# Chapter 10

## Female earnings 1977-1990 and the wage gap

This chapter follows on from the previous one in providing some fixed-effects estimates of wages for female full-time workers. The estimation method is the same, and the conclusions drawn regarding cross-sections versus fixed-effects and on parametric stability still apply, so this chapter mainly presents the unrestricted fixed effects (TVFE) results. Again, these are the first panel estimates on female earnings from the NES[1]. After discussing these results the endogeneity of occupational choice is considered. The chapter ends with a discussion of the male-female earnings gap, which the TVFE specification allows us to trace and break down over time.

### 10.1 Econometric issues

The basic equation is once again the Mincerian human-capital model used in the previous chapter with identical regressors included[2]; that is, the TVFE model:

$$w_{it} = x_{it}\beta_t + \alpha_i + \lambda_t + u_{it} \qquad \textbf{(10.1)}$$

An important feature of these reduced forms concerns the relationship between $\mathbf{x}_{it}$ and $\mathbf{u}_{it}$. It is quite plausible that some of the elements of $\mathbf{x}_{it}$ are endogenous, and thus the assumption that $\mathrm{Cov}(\mathbf{x}_{it}\mathbf{u}_{it})=0$ is invalid. In the literature on female earnings, one of the more significant sources of endogeneity is occupational choice. It has been argued that women self-select into "women's jobs", and this crowding forces down earnings in those occupational groupings and so lowers relative female wages; thus the coefficients on occupation should not be seen as the result of a random allocation to an occupation (see Miller (1987)).

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[1] This chapter is based on Bell and Ritchie (1995b). An earlier paper, Bell and Ritchie (1993a), presented cross-section results.

[2] Two occupational categories were dropped (top management and mining) due to lack of observations.

There are two well-known methods of dealing with this problem. The first of these, the control function (or switching regression) approach, was popularised by Heckman (1979). It usually proceeds by augmenting the standard regression with a correction factor from a probabilistic model of the self-selection process. In the case of unionisation, for example, this may be a probit including as regressors those characteristics most likely to encourage individuals to join a union. The second approach is the instrumental variables method. This replaces those regressors which are correlated with the disturbances with instruments which are purged of such correlation. Thus, the unionisation dummy would be replaced by a fitted value from some auxiliary regression, which again models the factors influencing whether an individual will join a union or not.

As was discussed in section 9.1.3 in the context of the attrition variables, these two approaches are closely related to each other and to the proxy-variable method (Robinson(1989); Vella and Verbeek(1993); Lanot and Walker (1993a)). As before, separate probit models to take account of absence (and endogeneity) are not feasible, and the linear IV and proxy-variables approaches are used. In the case of female earnings, the AVs may be expected to capture some of the effects of 'home-time' on female earnings.

Wright and Ermisch (1991) argue that occupational variables should not be included in studies of female earnings as the crowding of women into occupations is a part of the 'discrimination' which such studies may hope to measure[3]. If occupational dummies are included then any results are conditioned on the choice of occupation and an important source of discrimination has therefore been side-stepped.

However, this approach means that a potentially significant explanatory variable has been left out. The omission of occupation implies that its defining characteristic is a way of categorising workers, with no inherent features that affect wages. However, "occupation"

[3] Blinder (1973) also left out these characteristics, but this was in an attempt to distinguish between "reduced" and "structural" forms rather than making any explicit claim for the endogeneity of the variables.

captures a number of job characteristics which are important in the determinant of wages; coefficient estimates thus reflect more than just the supply-side impacts of occupational crowding. Omission of occupational variables may therefore lead to inefficient and biased estimates. In addition, it can be argued that occupational choice is determined outside of the model under review, in which case conditioning on the occupational distribution of female workers is an appropriate response. Therefore, categorical variables for occupation are included in these estimates, although in section 10.4 the effect of leaving out these variables is considered.

## 10.2 Fixed-effects results

This section reviews the results from the TVFE model; subsection 10.2.10 discusses the effect of instrumenting the occupational dummies. The dependent variable is the natural logarithm of hourly earnings; the sample is all females in the NES employed full-time whose earnings are not affected by absence from work.

As before, to save space all results for all years are not presented here. Instead, table 10.1 at the end of the chapter shows results for the sample year 1984, the middle of the period. The variables are those listed in table A9.3 in the appendix to chapter nine; the default categories remain the same except for the two omitted occupations.

### 10.2.1Means and constants

Figure 10.1 gives the unrestricted constant terms and means of log earnings for males and females. The intercept for 1977 represents the mean of the whole regression[4]. Note that mean log earnings for males is around 25%-30% higher, and this gap does not noticeably fall over

[4] Only T-1 intercepts may be estimated to avoid perfect collinearity. These intercepts are therefore estimated as deviations around the mean of the regression with a constant intercept in t=1 of zero. The near-coincidence of the intercepts in this model is not a general result.

time[5]. However, this is conditional on the choice of representative individual.

### 10.2.2 Region

Figure 10.2a shows the fixed effects results for females, and figure 10.2b compares the coefficients in 1990 for males and females. The regional coefficients for females are rather larger than those for males although they show the same general pattern: females in the 'south' generally earn a significant premium over women in the 'north' with otherwise identical observed characteristics. Joshi (1986) argued that women's ability to search for paid work is much more constrained than men's options, due to family factors such as partner's income or children at school. The wider differentials for females may therefore be an indication of greater geographical immobility.

### 10.2.3 Industry

Figure 10.3 displays the coefficients by division and compares those for males and females in 1990. The effect of industry on female earnings appears relatively less stable over the period in question (compare figure 9.3a) although for males there is a noticeable fall in the earnings in farming and fishing over this time. Note that the remarkable improvement in the returns to banking, finance and insurance for males is much smaller for females. Overall, the implication of figure 10.3 is that, in 1990, inter-industry differentials are larger for males than for females. Moreover, these differentials appear to be fairly constant apart from the fluctuations in the reference category.

### 10.2.4 Occupation

Figure 10.4a shows occupational coefficients for female manual workers, and figure 10.4b

[5] Wright and Ermisch (1991), using the Women and Employment Survey, report a difference between average wages of 49% of the average female wage rate, which equates to 33% of the average male wage rate.

those for non-manual workers. The position of junior clerical workers has improved slightly in comparison with manual workers, but fallen sharply against other non-manual workers. This is much the same result as for males. Robinson (1994) places clerical work for females in the "middle-paid" sector of the economy, rather than the "low-paid" sector of male clerks, but, as for males, notes that this sector has been losing shares of employment to professional and managerial occupations. For females, this rise in the "professional classes" is particularly notable in the 1980s (Robinson (1994, table 12)). Again, the increase in women in professional and managerial positions, and the higher associated earnings, imply a significant demand effect[6].

Figure 10.5 compares coefficients in 1990 for both sexes. Non-manual occupational differentials are much the same for both sexes, but for females the returns to manual occupations vary much less than for males. However, even ignoring the endogeneity issue, interpretation of coefficients on occupation is problematic. As has been noted, occupation embodies a wide range of characteristics including flexibility in working time and the importance of employment experience. The fact that neither these characteristics nor the employment and family history of employees are directly observed may affect estimated coefficients and may bias the allocation of male-female differentials between explained and unexplained components. This issue is discussed further below.

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[6] Sloane and Theodossiou (1994) argue that a significant proportion of the improvements in female earnings since the mid-1970s has been due to increased demand for female labour. The evidence here suggests that this increased demand is concentrated in the "senior" occupations.

### 10.2.5Age

Figure 10.6 reproduces cross-sectional (rather than fixed-effects) age coefficients, for the reasons of collinearity discussed earlier in section 9.2.6. Figure 10.6b reproduces figure 9.6a for comparison. In general, the overall dataset profiles in figure 8.12 appear to be a good approximation for the estimated profiles, in that females have a lower and flatter age-earnings profile compared to males; however, the estimated coefficients do suggest that the relative wages for the young rise more quickly than the overall figures indicate.

These profiles raise three issues. First, there has been very little shift in the coefficients over time apart from some small variation at the far ends of the range where numbers of observations are small[7]. The profiles for females show marginally more variation over time.

Secondly, the variation in age effects on the earnings of full-time females is much smaller than that for full-time males. The female coefficients have a range of 0.6 while males vary by 0.9, and the difference is most marked in the steep age-earnings profile for young males. For males, the age variable is likely to be a reasonably proxy of years of experience in the labour market. For females, due to career interruptions, this is less likely to be true. Thus, one might expect the profile of age coefficients for females to be somewhat flatter than that for males.

Becker and Lindsay (1994) argue that the age-earnings profile for young females should be steeper than for young males in some firms, as expected interruptions in work patterns lead to females bearing more of the risk of firm-specific investment through lower starting wages. The evidence here seems to refute this, presumably because such schemes would be likely to fall foul of equal pay legislation[8].

[7] Bell and Ritchie (1993a) found a significant difference between the 1976 and 1990 cohorts for both sexes. In the light of Figure 10.6, this suggests that the earlier result is more probably due to the peculiar characteristics of the 1975/1976 data, when the dataset was being set up.

[8] If the amount of firm-specific investment varies between men and women, then there is a problem of

Third, female wage rates peak before those of males. Allowing for the implicit coefficient of zero on the default 31-35 age group, the age coefficients for full-time females reach a peak in the 26-35 range while those of males reach a maximum which is broadly constant over the age range 36-45 (although it should be noted that coefficients around the reference age tend to be insignificant). The overall profile in figure 8.12 reflects this difference in peak earnings fairly accurately. The earlier peak of female age coefficients is consistent with their accruing less labour market experience during their working life.

### 10.2.6Union coverage

Figure 10.7 displays coefficients and mean levels of coverage for both male and female full-timers. An interesting implication is that females derive more benefit than males from national collective agreements. For both sexes, there was a decline in the benefits from coverage during the late 1970s from around 3% of mean wages to around 1.5%; some recovery during the early 1980s, peaking in 1982 at 5% for females; and then a considerable reduction to less than 2% in the subsequent period.

These results are conditioned by the sector to which the individual belongs, and it is worth noting the contrast between the numbers of females covered by collective agreement in the public, as opposed to the private sector. In the government sectors, the proportion covered never falls below 80%[9]. In contrast, and recalling that the absence of information on local agreements will lead to a downward bias on coverage statistics, particularly for the private sector, the proportion of females covered in the private sector had fallen below 10% by 1990.

It may be noted that the cross-section estimates for females exceed the fixed-effects estimates.

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identifying the true effect from this result.

[9] For both the public sector as a whole and for government and public corporations separately; see Bell and Ritchie (1993a).

Thus allowing for individual differences depresses the union effect for females and raises it for males, in contrast to males (see section 9.2.7). The implication is that unions have an *equalising* effect on the wages of males of differing 'ability' (or whatever the unobserved heterogeneity represents) and a *discriminatory* effect on female earnings.

These estimates are much smaller then other studies which have mainly used cross-sectional data. For example, Nickell (1977) estimates a "union effect" of 20% using aggregated data; Yaron (1990) a 10% gap for manual workers in the 1983 General Household Survey; and Main and Reilly (1992) using the 1986 SCELI dataset find union gaps of around 15%. Jakubson (1991) finds that moving from a cross-section to a fixed-effects specification can have a large (15%) effect on union coefficients, but cross-section studies on this data indicate the union effect to be a fairly constant 4% higher for most years; thus the cross-section results are also lower than comparative estimates.

As for males, one possibility for the difference is that the equation used here has more detailed industry and occupational variables, both of which may be correlated with the level of union coverage. Further, Andrews and Bell (1995), using male data from the NES, found that the inclusion of local bargains increased cross-sectional estimates by around 8%. If this holds true for females, then these results are comparable with the other studies. One final reason for the difference may be that the TVFE model makes no explicit correction for the selection mechanism which Main and Reilly (1992), for example, found to be significant.

One important issue raised by figure 10.7 is that the estimated coefficient varies greatly over the period (all coefficients are significant at the 5% level), suggesting that the period of measurement is important to the interpretation (see also Meghir and Whitehouse (1987), Lanot and Walker (1993b)). For example, the TVFE models estimates that the union markup in 1982 is over three times that in 1979; the latter figure indicates that the markup is negligible, while the former indicates that it is at least as important an influence as sector.

### 10.2.7Wages Council coverage

The coefficients for Wages Councils (WCs) in figure 10.8 suggest that those who are covered by such arrangements should expect, ceteris paribus, to receive substantially lower wage rates. As for males, this is likely to indicate that those whose wages are determined by such arrangements have a very weak bargaining position in the labour market which is not fully offset by the effects of the WCs, rather than suggesting that these bodies directly reduce workers wages. Both sexes experience much the same effect, and the increasing disparity between those affected by WC agreements and other workers is consistent with the increasingly dispersion of wage rates over this period (see Bell (1995)).

### 10.2.8Sector

Figure 10.9 indicates how employees of both sexes in the private sector fared relative to the public sector during the period, ceteris paribus. There is a general upward trend in the coefficients for both males and females, and this evidence certainly supports the view that private sector workers improved their hourly wage rates relative to public sector workers during the 1980s. Nevertheless, even in 1990, most public sector workers' hourly wage rates were above those of otherwise similar workers in the private sector. Bell and Ritchie (1993a), using weekly wages in cross-section, note that this public sector premium largely arises amongst those working in government; for females in public corporations the premium is small and generally negative. As for males, the lack of "governmental" jobs in the private sector may mean that this premium is a misspecified occupational characteristic rather than a pure response to employment in the public sector; in addition, there may be some form of non-wage compensation in the private sector not picked up by the variables used here.

This finding carries over to weekly earnings, but less strongly. Higher levels of overtime, piecework and bonus payments in the private sector raise the private sector weekly wage by relatively more, although this is not usually by enough to eliminate the public sector premium.

It is noticeable that there is much greater variation between fixed-effects and cross-sectional estimates when weekly wages are used, suggesting that individual characteristics have a significant influence when deciding the amount of "effort" to put in.

Until the mid-1980s, the premium for employment in the public sector was larger for females but by the end of the period was much the same for both sexes. At least three interpretations can be put on this finding. First, higher wage rates in the public sector may reflect lower levels of discrimination against females than in the private sector. The decline in the public sector premium could then be due to the delayed impact of the equal pay legislation.

Second, the impact of coverage by collective agreement may vary by sector. At low levels of coverage, bargaining power is likely to be low and the consequent returns relatively small. The decline in the public sector premium may reflect the privatisation of large, highly-unionised public corporations (with, in some cases, private sector counterparts) throughout the 1980s. In the absence of interactive dummies, the sector coefficients may partly reflect differences in the effectiveness of collective bargaining.

Third, Sloane (1994) argues that the relative increase in women's wages throughout the period was largely due to demand pressure. In this view, the fall in the public sector premium is due to the rapid growth in private sector service industries providing (according to Robinson(1994)) well-paid jobs.

### 10.2.8Length of time in the job

Figure 10.10 calibrates the effect on wage rates of having spent less than 12 months in the present job. Until 1983, the disadvantage of a short tenure was broadly equivalent for both sexes but since then there has been a marked divergence. By 1990, the impact on female earnings of not having been in a specific job for twelve months is broadly neutral, while for males the discount persists. This perhaps suggests that females are increasingly participating in jobs where skill acquisition on the job is not particularly important; it may be that for females, human capital and experience is less closely tied to years of service. However, the coefficients are small (discounts of around 2% on the hourly wage) and this variable does not distinguish between acquiring and changing jobs, so only limited inferences can be drawn.

### 10.2.9Attrition variables

As for males, AVs are included to take account of absence from the panel. It may be expected that females, with their more variable participation rates and longer absences from the labour market, would experience different effects on wage rates from males (see, for example, Joshi(1986, pp225-227); Main(1989); Mincer and Ofek(1982)). It could also be argued that the women face a greater variety of work options than men (in that full-time work, part-time work, and home working all form a large part of the typical female employment history), and so the likelihood of selection bias is higher than for males (Ermisch and Wright (1993)).

However, the coefficients shown in figure 10.11 indicate little difference from those for males given in figure 9.11. The coefficient on YrsIn indicates that both men and women gained a premium for additional years in the panel. Clearly, this result is consistent with the view that this variable is a proxy for labour market experience, albeit rather an imperfect one. The declining coefficient reflects the increasing mean of the variable.

The coefficient on CurrStay is very small and rarely significant; as YrsIn is always large and significant, this seems to contradict Main (1989) who found that immediate employment history was a more important component of earnings than general employment experience. However, this finding must be treated with some suspicion. Firstly, observation in the panel cannot be directly related to employment, and CurrStay is more affected by errors in the construction of the panel than YrsIn. Secondly, these two variables are affected by the TVFE collinearity problem (section 9.2.6), which may be indicated by the fact the CurrStay is often insignificant. Cross-section estimates give higher values for CurrStay and lower ones for

YrsIn, although the latter still dominates. Thirdly, part-time and full-time observations were used for the AVs, and Main(1989) argues that it is the *type* of experience that matters.

### 10.2.10 Instrumental variable estimation

This section discusses an instrumental variable (IV) approach to the endogeneity issue. It was noted in the previous chapter that a case can be made for the endogeneity of any and all regressors, but here the focus is on the occupational groupings. The reason is twofold; firstly, the 'crowding' of females into certain occupations implies that the dummy coefficients do not necessarily represent the effect of being randomly assigned to an occupational grouping (P.W. Miller (1987))[10]. For example, C.F. Miller (1993) argues that to a significant degree occupational choice depends on initial career decisions and life cycle patterns of labour market participation, which may be influenced by earnings.

Secondly, an occupation can embody a number of unmeasured characteristics which influences the choice of job: flexibility on working hours, compensating differentials, social influences, and so on. Helwege (1992) notes that there is a strong correlation between occupation and industry; however, occupation (rather than industry) appears more likely to embody the particular characteristics which will lead to the selection of a position.

Following Bowden and Turkington (1984, Ch. 2), an admissible instrument to counter the endogeneity in occupational choice should be an exogenously determined probability of observation[11]. Assuming a vector of exogenous variables is available, one possibility is to use discriminant analysis to generate the probability that individual i will select occupation j. The probabilities are normalised to sum to one. A simpler alternative, the approach taken, is to

[10] Sloane and Theodossiou (1994, note 8) report that in 1982 4% of females work in 'female-only' occupations, whereas 22% of males work in 'male-only' posts. This result is reflected in the necessity to drop some occupations from the female regressions due to lack of observations.

[11] An alternative is to calculate binary variables, setting p=1 for the most likely occupational choice and p =0 for all other j. As the occupation data is already categorical, the probabilities must be used as instruments.

use the actual proportion of women in each occupation as a probability instrument. The proportion of women in each occupation is relatively stable over time, and so the proportions over the whole sixteen years of the NES was used.

Use of these instruments makes almost no difference to the estimates, a Wu-Hausman test failing to reject the null hypothesis of no endogeneity. One possible explanation is that the instruments are not statistically independent of the residual. As the Wu-Hausman test actually compares OLS and IV specifications rather than testing for endogeneity directly, the test is not appropriate where the instruments are still correlated with the error term. Given the nature of the instruments this seems unlikely.

It may be that individual heterogeneity manifests itself in a non-random choice of occupation; for example, it has been argued that occupational choice is significantly affected by educational and social choices made before entry into the labour market (see Dolton and Kidd(1994); Polacheck (1981); Vella (1994); and Elliott (1991, pp404-409) for a more general discussion). However, cross-sectional results, which cannot pick up individual heterogeneity, are also unaffected by the use of instruments.

These results seem to imply that the categorical variables for occupation are strictly exogenous; that is, the "crowding" of female occupations is due to factors not reflected in the Mincerian wage equation. For example, the significant influence of gender "attitudes" in occupational choice claimed by Vella (1994) may persist throughout an individual's working life. This still leaves open the question of whether wage variations in occupations are due to crowding or the differing characteristics of workers in different posts.

A number of authors have argued that inter-occupational differentials are less important in explaining wage differentials than intra-occupational differences[12]. This may explain why the

[12] For example, Dolton and Kidd(1994) use UK data; Harland and Sahellarion(1993) for Canada; Lucifora (1993) for Italy; Reilly (1991) on Irish data.

categorical dummies used to determine occupational intercepts appear to be exogenous. This could be tested by increasing the number of occupational groupings from eighteen (there are over four hundred in the NES); however, the results presented here are already much more detailed than the other studies, and the coefficients are highly significant. A further refinement of the categories is unlikely to change the result markedly.

## 10.3 Male-female differentials

In this section the method of Blinder (1973) and Oaxaca(1973) is used to study the differences between male and female earnings. Differences in the male-female hourly wage-rate can be decomposed into that which can be explained by systematic differences in identifiable characteristics and that which appears to result from differences in returns to the same characteristics. Specifically,

$$ln(\overline{w}_{mt}) - ln(\overline{w}_{ft}) = \overline{x}_{mt}\beta_{mt} - \overline{x}_{ft}\beta_{ft} = (\overline{x}_{mt} - \overline{x}_{ft})\beta_{mt} + \overline{x}_{ft}(\beta_{mt} - \beta_{ft}) \qquad \mathbf{(20.2)}$$

where $w_{ft}$, $w_{mt}$ are wages of females and males at time period t, respectively, $\mathbf{x_{ft}}$, $\mathbf{x_{mt}}$ are the mean values of the regressors for males and females respectively, and $\boldsymbol{\beta}_{\mathbf{ft}}$ and $\boldsymbol{\beta}_{\mathbf{mt}}$ are values of the female and male regression coefficients at time t respectively. The first term on the right-hand side of (10.1) is the contribution to the difference in average male and female characteristics of the mean wage differential, while the second term provides a measure of the difference in returns between the sexes[13]. Figure 10.12 plots these components. It shows the total earnings gap, the "explained" component (due to differences in characteristics) and the "unexplained" component (due to differences in returns).

The raw wage gap peaked at around 27% of mean male wage in 1979, but had fallen to 21% by 1990. However, while the "explained" component also fell, the "unexplained" component

[13] The Oaxaca decomposition suffers from the usual index number problem; Oaxaca and Ransom(1994) offer alternative formulations. However, in the present example, the differences between the various methods are minimal and so are not considered here.

rose until it exceeded the total gap. Note that the estimates of the "unexplained" component are comparable with those of Wright and Ermisch (1991) from the WES, although they omit industry and occupation from the set of explantory variables.

The implication of Figure 10.12 is that, after allowing for differences in the characteristics of employees (including individual heterogeneity as these are fixed-effect estimates) the expected earnings for females are higher than for males in 1990; that they are actually lower is entirely due to the lower value placed upon those characteristics in the labour market. However, it can be shown (Bell and Ritchie (1995c)) that this negative differential is largely due to the age coefficients, and so this result should be taken with some caution. On the other hand, the other explained components (apart from the AVs) are also declining over time, which would seem to indicate a general narrowing of the explained differentials between males and females.

Bell and Ritchie (1995c) discusses the TVFE and TVCS decompositions in more detail. Around two-thirds of the unexplained component is made up by the residual difference in the constant term. Of the rest, region has been a steady but significant contributor, but the major change has been in the large unexplained difference due to the different returns to industry. The industrial differential varies greatly, but appears to move cyclically with male employment prospects; from the early 1980s it contributes positively to the unexplained differential. It is interesting to note that cross-section studies (the TVCS model) allocate a significant part of the unexplained component to occupation and agreement, and almost none to industry; moreover, the explained component due to occupation has moved significantly in women's favour.

There are two important caveats when considering the decomposition results. First, it should be noted that omitted regressors (such as a direct valuation of experience or some measure of compensating differentials) may result in some of the differential being wrongly allocated to the unexplained, rather than the explained category. Second, the Oaxaca decomposition assumes that both sexes have the same responses to the variables used, but this is not necessarily the case, especially for "human" variables. For example, a dummy for 'married' may lead to a fundamentally different option set for males and females, and this appears to be reflected in the positive coefficients for males and negative ones for females typically found in empirical work. As most of the variables relate to job characteristics, it seems reasonable to assume that the response to measured variables is the same for both sexes in the absence of any unmeasured effects[14].

## 10.4 Regression *sans* occupation, *sans* industry

Wright and Ermisch (1991), and to some extent Blinder (1973), argued that occupational variables should be omitted from the regression as the occupational crowding should be interpreted as an element of discrimination in wage differentials, not an explanatory factor. For the reasons outlined in section 10.1, occupational dummies have been included in this regression, but here the results of leaving out these variables are discussed.

If occupation is omitted as a regressor, then industry also should be omitted, due to the close relationship between the two. The TVFE model was then run on the remaining variables in table 10.1.

The omission of industry and occupation has little effect on the age, tenure, or attrition variables. It does reduce the public sector premium, but this premium now appears to be increasing for women, from zero in 1977 to around 7% by 1990. It also has a significant effect on the regional coefficients, increasing them by around 20%-30%, which is to be expected given the regional differences in industrial structure.

The most notable difference is on the agreement coefficients. For males and females, omitting industrial and occupation variables increases the "union effect" by around 2% and 1%

[14] The Oaxaca decomposition has also been criticised for its reliance on mean differences rather than distributive effects (see Dolton and Makepeace (1985); Munroe (1988); and Jenkins (1994)). A number of papers have recently appeared using variations on the Lorenz curve methodology; for example, Deutsch, Fluckiger and Silber (1994); Jenkins(1994); and Sloane and Theodossiou (1994).

respectively in the late 1970s. However, this effect falls, and although the peak in 1982 is similar in both regressions, the decline in the union effects is larger and faster when no industrial/occupational dummies are used. This result may be due to the concentration of unions in declining industries, particularly manufacturing workers. The end result is that, by 1990, there appears to be a *discount* of 1%-2% for being covered by a collective agreement.

The effect on the Oaxaca decomposition is that the explained component of the differential is almost halved (see Bell and Ritchie (1995c)). The main increase in the unexplained component is found in the residual, due to differences in the constant terms, although there is some increase in the regional and sectoral components. Overall, these results would seem to support the view that industry and occupation are both significant explanatory variables and exogenous in the models estimated.

## 10.5 Conclusion

In this chapter the fixed-effects estimator has been applied to the female data in the NES, and the results compared with those of males obtained earlier. The impact of coverage by collective agreement on hourly wage rates for full-time females fell during the 1980s as did the premium for belonging to the public sector. Age coefficients suggested a much flatter earnings profile for females and that earnings were likely to rise more sharply for young males than for females. The TVFEIV estimator failed to show evidence of endogeneity in occupational choice, but the basic model suggested that occupational differences in wages are concentrated in the manual sector. There is some evidence that females have been moving up the occupational ladder.

A decomposition of the male-female differential suggested that, while the overall wage difference has fallen, this has been largely due to changes in the characteristics of females in the labour market - especially the younger age profile of women. The unexplained differential, which includes unmeasured effects and individual heterogeneity as well as 'discrimination', has been rising steadily since the late 1970s.

Finally, regression without occupation and industry dummies seemed to support the TVFEIV findings that the variables used here are exogenous. There is some effect on the regional and agreement coefficients, but the decomposition of the differential suggests that these variables are absorbed into the differences in the means.

**Table 10.1 Time-varying fixed-effect regression results (females, part: 1984)**

| Variable | | Mean | Coefficient | Error | T-value | T-prob |
|---|---|---|---|---|---|---|
| Constant | | 1.000 | -0.2096 | 0.033 | -6.354 | 0.000 |
| InLast | | 0.813 | 0.0101 | 0.003 | 3.303 | 0.001 |
| YrsIn | | 6.151 | 0.0304 | 0.001 | 35.341 | 0.000 |
| CurrStay | | 4.710 | -0.0022 | 0.001 | -4.250 | 0.000 |
| reg | 45 | 0.165 | -0.1269 | 0.004 | -36.324 | 0.000 |
| reg | 48 | 0.030 | -0.1752 | 0.007 | -25.638 | 0.000 |
| reg | 55 | 0.072 | -0.1845 | 0.005 | -36.513 | 0.000 |
| reg | 60 | 0.091 | -0.1777 | 0.005 | -35.063 | 0.000 |
| reg | 66 | 0.064 | -0.1793 | 0.005 | -33.430 | 0.000 |
| reg | 70 | 0.080 | -0.1844 | 0.005 | -35.712 | 0.000 |
| reg | 74 | 0.118 | -0.1666 | 0.005 | -35.151 | 0.000 |
| reg | 79 | 0.054 | -0.1920 | 0.006 | -30.681 | 0.000 |
| reg | 88 | 0.041 | -0.1855 | 0.007 | -27.118 | 0.000 |
| reg | 98 | 0.107 | -0.1731 | 0.005 | -31.831 | 0.000 |
| agt | 998 | 0.502 | 0.0371 | 0.003 | 14.032 | 0.000 |
| wbc | 248 | 0.109 | -0.0244 | 0.004 | -6.315 | 0.000 |
| j12 | 2 | 0.168 | -0.0210 | 0.003 | -7.808 | 0.000 |
| sector | 0 | 0.574 | -0.0205 | 0.004 | -4.636 | 0.000 |
| div | 1 | 0.018 | 0.1462 | 0.022 | 6.659 | 0.000 |
| div | 2 | 0.030 | 0.0770 | 0.021 | 3.606 | 0.000 |
| div | 3 | 0.083 | 0.0577 | 0.021 | 2.761 | 0.006 |
| div | 4 | 0.115 | 0.0521 | 0.021 | 2.497 | 0.013 |
| div | 5 | 0.011 | 0.0158 | 0.022 | 0.705 | 0.481 |
| div | 6 | 0.153 | 0.0161 | 0.021 | 0.775 | 0.438 |

| | | | | | | |
|---|---|---|---|---|---|---|
| div | 7 | 0.045 | 0.0892 | 0.021 | 4.203 | 0.000 |
| div | 8 | 0.140 | 0.0664 | 0.021 | 3.184 | 0.002 |
| div | 9 | 0.402 | 0.0248 | 0.021 | 1.188 | 0.235 |
| age | 16 | 0.008 | -0.1751 | 0.015 | -11.986 | 0.000 |
| age | 18 | 0.054 | -0.0675 | 0.009 | -7.498 | 0.000 |
| age | 20 | 0.091 | 0.0032 | 0.008 | 0.426 | 0.670 |
| age | 22 | 0.094 | -0.0023 | 0.007 | -0.352 | 0.725 |
| age | 24 | 0.082 | -0.0120 | 0.006 | -1.977 | 0.048 |
| age | 26 | 0.067 | -0.0218 | 0.006 | -3.862 | 0.000 |
| age | 30 | 0.090 | -0.0071 | 0.005 | -1.499 | 0.134 |
| age | 40 | 0.094 | -0.0113 | 0.005 | -2.477 | 0.013 |
| age | 45 | 0.091 | -0.0010 | 0.005 | -0.187 | 0.852 |
| age | 50 | 0.092 | 0.0030 | 0.006 | 0.516 | 0.606 |
| age | 55 | 0.085 | -0.0043 | 0.007 | -0.662 | 0.508 |
| age | 60 | 0.055 | -0.0076 | 0.008 | -1.014 | 0.311 |
| age | 120 | 0.013 | -0.0180 | 0.011 | -1.686 | 0.092 |
| kos | 122 | 0.032 | 0.0966 | 0.005 | 18.514 | 0.000 |
| kos | 147 | 0.178 | 0.0718 | 0.004 | 19.792 | 0.000 |
| kos | 156 | 0.007 | 0.1014 | 0.012 | 8.681 | 0.000 |
| kos | 189 | 0.015 | 0.0949 | 0.008 | 11.969 | 0.000 |
| kos | 211 | 0.023 | 0.1015 | 0.006 | 16.300 | 0.000 |
| kos | 246 | 0.060 | 0.0088 | 0.005 | 1.817 | 0.069 |
| kos | 254 | 0.004 | 0.2853 | 0.015 | 19.141 | 0.000 |
| kos | 281 | 0.090 | -0.0507 | 0.004 | -12.643 | 0.000 |
| kos | 295 | 0.002 | -0.0085 | 0.024 | -0.348 | 0.728 |
| kos | 327 | 0.015 | 0.0028 | 0.008 | 0.336 | 0.737 |
| kos | 385 | 0.043 | -0.0108 | 0.006 | -1.853 | 0.064 |
| kos | 462 | 0.015 | 0.0251 | 0.008 | 3.031 | 0.002 |
| kos | 477 | 0.054 | 0.0271 | 0.005 | 5.423 | 0.000 |
| kos | 533 | 0.008 | -0.0068 | 0.011 | -0.648 | 0.517 |
| kos | 540 | 0.003 | 0.0171 | 0.019 | 0.911 | 0.362 |