Employment Effects of a Minimum Wage:
A Density Discontinuity Design Revisited*

Joseph J. Doyle Jr.
MIT Sloan School of Management and NBER

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Abstract:

The minimum wage has a dramatic effect on the wage distribution, and this distortion has been used to estimate large disemployment effects. The main criticism of this approach is its reliance on functional form assumptions. This paper relaxes these assumptions and applies methods commonly used in regression discontinuity designs to this density discontinuity design problem. The estimates suggest that 60% of young workers who would have earned wages below the minimum can no longer find employment, representing roughly 10% of all young people. It appears that large disemployment effects do not stem solely from functional form assumptions. The approach also provides a method to compute the wage distribution in the absence of a minimum wage, and the minimum wage is found to substantially reduce inequality among young workers.

Keywords: Minimum Wage, Employment, Inequality, Discontinuity Design

* Joseph Doyle, MIT Sloan School of Management and NBER, 50 Memorial Drive, E52-447, Cambridge, MA 02142. Tel: (617) 452 3761; Fax: (617) 258 6855; email: jjdoyle@mit.edu I would like to thank Victor Aguirregabiria for helpful comments and ideas, in addition to Mark Duggan, Michael Greenstone, Steve Levitt, Roberto Rigobon, and Tom Stoker. This research was assisted by fellowships from the Social Science Research Council Program on Applied Economics. All remaining errors are my own.

1. Introduction

There is a debate over the effect of a minimum wage on employment, with recent papers largely suggesting small disemployment effects (see, for example, Card and Krueger (1995), Neumark and Wascher (1995), Card and Krueger (1998), and Abowd, Kramarz, and Margolis (1999)). Labor demand theory suggests that in a competitive market for low-skilled labor, all workers with productivity levels associated with sub-minimum wages would no longer find employment, and businesses may further substitute away from low-skilled labor. If the labor market were not competitive, however, employment could rise following the introduction of a minimum wage.

In contrast to the recent empirical papers, a classic study by Meyer and Wise (1983a, 1983b) found substantial disemployment effects. They estimated that 30-50% of those who would have earned sub-minimum wages can no longer find employment, a group representing 7% of all young men. The idea in their paper was to consider the distortion of the wage distribution caused by the minimum wage to identify the employment effects from a single cross section: the more the minimum wage distorted the wage distribution, the greater the estimated effect on employment.

The chief criticism of the Meyer and Wise approach is its reliance on functional form assumptions about the wage distribution (Brown, Gilroy and Kohen (1982); Card and Krueger (1995)). In order to estimate the size of the distortion, some information is necessary about the counterfactual wage distribution in the absence of a minimum wage. Meyer and Wise focus on a log normal wage distribution. Dickens, Machin, and Manning (1994) consider a range of functional forms and find the estimates sensitive to the choice. They argue that the main reason the approach is not more widely used is because of the functional form assumptions.

This paper relaxes the distributional assumptions by applying the techniques commonly used in regression discontinuity designs to this density discontinuity design problem. In particular, the wage density is estimated above and below the minimum wage using a local linear density estimator. Substituting the functional form assumption with an assumption that the counterfactual wage distribution is continuous, it is then possible to test the effect of the minimum wage on employment and wages.

Using a 1978 sample of young hourly wage earners similar to Meyer and Wise, only ten percent of sub-minimum wage workers are estimated to be unemployed due to the minimum wage. The assumptions of the model do not appear tenable during that time period, however, though more recent years appear more promising. Recent estimates again suggest large disemployment effects. For example, an estimated 56% of young workers who would have earned sub-minimum wages are no longer employed in 2000, a group that represents 8% of all young people. In addition, groups that are more likely to receive the minimum wage, such as women and part-time workers, are found to have larger disemployment effects. While there are limitations to the approach, the estimates here suggest that large disemployment effects are not driven solely by functional form assumptions.

The approach also provides a way to estimate the counterfactual wage distribution if there were no minimum wage. In recent years, the median wage is found to be 5% higher among young wage earners due to the minimum wage. Further, the minimum wage appears to have a large effect on inequality as well. For example, in 2000 the median worker earned wages that were 40% higher than the tenth-percentile worker. Without a minimum wage, the model predicts the difference would have been 55%.

The paper is organized into four remaining sections. Section 2 presents the empirical strategy to estimate the disemployment effect and the counterfactual wage distribution. Section 3 describes the Current Population Survey data used in the analysis. Section four discusses the results using all young workers and across subgroups. Robustness checks are provided, including a simulation that suggests the results are not driven by sub-minimum wage reports that stem solely from measurement error. Section five concludes.

2. Empirical Strategy

The empirical strategy relates the observed wage distribution to a counterfactual distribution that would occur in the absence of a minimum wage. The idea is that the discontinuity in the wage distribution provides information about the change in employment. Two main assumptions are used to relate the observed density, $h(\cdot)$, to the counterfactual density, $f(\cdot)$. Let w represent the wage and M represent the minimum wage:

- (A-1) No spillover effects: For w>M, $h(w) = \frac{f(w)}{D}$, where D (defined below) rescales the density to take into account the decreased number of workers, if any.
- (A-2) For w<M there are 3 cases: (1) with probability P1, the wage continues to be observed (due to non-compliance or non-coverage); (2) with probability P2, a person

will be observed with a wage at the minimum, w=M; and (3) with probability 1-P1-P2, a person will become unemployed.

With these assumptions the observed pdf can be written as:

$$(1) \quad h(w) = \begin{cases} \frac{P_1}{D} \cdot f(w) & if\ w < M \\ \\ \frac{P_2}{D} \cdot F(M) & if\ w = M \\ \\ \frac{1}{D} \cdot f(w) & if\ w > M \end{cases}$$

where M is a small interval around the minimum wage, and D=1 – F(M)(1 – P1 – P2). D is the fraction of workers who continue to be employed after the minimum wage is introduced, and the re-scaling ensures that $h(\cdot)$ integrates to one. Figure 1 shows the change in the wage distribution: the observed density will be lower than the counterfactual density below M, have a spike at M, and will be higher than the counterfactual density above M (due to the rescaling when D<1). The presence of the spike at the minimum wage, and a compression of the wage density, is consistent with the empirical evidence as shown by Dinardo, Fortin, and Lemieux (1996).

The disemployment effect is given by F(M)(1 – P1 – P2): the fraction of workers who lose their jobs. These effects will be small when F(M) is small—the minimum is not binding because almost all workers earn more than the minimum—or if P1 or P2 is close to one. If P1=1 then the law is not binding as workers continue to receive the sub-minimum wages. If P2=1 then all workers who previously made less than the minimum are employed with wages equal to the minimum and no one becomes unemployed as a result.

To estimate the model, Meyer and Wise imposed an additional assumption:

- (A-3) $f(\cdot)$ is lognormal.

Box-Cox transformations were tested as well, and the logarithm of wages was found to fit the data best. Nevertheless, the chief criticism of the approach is its reliance on functional form assumptions about the wage distribution.

This paper relaxes the functional form assumption and instead relies on a continuity assumption that is implicit in the approach:

- (A-3') $\lim_{e\to 0} f(M-e) = \lim_{e\to 0} f(M+e)$

This assumption makes use of the original idea that the minimum wage creates an artificial distortion in the wage distribution, while the underlying wage distribution is likely to be smooth. For example, it is unlikely that the distribution of worker productivities jumps at a legislatively imposed minimum wage such as $4.25 or $5.15 per hour.

Using assumptions (A-1), (A-2), and (A-3'), F(M), P1, and P2 can be estimated. First, consider the wage distribution after the minimum wage is in effect. A fraction π_1 will continue to receive a wage below the minimum, while a fraction π_2 will earn exactly the minimum. These fractions can be expressed in terms of the counterfactual distribution by using (1):

(2) $$\pi_1 = \frac{P_1}{D} \cdot F(M)$$

and $$\pi_2 = \frac{P_2}{D} \cdot F(M)$$

Substituting π_1 and π_2 for P1 and P2 in (1), the observed pdf can be rewritten:

$$(3) \quad h(w) = \begin{cases} \dfrac{\pi_1}{F(M)} \cdot f(w) & \text{if } w < M \\ \pi_2 & \text{if } w = M \\ \dfrac{1-\pi_1-\pi_2}{1-F(M)} \cdot f(w) & \text{if } w > M \end{cases}$$

For wage earners above or below the minimum wage, the observed density is simply a re-weighting of the underlying density. These weights do not vary with the wage, resulting in a simple likelihood function. Letting N_1 equal the number of individuals with wages below the minimum wage, N_2 equal the number receiving the minimum wage, and N_3 equal the number earning more than the minimum wage. The log-likelihood can then be written as:

$$\begin{aligned}(4) \quad \log L = {} & 1(w_i < M) \cdot \sum_{i=1}^{N_1} \left[\log \pi_1 - \log F(M) + \log f(w_i)\right] \\ & + 1(w_i = M) \cdot \sum_{i=1}^{N_2} \log \pi_2 \\ & + 1(w_i > M) \cdot \sum_{i=1}^{N_3} \left[\log(1-\pi_1-\pi_2) - \log(1-F(M)) + \log f(w_i)\right]\end{aligned}$$

where $1(\cdot)$ is an indicator function.

Letting N equal the total number of individuals in the sample, the maximum likelihood estimates of these proportions are simply the sample proportions:

(5) $\pi_1^{MLE} = \dfrac{N_1}{N}$

(6) $\pi_2^{MLE} = \dfrac{N_2}{N}$

The estimation of P1 is derived from the description of the wage distribution in (1):

(7) $h(M-e) = \dfrac{P_1}{D} \cdot f(M-e)$

(8) $h(M+e) = \dfrac{1}{D} \cdot f(M+e)$

Dividing these two expressions and using the continuity assumption (A-3'),

(9) $\hat{P}_1 = \dfrac{\lim_{e\to 0} h(M-e)}{\lim_{e\to 0} h(M+e)}$

P1 can be estimated using a kernel density estimator for $h(w)$ above and below the minimum wage, though estimates close to a boundary require special consideration described below.

Recall that P1 is the probability that a sub-minimum wage worker keeps a job earning below the minimum wage. If the observed wage distribution were continuous—implying no distortion from the minimum wage—the estimate for P1 would be one. Also, the estimate of P1 declines as fewer workers are observed earning wages below the minimum relative to those earning wages above the minimum.

In an alternative model, P1 may be expected to vary with the wage level—those earning far less than the minimum wage may have a different probability of remaining at a low wage compared to those earning wages just below the minimum. The estimator here considers the P1 at the margin of the minimum wage, as made explicit in (7). Meyer and Wise estimate that the probability of job loss falls as the wage increases toward the minimum wage, suggesting that the P1 estimated here likely results in conservative disemployment estimates.

The estimation of P2 can be derived by dividing the expressions for π_1 and π_2 in (2) and substituting the estimate of P1 from (9) into:

$$(10) \qquad \frac{\pi_2}{\pi_1} = \frac{P_2}{P_1} \qquad \text{or,} \qquad P_2 = \frac{\pi_2}{\pi_1} * P_1 .$$

Last, the estimation of F(M) can be derived from the description of the observed wage distribution in (3):

$$(11) \qquad h(M-e) = \frac{\pi_1}{F(M)} \cdot f(M-e)$$

$$(12) \qquad h(M+e) = \frac{1-\pi_1-\pi_2}{1-F(M)} \cdot f(M+e)$$

Dividing (11) and (12) and again using the continuity assumption (A-3'), F(M) can be solved as:

$$(13) \qquad F(M) = \frac{\pi_1}{\frac{\lim_{e\to 0} h(M-e)}{\lim_{e\to 0} h(M+e)} \cdot (1-\pi_1-\pi_2)+\pi_1} = \frac{\pi_1}{\hat{P}_1 \cdot (1-\pi_1-\pi_2)+\pi_1}$$

With estimates for F(M), P1, and P2, the disemployment effects are F(M) (1 – P1 – P2), and the observed wage density can be re-weighted above and below the minimum wage as in (3) to estimate the counterfactual density.

Potential Limitations

Card and Krueger (1995) argue that one shortcoming of the approach is the restriction of employment effects to be zero or negative. The estimation here does not restrict 1- P1 - P2 to be positive. In particular, if the minimum wage were associated with increased employment at the minimum wage, the estimated π_2 would be larger. The disemployment effect is decreasing in π_2, and can be negative as the estimate of P2 rises. A negative estimate would therefore suggest job gains.

Spillover Effects

Another criticism of the approach is the reliance on the lack of spillover effects. That is, this method assumes that there is no effect of the minimum wage on wage earners who earn above the minimum. In fact, there is some evidence of a "ripple effect" in wages with an increase in the minimum, though the effects may be small (Brown, 1999, Card and Krueger, 1995). In a growing literature on the effect of the minimum wage on inequality, the minimum wage has been thought to affect wages above the minimum, through employment and general equilibrium effects (Lee, 1999, Teulings, 2003). This paper uses the change in the wage distribution that reflects changes in employment to estimate the disemployment effects.

In addition, as Teulings (2003) points out, when the wage density above the minimum wage is considered, it tends to peak just above the minimum wage for young workers. Given the no spillover assumption, this implies that the estimated counterfactual distribution using the methods in this paper will also have a maximum at the minimum wage. While it is possible that this young sample does have a maximum near the minimum wage, it suggests the possibility of an influence of the minimum wage on the estimated counterfactual. From 1995 to 2000, however, the mode of the density is well above the minimum, suggesting that the shape of the distribution above the minimum wage may be informative of the shape of the counterfactual distribution. As such, the main results will emphasize the estimates in the more recent years.

Last, the focus here is on wages just above and below the minimum, and Green and Paarsch (1996) find a reduction in wages just above the minimum wage for young workers in Canada, possibly due to the minimum wage acting as a focal wage. If these estimates apply to young workers in the US, then these "reverse spillover effects" would result in estimates closer to zero, or job gains.

Local Linear Density Estimation

The identification hinges on estimating the density about the boundary M. Kernel estimation relies on smoothing density estimates, but within one bandwidth, h, of the boundary, there is a smaller interval to carry out the estimation. This results in a bias of order h near the boundary which is worse than the usual bias of order h^2 in the interior. The problem is addressed in a kernel regression setting by using a local linear regression estimator (Fan, 1992; Hahn, Todd, and Van der Klaauw, 1999). In an analogous way, Jones (1993) shows that local linear density estimation can be used to address the boundary problem. In particular, a and b are chosen to minimize:

$$(13) \quad \int h^{-1} K\left(\frac{(w-u)}{h}\right)\left\{f_n(u) - a - b(w-u)\right\}^2 du$$

Here, $f_n(u) = n^{-1}\sum_{i=1}^{n}\delta(w - W_i)$, where δ is the Dirac delta function, is the empirical density function.

Jones shows that away from the boundary this is the usual kernel density estimator. Within h of the boundary, an explicit solution to (13) can be derived where the kernel is automatically adjusted as it reaches the boundary. Consider a boundary located at zero and positive data. Letting p=x/h, the boundary kernel $K_L(x)$ that results is:

$$(14) \quad K_L(x) = \frac{a_2(p) - a_1(p)x}{a_0(p)a_2(p) - a_1^2(p)} \cdot K(x)$$

where

$$(15) \quad a_l(p) = \int_{-1}^{p} u^l K(u)\, du$$

For example, the expression using the normal kernel is:

$$(16) \quad K_L(x) = \frac{\Phi(p) + (x-p)\phi(p)}{\Phi(p)\big(\Phi(p) - p\phi(p)\big) - \phi^2(p)} \cdot \phi(x)$$

When the boundary is from above, the terms in the numerator are subtracted instead of added. For example, at the boundary p=0 and the expression simplifies to:

$$(17) \quad K_L(x) = \frac{\Phi(0) + x\phi(0)}{\Phi^2(0) - \phi^2(0)} \cdot \phi(x) = \left(\frac{2\pi}{\pi - 2} + x \cdot \frac{2\sqrt{2}\pi}{\pi - 2} \right) \cdot \phi(x)$$

In the Current Population Survey data used in the analysis, the sampling weights can be incorporated. The appendix shows the derivation of the resulting kernel density estimator with weight θ_i:

$$(18) \quad h(w) = h^{-1} \sum_{i=1}^{n} \theta_i K_L\left(\frac{w - w_i}{h} \right)$$

Figure 2 shows the kernel density estimates with and without the boundary correction for non-student wage earners ages 16-24 in 2000.[1] These densities are estimated separately above and below the minimum, and the density peaks at $6.75, well above the minimum wage of $5.15. The correction results in higher estimates both below and above the minimum wage, though the estimates with the boundary correction appear more conservative as discussed below.

A second issue is the choice of a bandwidth. There are many methods of choosing a local bandwidth near the boundary (Muller, 1991). Zhang and Karunamuni (1998) found that when estimating a function at an endpoint, the optimal bandwidth choice is twice the bandwidth that would be optimal for interior points. Intuitively, increasing the size of the bandwidth at the boundary allows more observations to be used to estimate the density. The main results will use two times Silverman's rule of thumb and the estimates are tested for sensitivity to the choice of bandwidth.

3. Data Description

Meyer and Wise used the May 1978 supplement to the Current Population Survey, which recorded hourly wages. This paper also uses the May 1978 data for comparability, along with the outgoing rotation groups for 1979-2000. These later datasets use twelve months of data resulting in much larger samples. To concentrate on the groups most likely to be affected by the minimum wage and to compare the results to earlier estimates, the sample is defined in the same way as Meyer and Wise. First, the focus is on young workers, those aged 16-24. Results will be presented separately for

[1] The bandwidth is $1.03 above the minimum wage and $0.67 below the minimum wage. As described below, this is a rule of thumb bandwidth for estimation at the boundary—the primary interest in this paper.

those aged 25-36. Second, given the young age, students are excluded.[2] Third, the individual had to report an hourly wage. Last, in recent years, up to twelve states had minimum wages greater than the federal minimum wage. These states are dropped from the later analyses to estimate the single discontinuity created at the federal minimum wage. These restrictions result in 6010 observations in 1978, and roughly ten to twenty thousand observations for 1979-2000. Three to nine percent of the sample report wages below the minimum wage.

Table 1 provides summary statistics for young workers in 2000 who earn wages below, at, or above the minimum wage. Not surprisingly, those at or below the minimum wage differ from those above the minimum in terms of observable characteristics. Estimates will be presented within these sub-groups to test the robustness of the results. In particular, Table 1 shows that low-wage workers tend to be female, work part-time, live in the South, and are high school dropouts, though some higher educated workers are found in the sub-minimum wage category. Meanwhile, workers at the minimum wage are concentrated in the retail industry, partly due to the allowance of wages below the minimum for tipped workers. To the extent that restaurant workers have a different minimum wage (currently $2.13 per hour), the estimates here have the advantage of focusing on the wage distribution just above and below the federal minimum.

4. Results

[2] From 1978-1993, non-students are defined as those whose major activity is either working or looking for work, as opposed to a student. From 1994 onward, the variable definitions change and the analysis here considers those who reported not being a full or part-time student.

As described above, the no spillover assumption that allows the shape of the observed wage distribution to inform the shape of the latent wage distribution appears to be violated prior to 1995, as the estimated density using only the observations above the minimum wage peaks at the minimum wage. That is, the minimum wage appears to distort the wage distribution in such a way that the shape above the minimum wage cannot be assessed. Fortunately for the analysis, the years 1995-2000 have observed wage distributions that peak well above the minimum wage.

Figures 3A and 3B provide a first look at the results for 1995 and 2000. First, the observed wage density is shown, as in Figure 2. Second, the counterfactual wage density is shown using estimates of the disemployment effects to rescale this observed density according to equation (3). The counterfactual is above the observed density in the range of wages less than the minimum wage, and below the observed density at wages higher than the minimum, a result that reflects the disemployment effects found.

The point estimates of the disemployment effects are reported in Table 2. The table includes 1978 to consider the same year as Meyer and Wise, as well as 1995-2000 (all intervening years are reported in the appendix). Columns (2) and (3) report the nominal and real minimum wage, which has declined since the late 1970s in real terms. In nominal terms, the $4.25 minimum wage began in 1990, and increases were enacted in 1997 and 1998. Columns (4) and (5) report the fraction of young workers who report wages below or at the minimum. The fraction below tends to increase in the year of a minimum wage increase, though declines to 4-5%.

Columns (6) – (9) report the model estimates of P1—the fraction of workers who remain employed at sub-minimum wages, P2—the fraction of sub-minimum wage workers who are promoted to the minimum, the probability of job loss (=1 – P1 – P2), and the overall disemployment effects: F(M)(1 – P1 – P2). In 1978, the same year as Meyer and Wise (1983b), P1 is estimated to be 0.31, somewhat higher than the Meyer and Wise estimate of 0.23. P2 is estimated to be 0.59, again higher than the 0.34 found previously. The resulting estimate of the probability of job loss is therefore smaller using the kernel density approach: 10%, with a disemployment effect for all young, hourly wage earners of 2.2% (s.e.=1.6%).[3]

Table 2 also reports the results for the years where the shape of the wage distribution appears more informative about the potential shape of the wage distribution in the absence of a minimum wage. While the estimates are somewhat noisy, especially in years when the minimum wage increased, the probability of job loss in these years is generally close to 60%, with overall disemployment effects of roughly 10-15%. The smaller disemployment effect calculated in 1998 partially reflects the greater percentage of workers found working below the minimum wage, possibly at the focal wage of $5.00. 1999 and 2000 show the fraction working below the minimum wage declining and estimated disemployment effects rising. Taken together, these results suggest that large disemployment effects can be found when the functional form assumption is relaxed.

Effects across Sub-groups

The relationship between the likelihood of receiving a low wage and the disemployment effects may be positive or negative as employers substitute toward or away from these particular groups. Table 3 reports the results for subgroups in 2000 that were found to differ between the wage groups in Table 1. The results suggest that greater

[3] Three hundred samples were re-drawn to calculate the bootstrapped standard errors.

exposure to the minimum wage tends to result in greater disemployment effects. The first row of Table 3 replicates the earlier result for all young workers, where the disemployment effect was 8.2%. The Meyer and Wise estimates focused on men, and the estimated disemployment effects are similar for men with the probability of job loss of 63% and an overall disemployment effect of 7%. Women are roughly twice as likely to report wages below or at the minimum wage, and the disemployment effect is larger as well: 14%. Meanwhile, blacks have a similar disemployment effect (9%) compared to the full sample.

Hourly wage earners aged 25-34 are less likely to receive wages at or below the minimum wage, reflecting their greater in experience, and the disemployment effect is smaller at 4%. Nevertheless, those older workers who do earn wages below the minimum have a similar estimated probability of job loss of 57%.

Across industries, the positive relationship between minimum wage exposure and disemployment effects is particularly strong. Table 3 shows that manufacturing industries tend to have the fewest hourly workers at or below the minimum wage, followed by service industries, while retail industries have the greatest exposure. The disemployment effects are found to be smaller for the manufacturing sector (4.1%) and the largest for the retail sector (20%). Meanwhile, part-time workers and those in the south are more likely to receive low wages and have larger disemployment effects as well, while high school dropouts are estimated to have disemployment effects similar to the full sample.[4]

[4] When restaurant workers were excluded from the analysis, the probability of job loss does not change, though the overall disemployment effect is smaller (4%). The main results include restaurant workers as this is a common industry to find minimum wage workers.

Robustness

The minimum wage law attempts to prohibit the very wages used to estimate the model. This suggests that the approach may rely on measurement error to observe these sub-minimum wages. One test reported in Table 4 considers estimates from a model where the sub-minimum wage observations were constructed to be the result of measurement error. All observations below the minimum wage were excluded, and a noise term was added to each of the wages observed above the minimum wage. This term is normally distributed with mean zero and a standard deviation set to seventy-five cents so that the fraction of observations below the minimum wage matches the original dataset. In addition, a fraction of observations at the minimum wage, equal to the fraction of observations below the minimum wage in the original sample, was excluded so that the fraction observed at the minimum wage again matched the original sample. Table 4 shows that the estimated P1 is much higher at 0.70. P2 is derived from this P1 estimate and is larger as well. The resulting disemployment effect is negative, a result found in all earlier years as well. These estimates essentially consider the shape of the wage distribution above the minimum wage, with the measurement error reflecting these observations across the boundary at the minimum wage. The results suggest that sub-minimum wage reports that are due solely to measurement error are unlikely to result in large disemployment effects.

Table 4 shows that the results are also similar for two additional robustness checks. First, Figure 2 showed that the local linear kernel density estimation tended to increase the estimates of the density both above and below the minimum wage.

Depending on which side is increased more, the estimate of P1 may rise or fall. Kernel density estimates using the same bandwidths and a normal kernel, but no local linear correction term, result in smaller estimates of P1 and larger estimated disemployment (23%). The local linear correction appears to result in more conservative estimates of the disemployment effects.

Second, the main results estimate the density one cent above and below the minimum wage. Wages tend not vary at the one-cent level, however, and this can lead to smaller estimates of the density just below and above the minimum wage. When the density is estimated five cents above and below the minimum wage instead, similar results are found, however.

A final robustness check tests the effect of the bandwidth choice. Recall that a larger bandwidth is thought to be appropriate at a boundary to allow more observations to be used in the estimation. In 2000, the bandwidth calculated with Silverman's rule of thumb is $0.51 above the minimum wage and $0.33 below the minimum wage, and the main results of density estimates described above used bandwidths twice as large.[5] Table 5 shows that the disemployment estimates increase with the bandwidth. With bandwidths half as large as the main results, the probability of job loss is estimated to be 47% in 1995 and 25% in 2000, where the overall disemployment effect shrinks to 8% in 1995 and 1% in 2000. When bandwidths are twice as large, the estimates are 73% and 81%, respectively, and the overall disemployment effect is roughly 20% for both years. These estimates demonstrate one of the limitations of relying on estimates just above and below

[5] Bandwidths used in 1978, 1980, 1985, 1990, 1995, and 2000 above the minimum wage were 70, 60, 80, 88, 96, 103, respectively, while below the minimum wage the bandwidths were 30, 30, 39, 41, 46, and 67, all in nominal dollars.

the minimum wage—their estimation sensitivity. Nevertheless, the estimates tend to show large disemployment effects across a wide range of bandwidths.

Effect on Wage Inequality

While the minimum wage may lower employment, it can also have a large impact on wage inequality. Indeed, Figures 3A and 3B demonstrated the compression in the wage distribution brought about by the minimum wage. Table 6 reports percentile estimates of the actual and counterfactual wage distributions for 1995 and 2000.[6]

Columns (4)-(6) report the 10th, 50th, and 90th percentiles. The distributions include the mass of observations at the minimum wage, resulting in the 10th percentile worker earning the minimum wage. In 1995 and 2000, the median wage is found to increase by approximately 5% attributed to the disemployment of lower wage workers. In terms of inequality, the 10th percentile is substantially below the minimum wage in the counterfactual distribution. For example, in 2000 the 10th percentile in the counterfactual distribution is estimated to be $4.38, compared to the minimum wage of $5.15.

The last three columns show that the difference between the 90th and the 50th percentiles are similar in the actual and counterfactual distributions for these young hourly wage earners. The difference between the 50th and the 10th percentiles is much larger. In 1995, the median wage earner makes 38% more than the 10th percentile worker with the minimum wage, and 63% more than the 10th percentile worker in the

[6] The appendix includes 1978 and five-year intervals from 1980-2000 due to the interest in the effect of the minimum wage on inequality trends (Lee, 1999; Teulings, 2003; Autor, Katz, and Kearney, 2005). While the pre-1995 estimates should be taken with some caution, the results suggest that over time the effect of the minimum wage on inequality appears much larger in the early-to-mid 1980s compared to 1990. This is consistent with earlier findings that the fall in the minimum wage over this time period contributed to the rise in inequality.

counterfactual distribution without the minimum wage. In 2000, the comparison is somewhat smaller though still substantial: 43% versus 55%.

5. Conclusion

A chief criticism of using the distortion of the wage distribution to estimate employment effects of a minimum wage has been its reliance on functional form assumptions. This paper substitutes these assumptions with an assumption that the counterfactual wage distribution in the absence of the minimum wage is continuous. When local linear estimation common in the regression discontinuity design context is applied to this density discontinuity design problem, large disemployment effects are again found. While the no spillover assumption does not appear valid in earlier years, from 1995-2000 the wage density peaks well above the minimum wage suggesting that its shape may inform the shape of the counterfactual density in the absence of a minimum wage. In 2000, the probability of job loss for a worker who would have earned a wage below the minimum is approximately 50%, and the overall disemployment effect is 8%. Meanwhile, workers who are more likely to earn low wages have larger disemployment effects.

Using the simple re-scaling model, it is also possible to construct the counterfactual wage distribution in the absence of the minimum wage. The disemployment of low-wage workers in 2000 is found to increase median wages by about 5%. Further, the minimum wage is found to compress the wage resulting in significantly smaller measures of inequality even among this sample of young, hourly wage earners.

The approach has a number of limitations. First, it relies on sub-minimum wage reports that place a greater emphasis on the potential for measurement error, though no disemployment effect is found in a simulation where all sub-minimum wage observations are due to measurement error by construction. Second, the estimation procedure continues to rely on an assumption of no spillover effects. To the extent that the minimum wage depresses the frequency of wages just above the minimum, the results here may understate the true effect, while the effect may be overstated if the minimum wage is associated with an increase in the frequency of wages just above the minimum. Finally, the estimates are somewhat sensitive to the choice of bandwidth, though large disemployment effects are found for a wide range of choices. In sum, the results suggest that large disemployment effects are not solely the result of functional form assumptions.

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Appendix: Incorporating CPS Sampling Weights

The CPS sampling weights represent how many people the individual in the survey represents. Let N equal the population of young hourly wage earners in the United States. If we had data on the entire population the kernel estimate would be:

$$(A1) \quad h(w) = (Nh)^{-1} \sum_{i=1}^{N} K_L\left(\frac{w - w_i}{h}\right)$$

But, instead we have weights. Letting N_i equal the weight and n equal the sample size:

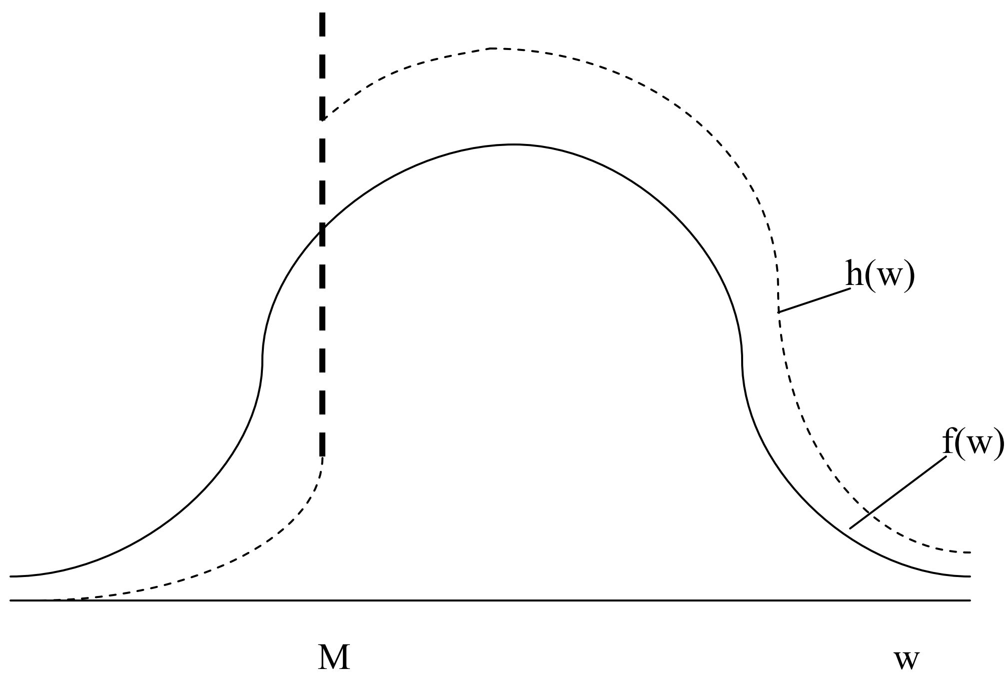
$$(A2) \quad h(w) = (Nh)^{-1} \sum_{i=1}^{n} N_i K_L\left(\frac{w - w_i}{h}\right)$$

or

$$(A3) \quad h(w) = h^{-1} \sum_{i=1}^{n} \theta_i K_L\left(\frac{w - w_i}{h}\right)$$

For subgroups such as individuals who earn more than the minimum wage, N equals the number of such people in the population.

Figure 1: Wage Distribution With & Without Minimum



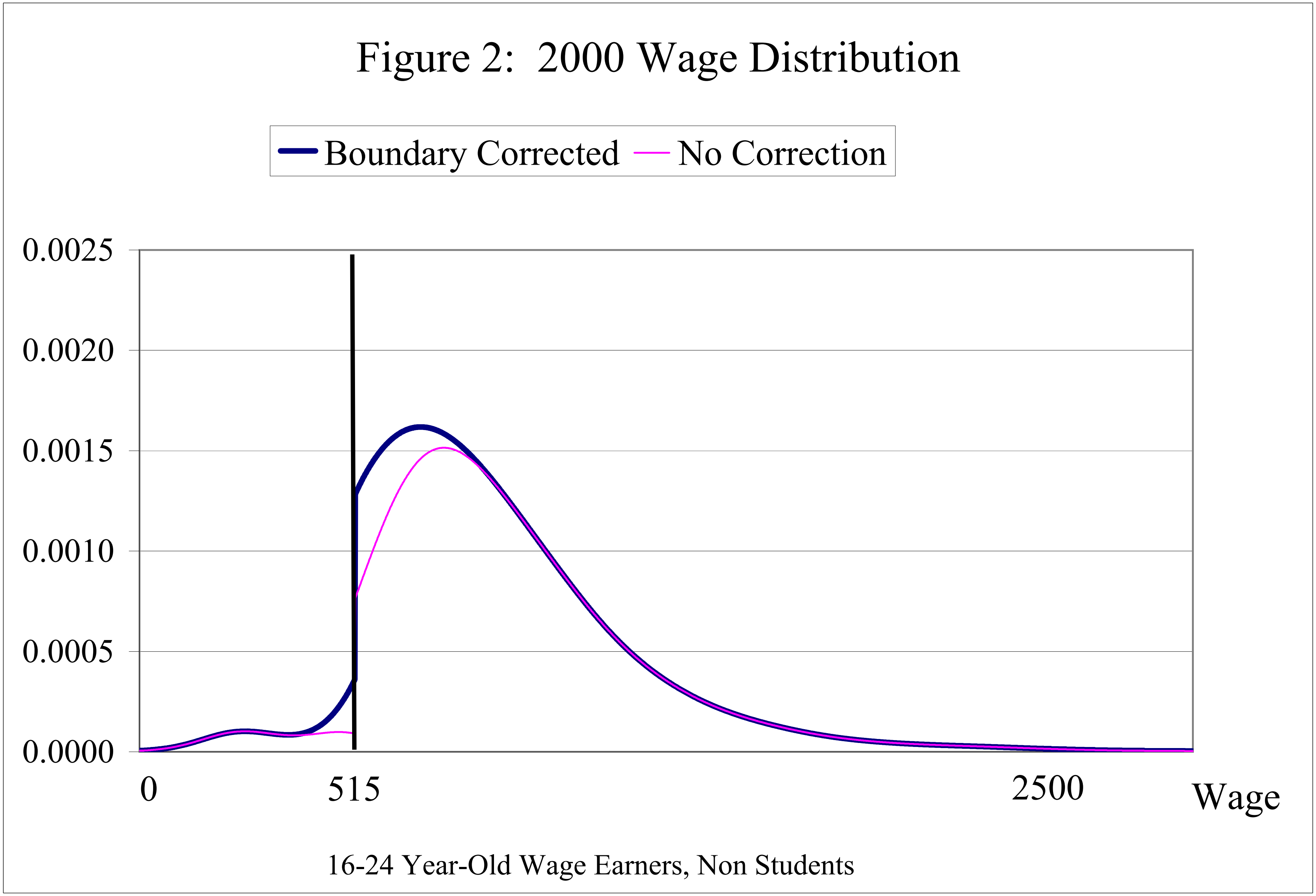
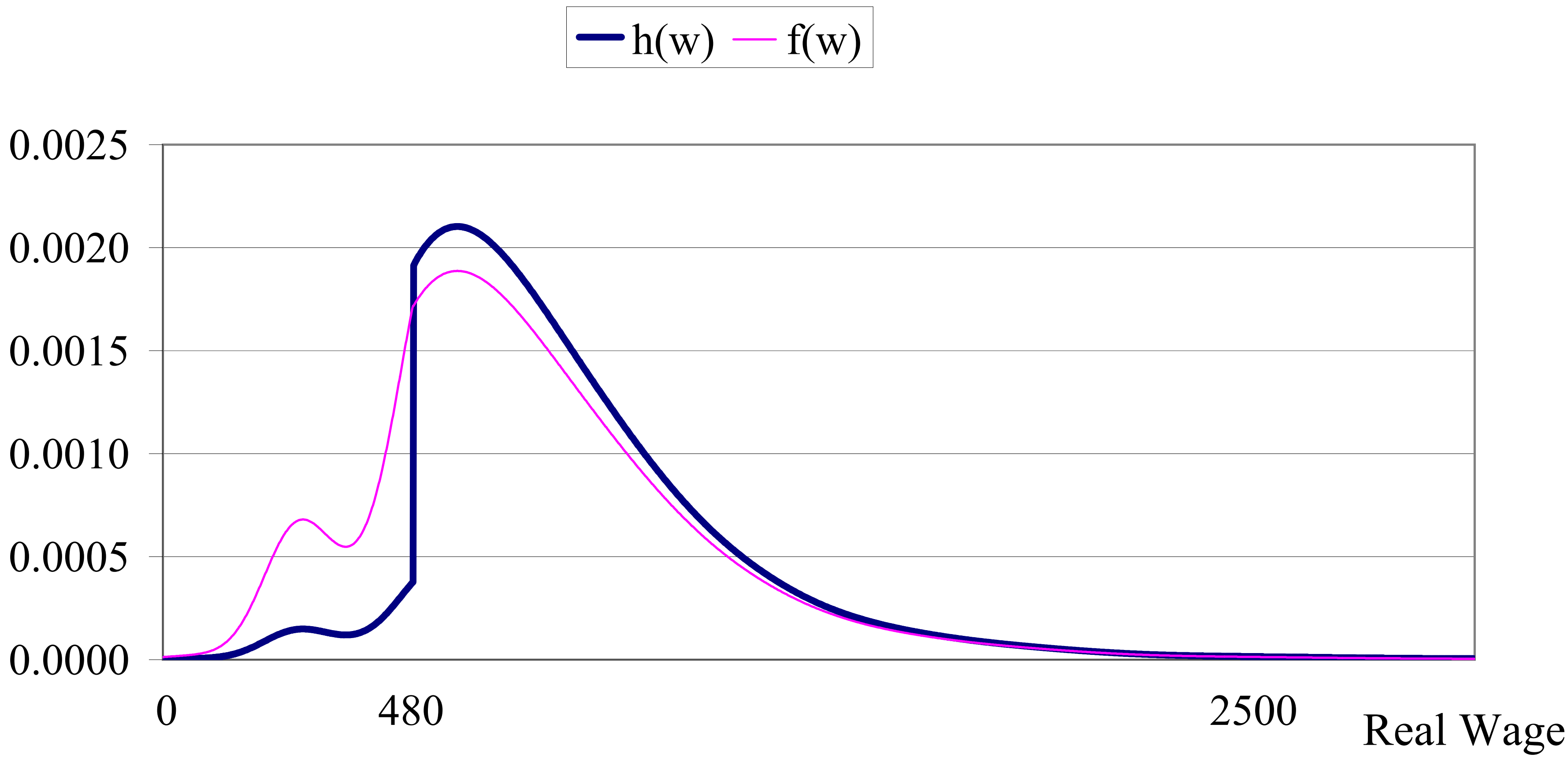


Figure 2: 2000 Wage Distribution
Boundary Corrected
No Correction
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0
515
2500
Wage
16-24 Year-Old Wage Earners, Non Students

Figure 3A: 1995 Observed & Counterfactual Wage Distibutions



16-24 Year-Old Wage Earners, Non Students

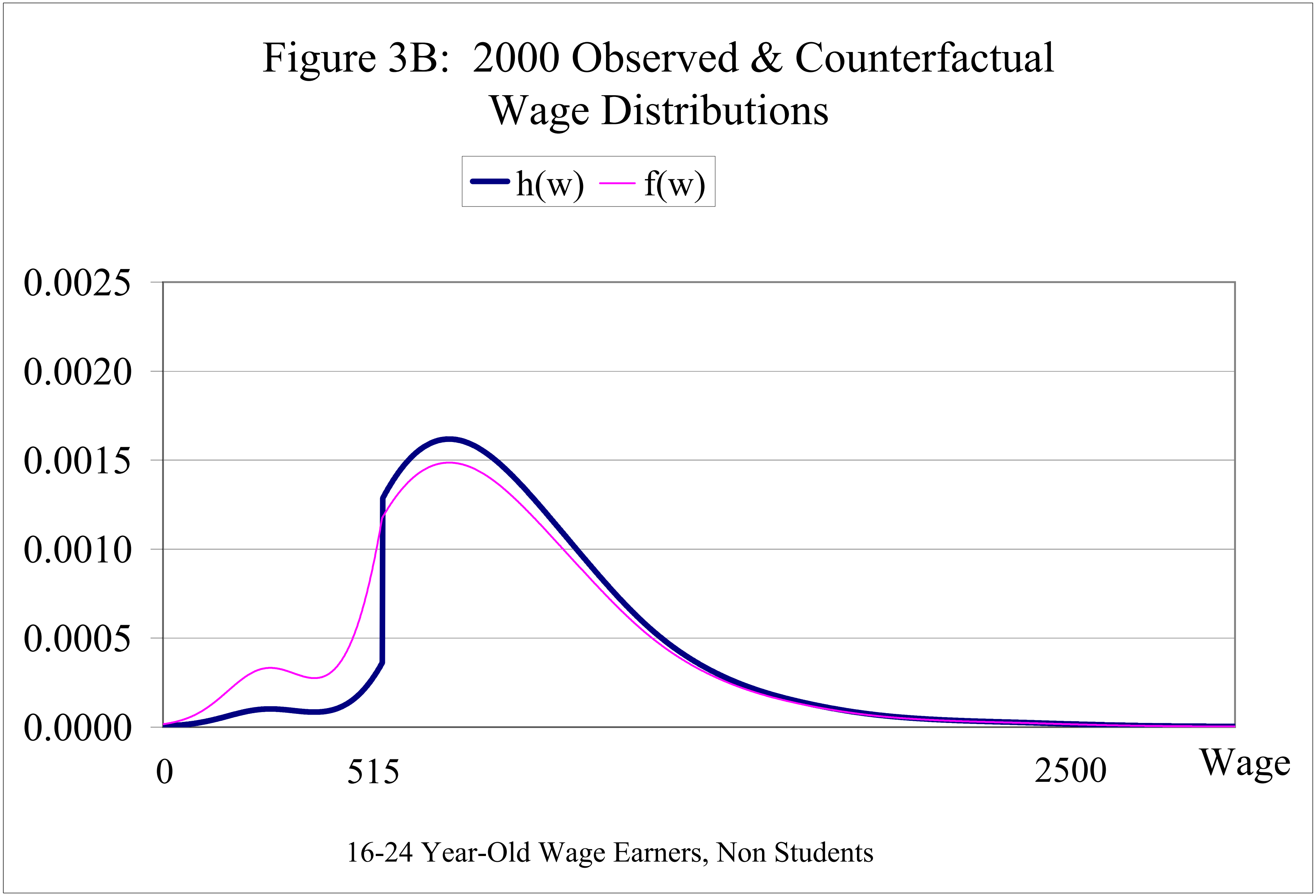


Figure 3B: 2000 Observed & Counterfactual
Wage Distributions
h(w)
f(w)
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0
515
2500
Wage
16-24 Year-Old Wage Earners, Non Students

Table 1: Descriptive Statisitics
Non-student, Hourly Wage Earners, Ages 16-24: 2000

		Wage < Minimum		Wage = Minimum		Wage > Minimum	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
	Wage (cents)	352	128	515	0	878	349
	Age	20	2.5	20	2	21.1	2
	Male	0.37	0.48	0.35	0.48	0.55	0.50
	Part-time	0.49	0.50	0.59	0.49	0.24	0.43
Race	White	0.86	0.35	0.83	0.38	0.82	0.38
	Black	0.11	0.32	0.14	0.35	0.15	0.36
Educational Attainment	Less than High School	0.37	0.48	0.48	0.50	0.23	0.42
	High School	0.31	0.46	0.36	0.48	0.45	0.50
	Some College	0.23	0.42	0.12	0.33	0.22	0.42
	College	0.09	0.28	0.03	0.17	0.10	0.30
Industry	Manufacturing	0.02	0.13	0.06	0.24	0.15	0.36
	Service	0.20	0.40	0.24	0.43	0.27	0.44
	Retail	0.71	0.45	0.56	0.50	0.30	0.46
	Restaurants	0.63	0.48	0.35	0.48	0.10	0.31
	Other	0.07	0.25	0.14	0.35	0.28	0.45
Region	Northeast	0.15	0.36	0.15	0.36	0.15	0.36
	South	0.51	0.50	0.49	0.50	0.43	0.50
	Midwest	0.25	0.43	0.25	0.44	0.32	0.47
	West	0.09	0.28	0.10	0.31	0.10	0.29
	Observations	446		269		9723	

All non-student, hourly wage earners, aged 16-24. Data: Current Population Survey Merged Outgoing Monthly Samples.
Estimates weighted by CPS weights.

Table 2: Disemployment Estimates

Year	Minimum Wage: Nominal ($)	Minimum Wage: Real (2000$)	Minimum Wage: Fraction Below π_1	Minimum Wage: Fraction At π_2	Model Estimates: P(Keep W<Min) P1	Model Estimates: P(Raise to Min) P2	Model Estimates: P(Job Loss) 1 - P1 - P2	Model Estimates: Disemployment F(M) (1-P1-P2)	Obs.
1978	2.65	7.00	0.073	0.137	0.314	0.588	0.098	0.022	6010
			(0.004)	(0.005)	(0.027)	(0.045)	(0.066)	(0.016)	
1995	4.25	4.80	0.043	0.060	0.196	0.278	0.526	0.103	12425
			(0.002)	(0.002)	(0.018)	(0.025)	(0.041)	(0.014)	
1996	4.25	4.66	0.036	0.058	0.128	0.207	0.664	0.157	9738
			(0.002)	(0.002)	(0.011)	(0.018)	(0.028)	(0.012)	
1997	4.75	5.10	0.064	0.040	0.201	0.127	0.672	0.177	8353
			(0.002)	(0.003)	(0.013)	(0.010)	(0.022)	(0.013)	
1998	5.15	5.44	0.072	0.048	0.473	0.318	0.210	0.031	10606
			(0.002)	(0.002)	(0.021)	(0.015)	(0.032)	(0.006)	
1999	5.15	5.32	0.052	0.029	0.270	0.152	0.579	0.100	10191
			(0.002)	(0.002)	(0.017)	(0.013)	(0.026)	(0.009)	
2000	5.15	5.15	0.044	0.024	0.281	0.153	0.565	0.082	10438
			(0.002)	(0.002)	(0.030)	(0.017)	(0.044)	(0.012)	

All non-student, hourly wage earners, aged 16-24. Data: 1978 from May Current Population Survey, 1995-2000: Merged Outgoing Monthly Samples.
Minimum wage as of May in each year; 1990 includes May 1990 - March 1991; 1991 includes May 1991 - March 1992;
1997 includes November 1996 through August 1997; 1998 includes October 1997 through September 1998.
Estimates weighted by CPS weights. Bootstrapped standard errors in parentheses.

Table 3: Estimates by Subgroups: 2000

	Minimum Wage		Model Estimates				
	% Below	& At	P(Keep W<Min)	P(Raise to Min)	P(Job Loss)	Disemployment	Observations
	π_1	π_2	P1	P2	1 - P1 - P2	F(M) (1-P1-P2)	
Groups							
All	0.044	0.024	0.281	0.153	0.565	0.082	10438
Men	0.030	0.016	0.243	0.127	0.631	0.073	5530
Women	0.061	0.034	0.243	0.136	0.622	0.135	4908
Black	0.033	0.022	0.216	0.143	0.641	0.090	1219
Ages 25-34	0.025	0.008	0.322	0.107	0.570	0.042	17243
Industry:							
Manufacturing	0.006	0.010	0.094	0.169	0.736	0.041	1379
Service	0.034	0.022	0.237	0.154	0.609	0.080	2841
Retail	0.098	0.042	0.254	0.108	0.638	0.197	3441
Other Industries	0.011	0.013	0.192	0.227	0.581	0.032	2777
Low-Wage Groups:							
Part-time Workers	0.083	0.055	0.217	0.143	0.640	0.197	2789
South	0.052	0.027	0.211	0.110	0.678	0.144	3687
Less than High School	0.068	0.049	0.328	0.236	0.436	0.083	2516

All non-student, hourly wage earners within each category; All comparisons are for workers aged 16-24 except where indicated.
Estimates weighted by Current Population Survey weights.

Table 4: Specification & Robustness Checks: 2000

	Model Estimates				
	P(Keep W<Min) P1	P(Raise to Min) P2	P(Job Loss) 1 - P1 - P2	Disemployment F(M) (1-P1-P2)	Observations
A. Simulated Measurement Error	0.699	0.407	-0.106	-0.006	9967
B. No Local Linear Boundary Correction	0.119	0.065	0.816	0.234	10438
C. 5-cent interval around the Minimum	0.274	0.149	0.576	0.085	10437

Estimates weighted by Current Population Survey weights.

Table 5: Bandwidth Sensitivity

	Bandwidth Below the Min	Bandwidth Above the Min	Model Estimates: P(Keep W<Min) P1	P(Raise to Min) P2	P(Job Loss) 1 - P1 - P2	Disemployment F(M) (1-P1-P2)	Observations
A. 1995							
Bandwidth 1/2 as large.	23	48	0.218	0.308	0.474	0.085	
Bandwidth 2 times as large.	92	192	0.113	0.159	0.728	0.216	12425
B. 2000							
Bandwidth 1/2 as large.	34	52	0.576	0.176	0.248	0.008	
Bandwidth 2 times as large.	134	206	0.126	0.069	0.805	0.221	10438

Estimates weighted by Current Population Survey weights. Bandwidths in (nominal) cents.

Table 6: Disemployment and Wage Inequality

Year		Real Minimum (2000$)	10th Percentile	Median	90th Percentile	log(90th/50th)	log(90th/10th)	log(50th/10th)
1995	Observed, h(w)	4.80	480	703	1145	0.49	0.87	0.38
	Counterfactual, f(w)		354	665	1114	0.52	1.15	0.63
2000	Observed, h(w)	5.15	515	792	1241	0.45	0.88	0.43
	Counterfactual, f(w)		438	759	1216	0.47	1.02	0.55

Data: Current Population Survey, Merged Outgoing Monthly Samples;

Wages measured in cents (2000$). All non-student, hourly wage earners, aged 16-24. Estimates weighted by CPS weights.

Appendix Table A1: Disemployment Estimates: 1978-2000

Year	Minimum Wage				Model Estimates				Observations
	Nominal	Real (2000$)	% Below π_1	& At π_2	P(Keep W<Min) P1	P(Raise to Min) P2	P(Job Loss) 1- P1 - P2	Disemployment F(M) (1-P1-P2)	
1978	2.65	7.00	0.073	0.137	0.314	0.588	0.098	0.022	6010
1979	2.90	6.88	0.067	0.116	0.121	0.207	0.672	0.273	19354
1980	3.10	6.48	0.073	0.145	0.363	0.716	-0.079	-0.016	25023
1981	3.35	6.35	0.094	0.131	0.511	0.709	-0.220	-0.042	22145
1982	3.35	5.98	0.066	0.134	0.238	0.485	0.277	0.071	20170
1983	3.35	5.79	0.057	0.148	0.148	0.386	0.466	0.152	19695
1984	3.35	5.55	0.045	0.125	0.114	0.318	0.568	0.182	16703
1985	3.35	5.36	0.040	0.119	0.101	0.298	0.602	0.194	16558
1986	3.35	5.26	0.037	0.103	0.104	0.287	0.609	0.180	16476
1987	3.35	5.08	0.034	0.090	0.086	0.227	0.687	0.215	14492
1988	3.35	4.88	0.033	0.077	0.093	0.216	0.691	0.199	12983
1989	3.35	4.65	0.033	0.064	0.065	0.125	0.810	0.294	11132
1990	3.80	5.01	0.062	0.038	0.229	0.137	0.634	0.148	10935
1991	4.25	5.37	0.056	0.109	0.180	0.352	0.468	0.126	12217
1992	4.25	5.22	0.041	0.097	0.103	0.240	0.657	0.209	12060
1993	4.25	5.06	0.041	0.086	0.091	0.192	0.717	0.244	11650
1994	4.25	4.94	0.049	0.064	0.240	0.313	0.447	0.084	12732
1995	4.25	4.80	0.043	0.060	0.196	0.278	0.526	0.103	12425
1996	4.25	4.66	0.036	0.058	0.128	0.207	0.664	0.157	9738
1997	4.75	5.10	0.064	0.040	0.201	0.127	0.672	0.177	8353
1998	5.15	5.44	0.072	0.048	0.473	0.318	0.210	0.031	10606
1999	5.15	5.32	0.052	0.029	0.270	0.152	0.579	0.100	10191
2000	5.15	5.15	0.044	0.024	0.281	0.153	0.565	0.082	10438

All non-student, hourly wage earners, aged 16-24; Data: 1978 from May Current Population Survey, 1980-2000: Merged Outgoing Monthly Samples.
1990 includes May 1990 - March 1991; 1991 includes May 1991 - March 1992; 1997 includes November 1996 through August 1997; 1998 includes October 1997 through September 1998.
Minimum wage as of May in each year. Estimates weighted by CPS weights.

Appendix Table A2: Disemployment and Wage Inequality: 1978-2000

Year		Real Minimum (2000$)	10th Percentile	Median	90th Percentile	log(90th/50th)	log(90th/10th)	log(50th/10th)
1978	Observed, h(w)	7.00	700	913	1672	0.61	0.87	0.27
	Counterfactual, f(w)		569	903	1664	0.61	1.07	0.46
1980	Observed, h(w)	6.48	648	812	1479	0.60	0.83	0.23
	Counterfactual, f(w)		551	818	1487	0.60	0.99	0.40
1985	Observed, h(w)	5.36	536	745	1327	0.58	0.91	0.33
	Counterfactual, f(w)		326	664	1252	0.63	1.34	0.71
1990	Observed, h(w)	5.01	501	725	1220	0.52	0.89	0.37
	Counterfactual, f(w)		381	662	1169	0.57	1.12	0.55
1995	Observed, h(w)	4.80	480	703	1145	0.49	0.87	0.38
	Counterfactual, f(w)		354	665	1114	0.52	1.15	0.63
2000	Observed, h(w)	5.15	515	792	1241	0.45	0.88	0.43
	Counterfactual, f(w)		438	759	1216	0.47	1.02	0.55

Data: 1978 from May Current Population Survey, 1980-2000: Merged Outgoing Monthly Samples; 1990 includes May 1990 - March 1991

Wages measured in cents (2000$). All non-student, hourly wage earners, aged 16-24. Estimates weighted by CPS weights.