Journal of Industrial Relations

Wage inequality and neoliberalism: the Australian experience

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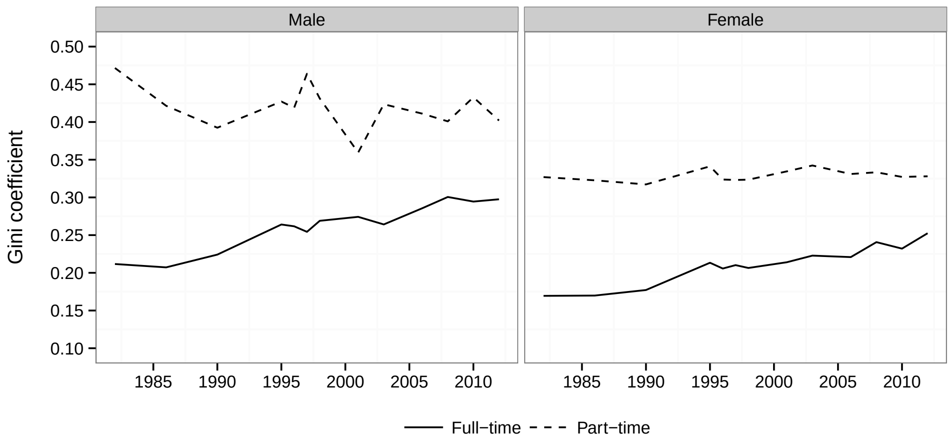
Online appendix

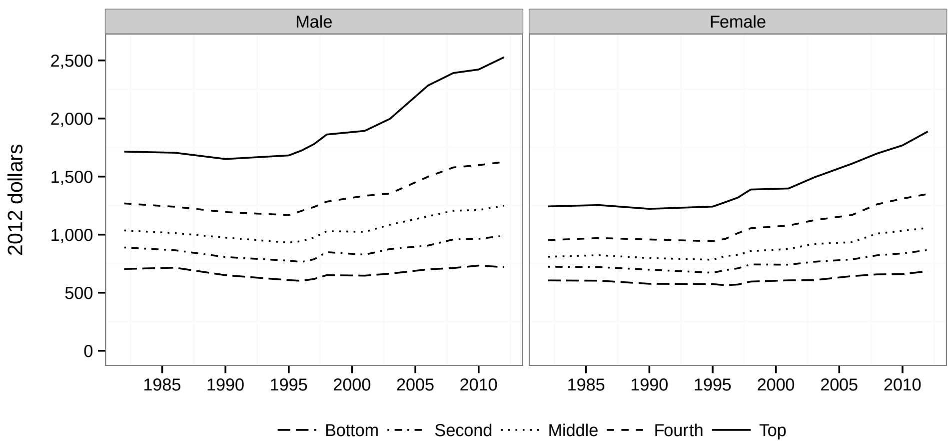
Figures referred to in the text

Figure 1. *Gini coefficients*



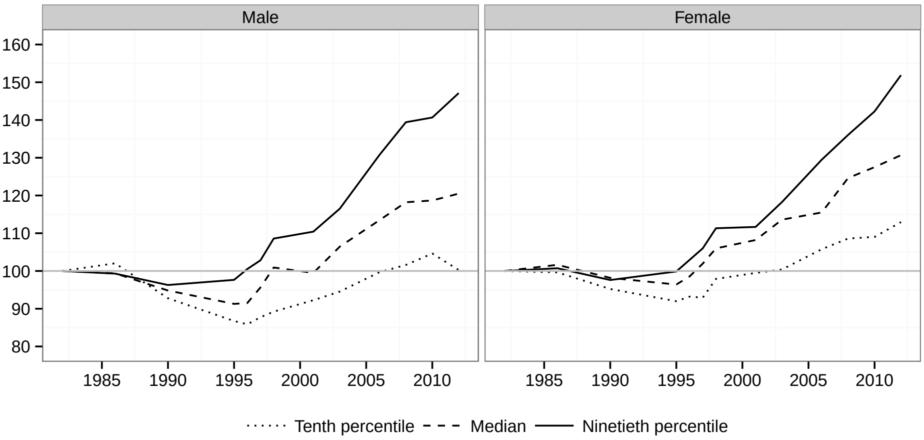
Note: The Gini coefficient for weekly wages for full-time adult employees (solid line) and for the hourly rate of pay for part-time adult employees (dashed line). *Source:* Based on data from ABS IDS 1982 to 2012.

Figure 2. *Quintile average wages*



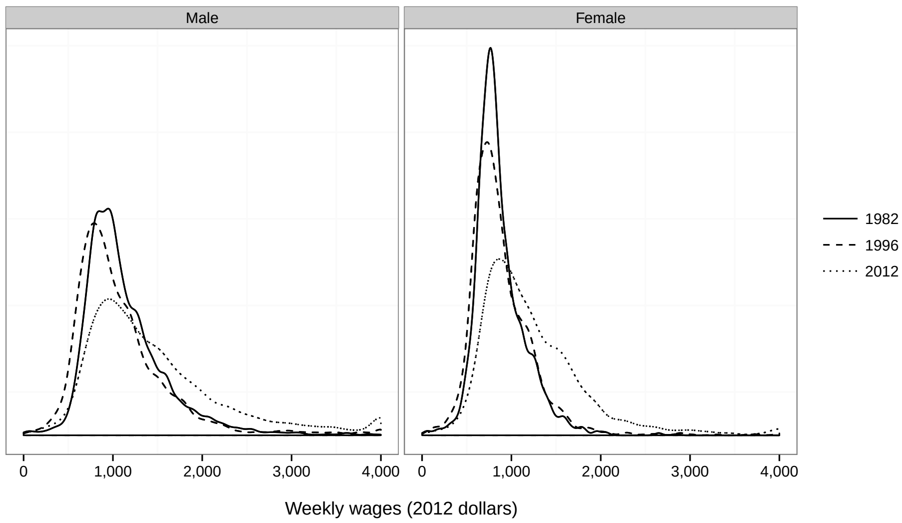
Note: Average wages in each quintile of the wages distribution. Weekly wages for full-time adult employees (in 2012 dollars) with average based on the median within each quintile. *Source:* Based on data from ABS IDS 1982 to 2012.

Figure 3. *Real wages and inequality*



Note: Weekly wages for full-time adult employees. Note that wages are adjusted by the CPI and then indexed to a common starting point of 100 for 1982. *Source:* Based on data from ABS IDS 1982 to 2012.

Figure 4. *Distribution of real weekly wages 1982, 1996 and 2012*



Note: Kernel density graphs for the weekly wages of full-time employees for 1982 (solid), 1996 (dotted) and 2012 (dashed). Wages are truncated at $4000 per week for readability (and have no effect on the remainder of the distribution). The data are converted to constant dollars using the CPI, with 2012 as the base year. Note that the y-axis scale for both males and females is the same, thereby allowing direct comparison. *Source:* Based on data from ABS IDS 1982, 1996 and 2012.

Figure 5. *Male quantile regression coefficents, 1982, 1996 and 2012*

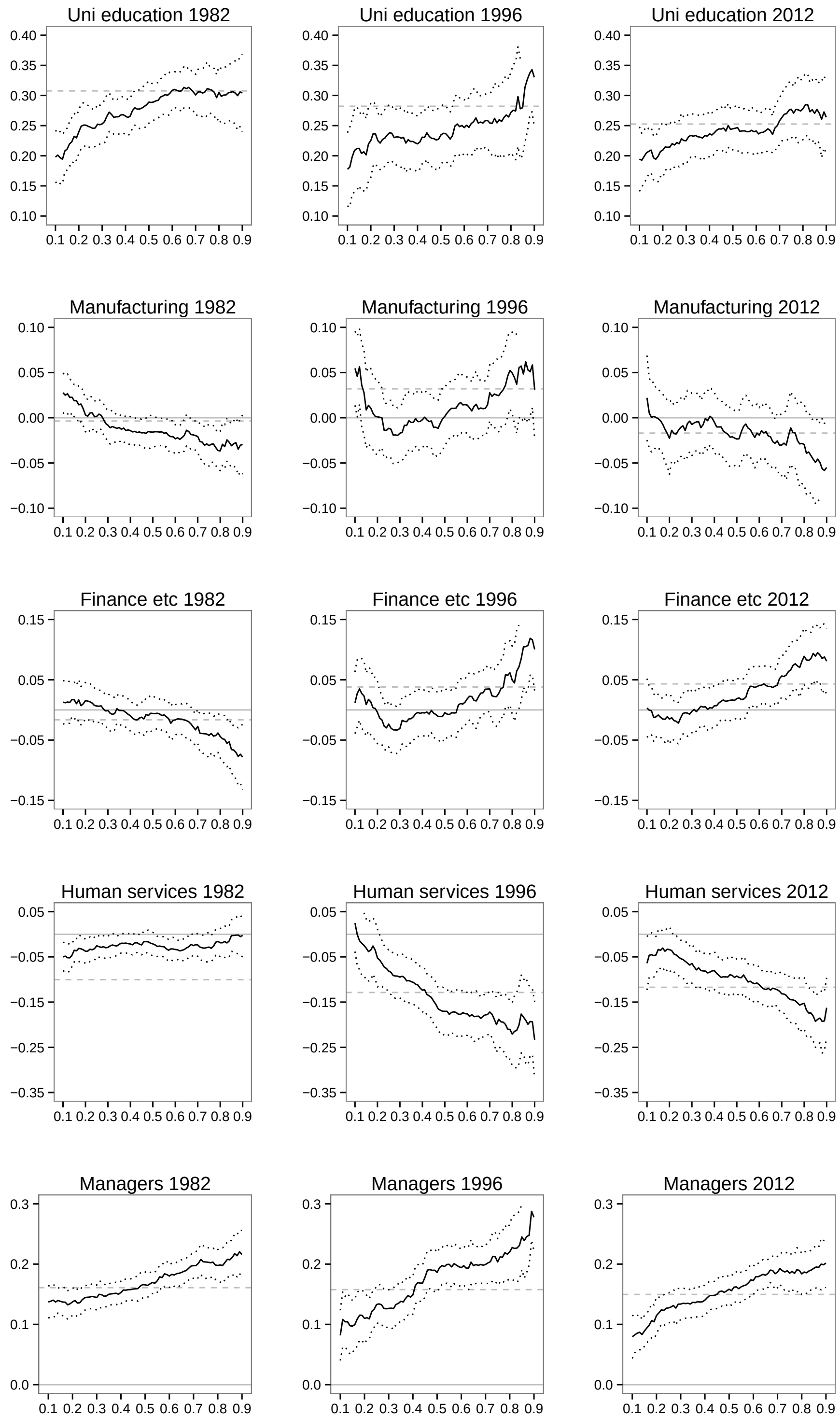


Figure 6. *Female quantile regression coefficents, 1982, 1996 and 2012*

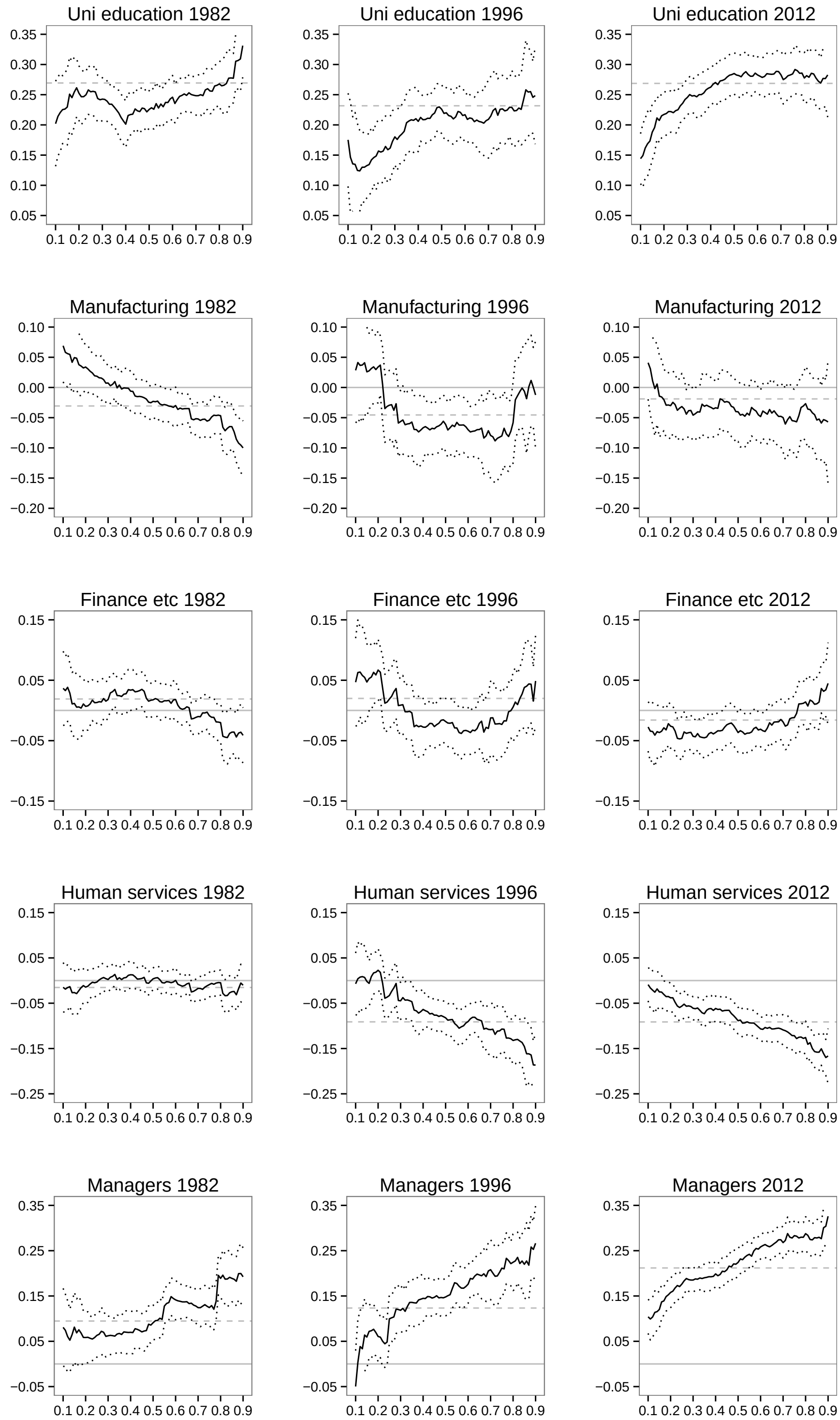
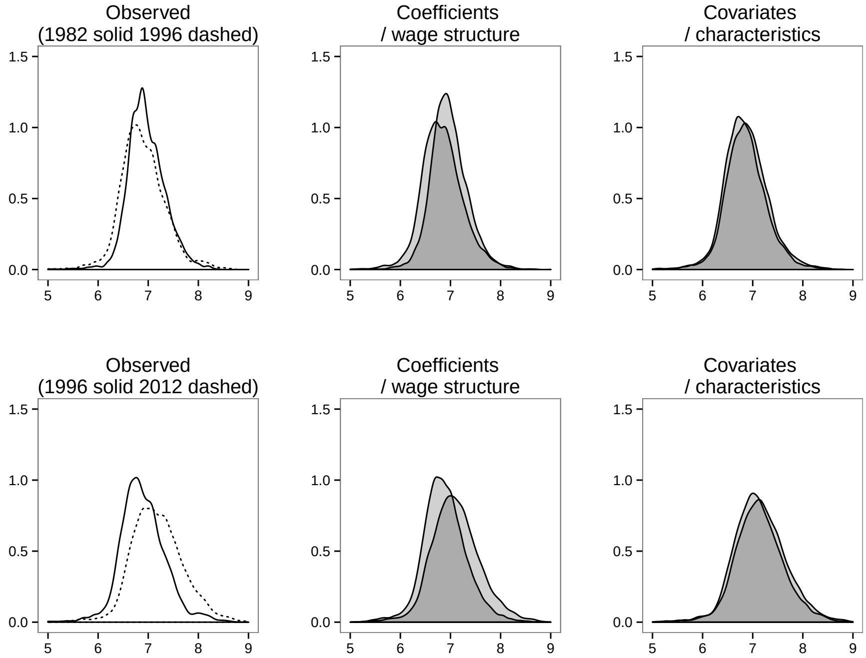
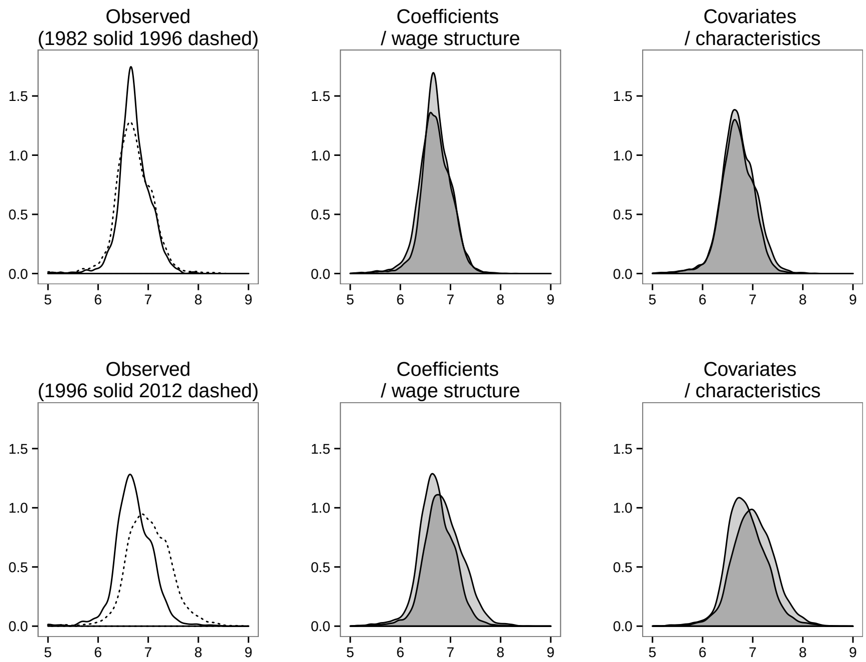


Figure 7. *Conditional wage densities, male employees, 1982, 1996 and 2012*



The lighter shaded areas reflect the part contributed by the component shown by the title. The x-axis shows the log weekly wage and the y-axis shows the densities.

Figure 8. *Conditional wage densities, female employees, 1982, 1996 and 2012*



The lighter shaded areas reflect the part contributed by the component shown by the title. The x-axis shows the log weekly wage and the y-axis shows the densities.

Tables referred to in the text

Table 1. *Descriptive statistics, full-time employees*

	Male			Female		
Variable	1982	1996	2012	1982	1996	2012
Age	37.7	38.7	40.9	33.8	37.4	39.6
Uni quals	9.9	18.0	26.1	9.8	21.9	41.8
Diploma quals	14.4	10.7	11.3	30.0	10.4	13.7
Trade quals	27.9	26.3	27.3	4.0	11.7	13.6
No post-school quals	47.8	44.9	35.3	56.2	56.0	30.9
Managers	10.1	12.5	17.8	2.7	6.1	14.1
Professionals	11.5	17.0	20.7	23.2	19.8	32.5
Technicians & trade Workers	34.7	25.8	22.6	11.4	10.8	3.6
Clerical, sales and service workers	18.8	17.6	17.4	57.3	50.3	43.2
Labourers & machinery ops & drivers	24.8	27.2	21.6	5.4	13.1	6.5
Agriculture	2.4	2.4	2.1	0.7	0.7	0.8
Mining	2.9	1.9	3.5	0.4	0.6	1.4
Manufacturing	26.4	23.9	14.7	18.3	12.1	7.2
Utilities	4.6	1.8	2.4	0.5	0.9	1.0
Construction	7.0	8.1	12.0	1.2	1.8	2.1
Wholesale & retail	14.5	17.5	13.4	16.0	15.2	11.7
Transport	8.5	6.4	7.1	2.5	2.5	3.1
Communication	3.7	3.7	2.4	2.4	1.5	2.0
Finance & business services	7.1	12.2	15.8	11.6	17.2	20.4
Government	8.6	7.1	9.1	7.1	8.0	11.0
Education, health & community	11.4	8.0	8.8	34.0	29.1	32.6
Recreation, accomm, other services	2.9	6.9	8.8	5.4	10.5	6.7
Born Aust	72.0	73.0	70.0	73.8	73.8	70.3
Born OS	28.0	27.0	30.0	26.2	26.2	29.7
Married	72.5	71.5	71.3	54.0	63.7	62.8
Not married	27.5	28.5	28.7	46.0	36.3	37.2
No dep child	56.9	59.3	65.1	77.2	73.5	76.4
One dep child	15.0	15.9	15.1	11.2	14.8	12.8
Two dep child	19.0	17.1	14.0	9.2	9.4	8.6
Three dep child	7.1	6.3	4.9	2.1	2.0	1.8
Four or more dep child	1.9	1.5	0.8	0.3	0.4	0.3

Notes: Data weighted by population weights. Source: ABS IDS data 1982, 1996 and 2012. Population: Adult full-time employees.

Table 2. *Decomposition of wage densities, male employees, sub-periods 1982 to 1996 and 1996 to 2012*

	Log wages						Proportions		
				Decomposed into:			Decomposed into:		
Percentile			Change	Coef	Cov	Res	Coef	Cov	Res
	1982	*1996*							
10th	6.553	6.400	-0.152	-0.164	0.018	-0.007	1.074	-0.118	0.044
25th	6.720	6.624	-0.096	-0.138	0.025	0.017	1.438	-0.261	-0.176
50th	6.927	6.851	-0.077	-0.106	0.037	-0.008	1.379	-0.478	0.099
75th	7.185	7.154	-0.031	-0.088	0.053	0.004	2.811	-1.689	-0.122
90th	7.441	7.456	0.016	-0.055	0.059	0.011	-3.481	3.764	0.717
	1996	*2012*							
10th	6.400	6.593	0.193	0.175	0.016	0.002	0.908	0.081	0.011
25th	6.624	6.835	0.212	0.201	0.034	-0.024	0.951	0.162	-0.114
50th	6.851	7.140	0.289	0.234	0.054	0.001	0.809	0.187	0.004
75th	7.154	7.496	0.342	0.284	0.058	-0.000	0.831	0.169	-0.000
90th	7.456	7.847	0.391	0.321	0.067	0.003	0.821	0.171	0.008

Notes: Based on evaluating the conditional wage densities shown in Figure 7 at the quantiles shown. Coef = Coefficients; Cov = Covariates; Res = Residuals. The standard errors for these estimates can be found in Table 3. *Source:* Empirical and counterfactual densities using QR model results for IDS data 1982, 1996 and 2012. *Population:* Male adult full-time employees.

Table 3. *Standard errors for Table 2*

	1982 to 1996				1996 to 2012			
Percentile	Change	Coeff	Cov	Resid	Change	Coeff	Cov	Resid
10th	0.005	0.014	0.008	0.010	0.014	0.014	0.008	0.012
25th	0.005	0.009	0.006	0.007	0.011	0.010	0.007	0.008
50th	0.013	0.009	0.007	0.007	0.016	0.010	0.007	0.010
75th	0.013	0.010	0.008	0.007	0.015	0.011	0.008	0.008
90th	0.020	0.015	0.010	0.011	0.022	0.016	0.010	0.013

Notes: Note that these are the standard errors for the log wage estimates, not the proportions. They are based on bootstrapping the estimates 1000 times. Source: Empirical and counterfactual densities using QR model results for IDS data 1982, 1996 and 2012. Population: Male adult full-time employees.

Table 4. *Decomposition of wage densities, female employees, sub-periods 1982 to 1996 and 1996 to 2012*

	Log wages						Proportions		
				Decomposed into:			Decomposed into:		
Percentile			Change	Coef	Cov	Res	Coef	Cov	Res
	1982	*1996*							
10th	6.403	6.336	-0.067	-0.078	-0.004	0.016	1.175	0.058	-0.233
25th	6.553	6.498	-0.055	-0.061	0.010	-0.004	1.114	-0.180	0.066
50th	6.693	6.701	0.008	-0.030	0.026	0.013	-3.809	3.224	1.585
75th	6.902	6.947	0.045	-0.004	0.046	0.003	-0.086	1.016	0.070
90th	7.125	7.154	0.029	-0.024	0.077	-0.024	-0.827	2.665	-0.838
	1996	*2012*							
10th	6.336	6.537	0.201	0.183	0.022	-0.005	0.913	0.110	-0.023
25th	6.498	6.731	0.233	0.178	0.068	-0.012	0.763	0.290	-0.054
50th	6.701	7.003	0.303	0.210	0.098	-0.006	0.696	0.325	-0.021
75th	6.947	7.311	0.364	0.238	0.110	0.016	0.654	0.302	0.044
90th	7.154	7.550	0.395	0.283	0.100	0.012	0.715	0.253	0.031

Notes: Based on evaluating the conditional wage densities shown in Figure 8 at the quantiles shown. Coef = Coefficients; Cov = Covariates; Res = Residuals. The standard errors for these estimates can be found in Table 5. *Source:* Empirical and counterfactual densities using QR model results for IDS data 1982, 1996 and 2012. *Population:* Female adult full-time employees.

Table 5. *Standard errors for Table 4*

	1982 to 1996				1996 to 2012			
Percentile	Change	Coeff	Cov	Resid	Change	Coeff	Cov	Resid
10th	0.015	0.020	0.013	0.010	0.015	0.019	0.011	0.010
25th	0.013	0.012	0.010	0.007	0.016	0.011	0.009	0.009
50th	0.016	0.011	0.009	0.008	0.016	0.011	0.010	0.009
75th	0.016	0.014	0.012	0.008	0.014	0.013	0.011	0.009
90th	0.015	0.015	0.013	0.009	0.017	0.015	0.012	0.010

Notes: Note that these are the standard errors for the log wage estimates, not the proportions. They are based on bootstrapping the estimates 1000 times. Source: Empirical and counterfactual densities using QR model results for IDS data 1982, 1996 and 2012. Population: Female adult full-time employees.

Table 6. *Regression slopes for QR coefficients*

	Male			Female		
Variable	1982	1996	2012	1982	1996	2012
Age (in 10 years)	0.11	0.12	0.06	0.13	-0.11	0.02
Age (quadratic)	-0.01	-0.00	0.00	-0.02	0.02	0.00
Uni quals	0.13	0.11	0.09	0.06	0.13	0.13
Diploma quals	0.04	-0.05	-0.05	0.00	0.11	0.06
Trade quals	-0.08	-0.09	-0.07	0.04	0.18	-0.01
Agriculture	0.18	0.26	0.34	0.27	0.96	0.16
Mining	0.24	0.07	-0.01	0.22	0.32	0.07
Manufacturing	-0.06	0.05	-0.05	-0.16	-0.07	-0.05
Utilities	-0.06	-0.14	-0.11	-0.06	-0.33	-0.00
Construction	-0.05	0.08	0.17	0.14	-0.04	-0.01
Transport	0.07	0.20	-0.01	-0.11	-0.04	0.08
Communications	-0.12	-0.15	0.12	-0.11	-0.23	0.14
Finance etc	-0.10	0.11	0.14	-0.07	-0.05	0.07
Government	-0.11	-0.26	-0.24	-0.04	-0.18	-0.15
Human services	0.03	-0.25	-0.19	-0.01	-0.21	-0.17
Managers	0.11	0.19	0.14	0.18	0.26	0.23
Professionals	-0.08	-0.05	0.03	-0.06	-0.03	-0.04
Tradesworkers	0.01	-0.04	-0.02	0.01	0.10	-0.06
Clerical, sales etc	-0.03	-0.07	-0.11	-0.08	-0.14	-0.05
Not married	0.00	0.02	-0.01	0.10	-0.01	-0.04
One child	-0.00	-0.00	-0.00	0.02	0.05	0.05
Two child	-0.03	0.04	0.08	-0.03	0.10	0.10
Three child	-0.02	0.15	0.12	0.08	0.07	-0.01
Four or more child	0.04	0.27	0.10	-0.21	0.69	0.27
Born overseas	0.03	-0.05	0.00	0.03	0.07	0.02
NSW	0.02	0.08	0.03	0.02	-0.01	0.01
Victoria	0.00	-0.02	0.04	0.02	0.02	0.04
Queensland	0.05	0.01	0.04	-0.00	0.02	0.02
SA	-0.07	-0.08	-0.09	0.01	-0.02	-0.02
WA	-0.03	0.11	0.12	-0.04	0.04	0.03
Tasmania	0.04	-0.08	-0.11	-0.04	-0.02	-0.05

Notes: Based on regressing the quantile regression coefficients against the tau values. Source: QR model results for IDS data 1982, 1996 and 2012. Population: Male and female adult full-time employees.

Data

A number of researchers have raised concerns about using the ABS IDS data for analysing inequality over time, though their concerns have mainly concerned the analysis of household income rather than individual wage and salary earnings. Siminski et al. (2003), for example, have warned researchers to exercise caution in using the IDS 1982 data for trend analysis due mainly to 'definitional anomalies' related to income from own incorporated businesses. This makes it likely that the 1982 estimates for wages and salaries is under-estimated in aggregate. While this may have implications for the top end of the distribution, its impact in the bottom and middle is less likely. Saunders (2005: 81) also expressed concern about possible 'understatement of wage incomes among low wage employees' in the IDS data for the period between 1994 and 2001 when compared to the ABS EEH data (Employee Earnings and Hours). However, when Saunders compared the IDS aggregate findings with those from the ANA (Australian National Accounts), he found no discrepancy. There was nevertheless, some sensitivity in the findings for Gini inequality when Saunders re-estimated his analysis and omitted the lowest 2.5 per cent of wage and salary incomes.

In the case of Wilkins (2013) his major criticisms were also mainly directed at the annual income data, rather than the weekly wages data. In terms of the latter, the data problems mainly concerned the treatment of salary sacrificed income in the period between 2003 and 2006 and the inclusion of additional payments (such as bonuses) from 2007–08 onward. The inconsistent collecting of salary sacrificed income led to average discrepancies at the *household* level of \$21 in 2003–04 and \$29 in 2005–06, with the mean value of excluded salary sacrificed income at just \$7 in 2003–04 and \$10 in 2005–06 (Wilkins, 2013: 8). If we roughly halve these estimates to arrive at *individual* salary sacrificed amounts, it is clear that the impact from these inconsistencies on the analysis carried out in this article is likely to be minimal.

Nevertheless, there is certainly evidence that the size of the dispersion on earnings from the early 2000s onwards in greater in the ABS IDS data compared to the HILDA data. While the comparisons between the IDS and HILDA data were very close for female full-time employees, among the male full-time workforce the extent of inequality was greater in the IDS data. This showed up in comparisons using the Gini coefficient, as well as in the trajectory of real wages at the 90th percentile, and to some extent, at the median. The story at the bottom of the labour market, at the 10th percentile, showed a much smaller difference.[18]

Do these data concerns have implications for the decomposition analysis in this article? It would seem the answer is no. When the IDS data for 2012 is replaced by the HILDA data for 2012, the wage distributions for both men and women remain almost identical. Similarly, the decomposition results are almost identical in magnitude and the substantive arguments of this article are strengthened, rather than weakened, by the use of the HILDA data. The decomposition proportions for men in Table 3 are very close, and those for women, in Table 5, are even more strongly in favour of the coefficients. The visual differences between density plots from the IDS and the HILDA data are imperceptible. Carrying out the decomposition for the period from 2001 to 2012, using both HILDA and the IDS, produce similar results, and both point strongly towards the findings reported in this article. These results are not shown here, but are available from the author.[19]

Methodology

It is important to stress that the difference between quantile regression (QR) and linear regression is that one focusses on conditional wage *distributions*, rather than conditional *means*. Consequently, model fitting is usually applied using a vector of quantiles, for example, various deciles or percentiles. As with the Blinder-Oaxaca approach to decompositions of the gender or racial wages gap, the core insight is that model coefficients can be interpreted as the effects of the wage structure (prices, or returns on characteristics) while the sample covariates can be interpreted as the effects of the workforce characteristics (quantities, or 'endowments'). This tradition also makes use of a kind of 'counterfactual by substitution' strategy, in which the substitution of one component in the decomposition by its opposite (for example, 'combining' male characteristics with female returns) allows one to assess the effect of each component on the size of the wages gap (see, for example, Blinder, 1973; Oaxaca, 1973; Watson, 2010). This approach to the construction of the counterfactual is also the basis for the methodology in this article, though the implementation is obviously different.

In the following exposition I make use of the terminology and presentation used by Machado and Mata (2005: 447–450) who show that the conditional wage quantiles of the distribution can be modelled by:

$$Q_\theta(w|z) = z\prime\beta(\theta) \tag{1}$$

where $Q_\theta(w|z)$ for $\theta \in (0,1)$ is the θth quantile of the log wage (w) conditional on a vector of covariates (z) while $\beta(\theta)$ is the vector of QR coefficients. These can be estimated by minimizing in β

$$n^{-1}\sum_{i=1}^{n}\rho_\theta(w_i - z_i\prime\beta)$$

with

$$\rho_\theta(u) = \begin{cases} \theta u & \text{for} \quad u \geq 0 \\ (\theta-1)u & \text{for} \quad u < 0 \end{cases}$$

The marginal density function of the wage distribution is constructed as follows. Let $W(t)$ stand for the QR coefficients for period t and $Z(t)$ stand for the sample covariates for period t. To construct the density 'implied by the model' the same t is used for both terms in the conditional wage function:

$$W^*(t) \equiv Z^*(t)\prime\hat{\beta}^t \tag{2}$$

To construct the counterfactual density, one alternates the period, t. Thus, if $f^*(W(0); Z(0))$ is the density implied by the model in the first period, then

$f^*(W(0); Z(1))$ is the counterfactual for that period. Similarly, if $f^*(W(1); Z(1))$ is the density implied by the model in the second period, then $f^*(W(1); Z(0))$ is the counterfactual. For example, one can analyse the change in wage densities between 1982 and 1996 by comparing $f^*(W(1); Z(0))$ with $f^*(W(0); Z(0))$, which basically asks how the wage structure in 1996 applied to the workforce characteristics in 1982 changes the shape of the wages density. At the same time, a comparison of $f^*(W(1); Z(1))$ with $f^*(W(1); Z(0))$ provides an estimate of the contribution of the changes in the workforce to the changes in density. The top row in Figure 7 illustrates these two comparisons.[20]

As well as a visual inspection of the wages density it is also useful to construct various summary measures (see Tables 3 and 5). If $\alpha(\cdot)$ is such a measure (for example, a particular percentile) and $fW(t)$ is the *observed* wage density in period t, then the decomposition for changes in α is:

$$\begin{aligned} \alpha(f(W(1))) - \alpha(f(W(0))) = & \quad \underbrace{\alpha(f^*(W(1); Z(0)) - \alpha(f^*(W(0); Z(0)))}_{\text{coefficients}} \\ & + \quad \underbrace{\alpha(f(W(1); Z(1)) - \alpha(f^*(W(1); Z(0)))}_{\text{covariates}} \\ & + \quad \text{residual} \end{aligned} \tag{3}$$

As equation 3 shows, the $\alpha(f^*(W(1); Z(0))$ terms cancel out, leaving only the 'model implied' densities. This demonstrates that the only difference between the LHS and RHS of this equation is the residual, that is, the part not accounted for by the modelling.

Notes

1. This article makes use of confidentialised unit records files (CURFs) provided by the Australia Bureau of Statistics under the ABS/AVCC CURF Agreement.

2. Though Harvey argues that a capitalism without the production of commodities—where all money capital was invested solely in financial 'products'—would produce no surplus value and hence be doomed as a system (Harvey, 2013).

3. Although the return to university degrees among women began to increase slightly in the early 1990s (Borland, 1999: 186–188) and research by Coelli and Wilkins (2009) suggested that changes in the higher education system (particularly among teachers and nurses) had produced misleading results.

4. Whether there had been an actual growth in low paid jobs was source of controversy during the 1990s. Part of this debate hinged on a methodological artifact: a situation where relative wages changed more than employment numbers. For example, with an absolute increase in high skill jobs alongside an absolute decline in low skill jobs—which most of the evidence suggested had happened—the result could be a decline in the relative wages of the low skilled workers. As a result, more workers would be caught up in the low pay definitional net, since the boundary for being low paid is pegged to median wages, and this cut-off is

raised by the increase in high skilled jobs. If the median remains stagnant, as it did in the United States during the 1980s, then the results are not ambiguous. In Australia, however, median wages did increase during this period. How one accounts for inflation over time, and which techniques are used, both seem to influence the conclusions drawn. See, for example, the debate between Belchamber and Gregory concerning the correct way to deflate wages over time: (Belchamber, 1996; Gregory, 1996).

5. The Accord was fashioned in the period leading to the accession to power of the Australian Labor Party in 1983. It was a Prices and Incomes Accord which aimed to restrain wages growth and to increase the profit share of national income in return for employment creation and increases in the social wages, particularly universal health insurance. See Stilwell (1986) for a comprehensive analysis.

6. The analysis in this article was carried out using the R statistical language (R Core Team, 2013). The quantile regressions made use of Roger Koenker's `quantreg` package (Koenker, 2013) and the kernel density plots were produced using the `ggplot2` package (Wickham, 2009).

7. These data, and the data which follow throughout this article, come from the author's calculations using the unit record files of these ABS household income surveys and cover the period from 1982 to 2012. As well as the IDS, other studies of wage inequality use the ABS *Labour Force Survey* (LFS) or the ABS *Employee Earnings and Hours* survey (EEH). In more recent years researchers have begun to use cross-sectional estimates based on the Melbourne Institute's longitudinal *Household, Income and Labour Dynamics in Australia* (HILDA) survey. While the precise magnitude of the results depend on the data source, the overall conclusions about the extent of inequality do not appear to depend on the choice of data source (for example Borland, 1999: 181).

8. The restriction to full-time workers in this article is necessary because assessing inequality in the part-time workforce is problematic without access to adequate hourly earnings data, which requires good measures of hours worked. Hourly measures can also be misleading for the full-time workforce because it can artificially deflate the earnings of high-paid workers who are paid a salary and work long hours, sometimes taking time in lieu.

9. The Theil index is part of a group of inequality measures, the General Entropy class, and has a number of desirable statistical properties for measuring cross-sectional inequality. Its interpretation, however, is less intuitive than the Gini index. See Burkhauser and Couch (2009: 524–28).

10. This coding scheme, which differs from the more conventional indicator coding approach, provides identical model results. All that differs is the interpretation placed on the coefficients.

11. CCLO is Census Classification and Classified List of Occupations; ASCO is Australian Standard Classification of Occupations; ANZSCO is Australian and New Zealand Standard Classification of Occupations.

12. The full set of QR regressors are shown in Table 6, where slopes for these

QR coefficients have been calculated to provide a simple, albeit crude, summary of the overall effect of each regressor. These slopes have been constructed by regressing the QR coefficients against the tau values. Where these slopes are positive, this implies an *inequality-inducing* effect, where they are negative, this implies an *inequality-suppressing* effect.

13. These results can be influenced by the order of the decomposition (see Machado and Mata, 2005: 450), so the analysis reported here was repeated in the reverse order. The results were substantively the same.

14. Mining has provided low wage workers with a substantial premium, well beyond their reach in any other industry. These wages have been one of the factors sustaining the fly-in-fly-out phenomenon across regional and remote Australia. In this respect, mining has been one neoliberal industry where inequality has been constrained, rather than accelerated.

15. The Gini coefficients for male part-time workers using HILDA data for 2010 and 2012 were 0.37 and 0.34, whereas for the ABS data they were 0.43 and 0.42 respectively. For male full-time workers, the differences were much less: 0.28 in HILDA (both years) and 0.30 for the ABS (both years). In the case of female workers, the figures for full-time workforce were 0.23 and 0.24 (HILDA) and 0.23 and 0.25 (ABS) for 2010 and 2012; for part-time workers the figures were 0.30 and 0.26 (HILDA) and 0.33 and 0.33 (ABS).

16. This comparative analysis made use of the unit record data from the HILDA Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views based on this analysis are those of the author and should not be attributed to either FaHCSIA or the MIAESR.

17. One can also reverse this process to test for the robustness of the decomposition since the results can be sensitive to the order of the decomposition. I discuss this issue further in the results section.

18. The Gini coefficients for male part-time workers using HILDA data for 2010 and 2012 were 0.37 and 0.34, whereas for the ABS data they were 0.43 and 0.42 respectively. For male full-time workers, the differences were much less: 0.28 in HILDA (both years) and 0.30 for the ABS (both years). In the case of female workers, the figures for full-time workforce were 0.23 and 0.24 (HILDA) and 0.23 and 0.25 (ABS) for 2010 and 2012; for part-time workers the figures were 0.30 and 0.26 (HILDA) and 0.33 and 0.33 (ABS).

19. This analysis made use of the unit record data from the HILDA Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views based on this analysis are those of the author and should not be attributed to either FaHCSIA or the MIAESR.

20. One can also reverse this process to test for the robustness of the decomposition since the results can be sensitive to the order of the decomposition. I discuss this issue further in the results section.

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