multiplicative transformation to q_{it} (e.g.: $q_{it}^* = \gamma\ q_{it}$) can be offset by a contrary transformation of the function $w_t(.)$ [e.g.: $w_t^*(q_{it}^*) = w_t(q_{it}^*/\gamma)$]. Hence, the contribution of one of the human capital components to q_{it} has to be fixed a priori. A convenient choice is to set the variance of $\underline{q}_{it}$ equal to unity.[3]

We now turn to the specification of $w_t(.)$. Since $w_t'(.) > 0$, $w_t(.)$ has a well-defined inverse function, which will be denoted $q_t(.)$. A flexible specification that encompasses many possible shapes of the wage function is a polynomial:[4]

$$q_{it} = \Sigma_{k=0}^{K}\ a_{kt} wm_{it}^{k} \tag{4}$$

Combining the equations (2) and (4) yields:

$\Sigma_{k=0}^{K}\ a_{kt} wm_{it}^{k} = x_{it}'\beta + \underline{q}_{it}$.

The log likelihood of this class of models is given in Teulings (1995, Appendix 3). Where the parameters d_{lt} can be estimated independently for each t, the parameters a_{kt} are interrelated because the parameter vector β applies to all economies.

The models (1) and (4) will be estimated both including and excluding the observations earning a wage below the minimum. Unlike the case of the wage distribution discussed in Section 2.2, truncation is a serious problem in this case. The elimination of the sub-

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[3]For similar reasons, an intercept in q_{it} would be unidentified. Hence, it is omitted in equation (2).

[4]The drawback of specifying $w_t(.)$ instead of $q_t(.)$ is that we have data on w_{it} and not on q_{it}. Hence, we would have to invert $w_t(.)$ for each individual observation, and repeat that process for each iteration in the maximization of the likelihood. Fortin and Lemieux (1999) estimate exactly the same model using an ordered probit model. The parameterization applied here is much more easier to handle.

minimum wage observations affects a serious number of observations, up to 10 percent in the economy most affected. This introduces selection bias in the distribution of the unobserved skill characteristics $\underline{q}_{it}$ among the remaining observations. As a partial remedy to this problem, a truncated model is fitted to the remaining data, similar to Meyer and Wise (183a,b). Equation (4) is used to calculate $qmin_t = q_t(0)$. By the assumed normality of the distribution of $\underline{q}_{it}$ the truncation term in the likelihood is equal to $\Phi[x_{it}'\beta - qmin_t]$. The extension of the derivatives of the log likelihood function to account for these extra terms is straightforward. However, it is by now well known that these models are highly sensitive to assumptions on the functional form and the underlying distribution of the unobserved characteristics. In Subsection 4.4, I shall therefore present a plausibility test of these assumptions.

2.4 Stage 2: the impact of the minimum

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

$$d_{lt}^{e} = \delta_{0l} + wmin_t\, \delta_{1l} + \underline{d}_{lt} \qquad (5)$$

where d_{lt}^{e} is the estimate of d_{lt} derived from the maximum likelihood estimation discussed in Section 2.2, and where $\underline{d}_{lt}$ is a random variable.

In matrix notation we have:

$$d^{e} = \mathbf{X}\, \delta + \underline{d}, \qquad (5a)$$

where d^e and $\underline{d}$ are (TL)x1 vectors with elements d_{lt}^e and $\underline{d}_{lt}$ respectively, where **X** is the (TL)x(2L) matrix of explanatory variables, and where δ is a (2L)x1 vector with elements δ_{0l} and δ_{1l}. The error term $\underline{d}$ in equation (5) is composed of two independent components.

The first component is the estimation error d^e-d of the first stage of the estimation procedure. An estimate of the covariance matrix **V** of this component is available from the maximum likelihood estimation discussed in Section 2.2. Accounting for the covariances d^e-d within an economy t is crucial, for the estimation errors can be expected to be highly correlated, in particular when L is set at a higher value.[4]

The second component covers the impact on the wage distribution of factors other than the minimum wage, like unionization, the composition of labor supply and skill biased technological progress. We have no idea about their covariance matrix. For the sake of convenience, this covariance is assumed to be proportional to **V**. Hence: $\underline{d} \sim N(0,\sigma^2\mathbf{V})$. When $\sigma^2 = 1$, $\underline{d}$ can be fully ascribed to the first component, the estimation error in d^e. When $\sigma^2 > 1$, part of the variation in d not explained by the minimum wage must be due factors other than the minimum wages.

The GLS estimator of δ reads:

$$\delta^e = [\mathbf{X'V}^{-1}\,\mathbf{X}]^{-1}\,\mathbf{X'V}^{-1}\,d^e.$$

It is useful to have an idea about the power of the minimum wage in explaining the

[4]For the wage distribution, the matrix **V** is block diagonal because the estimates of d_{lt} are independent across different economies t. For the return on human capital, the estimates for different economies are linked by the estimate for β. This difference is inconsequential for the subsequent discussion.

variance in d_{lt}. For that purpose, we need a suitable null hypothesis reflecting the case where minimum wages do not affect the wage distribution at all. Consider the null hypothesis $d_{lt} = \delta_{0l} + \underline{d}_{lt}$. As discussed in Section 2.2, the coefficients d_{lt} measure the wage distribution with the log minimum wage as a point of reference. Hence, the null specified above implies that a change in $wmin_t$ would leave the distribution of wages relative to the minimum wage the same. This contradicts the starting point of a change in $wmin_t$ (requiring a change of the log median wage relative to the log minimum wage). This null is therefore logically inconsistent.

The correct null hypothesis is based on the coefficients d_{lt}^*. These coefficients satisfy the transformation rule $d^* = \mathbf{D}\, d$, where $\mathbf{D}$ is a block diagonal matrix with the matrices $\mathbf{D}_t$ on the diagonal, and where d^* and d are (TL)x1 vectors of d_{lt}^* and d_{lt} respectively, see footnote 2. Then, the null hypothesis reads:

$$d^e = \mathbf{D}^{-1}\mathbf{X}_0\delta^* + \underline{d}, \tag{5b}$$

where $\mathbf{X}_0$ is a (TL)xL matrix of intercepts for every l and where δ^* is a Lx1 vector of parameters. Equation (5b) uses d^* as the variable to explain, but it is premultiplied by $\mathbf{D}^{-1}$ to make it comparable to equation (5a). This null hypothesis will be used for the calculation of a R^2 statistic, comparing model (5a) to model (5b). This R^2 will be corrected for the covariance matrix of $\underline{d}$, $\mathbf{V}$. Hence, elements of d^e that are measured inprecisely in the first stage are weighed less heavily. Details are discussed in the appendix.

A drawback of comparing model (5a) to model (5b) is that the latter is not nested in the former. Hence, we cannot apply a F-test. For that reason, I shall estimate the following model:

$$d^e = \mathbf{D}^{-1}\mathbf{X}\delta^* + \underline{d}. \tag{5c}$$

Model (5b) is nested in (5c), and hence we can apply the F-test. I shall present three test statistics of this type. In the first, $\mathbf{X}_0$ contains only dummies for each order l of the polynomial, so altogether L dummies. In the second, $\mathbf{X}_0$ contains one separate dummy for each year and each l, so altogether 5 X L dummies. The third statistic is the same as the second, but now with dummies for each region instead of each year, so altogether 4 X L dummies. In each of these three cases, $\mathbf{X}$ equals $\mathbf{X}_0$ extended with the vector *wmin*. These statistics allow us to analyze whether the minimum wage variable in fact covers fixed time or region effects that are not included in the model. The 20 economies in our sample offer insufficient information to enter year and region dummies simultaneously, as is done in Lee (1999).

One might ask why equation (5a) is applied at all, when only equation (5c) allows formal testing. The reason is that model (5a) fits the data substantially better, as will be demonstrated by comparing the R^2 statistics, see Table 2 and 3 below. The non-linear transform of $\mathbf{D}$ in $wmin_t$ contributes to a proper description of the density functions $d_t(.)$. The intuition for this result is that most of the non-linearity in the density is at the minimum wage, where the density functions jump upward. The parameter d_{lt} measures directly the l-th derivative (up to a fixed combinatorial term) because higher order terms cancel at the minimum wage, since $wm_{it} = 0$. Hence, equation (5) implies a linear relation between the derivatives of the wage function at the minimum on the one hand, and the minimum wage on the other hand. When using d_{lt}^*, this relation would be non-linear. Apparently, this linear relationship is best at tracking down the complicated effects on the density at the minimum. Hence, where

F-test will be based on model (5c), the simulation results in Section 4 will be based on model (5a).

Mutatis mutandis the same analysis applies to the return to human capital, where the following equation is estimated in Stage 2:

$$a_{kt}^{e} = \alpha_{0k} + wmin_t\, \alpha_{1k} + \underline{a}_{kt} \qquad (6)$$

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.[5] The four main regions are viewed as separate economies.

The analysis is motivated in part by the potential effect of changes in the minimum on relative wages, due to substitution between types of labor. Increases in the minimum may eliminate low-skilled workers from employment, thereby raising the wages for close substitutes of this group of workers. With that focus in mind, it is appropriate to

[5]We use the March data for 1973, and data from outgoing rotation groups for the other years. The data for 1979 and 1985 were extracted from NBER CD-Rom CPS Labor Extracts. For 1991, only observations interviewed after May 1 are included, so that they all refer to the period after the minimum wage increase at April 1. Hourly wages are defined as weekly wages divided by usual hours, unless hourly wages are directly available. The author thanks Thomas Lemieux for assistence with the data for 1973, Dan Feenberg for 1979 and 1985, and David Lee for 1989 and 1991.

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.[5] All self-employed persons are deleted. Following this selection and after deleting all observations 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 $wmin_t$, 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 $wmin_t$-1 are deleted.[6] 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

[5] Imputing weights directly in the maximum likelihood procedure would be a more efficient alternative. However, due to the large number of observations available, I can afford the loss of information. The approach in the paper is more convenient.

[6] For the return on human capital, the truncated model discussed in Subsection 2.3 is applied to correct for the selection bias.

Figure 1 plots the estimated log wage distributions for the 20 economies.[7] The dotted lines refer to the distribution including the sub-minimum wage observations, using $L = 12$; the solid lines refer to the distribution using only the observations for which $w_{it} > wmin_t$ (so excluding the spike), 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 real phenomenon (a focal point in wage bargaining) or due to imperfect reporting is unclear. However, their smoothing is no problem for the analysis in Section 4. More serious is the smoothing of the spike at the minimum. The impact of the minimum is still clearly visible. 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. However, it is somewhat difficult to tell whether this impact is only at the spike, or that the supra-minimum distribution is also affected. The estimation results using only the supra-

[7]The wage data are right censored due to top coding in particular for 1979. The extreme right tail is added to the estimated density function using an exponential distribution for w with $\lambda = 5.0$. This value fits the data on the right tail for other years. When the estimated density function is used for the calculation of summary statistics like the standard deviation or 10-50 and 50-90 wage differential, this supplement for the right tail is included.
To test whether differences in top coding rules had a serious impact on the estimates for the return to human capital, we re-estimated a model excluding the observations in the top percentile of wages. This turns out to have a minor effect, see a footnote 9.

minimum observations provide a clear 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.

Some commentators worried about the potentially large impact of observations in the extreme tails on the estimation results for intermediate ranges when using high order polynomials. A comparison of the results with and without the sub-minimum observations in Figure 1 gives an insight into the sensitivity of the estimation results on this issue. 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 is substantial number of observations are deleted, see Table 1. Only when the spike is huge, like in the South in 1979, the estimation results differ. The main reason is that the probability mass in the spike is smoothed out when all observations are used in the estimation. This smoothing is partly in the direction of the supra-minimum part of the distribution. This explains why the dotted line is above continuous line just above the minimum. The estimation method is therefore robust to the in/exclusion of the observations in the tail, but has some difficulty in accommodating the spike. The results using a separate estimate for the spike are therefore more reliable.

Table 2 lists the sum of the log likelihood of the models for all 20 economies for a range of values of L.[8] In each case, the procedure converges to an optimum quickly. Each further increase in L yields a significant 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

[8]Estimates for the parameters d_{lt} and their standard errors are available from the author on request.

included reveals that increasing the order of the polynomial yields a more pronounced spike around the minimum. This is the motivation for setting L at a lower value for the estimation using only the observations above the minimum wage. Note also 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. The estimation results do not suggest a natural cut-off 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 R^2 statistics and F-test will be discussed in Section 4.

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 $wmin_t$, 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 difference in $wmin_t$ for both sexes is much larger in 1973 than in 1991. This effect 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 testing of this first impression.

3.3 The return to human capital

The usual variables are included in the vector x_{it} for the estimation of equation (4). 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. 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, β has to be multiplied by this number to make these coefficients comparable to those of a standard wage regression. The first derivative of $q_t(w)$ is positive for the full domain of w, 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 t. This return can be calculated from equation (4) by the inverse function theorem:

$w_t'[q_t(w_{it})] = 1/q_t'(w_{it}) = [\ \Sigma_{k=1}^{K}\ k\ a_{kt} w_{it}^{k-1}\ ]^{-1}$.

Since the standard deviation of the residuals is normalized to unity while it is estimated about 0.40 in standard wage regressions, the average return will be around 0.40. For the sake of convenience, a normalization to unity is applied, by dividing the calculated number by 0.40. This practice will be maintained subsequently.

The returns are depicted in Figure 3. 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. The return is depicted only for the wage interval [-1,1]. There is some erratic behavior in the extreme tails which, however, effects only a small number of observations.

Table 3 also lists the log likelihood of the model for different values of K. The value of β 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 off, but again the actual choice of the polynomial does not matter much for the Stage 2 results. Subsequent results will be based on $K = 9$.

As with the distribution, the return to human capital is also estimated using only the observations exceeding the minimum wage, where the truncated model discussed in Subsection 2.3 is applied. The β-vector is not much affected by the exclusion of observations. The earnings schedule is flattened 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 immediately from Figure 3. There can be two explanations for this difference. The first is that the return to human capital jumps upward when one moves from just above to just below the minimum. By including data from both sides of the minimum in the analysis, the estimation procedure will smooth the jump, thereby pushing up the return just above the minimum to above its true level. If this will be true, then the truncated model yields the more reliable answer. The second explanation is that low return just above the minimum is just an artefact of the truncation model. This question will be analyzed more deeply in Subsection 4.4.

Since the non-linearity in the return to human capital is much smaller than in the distribution function, we can use a much lower value of K for the case excluding the observations below the minimum (a value of 4 will be applied). The R^2 statistics and F-tests will again be discussed in Section 4.

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 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. However, even slight deviations will cause the rejection of any restriction with close to 100,000 observations.

The assumption can be tested by dividing the sample of 20 economies in a number of subsets and estimating separate β-vectors 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 by 2 on the one hand (introducing 2 x 20 = 40 additional parameters) and by allowing separate β 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 a value of *K* of 9, see Table 3. Hence, the single index assumption is less harmful than the standard linearity assumption in most earnings equations. Another way to evaluate the power of the single index assumption is to look at the gain in explanatory power obtained by dropping the single index assumption, for example, across years. That would yield an increase in the log likelihood per observation of 500/100,000 = 0.5 percent, which translates in a reduction of the standard deviation of the error term by that amount.

The rejection of the equality restriction for the β's across years is mainly due to the gradual catch up of female wages. Separate estimates for both sexes deal with the latter problem. A number of observations on these estimation results are worth mentioning. First, the β vectors for both sexes are substantially different. In particular, the female experience profile is much flatter, see Table 3. Secondly, by adding up the log likelihoods for both sexes the significance of the extension of the model with separate

coefficients for both sexes can be tested. The extension cannot be rejected. Thirdly, the single index assumption does a much better job for both sexes separately, although it is still not statistically acceptable.

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 (5) and (6), 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 $wmin_t$ does not affect the wage distribution by comparing specification (5c) to the restricted model (5b). As has been discussed in Section 2.4, we do that for three cases: a single intercept, year dummies and region dummies (with x being 2, 6, and 5 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 for the results including the spike and the sub-minimum tail, even including either year or region dummies. Apparently, both time and spatial variation contribute to estimation of the effect of $wmin_t$. The fact that year dummies do not take away the significance of the minimum wage variable is of particular importance. Apparently, minimum wages are not a proxy for either skill-biased technological progress or de-unionization. When including the supra-minimum tail only, the results become either weakly or even

in-significant in some cases, in particular when only males are included. This fits an eyeball test of Figure 2, where the supra-minimum wagedistribution for males seems to be quite insensitive to the minimum, since the wages of a large fraction of males are way above the minimum. For females, the null-hypothesis is clearly rejected, except the case where we allow for year dummies.

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 model (5a) relative to model (5c). In all three cases, the R^2 statistic is substantially higher in panel I, in some cases even 10 percentagepoints. For this reason, the simulations will be based on model (5a).

The R^2 statistics for model (5a) tell a similar story on the difference between males and females as for model (5b), but now even clearer. The minimum wage explains 50 percent of the between-economy variation in the parameters of the wage distribution of females and much less for the distribution of males. This difference between males and females is further evidence that the minimum wage variable does not serve as a proxy for declining unionization. DiNardo, Fortin, and Lemieux (1996, p. 1024-1025) document that unionization affects exclusively the wage distribution for males, and exclusively at wage levels close to the median. The effect of minimum wages as estimated in this paper is orthogonal to this: if any effect for males, then only at or close to the minimum; large effects for the female wage distribution.

Similar R^2 and F-statistics are calculated for the return to human capital. They reject the null hypothesis of no effect of $wmin_t$ even more strongly, for all cases and at all

conventional levels of significance.[9] Again, the significance of the minimum wage variable in the presence of year dummies is particularly important evidence for ruling out competing hypotheses. The R^2 statistic in Panel I (comparing (5a) to (5b)) are higher than in Panel II (comparing (5c) to (5b)), though the difference is not as large as in the case of the density. The minimum explains about 40 percent of the between-economy variation in the parameters for the return to human capital, and even 70 percent for females. The latter result is again inconsistent with minimum wages being a proxy for unionization.

4.2 Counterfactual distributions for the mean of wmin_t

An appealing way to evaluate the impact of the minimum on distribution and return to human capital is to calculate counterfactuals using equations (5) and (6), i.e. how would wage distribution and return to human capital have looked when the average value of $wmin_t$ ($\equiv wmin = -0.818$) would have applied in all economies. So for the wage distribution, we calculate:

$$d_{lt}^{c.f.} = \delta_{0l} + (wmin - wmin_t)\,\delta_{1l} + \underline{d}_{lt}$$

The estimated parameters d_{lt}^{e} and the counterfactual parameters $d_{lt}^{c.f.}$ can then be applied to form a factual and a counterfactual distribution. These distributions can be plotted. Furthermore, all kinds of summary statistics can be calculated from these distributions, like the standard deviation of log wages and the 10-50 and 50-90

[9]In order to investigate the effect of top-coding, see footnote 7, estimation has been repeated excluding top percentile observations from the wage distribution in each economy for the case including the sub-minimum tail. This exclusion had a minor impact on the β-vector reported in Table 3. The R^2 reported in Panel I for K=9 dropped from 0.43 to 0.41 and the F-test from 9.33 to 9.00. Also the simulation results are not much affected.

percentile log wage differentials. These statistics are reported in Table 4 for the estimation results using all observations, jointly with the standard deviation of these statistics across the 20 economies. For space considerations, I report these statistics for each economy only for the estimation results using all observations. However, the standard deviation across the 20 economies are listed for all versions at the bottom of Table 4.

The minimum explains 28 percent [= 1 - $(0.022/0.026)^2$] of the between-economy variation in the standard deviation of log wages.[10] At the same time, a comparison of the 10-50 and 50-90 differentials reveals the main impact is in the lower half of the wage distribution. The minimum explains 74 percent of the variance of the 10-50 differential. However, the variation in 50-90 differential is completely unrelated to the minimum.

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 particular the demand for labor in the highest skill categories. Juhn, Murphy, and Pierce (1993) use the employment per industry/occupation cell as an indicator of the distribution of demand. They plot employment growth per cell by its initial wage level. They find that the plot is almost flat, except for the upper percentiles of the wage distribution, where is a strong employment growth relative to the rest of the distribution, thereby raising the wages for these skill types. Hence, one would expect in particular the 50-90 differential to be most affected. The puzzle of Juhn et.al. is that

[10]This estimate is an upperbound, since the parameter estimates are subject to sampling error. Accounting for the error is complicated since the relation between the parameters and the estimated effect is highly non-linear.

wage dispersion increased 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 explain 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 a 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.

When using the estimation results for the distributions excluding the sub-minimum observations, we need additional information on the factual and counterfactual probability mass in the spike and the right tail. These are calculated from the regressions reported in the upper panel of Table 5. The percentage of workers in the spike (defined as: $wmin_t$-0.005 < w_{it} < $wmin_t$+0.005) and below the minimum (w_{it} < $wmin_t$-0.005) is regressed on an intercept, $wmin_t$ and its square. The R^2 of the regression for the percentage below the minimum is high, that for the spike is lower. The related F-test of the restriction that the size of the spike and the sub-minimum tale are unrelated to $wmin_t$ is rejected at all conventional levels of significance, except in the case of the spike for males, where it is a rejected at a 10 percent level significance only. An eye on the data listed in Table 1 reveals that the lower R^2 for the spike is due to two outlier observations for 1973. These are due to state level minimum wage regulations exceeding the federal minimum in large states like New York, New Jersey

and California (Neumark and Wascher, 1992).

When combining the evidence on the supra-minimum part of the distribution in Table 2 with the evidence on the spike and the sub-minimum tail in Table 5 we can conclude that the null hypothesis that $wmin_t$ has no effect on the wage distribution is strongly rejected for the total and female wage distribution and weakly rejected for the male distribution.

The regressions on the spike and sub-minimum wage share are used for the calculation of the counterfactual 10-50 and 50-90 log wage differentials listed in Table 4.[11] The minimum explains as much as 90 percent of the variation in 10-50 differential for females [= 1 - $(.032/.103)^2$], but only 29 percent for males [= 1 - $(.058/.069)^2$]. 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 $wmin_t$ (South 1979 and Northeast 1989) in Figure 4. There is a strong convergence of the distributions when the average value of $wmin_t$ is applied. However, the implications of the estimation results come to surface most clearly where the highest minimum is applied in the economy with the lowest factual minimum wage and vice versa. A spike emerges in the distribution when the minimum is raised to substantial levels. Figure 5 provides similar results for males and females separately. The huge effect of the minimum on the shape of the female wage distribution springs

[11]The standard deviation of log wages cannot be calculated for these models since full information on the shape of the sub-minimum distribution is required for that purpose.

to the eye immediately.

4.3 Counterfactual return to human capital for the mean of wmin_t

A similar approach of calculating counterfactuals can be applied to the return to human capital. Here, wage differentials for fixed intervals of the human capital index are calculated:

$w_t(x_b\beta) - w_t(x_a\beta)$,

where x_b is x-vector for e.g. a white male without education and experience and x_a is a black female, also without education and experience. The error term q is set equal to zero.

Four statistics of this type are reported in Table 4. The minimum explains almost nothing in the first interval (white male versus black female, both without experience or education).[12] The reason might be that black women without any experience and education are predominantly employed in sub-minimum wage jobs, in particular in high minimum wage economies. A further increase in the minimum does not affect their wages very much or might even affect their wages negatively in these economies, as is suggested by Figure 3. However, the minimum explains most of the variance in the second 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

[12]The share of workers with grade = 0 is very small (0.2 %). Nevertheless, I take this group as a first benchmark, since minimum wages are a left tail phenomenon anyway. Moreover, each group is evaluated at the median value for its unobserved characteristics. Hence, there is still a large tail of people with adverse unobserved characteristics being lower skilled than the median worker without education or experience.

Table 4 is that the effects of minimum wages are heavily concentrated in the trajectory close to the minimum and that males are less affected than females. As discussed before, these conclusions run counter to the hypothesis that the minimum wage is a proxy for either the decline in unionization or skill biased technological progress.

Factual and counterfactual returns on 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 $wmin_t$ is applied.

4.4 Evaluating the effect of selection bias

As is set out in Subsection 2.3, the results on the return to human capital suffer from the potential effects of selection bias in the unobserved skill characteristics q_{it}. By focussing on the supra-minimum part of the wage distribution and by the elimination of low-skilled workers from employment, the unobserved characteristics in the remaining data will be an upwardly biased sample compared to the underlying distribution. The higher the minimum wage, the larger will be this bias. When wages controlled for observed skill characteristics are higher in a high than in a low minimum wage economy -as has been reported in Section 4.1-, this can either be due to spill-over effects of the minimum or to selection bias in unobserved characteristics. We tried to capture the effect of selection bias by allowing for truncation in the distribution of q_{it} as discussed in Subsection 2.3. However, the validity of this approach depends on all kind of assumptions on functional forms and the distribution of unobserved characteristics.

In order to evaluate the impact of selection bias in the estimations using only the supra-minimum wage part of the data, I calculate for each economy *t* the number of observations that has been truncated (as implied by the estimation results on Stage 1) relative to the number observations that is used in the estimation. Hence, this number, denoted S_t, satisfies:

$$S_t = \left(\Sigma_{i|t} 1\text{-}\Phi[x_{it}'\beta\text{-}qmin_t]\right) / \left(\Sigma_{i|t}\Phi[x_{it}'\beta\text{-}qmin_t]\right)$$

Furthermore, we calculate for each economy *t* the number of observations in the spike and below the minimum relative to the number of observations that is used in the estimation. The second panel of Table 5 reports the coefficients of regressions of these two statistics on $wmin_t$. The regression on the number of observations at or below the minimum wage shows that this number increases by some 0.20 percent for every percent increase in the minimum wage (depending on whether both sexes, only males or only females are included). Again, the effect is the largest for females. The regression on the number of truncated observations as implied by the estimation results yields much higher elasticities, varying between 0.40 and 0.80, where again the coefficient for females is by far the highest. By itself, the sign of these coefficient, their significance, and the fact that the coefficient is the largest for females raise the credibility of the measured truncation effect. An increase in the minimum is expected to raise the number of truncated observations. These coefficients are supposed to cover two effects of an increase in the minimum wage, first on the share of employment earning a wage at or below the minimum and second on the share of people that lost employment due to the minimum wage. An estimate of the first effect is available from the regression on the number of observations at or below the minimum wage. Hence,

by substraction, 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 higher than elasticities that are usely reported in the literature.[13] If anything, the truncation effect is therefore overestimated by the Stage 1 regression. Hence, the compression effect found in Stage 2 of the analysis cannot be attributed to an inadequate treatment of selection effects.

4.5 The elasticity of relative wages with respect to wmin_t

Another way to evaluate the implications of the model is to look at the elasticities of wage levels and wage differentials with respect to changes in the minimum. We have by definition:

$\mathrm{d}w_{it}/\mathrm{d}wmin_t = \mathrm{d}wm_{it}/\mathrm{d}wmin_t + 1.$

Equation (4) and (6) can be combined to yield a model of the form:

$Q(wm_{it}, wmin_t, \underline{a}_t) = q_{it},$

where $\underline{a}_t$ is $[\underline{a}_{1t} \ldots \underline{a}_{Kt}]'$. Differentiating this relation totally yields:

$Q_{wm}\ \mathrm{d}wm_{it} + Q_{wmin}\ \mathrm{d}wmin_t + Q_a\ \mathrm{d}\underline{a}_t = \mathrm{d}q_{it}.$

where Q_x denotes the partial derivative of $Q(.)$ with respect to x. By setting $\mathrm{d}\underline{a}_t$ and $\mathrm{d}q_{it}$ equal to zero, we get:

$$\mathrm{d}w_{it}/\mathrm{d}wmin_t \mid q_{it} = -\ Q_{wmin}/Q_w + 1 \qquad (7)$$

[13]E.g. in their survey paper, Brown, Gilroy, and Kohen (1982) conclude to an employment elasticity for youngsters in the range of 0.1-0.3. Since youngsters are the main group of which the employment is affected by the minimum wage, the overall elasticity must be much lower.

where Q_{wmin} and Q_w are equal to:

$Q_{wmin} = \Sigma_{k=0}^{K} \alpha_{1k} wm_{it}^{k}$,

$Q_w = \Sigma_{k=1}^{K} k\, a_{kt} wm_{it}^{k-1}$.

The elasticity $dw_{it}/dwmin_t \mid q_{it}$ in equation (7) analyzes the effect of a change in the minimum on w_{it} for a fixed skill level. It can be interpreted as a point estimate of the change in the return to human capital due a change in $wmin_t$, as opposed to the statistics discussed in Subsection 4.5, which measure the change in the return to human capital along an interval, for example $x_b\beta$ - $x_a\beta$.

Alternatively, we can analyze the wage differentials instead of wage levels, for example the compression of the wage differential between a worker with skill level q_{it} and a worker earning exactly the minimum before the increase in the minimum. I shall refer to this statistic as the compression elasticity. It reads:

$$\{dw_{it}/dwmin_t \mid q_{it}\} - \{dw_{jt}/dwmin_t \mid q_{jt}=qmin_t\} \tag{8}$$

which can be calculated straightforwardly from equation (7). The calculation of the full standard error of the estimated values of both elasticities is cumbersome. Estimated parameters show up both in the numerator (the α_{1k}'s) and in the denominator (the a_{kt}^{e}'s). One can apply standard second order Taylor expansions to approximate the standard errors. However, a more simple approach provides a reasonable approximation. The effect of the estimation error in a_{kt}^{e} is of minor importance relative to the error in α_{1k}, since the estimate of the former is based on the estimate of the latter. Hence, the parameter estimates in the numerator include the estimation error due

to omitted aggregate variables and due to the estimation error in the parameters a_{kt}^{e}, while the parameters in denominator include only the latter component. Since the estimates of σ^2 are much larger than unity, the former component is the most important. The latter component will therefore be ignored. The standard error of the former source can be calculated straightforwardly from the covariance matrix of the GLS estimates of equation (6), since the relative wage effect is a linear combination of α_{1k}.

Both elasticities are shown in Figure 7. The horizontal axis represents the initial wage level w_{it}. The upper panel presents the elasticity of wages relative to the median wage, using (7). The lower panel presents the elasticity of wages relative to the wage of the person earning the minimum before the change, using (8). The calculations are based on the mean of a_{kt}^{e} and $wmin_t$ over t. The mean for $wmin_t$ is depicted in the figure by the vertical line.

The elasticity in the upper panel has special interpretations when evaluated for w_{it} = 0 and for $w_{it} = wmin_t$. When it is evaluated for w_{it} = 0, the elasticity being positive (negative) implies that a worker earning the median wage before the minimum wage increase will earn an above (below) median wage afterwards. This can only be true if employment below the median increased (decreased) relative to employment above the minimum. Hence, standard economic reasoning would predict a negative elasticity for w_{it} = 0, since we expect an increase in the minimum to reduce below median employment relative to above median employment. Figure 7 shows the estimation results to point in the opposite direction, suggesting that employment below the median

increases relative to employment above the median. This can partly be explained by the increase in labor supply in the wage interval just above the minimum that is induced by wage increase in that interval due to the spill-over effects of the increase in the minimum. However, one would not expect these supply effects to exceed the disemployment effect of the increase in the minimum. Hence, these results are a bit puzzling and might be viewed as evidence for some monopsony effects. Since much more refined techniques for analyzing employment effects are available from other studies, I do not want to push any strong conclusions from this result.

When evaluated for $w_{it} = wmin_t$, the elasticity in the upper panel measures the relative wage increase a minimum wage worker gets when the minimum wage is increased by 1 percent. Hence, one minus this elasticity measures how much this worker ends up below the minimum after the minimum wage increase. Figure 7 shows that a worker earning the minimum will gain 5.2 percent by an increase in the minimum of 10 percent. After the increase he will therefore earn 4.8 percent less than the new minimum.

The lower panel shows that a 10 percent increase in the minimum will compress the wage differential between a worker who earned the minimum before the increase and workers earning higher wages by up to 3.5 percent. The strongest compression occurs in the interval between the minimum and twice the minimum, a finding that is consistent with the conclusion that the effect of a change in the minimum is concentrated in the lower half of the distribution. The confidence interval shows the estimated compression to be highly significant. This explains why this study attributes a much larger fraction of the increase in wage dispersion to the minimum wage than

DiNardo, Fortin, and Lemieux (1996), who restrict the impact of the minimum to the sub-minimum part of the wage distribution by assumption.

4.6 Why yields this methodology a much higher effect on the return to human capital?

The results reported in Table 4 suggest a much larger spill-over effect of the minimum wage on the return to human capital for wage levels above the minimum than has been reported by for example Lee (1999). Why is this the case? The problem in analyzing spill-over effects in the return to human capital is their non-linearity. The spill-overs are potentially large for wages just above the minimum, much smaller for wage levels further away from the minimum and even negative for the interval just below the minimum. Mean log wage differentials on an interval for one observable skill (mostly, years of education) are a bad variable to explain in this case. The argument can be clarified by writing the model as (ignoring factors affecting the return to human capital other than $wmin_t$ for the sake of convenience):

$w_{it} = W(q_{it}, wmin_t) = W(q_{0it}\beta_0 + q_{\#it}'\beta_\# + \underline{q}_{it}, wmin_t)$.

where we seperate the observed skill characteristics in the years of education q_{0it} on the one hand and the other observed characteristics $q_\#$ on the other hand. The question of interest is how the return to the skill variable q_{it} varies with $wmin_t$, that is, what is the cross derivative of $W(.)$. This cross derivative, denoted $W_{12}(.)$, is slightly negative or even positive for $W(.) < wmin_t$, it is highly negative for $W(.) > wmin_t$ and only slightly negative for $W(.) >> wmin_t$, see Figure 3 and 7. Hence:

$$W_{12}\left(q_0\beta_0 + q_\#'\beta_\# + E_{\underline{q}}[\underline{q}], wmin\right) \neq E_{wmin}\left[W_{12}\left(q_0\beta_0 + q_\#'\beta_\# + E_{\underline{q}}[\underline{q}], wmin\right)\right]$$

$$\neq E_{wmin,\underline{q}}\left[W_{12}(q_0\beta_0 + q_\#'\beta_\# + \underline{q}, wmin)\right]$$

$$\neq \; E_{wmin,\underline{q},q\#}\left[W_{12}(q_0\beta_0+q_\#'\beta_\#+\underline{q},wmin)\right].$$

where we omit subscripts *i* and *t* for the sake of transparancy. By estimating the effect of minimum wages on wage differentials by analyzing mean log wage differentials on an interval for one observed variable, the analyst focusses on the final expression. This expression differs from the variable of interest (the first expression) for three reasons. First, there is smoothing over the level of the minimum wage prevailing in different economies *t*. A skill level that corresponds to a wage just above the minimum in the one economy might correspond to a wage just below the minimum in the other economy, where a different value of $W_{12}(.)$ applies. Second, there is averaging over the unobserved skill characteristics $\underline{q}$ and third there is averaging over the other observed characteristics $q_\#$, both with the same effect as averaging over wage levels. All three mechanisms introduce a kind of measurement error in the explanatory variable, leading to an underestimation of its impact. The single index assumption is a fruitful tool for dealing with these problems.[14]

4.7 Minimum wages and the widening of the wage distribution

Finally, we ask the question according to this model, how much did minimum wages contribute to the rise in wage inequality during the 1980s? For this purpose, I calculate the mean decrease in $wmin_t$ across 4 regions from 1979 to 1989, which is 0.335. The

[14]Only when setting K = 1, both expressions are equal. Then, the return to a characteristic is constant along the whole wage schedule. Then, all three mechanisms collaps. For higher values of K, the wage schedule becomes non-linear and the return to a characteristic can therefore vary along the wage schedule. Hence, the concept of the return to human capital applied here is more general in that I allow for a non-linear wage schedule.

counterfactual for 1989 is calculated by deducting this number from $wmin_t$ 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 $wmin_t$ explains 80 percent of the 5 percentage point increase in the standard deviation of log wages.[15] 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. Wage differentials for 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.

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 spend great deal of effort 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

[15]A referee asked whether it is counterintuitive that the minimum wages explains more than the full increase in the 10-50 differential for males and less than the full increase for females, where we would expect the minimum wage to have a larger effect for females. This is not the proper comparison. Minimum wages yield a 0.11 increase for males and a 0.24 increase for females. There are relatively small other effects which can go in either direction.

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 differential by 10 percentage points. The impact of minimum wages is due not to truncation (low-skilled workers being eliminated from employment by high minimum wages) but to large spill-over effects of a change in the minimum to wage levels way above the minimum and hence to compression of wage differentials by a reduction in the return to human capital.

The most reliable results are those where only the supra-minimum wages observations are applied for estimation, and where separate regressions are used to evaluate the impact of the minimum wage on the spike. The discontinuities at the minimum are adequately dealt with in this approach. In particular for females, the null hypothesis of the supra-minimum wage distribution being independent of the minimum is strongly rejected. The possibility of statistically testing the contribution of minimum wages is an important advantage of the methodology applied here above, for example DiNardo, Fortin, and Lemieux (1996). The pictures of the female wage distributions, see Figure 2, show the impact of the minimum beyond reasonable doubt: the whole supra-minimum wage distribution is piled up to the minimum from the left in economies with high minimum wages, while it is nicely bell shaped in economies with low minimum wages. The impact of the minimum goes therefore well beyond just imposing a spike on the wage distribution, as has been assumed in some previous work (e.g. Meyer and Wise, 1983a,b).

For the return to human capital, the null hypothesis of the return to human capital being independent of the minimum is stongly rejected. Pictures for the return to human capital show the dip in the return to human capital in high minimum wage economies, see Figure 3.

In previous contributions to the literature on the causes of the rise in wage dispersion during the 1980s, a number of other explanations have been considered. The evidence in the paper rules out the possibility that the minimum wage variable is a proxy for the gradual decline of unionization in the United States. Unionization affects almost exclusively the male distribution close to the median wage (see e.g. DiNardo et.al. 1996, p. 1024-1025). Contrary to this, the estimation results in this paper suggest much stronger effects for females than for males, and much stronger effects just above the minimum than around the median.

The estimation results are also unfavourable to the hypothesis that minimum wages pick up the effect of asymmetric technological progress. The results from the first stage are indeed consistent with an ongoing skill bias in technological progress. Murphy, Pierce, and Juhn (1991) show this process to affect mainly the demand for labor in the upper percentiles of the wage distribution. Hence, one would expect most of its effect on the wage distribution to be in the upper half of the distribution.[16] Indeed, the 50-90 log wage differential continues to increase throughout the whole estimation period, from 1973 until 1991. Nevertheless, the minimum wage variable in our model explains

[16]An increase in the demand in the upper percentiles of the skill distribution can be expected to have spill-over offects to wage differentials for lower percentiles in the skill distribution. However, even in the DIDES structure analyzed in Teulings (1999), the main effect will be on the 50-90 log wage differential.

none of this variation. This is strong evidence that there is sufficient independent variation in the minimum wage to establish its effect independent of the impact of skill biased technological progress.

Finally, the decline in the minimum wage itself might be an endogenous response to other causes of the rise in wage dispersion. Suppose for example that low-skilled employment and hence the corresponding wage rates have been severely depressed by trade. Policy makers might have reacted by reducing the minimum. Could this explain my results? The answer is no. My results show the probability mass in the spike to be highly correlated to the level of the minimum. If trade were to increase wage dispersion, it would have increased the mass in the spike (since an equal minimum wage would have a larger impact with a higher dispersion). A policy makers response of reducing the minimum would offset the upward effect in the spike. Per saldo, the effect would be small. Hence, the endogenous minimum wage setting would reduce instead of increase the correlation of the minimum and the probability mass around the minimum.

The results on the wage distribution are closely in line with those of Lee (1999), but the effect on the return to human capital is much larger than in Lee reports. He takes the variation in high school-college completed mean log wage differential as a measure of the effect on the return to human capital. The procedure is likely to underestimate the effects of minimum wages. As shown in Figure 7, the compression of the return to human capital is non-linear, being the strongest in the wage interval just above the minimum wage. Comparing mean log wage differentials smoothes this non-linearity

for three reasons. First, the procedure does not account for the position of the wage level relative to the minimum wage. When a particular skill levels commands a wage close to the minimum in a particular economy, the effect of changes in the minimum will be larger. Similar arguments apply to the effect of other observed skill characteristics and unobserved skill characteristics, which also determine whether a particular worker earns a wage that is close to the minimum and that is therefore sensitive to changes in it. The results show the power of the single index methods proposed in this paper in dealing with these problems.

There are two ways to interpret the contribution of this paper. Either one reads it as a contribution to economic policy, establishing the huge impact of minimum wages on wage dispersion and return to human capital. But one can also take a more fundamental stance. The results might come as a surprise for many economists. However, the DIstance-Dependent-Elasticity-Structure, in which elastiticies of substitution between two worker categories depend on their skill distance, offers a straightforward explanation within a simple supply and demand framework (Teulings, 2000; and afterwards generalized in Teulings, 1999). Let us interpret the huge variation in minimum wages between 1973 and 1991 as a nice natural experiment for testing this structure of substitution against more standard CES functions as applied by e.g. Katz and Murphy (1992) and Autor, Katz, and Krueger (1998). By and large, minimum wages are likely to have eliminated some low-skilled workers from employment. Variation in the minimum is therefore a perfect instrument for changes in the skill

composition of the work-force.[17] This variation in minimum wages is an even more attractive instrument if one believes in DIDES structure. In that case, the elimination of the lowest skill types -by definition at long skill-distance of the mean- provides a lot more information than e.g. variations in school enrollment that shifts workers between various grades around the mean of the distribution. Furthermore, there is an easy way to identify the groups which are the closest substitutes to the workers that have been eliminated from employment, namely the workers with wages slightly above the minimum. Simulations based on empirical estimates of the key parameter of the DIDES model yield results that are in line with spill-over effects reported here, see Teulings (2000). Hence, the evidence presented in this paper supports the DIDES above the CES structure.

[17]DiNardo, Fortin and Lemieux (1996) argue that their results are evidence of a role of institutions in explaining wage differentials, next to the impact of the forces supply and demand. I am hesitant to repeat this phrase, first because I do not know what we have learned by a general phrase saying that institutions cause a particular outcome, and secondly because the impact of minimum wages can well be consistent with theories of supply and demand.

APPENDIX

Derivation of the R^2 and the F-test

Consider model (5a) to (5b) from Subsection 2.4. By definition, the variance of the estimation error $\underline{d}$ satisfies:

$$E[\ (d^e\text{-}d)\mathbf{V}^{-1}(d^e\text{-}d)\ ] = TL.$$

Hence, the R^2 associated of (5a) relative to (5b) that is corrected for the estimation error in d^e reads:

$$R^2 = 1 \ - \ \{d^{e\prime}\mathbf{V}^{-1}\, d^e - d^{e\prime}\mathbf{V}^{-1}\,\mathbf{X}\,[\mathbf{X}'\mathbf{V}^{-1}\,\mathbf{X}]^{-1}\,\mathbf{X}'\mathbf{V}^{-1}\, d^e - TL\} \ /$$

$$\{d^{e\prime}\mathbf{V}^{-1}\, d^e - d^{e\prime}\mathbf{V}^{-1}\mathbf{D}^{-1}\mathbf{X}_0[\mathbf{X}_0'\mathbf{D}'^{-1}\mathbf{V}^{-1}\mathbf{D}^{-1}\mathbf{X}_0]^{-1}\,\mathbf{X}_0'\mathbf{D}'^{-1}\mathbf{V}^{-1}\, d^e - TL\}$$

The null (5b) will be tested against the model (5c). This can be done by a standard F-test, which can be derived from a similar R^2 statistic as above, but now comparing model (5c) to model (5a).

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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			log wage diff. (data) 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

		all obs.		obs. > wmin		obs. > wmin (males)		obs. > wmin (females)	
	L	Log L.	R2[1)]	Log L.	R2	Log L.	R2	Log L.	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						

		L = 12			L = 9			L = 9			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)]	0,36	4,14	[5)]	0,31	5,77	[5)]	0,39	1,34		0,23
	F_L, region	4,08	[5)]	0,25	2,36	[4)]	0,16	1,65	[4)]	0,12	8,60	[5)]	0,48

Notes on separate sheet

Footnotes to Table 2:

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^* as the endogenous variable.

2) The H0 for the first F-statistic is a model with *L* dummies for each element of d^*, the second statistics refers to a model with 5 *L* dummies, one for each year and each element of d^*, and the third with 4 *L* dummies, one for each region and each element of d^*. The F-tests have *L* degrees of freedom in the numerator and (20-number of dummies-1)**L* in denominator.

3) Significance levels of the F-tests:

   (1) = .10-.05; (2) = .05-.025; (3) = .025-.010; (4) = .010-.005; (5) < .005.

Footnotes to Table 3:

See Table 2, but replace *L* by *K* and the endogenous variable *d* by *a* and d^* by a^*.

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	-5,00	0,36	16,32	-5,00	0,48	9,15	5,00-	0,35	43,65	-5,00	0,72
II	F_K,year	16,67	-5,00	0,62	24,07	-5,00	0,65	33,72	5,00-	0,75	19,77	-5,00	0,63
	F_K,region	5,78	-5,00	0,30	13,51	-5,00	0,48	5,99	5,00-	0,30	46,10	-5,00	0,77

	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

Notes on separate sheet

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-qc		qe-qd	
year	region	fact.	c.f.	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	0,327	0,341	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	0,654	0,666	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	0,415	0,412	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	0,436	0,421	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	0,668	0,675	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	0,443	0,430	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	0,429	0,436	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	0,583	0,579	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	0,557	0,563	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	0,471	0,469	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	0,495	0,489	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	0,414	0,419	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	0,407	0,401	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	0,473	0,463	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	0,437	0,423	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	0,405	0,390	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	0,610	0,597	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	0,466	0,447	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	0,397	0,380	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	0,554	0,525	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	0,093	0,094	0,042	0,024	0,046	0,048	0,033	0,035
	obs. > wmin			0,056	0,039	0,056	0,058	0,034	0,022	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 = black female without education and experience
qb = white male without education and experience
qc = white male with high school
qd = white male with six years of college
qe = white male 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	

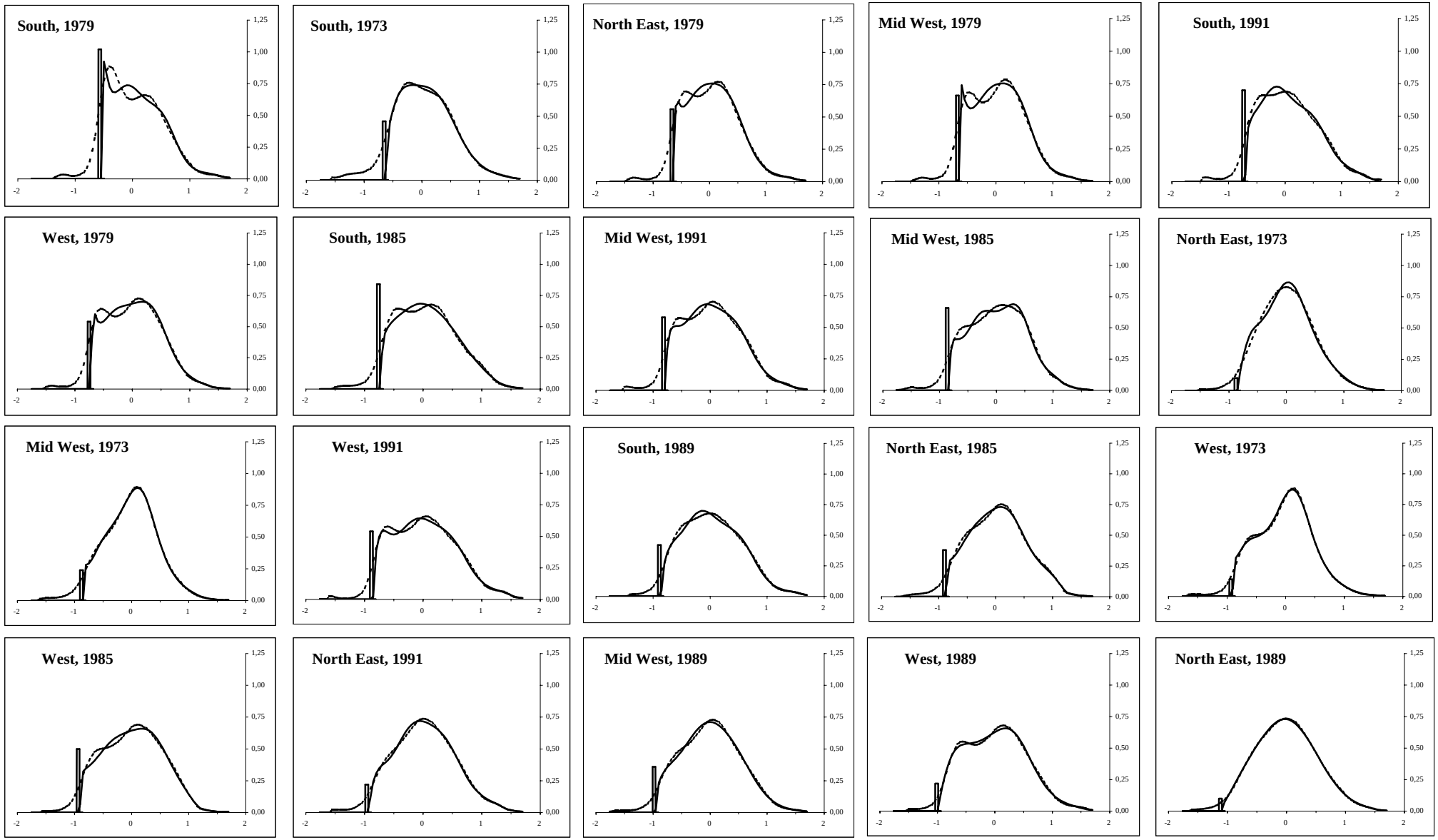
	spike plus below spike as a share of above spike observations						implied number of truncated observations as a share of above spike observations					
	all		male		female		all		male		female	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
wmin	0,184	0,015	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

	std.	log wage diff.		log wage diff. by skill			
year(y. wmin)	dev.(w)	10-50	50-90	qa - qb	qb - qc	qc - qd	qd - qe
all obs.							
1979(1979)	0,494	0,597	0,653	0,405	0,453	0,516	0,414
1989(1989)	0,542	0,691	0,715	0,456	0,537	0,553	0,465
1989(1979)	0,504	0,554	0,701	0,416	0,458	0,537	0,472
obs. > wmin							
1979(1979)		0,596	0,646	0,178	0,329	0,498	0,441
1989(1989)		0,693	0,713	0,242	0,426	0,563	0,485
1989(1979)		0,579	0,702	0,164	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 = black female without education and experience
qb = white male without education and experience
qc = white male with high school
qd = white male with six years of college
qe = white male with six year of college and twenty years experience

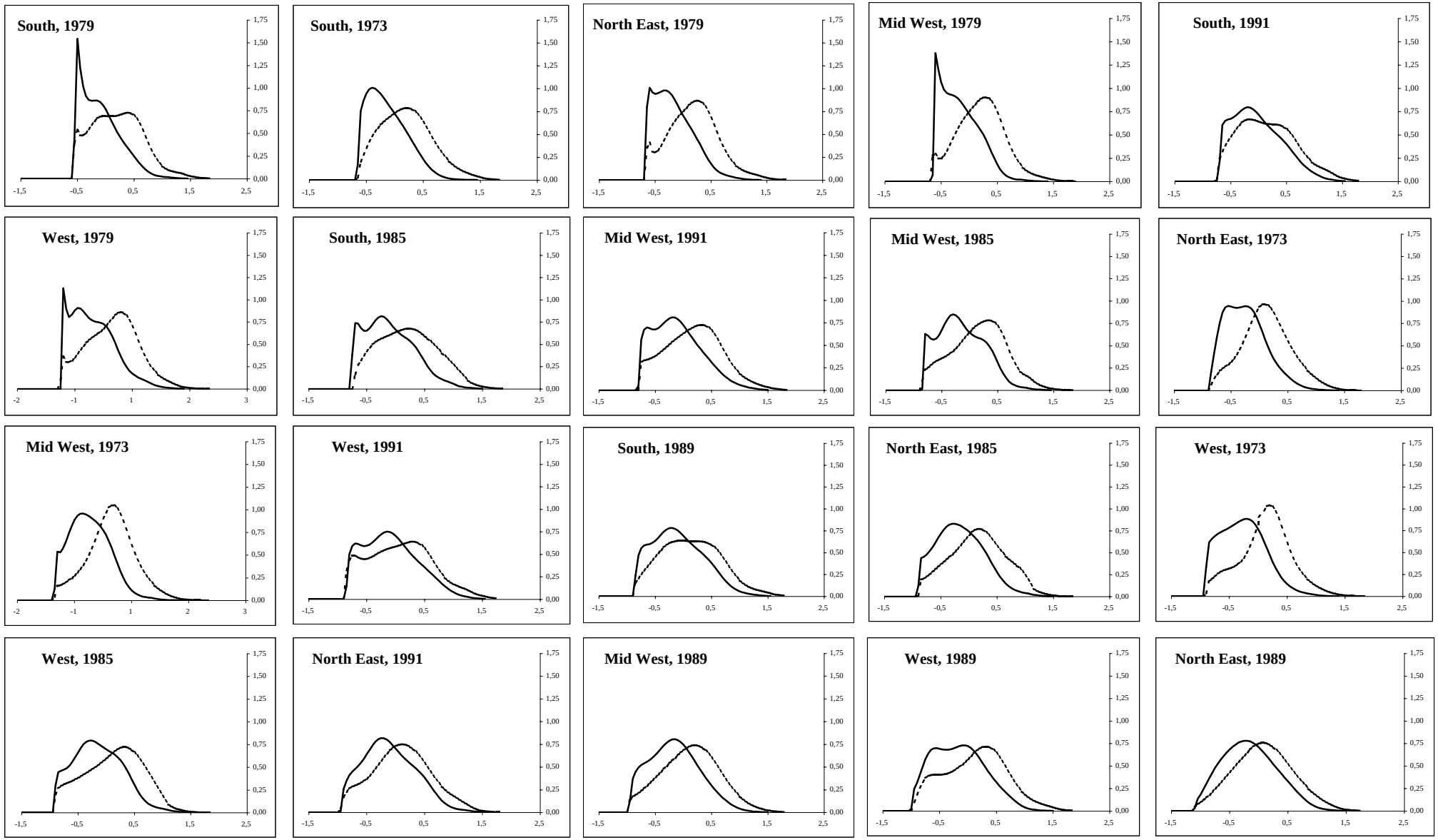
Figure 1: Log wage distribution, estimation results



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

Dotted line: including observations below the spike.

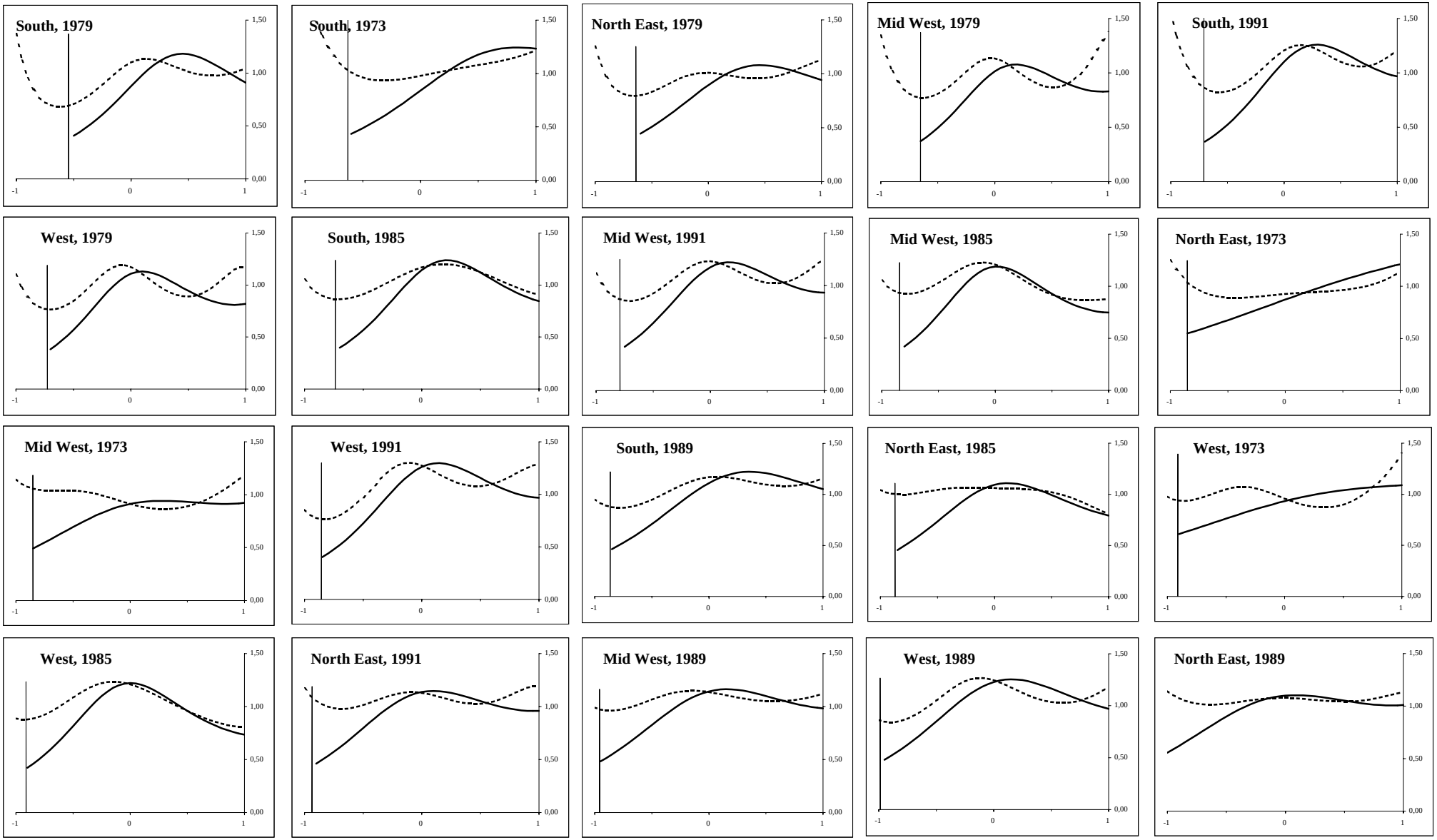
Figure 2: Log wage distributions for males and females separately, estimation results



Solid line: females

Dotted line: males

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

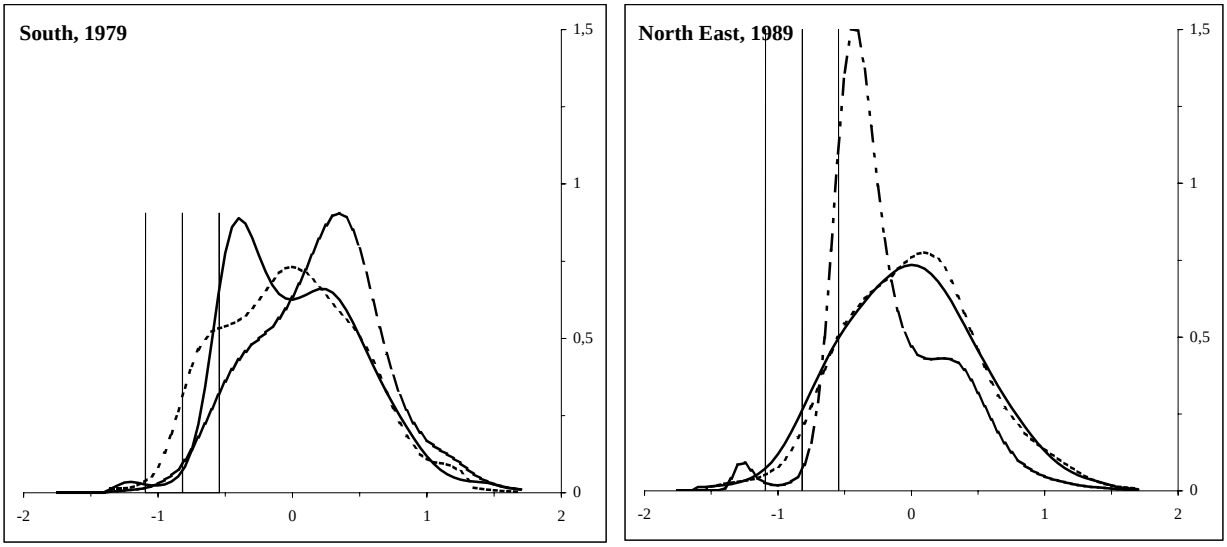


Solid line: excluding wage observations in the spike and below.

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

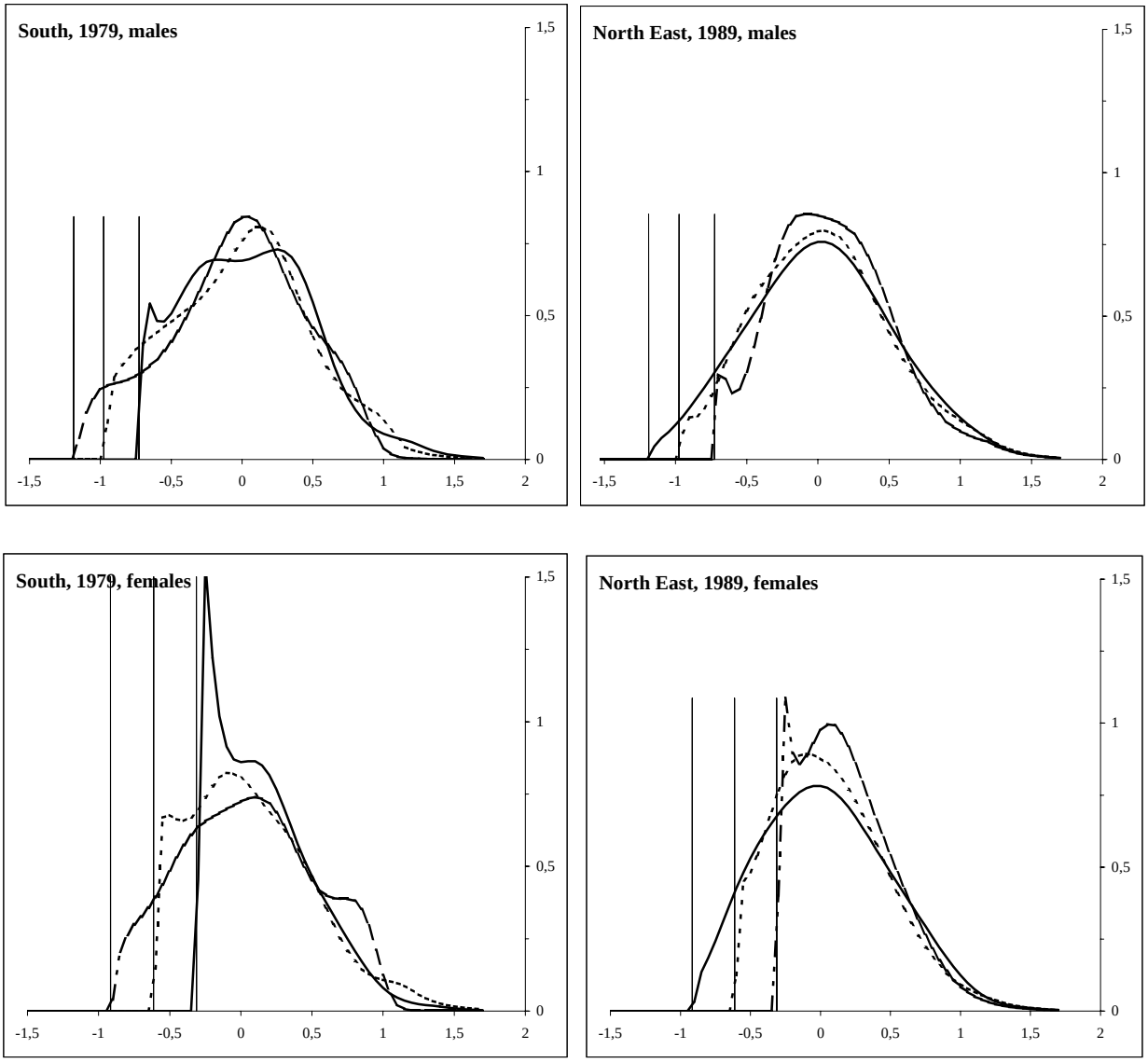


Solid line: factual density.

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

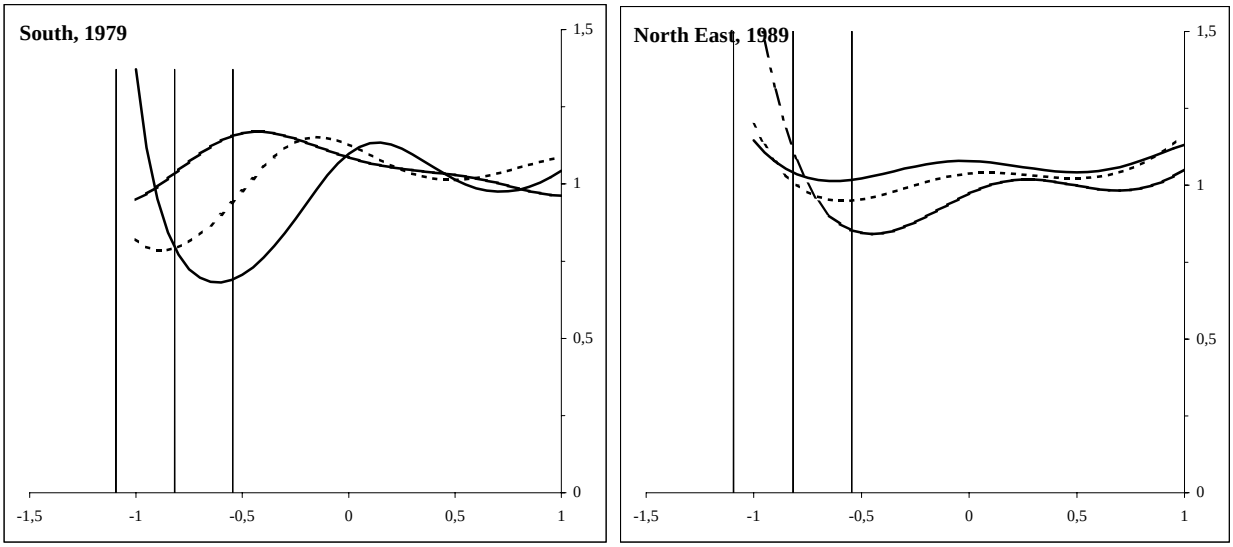


Solid line: factual density.

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.

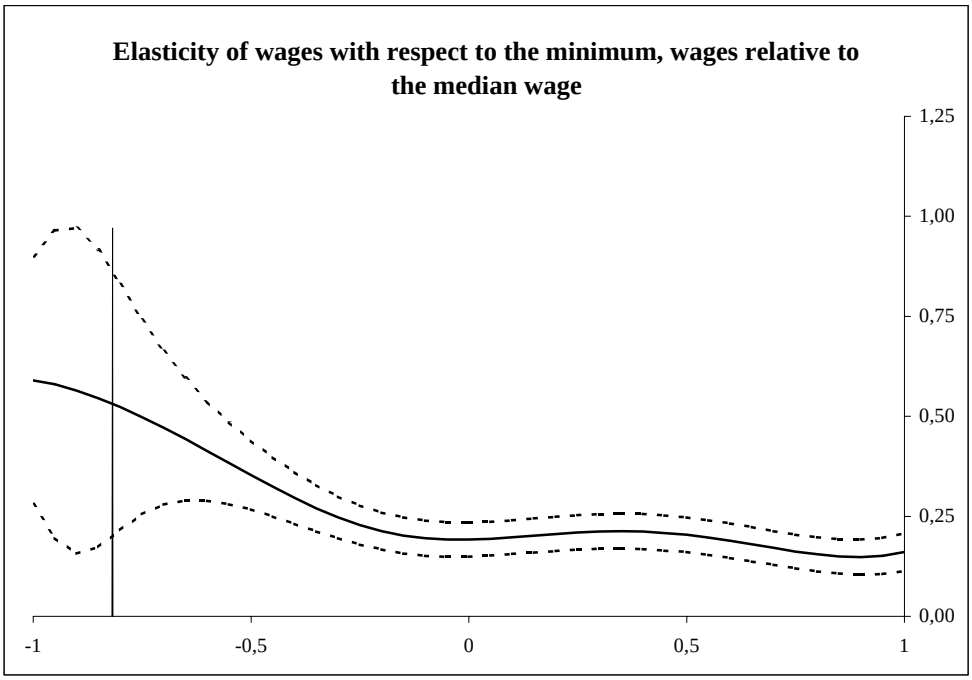


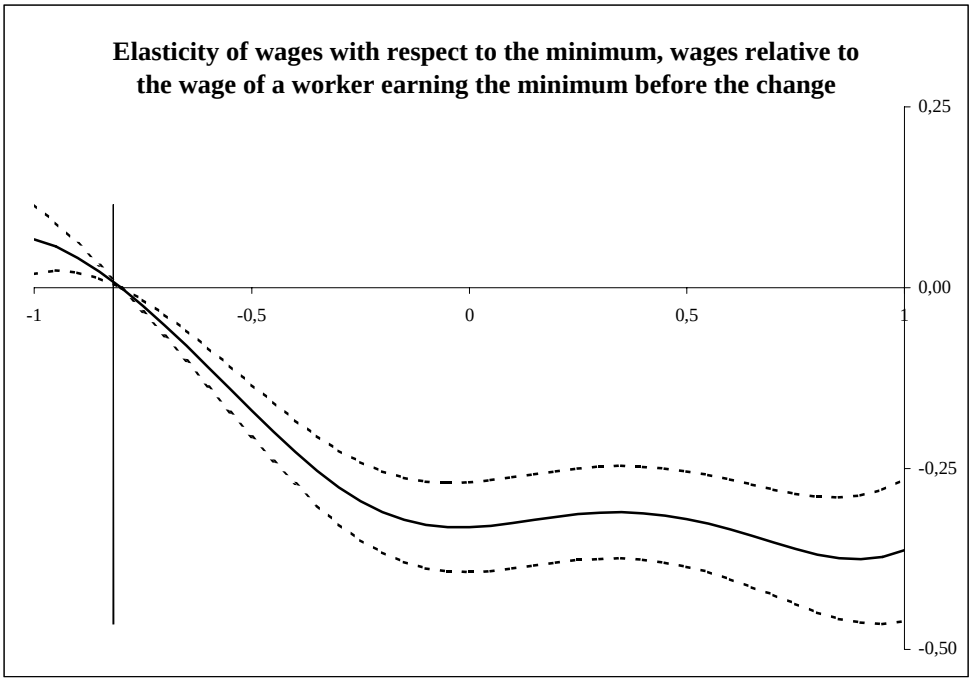
Solid line: factual density.

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.