Measuring Earnings Inequality in Full-Time Earnings: An Australian Example

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Over the last three decades, Australia and many other industrialised nations have seen increasing inequality of earnings. For the US and a number of other countries, the prevailing explanation for the increase in inequality centres on the notion of skill-biased technological change (SBTC). This paper investigates the increase in inequalities in full-time earnings in Australia and its likely causes. Section 1 introduces the topic, section 2 details the data used and discusses data limitations. Section 3 examines changes in occupational earnings using Australian occupational data. Section 4 calculates the return to skill and knowledge for two separate periods. The final section presents the conclusions.

JEL Codes: J31 and J38

1 Introduction

In this paper, I investigate whether there is any evidence of skill-bias in the generation of increasing earnings inequality across occupations. The analysis that follows takes a different approach to that found in the literature. I analyse increasing inequality in full-time earnings in terms of occupations rather than individual earnings. Thus, the first objective of this chapter is to measure the increased earnings variability across occupations between the periods of 1989-1995 and 1997-2002, using occupational data from the ABS's Employee Earnings, Benefits and Trade Union Membership (EEBTUM) (6310.0)[i]. There are two reasons for choosing these two periods for the analysis. Firstly, it is important to find out whether changes in earnings inequality in terms of occupations have been consistent over the last decade and a half. The second is to find out whether changes in occupational inequality have been consistent across different occupational distributions (i.e. ASCO 1st edition and ASCO 2nd edition). To do this, I measure the level and change over these two periods in occupational earnings inequality.

The second objective of this chapter is to examine evidence of a role of skill-bias in the generation of earnings inequality. The approach taken is that of

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Borland and Wilkins (1996) and Pappas (2001). This involves two stages. The first uses the O*NET data on skill and knowledge measures of occupations to estimate the relationship between the log of weekly earnings and the O*NET measures of skill and knowledge. The second uses the results to decompose growth in occupational earnings inequality between changes in the distribution of and return to skill and knowledge, and other unobserved factors.

2 Data Issues

As discussed in the literature review, studies over the last three decades have arrived at similar conclusions, namely, that inequality of earnings has been increasing in Australia. Three main sources of data have been used. Information on employees is obtained from two surveys, namely, the Labour Force Survey (LFS) and the Survey of Employee Earnings and Hours (SEEH), while a measure of individual earnings inequality can be derived from the Survey of Income and Housing Costs (SIHC)[ii]. Borland and Wilkins (1996) used the LFS to describe changes in earnings inequality in the 1970s and 1990s, while King et al. (1992), Gregory (1993) and McGuire (1994) have used the SEEH survey. More recently, Borland and Kennedy (1998) and Pappas (2001) used the IDS survey to measure individual earnings inequality over time.

The approach taken here is to examine earnings inequality across occupations rather than individuals. The reason for this is the difficulty of doing unit record data type analysis in Australia using detailed occupational data on individuals. If a full unit record database were available (such as the March files from the US Current Population Survey), with earnings, detailed occupation and other variables for each individual, then it would be possible to approach earnings inequality across individuals through occupations. These data would make it possible to decompose the increase in inequality into that due to changes in employment across occupations, changes in average earnings across occupations, and a residual, which is change in inequality within groups (that is, the component that cannot be explained through an occupational analysis). The justification for using occupations in my analysis rather than individuals is not only constrained by data limitations, but also follows research conducted by Sheehan, Dunlop and Yu (2004) who use the US Current Population Survey. Their research shows that inequality of earnings across occupations is quite significant in the US.

To investigate changes in the dispersions of earnings across occupations, I use the results of the ABS's EEBTUM survey (ABS cat. no. 6310.0) for the periods 1989-1995 and 1997-2002. This source provides information by detailed occupation, numbers employed, mean hours worked and mean weekly earnings of non-managerial employees. Two major problems arise with this data source. The first is that earnings concordances across the two occupation classifications cannot be constructed with any degree of accuracy for the two periods in question. For this reason, occupations for male and female employees are analysed using two separate periods, namely, 1989-1995, which corresponds to ASCO 1st edition, and 1997-2002, which corresponds to ASCO 2nd edition. The second problem relates to missing occupations, which as advised by the ABS are due to unacceptably high sampling errors. Hence, for

the 1989-1995 period 161 female and 263 male occupations are used in the analysis out of a total of 282 occupations. For females the 161 occupations account for 91 per cent of the total full-time employed population for 1989-1995, while for males the 263 occupations account for 94 per cent of total full-time employment for 1989-1995. For ASCO 2nd edition, 195 occupations for females and 294 occupations for males are used in the analysis out of a total of 340 occupations. This accounts for 93 per cent of the total of full-time employed women and 96 per cent of the total of full-time employed men for 1997-2002. For the analysis of distributional changes over time, real earnings are calculated by deflating nominal earnings by using the Consumer Price Index (CPI).

3 Measuring Earnings Inequality Across Occupations

The objective of this section is to measure changes in the distribution of earnings across occupations using the results of the EEBTUM survey for males and females for the 1989-1995[iii] and 1997-2002 periods. To do this I use the variance, the Gini coefficient, the mean log deviation, and half the coefficient of variation. The last two measures belong to the family of generalised entropy inequality measures. The mean log deviation is sensitive to changes at the lower end of the distribution, while half the coefficient of variation is responsive to changes in the upper end of the distribution. The Gini coefficient, for its part, is sensitive to changes in inequality around the median. Thus, these measures of inequality may not rank the same distribution in the same way. By computing these four measures, even if the level and percentage changes differ, if all indices are changing in the same direction, it is possible to draw conclusions about increasing or decreasing earnings inequality (Johnson and Shipp, 1995). The inequality measures and changes in the log of earnings are reported in Tables 1 and 2.

The pattern of increasing inequality in the distribution of occupational earnings over the two periods for men and women can also be seen by examination of changes in the summary inequality statistics detailed in Tables 1 and 2. For male and female occupations, each of the summary measures of earnings inequality (i.e. the Gini coefficient, the mean log deviation, half the squared coefficient of variation and the variance) show that earnings inequality increased in the two periods. In terms of the difference in the log weekly earnings of occupations, between 1989 and 1995, males experienced rises in inequality in each of the log weekly earnings with the exception of the 75th and 25th decile differences. Between 1997 and 2002, the dispersion of earnings in occupations for men increased between the top and the bottom of the distribution, but declined in the 75th and 25th decile differences and the 50th and 25th decile differences.

Table 1: Summary statistics of the distribution of log weekly earnings of full-time non-managerial male occupations, 1989-2002

Males	*1989*	*1995*	*1997*	*2002*	*1989-1995*	*1997-2002*
		Percentile ratio			*Change in percentile ratio*	
90-10	0.577	0.679	0.740	0.816	0.102	0.076
90-50	0.353	0.410	0.464	0.482	0.057	0.018
50-10	0.224	0.268	0.276	0.334	0.044	0.058
75-25	0.342	0.382	0.453	0.452	0.040	-0.001
75-50	0.170	0.169	0.267	0.277	-0.001	0.010
50-25	0.172	0.213	0.186	0.174	0.041	-0.012
Inequality Measures						
Gini	0.097	0.107	0.119	0.129	0.010	0.010
MLD	0.040	0.051	0.053	0.056	0.011	0.003
Half squared coefficient of variation	0.040	0.061	0.072	0.078	0.021	0.006
Variance	0.076	0.097	0.111	0.119	0.021	0.008

Source: Employee Earnings, Benefits and Trade Union Membership, Australia – August 1989, 1995, 1997 and 2002. Using Consumer Price Index, base 2002 = 100. Note: '90-10' is the difference in log weekly earnings of occupations at the 90th and 10th percentiles of the distribution of earnings. Other measures of earnings inequality are defined in the same way.

Table 2: Summary statistics of the distribution of log weekly earnings of full-time non-managerial female occupations, 1989-2002

Females	*1989*	*1995*	*1997*	*2002*	*1989-1995*	*1997-2002*
		Percentile ratio			*Change in percentile ratio*	
90-10	0.562	0.643	0.659	0.696	0.082	0.037
90-50	0.312	0.309	0.381	0.388	-0.002	0.007
50-10	0.250	0.334	0.278	0.308	0.084	0.030
75-25	0.316	0.383	0.387	0.450	0.067	0.063
75-50	0.122	0.176	0.266	0.261	0.054	-0.005
50-25	0.194	0.207	0.121	0.189	0.013	0.068
Inequality measures						
Gini coefficient	0.088	0.093	0.110	0.117	0.006	0.007
MLD	0.039	0.044	0.051	0.054	0.005	0.003
1/2 squared coefficient of variation	0.039	0.044	0.054	0.061	0.005	0.007
Variance	0.080	0.088	0.088	0.104	0.008	0.016

Source: Employee Earnings, Benefits and Trade Union Membership, Australia – August 1989, 1995, 1997 and 2002. Using Consumer Price Index, base 2002 = 100. Note: '90-10' is the difference in log weekly earnings of occupations at the 90th and 10th percentiles of the distribution of earnings. Other measures of earnings inequality are defined in the same way.

Females experienced similar trends to males in terms of differences in log weekly earnings of occupational changes. Between 1989 and 1995, the 90th

and 50th decile differences experienced declines, while for the 1997-2002 period, the 75th and 50th decile difference experienced a decline in earnings inequality. Although the above analysis has concentrated on understanding the earnings distribution in occupations for men and women, the results confirm the findings of other researchers (e.g. Borland and Wilkins, 1996; Norris and Mclean 1999; Borland et al., 2001; Keating, 2003) that earnings inequality in Australia has been increasing.

4 The Role of Skill and Knowledge in Earnings Inequality

The previous section provided evidence that earnings inequality in Australia has been increasing across male and female occupations over the 1989-1995 and 1997-2002 periods. The aim of this exploratory study is to identify what role our intensity measures play in these changes through the analysis of residuals from earnings regressions. This method was used by Borland and Wilkins (1996) to explain changes in individual log earnings using education and experience to proxy skill. Pappas (2001) used a different approach in which he sought to explain the change in occupational log earnings using cognitive, interactive and motor skill variables derived from the Dictionary of Occupational Titles, US Department of Labor (1991). This analysis, on the other hand, uses the O*NET data on worker requirement measures to analyse the change in occupational earnings. The independent variables used are knowledge, and skill intensity scores, which are obtained using measures of skill and knowledge intensities. The concept of a knowledge or skill intensity of Australian occupations entails the notion that an occupation is knowledge or skill or intensive because it involves the whole of the set of descriptors for each of the O*NET measures. To create such a measure for a given occupation, we calculate the knowledge and skill intensity scores separately, using all the O*NET indicators. To illustrate this, we calculate the Skill intensity score (SK_{ALL}) for a given occupation as follows using O*NET skill data:

- identify the skill score for each indicator (I_{SK_i}), by importance (0-100 scale);

- identify the work activity score for each indicator (L_{SK_i}), by level (0-100 scale);

- calculate the average of the sums of the cross-products of the importance and level scores for each skill descriptor, and use the result as a measure of the skill intensity of an occupation. This figure is divided by 100 to reduce the scale of the measure.

Symbolically, the above is determined by the equation below:

$$SK_{ALL} = \sum_{i=1}^{n} \frac{I_{SK_i} * L_{SK_i}}{n} \qquad \text{(n=46)} \qquad \text{(i)}$$

This measure (expressed in i) of skill intensity is the average of the cross-product of the 'level' and 'importance' required for the different skills of an occupation. This provides a measure which assists us in comparing the relative

skill intensity of different occupations across full-time employment for men and women. This exact procedure is applied to each of our knowledge measures. The dependent variable is the log of weekly earnings.

5 Method

The method used here follows to some extent the approaches taken by Borland and Wilkins (1996) and Pappas (2001). The approach is simpler than that taken by Borland and Wilkins and that taken in a number of US studies (e.g. Katz and Autor, 1999). It does not attempt to estimate the impact of the O*NET measures of skill and knowledge after correcting for other individual factors such as years of education and experience, gender and race. The data used in this study are solely based on occupations and are used to estimate the relationship between the log of earnings and the O*NET measures of skill and knowledge, but it is not possible to correct for other factors influencing individual earnings.

The first step is to regress the log of weekly occupational earnings on the skill and knowledge O*NET variables. Separate regressions are conducted for males and females for 1989 and 1995, and for 1997 and 2002. The second step is to recover the regression residuals, and measures of dispersion in the regression residuals are made up in the same way as for weekly earnings reported in Section 10.3. Thus, changes in the dispersion of regression residuals between 1989 and 1995 and between 1997 and 2002 represent the return on earnings dispersion of changes in the distribution of and return to unobserved factors. Calculating the difference between the changes in the dispersion of log weekly earnings and changes in the dispersion of the regression residuals provides a measure of the net effect on earnings dispersion of changes in the distribution of and return to skill and knowledge.

To conduct the analysis of residuals from an earnings regression, the following earnings equation was utilised:

$$\mathbf{O_{it} = X_i \beta_{it} + \varepsilon_{it}} \qquad \text{(ii)}$$

where O_{it}: is a vector of the log of weekly earnings of occupation i in period t; X_i is a vector of skill and knowledge characteristics of occupation i which do not change over time; and ε_{it} is the residual.

6 Results

Separate regressions of log real hourly occupational earnings on our intensity measures were carried out and the corresponding results are reported in Table 3. The table shows the coefficient estimate, standard error, degrees of freedom, F-statistic, adjusted R squared, and estimate coefficients for skill and knowledge.

Table 3: Skill and knowledge regression results, 1989-2002

Males						
Dependent variable	*Constant*	*Skill*	*Knowledge*	*Degrees of freedom*	*Adjusted R squared*	*F-Statistic*
1989						
Ln (WE)	6.393	0.002	0.004	260	0.340	66.486
	(0.025)	(0.0004)	(0.0014)			
1995						
Ln (WE)	6.391	0.002	0.004	260	0.318	62.001
	(0.029)	(0.0004)	(0.0016)			
1997						
Ln (WE)	6.421	0.001	0.007	291	0.304	59.514
	(0.031)	(0.0005)	(0.002)			
2002						
Ln (WE)	6.442	0.003	0.007	291	0.413	103.906
	(0.026)	(0.001)	(0.001)			
Females						
Dependent variable	*Constant*	*Skill*	*Knowledge*	*Degrees of freedom*	*Adjusted R squared*	*F-Statistic*
1989						
Ln (WE)	6.161	0.001	0.008	158	0.319	39.411
	(0.004)	(0.0006)	(0.002)			
1995						
Ln (WE)	6.184	0.002	0.006	158	0.421	59.057
	(0.034)	(0.0005)	(0.0005)			
1997						
Ln (WE)	6.155	0.002	0.008	192	0.365	55.012
	(0.038)	(0.00050	(0.002)			
2002						
Ln (WE)	6.237	0.002	0.007	192	0.488	93.356
	(0.0034)	(0.0004)	(0.002)			

Source: Employee Earnings, Benefits and Trade Union Membership, Australia – August 1989, 1995, 1997 and 2002. Using Consumer Price Index, base 2002 = 100. Numbers in brackets denote standard errors.

In all the regressions, multicollinearity was not strong enough to make any corrections, and statistical tests for heteroscedasticity (Breusch-Pagan) failed to reject the null hypothesis – H_0: $\rho_i = \rho_k$. The diagnostic results detailed in the above regressions reveal the following findings. First, the adjusted R squared figures of between 0.304 and 0.488 for all the regressions in both periods indicate that skill and knowledge explain a good deal of the variation in log earnings across occupations for males and females. Second, both skill and knowledge have a significant positive influence upon log earnings for male and female employees. The final step in our analysis is to use the effect of change in the distribution of and return to skill and knowledge upon the change in the dispersion of log real weekly occupational earnings for 1989-1995 and 1997-2002. The results are detailed in Tables 4 and 5 for the 1989-1995 and 1997-2002 periods, respectively.

Table 4: Change in percentile differences in log real weekly earnings between 1989 and 1995, attributed to skill and knowledge and other factors

Percentile	*Log Earnings*	*Residuals*	*Effect of change in the distribution of and return to skill and knowledge*
Males			
90-10	0.102	0.045	0.056
90-50	0.058	0.174	-0.116
50-10	0.044	-0.129	0.173
75-25	0.040	-0.044	0.084
75-50	-0.001	-0.012	0.011
50-25	0.040	0.100	0.140
Variance	0.021	0.016	0.005
Females			
90-10	0.082	-0.031	0.112
90-50	-0.002	-0.045	0.043
50-10	0.084	0.015	0.069
75-25	0.067	-0.134	0.201
75-50	0.054	-0.183	0.237
50-25	0.013	0.015	-0.002
Variance	0.008	-0.018	0.026

Source: Author's calculations.

For the 1989-1995 period, Table 4 shows that changes in the distribution of and return to skill and knowledge are responsible for the increase in inequality (the only exception being the $75^{th}/50^{th}$ percentile, where inequality declined by a small amount). This is evidenced by the increase in the $90^{th}/10^{th}$ percentile difference in log earnings between 1989 and 1995 of 0.102 being largely attributed (55 per cent explained) to changes in the distribution of and return to skill and knowledge.

The increase in the $75^{th}/25^{th}$ percentile difference in log earnings is more than explained by the changes in the distribution of and return to skill and knowledge, while the increase in the $90^{th}/50^{th}$ percentile difference in log occupational earnings of 0.058 is also attributed to factors other than skill and knowledge measures. Similarly, one quarter of the increase in the variance of log weekly earnings is explained by changes in the return to observable skill and knowledge. This suggests that much of the increase in the dispersion of earnings in occupations for men between 1989 and 1995 in the top of the distribution is due to changes in the distribution of and returns to our skill and knowledge measures. For females, observed factors more than explain the increase in earnings inequality at the $90^{th}/10^{th}$ percentile of the earnings distribution. Similarly, at the $75^{th}/50^{th}$ percentile, observed factors explain one-third of the increase in earnings inequality, the $50^{th}/10^{th}$ percentile explained 82 per cent of the variation, while for the lower half of the distribution, the observed factors of skill and knowledge were responsible for most of the increase in earnings inequality. In contrast to males, the increase in the variance of log weekly earnings more than explains changes in the return to observable skill

and knowledge, also indicating that much of the increase in female occupational earnings inequality in the top of the distribution for the period is due to changes in the distribution of and returns to our skill and knowledge measures. These findings are unlike those reported by Borland and Wilkins (1996) and Borland and Kennedy (1998) who attributed most of the increase in inequality in full-time individual earnings to unobservable factors.

Table 5 shows that most of the increase in the dispersion of earnings for men at the top of the distribution can be explained by changes in the distribution of and return to skill and knowledge. For example, at the $90^{th}/10^{th}$ percentile one-third of the increase in earnings inequality can be explained by our skill and knowledge measures. The increase at the $90^{th}/50^{th}$ percentile is explained by unobservable factors. In contrast, the $75^{th}/25^{th}$ percentile for males experienced a slight decrease in earnings inequality, which is totally explained by our observed factors. Finally, the increase in the variance of log weekly earnings more than explains changes in the return to observable skills and knowledge, also indicating that much of the increase in male occupational earnings inequality in the distribution of earnings is due to changes in the distribution of and returns to our skill and knowledge measures.

Table 5: Change in percentile differences in log real weekly earnings between 1997 and 2002, attributed to skill and knowledge and other factors

Percentile	*Log Earnings*	*Residuals*	*Effect of change in the distribution of and return to skill and knowledge*
Males			
90-10	0.076	0.051	0.025
90-50	0.018	0.102	-0.084
50-10	0.058	-0.051	0.109
75-25	-0.001	-0.071	0.069
75-50	0.010	0.038	-0.027
50-25	-0.012	-0.108	0.097
Variance	0.007	-0.015	0.016
Females			
90-10	0.037	0.013	0.024
90-50	0.007	-0.137	0.144
50-10	0.030	0.149	-0.119
75-25	0.063	-0.269	0.332
75-50	-0.005	-0.204	0.199
50-25	0.068	-0.065	0.133
Variance	0.016	-0.012	0.028

Source: Author's calculations.

The results for females in the 1997-2002 period show that changes in the distribution of and return to skill and knowledge are responsible for the large increase in earnings inequality in the top half of the occupational earnings

distribution. Evidence for this can be seen at the $90^{th}/10^{th}$ percentile where 64 per cent of the increase is explained by our observable factors. Similarly, the increase in inequality at the $90^{th}/50^{th}$ and $75^{th}/25^{th}$ percentiles more than explains changes in the return to observable skills and knowledge. These findings show that much of the increase in male and female occupational earnings inequality in the top of the distribution is due to changes in the distribution of and returns to our skill and knowledges measures. As with the 1989-1995 period, these findings are not consistent with those reported by Borland and Wilkins (1996) and Borland and Kennedy (1998).

7 Conclusion

The analysis found that earnings inequality for males and females across occupations had increased overall in both periods, irrespective of the inequality measures used. Earnings inequality grew stronger for males and females in the top of the occupational distribution between 1989 and 1995 but grew at a slower pace between 1997 and 2002. The difference in inequality growth could be explained by the fact that between 1989 and 1995 the Australian economy was recovering from a relatively strong recessionary period, whereas between 1997 and 2002, there was a period of steady economic growth.

The paper also sought to explain the causes of earnings inequality using measures of skill and knowledge derived from the O*NET. To do this, log occupational earnings are regressed on skill and knowledge characteristics of occupations for the 1989-1995 and 1997-2002 periods for males and females. The analysis found that differences in skill and knowledge explained a good deal of the variation in earnings across occupations for men and women across the two periods.

These findings provide some evidence, using average earnings across occupations rather than individual earnings that support the skill-bias hypothesis for full-time work in Australia. They contrast with those of Borland and Wilkins (1996) who found that 'between 1982 and 1990 changes in the distribution of and return to unobservable skill characteristics have increased earnings dispersion' (p. 22). Similarly, Borland and Kennedy (1998) using a different technique found that changes in unobservable factors explained most of the growth in male earnings inequality between the 1980s and mid-1990s.

8 References

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[i] Prior to 1998 this survey was known as the Weekly Earnings of Employees (Distribution) Australia, (ABS cat no. 6310.0).

[ii] Prior to 1994-1995 this survey was known as the Income Distribution Survey (IDS).

[iii] Comparisons between 1989 and 1995 may be affected by the business cycle. In August 1989 the economy was travelling towards the peak of 1990, whereas in 1995 Australia was at the recovery phase of the recession of 1991-1993.