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ESTIMATING THE EFFECT OF MINIMUM WAGES ON EMPLOYMENT FROM THE DISTRIBUTION OF WAGES: A CRITICAL REVIEW

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ABSTRACT

In two papers, Meyer and Wise (1983a,b) present an ingenious method for estimating the effect of minimum wage rates on wages and employment using data based only on the observed cross-sectional distribution of wages. They, and others who have used this method, have generally found that the minimum wage causes substantial losses in employment. In this paper we evaluate the robustness of this technique. We argue that the estimates, at least for the UK, are very sensitive to the functional form assumed for the distribution of wages and to the assumption made about how far up the wage distribution the minimum wage has spillover effects.

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Introduction

Most work on the effects of minimum wages on employment uses time series or panel data[1], or studies the impact of changes in the minimum on changes in employment.[2] But, in an original and ingenious model, Meyer and Wise (1983a,b) presented an alternative way of estimating the effect of minimum wages on employment and the wage distribution using data on only a single cross-sectional distribution of wages. This approach has a number of attractions over the others. First, it can provide a better picture of the differing effects of minimum wages on different groups of workers. And secondly, it can be used to evaluate the effect of minimum wages in situations where only cross-sectional information is available.

Given these potential advantages, it is perhaps surprising that their technique has not been more widely applied. Only in the Netherlands does it seem to have been used (Van Soest, 1989, 1993, and Teulings, 1992, for a more theoretical analysis). The reason for the lack of use is probably that, as Brown, Gilroy and Kohen argue "the estimate depends on the assumed functional form relating the wage to the personal characteristics and on the assumed distribution of the error term" (1982, p.512). However, Meyer and Wise do undertake a number of robustness tests and argue that their conclusions are not very sensitive to the precise assumptions used, so the charge that the results are not robust remains unproved.

In this paper, our aim is to apply the Meyer-Wise technique to UK data and to investigate more thoroughly how sensitive the estimates are to various assumptions. In particular, we focus on two issues: the choice of functional form for the distribution of wages in the absence of minimum wages; and the assumption about how the minimum wage affects the wage distribution. Our conclusions are that the estimates are not at all robust and that, at least for UK data, the

Meyer-Wise approach, while appealing on an intuitive level, can not be used safely in practice.

The plan of the paper is as follows. In the next section, we reformulate the Meyer-Wise model slightly, by generalising it in a way which we believe is more suitable. The second section describes our data and our results are presented in the third and fourth sections.

1. The Meyer-Wise Approach

In their papers, Meyer and Wise present a number of variants of their model. In our presentation here, we discuss only the most rudimentary version which, for our purposes, is probably sufficient. The basic idea is that in the absence of minimum wages there will be some distribution of wages. When the minimum is introduced some fraction, p, of those workers who were originally paid below the minimum have their wage raised to the minimum and remain in employment (they actually also allow some workers to continue to be paid below the minimum). These workers represent the spike in the wage distribution. A fraction, (1-p), lose their jobs and this is a measure of the adverse employment effect of the minimum wage. Meyer and Wise show how p can be estimated from observations on the distribution of wages among those paid above the minimum, inferring how many would be paid below the minimum in the absence of the legislation, and comparing this with the size of the spike.

Now consider, the following alternative set-up of their model. Suppose that in the absence of a minimum wage, employment is L_0 and the density function of wages is given by $f(W;\theta)$ where θ is a set of parameters to be estimated. Suppose that a minimum wage is introduced, causing employment to be L_1 and the density function of wages to be $f_1(W;\theta)$. $f_1(W;\theta)$ can, of course, be estimated from the observed distribution of wages. However, to infer the effect of the minimum wage on the wage distribution and employment, one needs to be able to infer $f(W;\theta)$ and L_0. Without further assumptions it is impossible to do this. But, one can make progress if one is prepared to make the following assumption:

Assumption: There is some wage, W_1, such that the wage and employment of those workers initially earning above this rate is unaffected by the minimum wage.

Meyer and Wise assume that W_1 is very close to the minimum wage. One of the contributions of this paper is to show that it is not necessary to do this.[3] Indeed, we will show that failing to specify W_1 correctly can have very serious consequences. Assuming that those earning substantially above the minimum are unaffected by it, appears, at first glance, to be a relatively weak (and attractive) assumption. Indeed, it seems surprising that quite so weak an assumption is all that is necessary to estimate the effects of the minimum.

Now let us show how this can be done. Suppose that we estimated a tobit model for a wage equation with the truncation at W_1. Order the workers so that the first j have wages above W_1 and the others have wages below. We can write the log-likelihood function as:

$$logL = \sum_{i=1}^{j} \log f_1(W_i;\theta) + (L_1 - j).\log F_1(W_1;\theta) \qquad \textbf{(1)}$$

Under the assumptions made above, we must have:

$$f_1(W;\theta) = \frac{L_0}{L_1}.f(W;\theta) = \phi.f(W;\theta) \quad for \quad W > W_1 \qquad \textbf{(2)}$$

$$\begin{aligned} L_1.\left(1 - F_1(W_1;\theta)\right) &= L_0.\left(1 - F(W_1;\theta)\right) \\ i.e. \quad F_1(W_1;\theta) &= 1 - \phi.\left(1 - F(W_1;\theta)\right) \end{aligned} \qquad \textbf{(3)}$$

where the ratio of employment before and after the minimum wages is defined as $\phi=(L_0/L_1)$, which is a measure of the employment effect of the minimum wage. Equation (2) says that the density function for wages with the minimum wage for those earning above W_1, is simply the density function for wages without the minimum scaled by a constant which is the change in employment. According to equation (3) the total number of workers earning above W_1 must be the same before and after the introduction of the minimum wage. Substituting (2) and (3) into (1) yields the likelihood function written in terms of $f(W;\theta)$ and ϕ, the employment effect of a change in the minimum wage:

$$logL = \sum_{i=1}^{j} \log f(W_i;\theta) + j.\log \phi + (L_1 - j).\log[1 - \phi.(1 - F(W_1;\theta))] \tag{4}$$

One can estimate (θ,ϕ) by maximisation of (4). If we maximise (4) with respect to ϕ, we obtain, after some rearrangement, the following expression for the maximum likelihood estimator of ϕ:

$$\phi_{MLE} = \frac{j}{L_1.[1 - F(W_1;\theta)]} \tag{5}$$

This has a very simple interpretation; whether employment increases or decreases depends on whether the actual fraction of workers with a wage below W_1 is greater or less than would be predicted on the basis of the distribution of wages among those paid more than W_1. By substituting (5) into (4), we can write the concentrated likelihood function as:

$$logL = \sum_{i=1}^{j} \log f(W_i;\theta) - j.\log [1 - F(W_1;\theta)] + constants \tag{6}$$

(6) is simply the likelihood function for estimating the distribution of wages from a sample of workers where the wage observations are truncated at W_1. After obtaining an estimate of θ from maximisation of (6), one can then estimate ϕ from (5). There are several important things to note about this procedure.

First, one can only concentrate the likelihood function in the way described above if one does not model the wage distribution as varying with individual characteristics. But, if one does introduce personal characteristics into the wage distribution then one should also model ϕ as varying with those characteristics. If one wants estimates of the total effect of minimum wages on employment, then it is probably best to work with the distribution of wages after having marginalised with respect to personal characteristics. This is what we do below.

Secondly, note that the only problem caused by setting W_1 too high is that one loses observations and hence the estimates are likely to be less precise. In contrast, setting W_1 too low will lead to inconsistent estimates of ϕ which is obviously more serious. Meyer and Wise only consider values of W_1 very close to the minimum wage. Such a procedure is only valid if there are no spillover effects of the minimum wage at all, on workers paid higher wages. Their results are likely to be sensitive to this problem and this is likely to lead to an overestimate of the employment losses from the minimum wage. But, as we have shown, there is no reason why their general approach cannot be used with a cut-off wage different from the minimum.

Thirdly, the specification of the likelihood function that we have used here, differs slightly from that of Meyer and Wise in that they estimate not ϕ, but $p=1+(\phi^{-1}-1).F(W_1;\theta)^{-1}$ which they interpret as the probability of a worker who was originally paid less than the minimum, retaining the job after the introduction of the minimum wage. We prefer to estimate ϕ for three reasons:

(i) it is a direct measure of the total employment effect and this is what we are ultimately interested in.

(ii) there is no guarantee that the estimated value of p will be less than 1 in which case it cannot be interpreted as a probability. This is the case where the introduction of a minimum wage raises employment. Meyer and Wise, who start from a competitive view of the labour market would not put much weight on this as a likely outcome, but we have argued elsewhere (Dickens, Machin and Manning, 1993) that it is possible to present a coherent theoretical model in which minimum wages raise employment and that it is very important not to prejudge this issue.

(iii) if we vary the cut-off W_1 (which we do below) the estimate of p will change but, if our model is correct, the estimate of ϕ should be invariant to this change.

To make (6) operational, one obviously needs to make a specific assumption about the form of $f(W;\theta)$. A serious concern is that incorrect specification of f, leads to incorrect inference on ϕ. Meyer and Wise are well aware of this potential problem and experiment with a Box-Cox transformation of the wage variable, ending up with the assumption that the distribution of wages is log-normal. Below, we try to deal with this problem by considering a number of choices of f; considering tests of the adequacy of functional form; and also by estimating the model for similar labour markets without minimum wages when we would expect to find ϕ=1, if we have correctly specified f.[4]

2. The Wages Councils

The Wages Councils were established by Winston Churchill in 1909. They set minimum wage rates in a number of different industries. Over the years, the number of industries covered, first increased (to a peak of about 60 covered sectors in the early 1960s) and then decreased. By 1993, the 26 remaining Wages Councils set minimum wages for approximately 3 million workers in low paid sectors (mostly in hotels and catering, retail, clothing manufacture and hairdressing but also including a number of very small industries). Until the 1986 Wages Act, the Councils generally set a myriad of minimum wages differentiated by age, occupation and region but since 1986 set only a single rate and young people under the age of 21 were removed from coverage. The 1993 Trade Union Reform and Employment Rights Act abolished the remaining 26 Councils so that from September 1993 onwards no form of minimum wages operated in the UK (except in agriculture). One of the Government's arguments for abolition was based on the claim that the minimum rates of pay set by the Councils were bad for employment (see Dickens et al., 1993).

The best source of information on workers covered by the Wages Councils is the New Earnings Survey (NES). This is a 1% sample of all workers who pay National Insurance contributions conducted in April each year. We have access to the data for the years 1975-90. There are two ways of identifying workers in Wages Council industries from the NES. First, employers are asked whether workers are covered by a Wages Council agreement. Secondly, we can use the detailed industrial and occupational information to work out who should be covered. Typically, the numbers obtained using the first method are substantially less than the numbers obtained by the second method and there seem to be a large number of misclassifications. For this reason, we prefer the numbers from the second method.[5]

For our wage numbers we use the basic hourly wage for workers aged over 21 and working in occupations covered by the Wages Councils (only a few small occupations in the relevant industries are not covered).

3. The Effect of Minimum Wages on the Wage Distribution

Before using the Meyer-Wise approach we consider the evidence on the effect of minimum wages on the distribution of wages. This is important because, as discussed above, it is necessary to choose as a truncation point a level of the wage which is unaffected by the minimum.

We investigated this by using data from 1975-90 on a panel of 14 Wages Councils industries (as used in Dickens, Machin and Manning, 1993). Only those Wages Councils large enough to have enough workers in the NES for the data to be reliable were included (the Councils used are listed in Dickens, Machin and Manning, 1993). Table 1 reports the results of a first differenced regression of the log hourly wage at each decile in the earnings distribution on the log of the minimum hourly wage, together with year dummies, where we let minimum wages have different effects for male and female Wages Councils. For the years before 1986 when there were many minimum wages, we used the lowest adult rate as our minimum wage variable.

As would be expected, the effect of the minimum wage on earnings' levels is strongest at the lowest deciles of the distribution. For male Councils, there is only a significant earnings' compression effect at the tenth percentile of the distribution. For female Councils, effects are strong up to the fortieth percentile, after which all effects are estimated to be insignificantly different from zero. Hence, Wages Council minimum pay rates appear to significantly compress the distribution of earnings, and do so more strongly for women covered by minimum wages than for men. This finding of a spillover effect, where minimum wages have an impact on wages higher up the wage distribution, is consistent with the findings of Grossman (1983) for the US and Van Soest (1989) for the Netherlands. It also implies that use of the Meyer-Wise assumption, that all workers paid above the minimum are unaffected, is likely to lead to serious biases.

4. The Effect of Minimum Wages on Employment

In this section we consider Meyer-Wise type estimates of the employment effects of Wages Councils. The way in which we do this is as described above. We choose a truncation point W_1, and a density function $f(W,\theta)$, estimate θ using (6) as the likelihood function and then estimate the employment effect of the minimum wage, ϕ, using (5). If ϕ is estimated as larger than one, this implies that there are employment losses from the minimum wage; if it is less than one there are employment gains.

For this exercise, we used data on workers in the two retail Wages Councils for the years 1987-90 inclusive. We chose these two Councils because they give us a reasonably large sample and they had the same minimum wage set in the chosen years. We restrict attention to those years after the 1986 Wages Act as a single minimum wage was in force at that time whereas previously there had been many rates. We also include workers in wholesale distribution as a control group who are not covered by the Wages Councils, to see whether the Meyer-Wise approach gives sensible results when applied to an industry without a minimum wage.

Some descriptive statistics on the data are given in Table 2. We use information on about 6000-7000 retail and wholesale workers for both males and females in each of the years 1987-90 inclusive. The Table shows that the minimum wage is located somewhere near the twentieth percentile of the female retail wage distribution for women, and lower down - around the third or fourth percentile - for men. Figures 1a-1d present the distribution of log hourly wages for men and women in retail and wholesale in 1990. It is noticeable how the left-hand tail of the retail distributions do look thinner, and there is some evidence of a spike at the minimum wage, particularly for women.

We experimented with two density functions for the distribution of wages in the absence of minimum wages. We used the log normal (which was Meyer and Wise's preferred model) and also the Singh-Maddala which has been found to provide a better fit to the distribution of income (Singh and Maddala, 1976; McDonald, 1984). The Singh-Maddala is a three parameter distribution with distribution function given by:

$$F(W;\theta) = 1 - [1 + (W/\theta_1)^{\theta_2}]^{-\theta_3} \tag{7}$$

where (θ_1, θ_2, θ_3) are all positive and W>0. There is an issue about whether we should include explanatory variables in estimating these distributions but we decided not to as, if one does this, one should then allow ϕ to differ with those characteristics and we want to have an overall measure of the employment effect of minimum wages. What experimentation we did, suggests that our results are not that sensitive to the exclusion or inclusion of other controls.

Table 3 presents the estimates of the employment parameter using the log-normal distribution (the estimates of the parameters of the model are contained in Tables A1 and A2). We present results for men and women separately, for retail and wholesale distribution, for the years 1987-90 and using a cut-off from the tenth to fortieth percentile. We do not present the estimates for the tenth and twentieth percentiles for women as the wage at this point in the distribution lies below the minimum wage.

The first point to note is that all the estimates of ϕ are significantly above one which, taken at face value, implies employment losses. This is the case for workers in the uncovered wholesale sector as well as in the covered retail distribution sector, which immediately suggests that we should be very suspicious of this as a measure of the employment loss associated with the minimum wage. The reason for this finding is that the log-normal assumption is an extremely poor one for characterising the distribution of wages. As a test of the adequacy of the assumed functional form, we used a Kolmogorov-Smirnov test, and p-values for the test statistic are reported in Table 4.[6] The distribution of this test statistic is not known when the null hypothesis is an estimated distribution but with our sample sizes this is probably not a serious problem particularly as the p-values for the test statistics are zero to the fourth decimal place (at least) in every estimation.[7] The basic problem is that the right tail is thicker than it should be if the distribution was log-normal (as can be seen by inspection of Figures 1a-1d), so there seems surprisingly little weight in the left tail which the procedure ascribes to the employment consequences of the minimum wage. This problem gets worse as one increases the cut-off, as the right tail then becomes more important in estimating the parameters of the wage distribution, and, as a result, the estimates of employment losses tend to be larger for higher cut-offs.

One obvious potential solution is to estimate a three parameter distribution so that we can have a distribution with some skewness. Table 5 presents results based on the Singh-Maddala distribution (the parameter estimates are presented in Tables A3 to A5). There are a number of pieces of evidence that this distribution is more satisfactory than the log-normal distribution. First, although the spot estimates of ϕ are all above unity for wholesale distribution, the estimates are generally not significantly different from one. And secondly, most of the Kolmogorov-Smirnov tests of functional form reported in Table 6 imply that one cannot reject the hypothesis that the Singh-Maddala distribution is an adequate representation of the data.

But, once we try to use the results to infer the effects of the minimum wage on employment, problems begin. First, the estimates of ϕ for retail distribution vary wildly. Particularly striking are the results for women. Using the thirtieth percentile as the cut-off, our estimates suggest (significant) employment gains from the minimum wage in 1987, but enormous losses in 1988-90 (although the estimates have enormous standard errors). However, using the fortieth percentile as the cut-off one would conclude that there were large employment losses from the minimum wage in 1987 and much smaller losses in 1990. It should also be noted that there is no systematic tendency for ϕ to be higher in the retail sector as compared to the wholesale sector.

It is difficult to have any confidence in these results. The basic problem is that if one chooses a high cut-off it is very difficult, if not impossible, to estimate the degree of skewness from the right-hand tail of the distribution alone. The result is huge imprecision in the estimate of the weight that should be in the left-hand tail. Choosing a low cut-off avoids these problems but, as we argued above, is likely to lead to overestimates of employment losses from the minimum wage, as it ignores the effect of the minimum wage in raising the wage of those workers paid above the minimum. This is a particular problem with the data on women as one does not have to move very far up the wage distribution before one has only the right-hand tail to work with.

5. Conclusions

At first glance, the Meyer-Wise approach appears to be an attractive way of estimating the employment consequences of minimum wages using cross-sectional information alone. But, at least for the UK, the fact that the minimum wage seems to affect the distribution of wages among workers paid above the minimum, and the fact that the distribution of wages cannot be adequately explained by a two-parameter model, conspire to make estimates of the employment effects derived in this way very dubious. Of course, it is possible that for other countries one may be able to obtain more sensible estimates using this modelling approach. This is likely to be true where one can more precisely estimate the wage distribution and where there are likely to be small spillover effects associated with minimum wages. But, what our results do suggest is that any paper using this approach should be extremely careful to present a wide range of experiments with truncation points and wage distributions, for it to be convincing.

ENDNOTES

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1. See Card (1992a), Neumark and Wascher (1992), Kaufman (1989), Machin and Manning (1994) and Dickens, Machin and Manning (1993), for recent studies of this type based on US and UK data.

2. Examples are the recent papers by Katz and Krueger (1992), Card (1992b), Card and Krueger (1993) who consider the impact of recent changes in US federal and state minimum wages on changes in employment.

3. In footnote 9 on p.1682 of Meyer and Wise (1983b), they do state that they experimented with having W_1 above the minimum and that it made little difference to the results. However, what remains unclear is the extent of the experimentation. Furthermore, the reported results use a value of W_1 that is only 1% above the minimum wage.

4. We are able to do this because, prior to abolition of minimum wages on August 30, 1993, the minimum wage system in the UK only covered certain industries.

5. But see Machin and Manning (1994) for estimates of employment functions based on the first numbers, which yield similar employment effects of minimum wages to those reported using employment numbers from the second method in Dickens, Machin and Manning (1993).

6. We used a non-parametric test rather than some more powerful test for normality because we want to have a test for functional form

for other specifications of the density function and because we are interested in testing for the presence of a truncated normal.

7. This dramatic rejection of log-normality occurs also if we include explanatory variables in our regressions.

FIGURE 1a

Log Hourly Wage Distribution for Female Retail Employees in 1990

FIGURE 1b

Log Hourly Wage Distribution for Male Retail Employees in 1990

FIGURE 1c

Log Hourly Wage Distribution for Female Wholesale Employees in 1990

FIGURE 1d

Log Hourly Wage Distribution for Male Wholesale Employees
in 1990

TABLE 1

The Effects of Minimum Wages on the Wage Distribution

Dependent variable:
Δith percentile or average of log real hourly earnings distribution

Dependent Variable	Coefficient (standard error) on ΔLog (real minimum hourly wage)	
	Male Councils	Female Councils
Δ10th percentile	.166 (.083)	.248 (.066)
Δ20th percentile	.065 (.107)	.309 (.066)
Δ30th percentile	-.056 (.086)	.207 (.054)
Δ40th percentile	-.108 (.097)	.150 (.050)
Δ50th percentile	-.169 (.096)	.071 (.046)
Δ60th percentile	-.123 (.122)	.059 (.042)
Δ70th percentile	-.080 (.137)	-.006 (.047)
Δ80th percentile	-.069 (.157)	-.060 (.060)
Δ90th percentile	-.068 (.243)	-.060 (.085)
Δaverage	.056 (.111)	.148 (.042)

Notes:
1. Sample size: 204; Estimation period: 1976-90.
2. Heteroskedastic consistent standard errors in parentheses.
3. Time dummies included in all specifications.

TABLE 2

Descriptive Statistics

Industry	Retail Distribution		Wholesale Distribution
	Number of individuals	Location of minimum in terms of percentile of earnings distribution	Number of individuals
Females			
1987	5701	22.05	1100
1988	5844	18.10	1201
1989	5685	16.15	1228
1990	6213	17.91	1272
Males			
1987	2835	4.76	2696
1988	2891	3.49	3019
1989	2824	3.33	3052
1990	2796	4.11	3139

Notes: 1. Based on New Earnings Survey micro-data.

TABLE 3

Maximum Likelihood Estimates of Employment Parameter ϕ, Assuming Log-Normal Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	1.861 (0.395)	–	2.730 (1.147)	$5.2\text{x}10^{4}$ ($1.8\text{x}10^{5}$)	5.080 (3.778)	$1.4\text{x}10^{72}$ ($1.8\text{x}10^{74}$)	8.974 (10.625)
1988	–	1.466 (0.200)	–	2.155 (0.660)	$4.3\text{x}10^{5}$ ($1.8\text{x}10^{6}$)	2.299 (0.952)	1050.78 (2221.01)	2.575 (1.479)
1989	–	1.582 (0.232)	–	2.063 (0.595)	$1.7\text{x}10^{13}$ ($2.2\text{x}10^{14}$)	4.459 (2.845)	$6.3\text{x}10^{5}$ ($2.9\text{x}10^{6}$)	4.422 (3.474)
1990	–	1.386 (0.172)	–	1.878 (0.498)	197.825 (241.818)	2.381 (1.016)	102.664 (119.382)	2.924 (1.816)

TABLE 3 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	1.317 (0.081)	1.542 (0.123)	1.577 (0.186)	1.929 (0.262)	2.356 (0.565)	2.095 (0.425)	3.694 (1.499)	2.195 (0.593)
1988	1.514 (0.112)	1.492 (0.104)	2.143 (0.334)	1.834 (0.237)	3.337 (0.915)	2.196 (0.446)	6.039 (2.850)	2.307 (0.604)
1989	1.429 (0.098)	1.571 (0.119)	1.829 (0.240)	2.120 (0.307)	2.042 (0.392)	2.409 (0.490)	3.751 (1.416)	3.180 (1.008)
1990	1.413 (0.094)	1.635 (0.132)	1.855 (0.246)	2.140 (0.311)	2.492 (0.563)	2.501 (0.523)	3.004 (0.967)	2.193 (0.528)

Notes: 1. Based on New Earnings Survey micro-data.

TABLE 4

Kolmogorov-Smirnov Test of Estimated Distribution (P-Values) Log-Normal Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	-	0.000	-	0.000	0.000	0.000	0.000	0.000
1988	-	0.000	-	0.000	0.000	0.000	0.000	0.000
1989	-	0.000	-	0.000	0.000	0.000	0.000	0.000
1990	-	0.000	-	0.000	0.000	0.000	0.000	0.000
Males								
1987	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1988	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1989	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1990	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: 1. Based on New Earnings Survey micro-data.

TABLE 5

Maximum Likelihood Estimates of Employment Parameter ϕ, Assuming Singh-Maddala Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	1.199 (0.110)	–	1.293 (0.234)	0.801 (0.048)	1.392 (0.443)	$8.5x10^{5}$ ($6.3x10^{7}$)	1.336 (0.600)
1988	–	1.198 (0.106)	–	1.891 (0.571)	$4.0x10^{9}$ ($3.7x10^{10}$)	1.821 (0.793)	5858.339 (735.015)	1.662 (1.066)
1989	–	1.149 (0.081)	–	1.093 (0.137)	$2.3x10^{7}$ ($6.7x10^{9}$)	1.800 (0.895)	$2.7x10^{10}$ ($2.1x10^{10}$)	1.122 (0.442)
1990	–	1.142 (0.079)	–	1.476 (0.335)	23.404 (52.650)	1.806 (0.768)	4.355 (0.988)	2.314 (1.872)

TABLE 5 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	1.126 (0.045)	1.406 (0.130)	1.125 (0.097)	2.323 (0.637)	1.599 (0.464)	2.647 (1.135)	3.760 (2.974)	3.231 (2.211)
1988	1.124 (0.052)	1.448 (0.135)	1.263 (0.180)	2.196 (0.475)	2.482 (1.593)	3.596 (1.675)	50.985 (36.919)	3.957 (2.690)
1989	1.169 (0.057)	1.276 (0.109)	1.361 (0.172)	2.549 (0.859)	1.116 (0.174)	4.827 (3.667)	2.481 (1.710)	17.538 (8.574)
1990	1.151 (0.055)	1.566 (0.214)	1.342 (0.182)	4.767 (2.500)	1.887 (0.691)	9.715 (2.992)	2.145 (0.790)	8.553 (2.851)

Notes: 1. Based on New Earnings Survey micro-data.

TABLE 6

Kolmogorov-Smirnov Test of Estimated Distribution (P-Values) Singh-Maddala Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	-	0.815	-	0.744	0.275	0.851	0.000	0.576
1988	-	0.925	-	0.945	0.000	0.933	0.239	0.824
1989	-	0.978	-	0.924	0.000	0.991	0.000	0.616
1990	-	0.848	-	0.926	0.296	0.971	0.445	0.960
Males								
1987	0.604	0.599	0.547	0.924	0.642	0.998	0.986	0.992
1988	0.832	0.100	0.799	0.332	0.581	0.516	0.000	0.456
1989	0.912	0.491	0.453	0.741	0.608	0.696	0.999	0.986
1990	0.992	0.374	0.986	0.677	0.967	0.944	0.912	0.894

Notes: 1. Based on New Earnings Survey micro-data.

TABLE A1

Maximum Likelihood Estimates of Mean of Log-Normal Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	0.727 (0.008)	–	0.490 (0.035)	-4.648 (6.080)	0.115 (0.131)	-87.833 (1.1×10^5)	-0.222 (0.379)
1988	–	0.951 (0.003)	–	0.710 (0.017)	-5.879 (11.812)	0.672 (0.029)	-2.647 (1.677)	0.608 (0.053)
1989	–	0.986 (0.004)	–	0.819 (0.015)	-16.509 (323.535)	0.347 (0.097)	-6.506 (18.695)	0.352 (0.139)
1990	–	1.161 (0.002)	–	0.975 (0.011)	-1.779 (0.581)	0.836 (0.028)	-1.410 (0.459)	0.720 (0.060)

TABLE A1 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	1.174 (0.001)	1.112 (0.003)	1.043 (0.004)	0.932 (0.008)	0.763 (0.018)	0.868 (0.017)	0.457 (0.058)	0.832 (0.029)
1988	1.119 (0.003)	1.214 (0.002)	0.841 (0.011)	1.050 (0.007)	0.499 (0.041)	0.915 (0.017)	0.049 (0.143)	0.878 (0.027)
1989	1.253 (0.002)	1.237 (0.003)	1.057 (0.007)	0.991 (0.011)	0.973 (0.015)	0.888 (0.022)	0.526 (0.070)	0.674 (0.055)
1990	1.327 (0.002)	1.297 (0.003)	1.107 (0.008)	1.077 (0.011)	0.878 (0.025)	0.955 (0.022)	0.738 (0.050)	1.053 (0.026)

Notes: 1. Based on New Earnings Survey micro-data.

TABLE A2

Maximum Likelihood Estimates of Standard Deviation of Log-Normal Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	0.583 (0.036)	–	0.655 (0.062)	1.301 (0.268)	0.749 (0.094)	4.915 (9.042)	0.820 (0.138)
1988	–	0.534 (0.027)	–	0.616 (0.046)	1.456 (0.342)	0.627 (0.057)	1.103 (0.174)	0.643 (0.070)
1989	–	0.561 (0.028)	–	0.616 (0.045)	2.341 (1.165)	0.741 (0.084)	1.579 (0.422)	0.740 (0.097)
1990	–	0.510 (0.025)	–	0.576 (0.040)	1.047 (0.118)	0.617 (0.055)	0.992 (0.110)	0.648 (0.072)

TABLE A2 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	0.600 (0.019)	0.697 (0.025)	0.649 (0.027)	0.759 (0.034)	0.734 (0.044)	0.779 (0.045)	0.813 (0.065)	0.789 (0.054)
1988	0.700 (0.024)	0.684 (0.022)	0.792 (0.040)	0.741 (0.033)	0.886 (0.060)	0.781 (0.044)	0.990 (0.092)	0.792 (0.052)
1989	0.674 (0.023)	0.727 (0.026)	0.743 (0.033)	0.809 (0.039)	0.768 (0.043)	0.839 (0.048)	0.885 (0.072)	0.895 (0.066)
1990	0.681 (0.023)	0.731 (0.026)	0.759 (0.035)	0.803 (0.039)	0.826 (0.051)	0.837 (0.048)	0.863 (0.065)	0.812 (0.051)

Notes: 1. Based on New Earnings Survey micro-data.

TABLE A3

Maximum Likelihood Estimates of Parameter θ_1, Singh-Maddala Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	4.514 (1.004)	–	4.060 (1.203)	31.282 (9.943)	3.750 (1.462)	2.838 (2.900)	3.919 (1.884)
1988	–	3.908 (0.849)	–	2.222 (0.691)	0.160 (0.056)	2.301 (1.008)	0.469 (0.006)	2.511 (1.498)
1989	–	4.474 (0.858)	–	4.962 (1.460)	1.891 (3.881)	2.778 (1.347)	0.137 (0.002)	4.290 (2.298)
1990	–	4.262 (0.825)	–	2.903 (0.899)	1.334 (1.019)	2.401 (1.010)	2.452 (0.072)	2.015 (1.246)

TABLE A3 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	3.481 (0.406)	2.285 (0.365)	3.537 (0.664)	1.407 (0.376)	2.305 (0.747)	1.233 (0.416)	1.284 (0.610)	1.084 (0.496)
1988	3.690 (0.500)	2.113 (0.332)	3.034 (0.747)	1.394 (0.278)	1.561 (0.808)	1.015 (0.316)	0.418 (0.052)	0.956 (0.382)
1989	3.143 (0.393)	2.732 (0.500)	2.497 (0.480)	1.265 (0.355)	3.264 (0.880)	0.833 (0.375)	1.569 (0.780)	0.488 (0.055)
1990	3.236 (0.419)	1.963 (0.410)	2.538 (0.541)	0.784 (0.254)	1.798 (0.617)	0.566 (0.049)	1.630 (0.500)	7.586 (0.054)

Notes: 1. Based on New Earnings Survey micro-data.

TABLE A4

Maximum Likelihood Estimates of Parameter θ_2, Singh-Maddala Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	2.527 (0.125)	–	2.512 (0.138)	2.201 (0.033)	2.498 (0.170)	0.052 (1.035)	2.510 (0.224)
1988	–	2.880 (0.205)	–	3.289 (0.631)	1.3×10^5 (2620.85)	3.245 (0.722)	3.241 (0.043)	3.162 (0.566)
1989	–	3.022 (0.145)	–	3.006 (0.127)	0.014 (1.234)	2.949 (0.302)	4.3×10^6 (5.7×10^4)	3.097 (0.194)
1990	–	3.432 (0.202)	–	3.662 (0.444)	1.628 (0.300)	3.803 (0.728)	2.025 (0.201)	3.959 (1.275)

TABLE A4 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	3.489 (0.168)	4.032 (0.409)	3.461 (0.175)	5.618 (2.065)	3.648 (0.452)	6.648 (3.977)	4.605 (2.363)	8.211 (8.367)
1988	3.398 (0.133)	4.690 (0.599)	3.432 (0.180)	6.504 (1.932)	3.847 (1.144)	10.739 (9.757)	3021.393 (86.446)	12.622 (15.050)
1989	3.971 (0.205)	4.174 (0.319)	4.135 (0.331)	6.749 (2.786)	4.025 (0.213)	18.012 (34.805)	4.373 (1.148)	$3.6x10^4$ (7350.37)
1990	4.170 (0.209)	5.360 (0.889)	4.340 (0.361)	41.461 (88.992)	4.682 (0.853)	$1.1x10^4$ (2541.15)	4.833 (1.033)	4511.049 (331.091)

Notes: 1. Based on New Earnings Survey micro-data.

TABLE A5

Maximum Likelihood Estimates of Parameter θ_3, Singh-Maddala Wage Distribution

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	0.770 (0.229)	–	0.871 (0.326)	0.118 (0.038)	0.952 (0.454)	1.302 (1.332)	0.907 (0.509)
1988	–	0.929 (0.293)	–	2.001 (0.990)	138.995 (21.011)	1.902 (1.268)	14.361 (0.183)	1.685 (1.391)
1989	–	0.762 (0.199)	–	0.673 (0.248)	1.748 (3.576)	1.331 (0.829)	184.339 (2.398)	0.810 (0.512)
1990	–	0.863 (0.241)	–	1.432 (0.649)	3.113 (2.985)	1.846 (1.156)	1.555 (0.022)	2.338 (2.172)

TABLE A5 continued

Cut-off Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Males								
1987	0.899 (0.155)	1.402 (0.350)	0.877 (0.223)	2.974 (1.483)	1.516 (0.693)	3.756 (2.563)	3.431 (2.689)	4.790 (4.747)
1988	0.710 (0.129)	1.627 (0.432)	0.901 (0.285)	3.170 (1.213)	2.130 (1.604)	5.730 (4.422)	74.855 (12.517)	6.567 (6.308)
1989	0.911 (0.165)	1.013 (0.266)	1.227 (0.336)	3.237 (1.677)	0.878 (0.302)	7.891 (10.224)	2.219 (1.575)	277.313 (70.016)
1990	0.852 (0.157)	1.670 (0.574)	1.165 (0.349)	12.501 (16.182)	1.836 (0.910)	228.599 (33.284)	2.098 (0.979)	150.409 (30.574)

Notes: 1. Based on New Earnings Survey micro-data.

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