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Mustafa Kamal
University of Tasmania, Australia

Paul Blacklow
University of Tasmania, Australia

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Mustafa Kamal
University of Tasmania

Paul Blacklow
University of Tasmania

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Abstract

This paper simultaneously examines the effects of age, period and birth cohort on the evolution of the Australian gender wage gap from 2001-18. It employs the proxy variable approach within the Mincerian earnings function to overcome the Age-Period-Cohort (APC) identification problem while also controlling for employment selection and individual human capital accumulation. The paper corroborates previous evidence of a widening gender wage gap with age. It also provides new evidence of period effects suppressing female wage rates compared to male rates. However, as opposed to expectations, the study finds no significant influence of birth cohort effects on the Australian gender wage gap. The results also suggest that the failure to control for period effects can lead to significant cohort effects or substantial overestimation of age or cohort effects on wages. The findings of the paper have implications for a range of studies that employ Mincer-type earnings functions in addition to policy implications.

Keywords: gender, wage gap, age, period, cohort, Australia

JEL classification: C33, J16, J31

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*Corresponding author: Paul Blacklow, Tasmanian School of Business and Economics, University of Tasmania, Private Bag 84, Hobart TAS 7001. Email: Paul.Blacklow@utas.edu.au.

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1 Introduction

Two different ways of measuring gender equality that assume particular significance in the economic literature are earnings and the wage rate. The earnings of an individual act as an indicator of his or her relative social and economic importance compared to another individual. The wage rate, in comparison, represents a person's education, training, previous work experience and expected future labour force participation likelihood in a single statistic(Goldin 2014). The gender difference in wages, therefore, is considered an important indicator of their respective socio-economic conditions and relations, and researchers have long been investing their time and energy to understand various aspects of this phenomenon. The present paper contributes to this literature by focusing on the effects of birth cohort (i.e., the effects of birth year) in comparison to age and period effects (represented by years since birth and current year, respectively) in the convergence or persistence of the Australian gender wage gap between 2001 and 2018.

In the last several decades, the human capital gap between men and women has significantly closed or even reversed, in Australia and several other OECD countries amid improvements in the legal framework that aimed at ensuring equal treatment of the genders. For example, in terms of upper secondary graduation rate, tertiary level education attainment and life expectancy, women have surpassed men across the OECD countries (OECD 2017, 2018). The story is analogous in Australia where women are performing better than men in attaining year 12 education or above and bachelor's degree or above. Australian women have also been shown to have higher life expectancy than men as well (ABS 2018b). In the legal arena, a considerable number of laws have been passed over time in many of the same countries to ensure equal pay and equal opportunity for all citizens and eradicate discrimination based on gender, age and such factors from the workplace (Pike 1982; Fagan and Rubery 2018; O'Reilly et al. 2015; Christofides, Polycarpou, and Vrachimis 2013; Cobb-Clark 2012; Byrnes 2013; Charlesworth and Macdonald 2015).

It is, therefore, reasonable to expect that such advances would reflect in women's labour market performance and outcomes. However, such expectation has not been materialized. Especially, the male-female wage gap has proved to be persistent after a certain point. For example, the median income of full-time female employees showed only little change across the OECD in the past decade to equal 14.3 percent less than that of male employees in 2015 (OECD 2017). Likewise, in the case of ordinary time weekly earnings of full-time employees in Australia, the average female earnings were 85 percent of the average male earnings in 2018. This figure also has been fairly persistent over the last decade (ABS 2018b).

Understandably, recent research has been increasingly concentrating on how the gender pay gap progresses over an individual's life cycle or how it varies between different cohorts (e.g., Tyrowicz, Velde, and Staveren 2018; Fortin 2019; Erosa, Fuster, and Restuccia 2016). However, these studies often ignore or poorly address the APC identification problem, which arises from the statistical difficulty of separating these three effects from each other due to the identity, survey year = birth year + age. Without this linearity problem properly addressed, it would continue to be unclear, for example, whether any difference in the observed gender wage gap between two cohorts at a single time period is actually the result of birth cohort effects or age effects.

Under these circumstances, the present paper develops a number of appropriate proxies and uses them within the Mincer wage equation to estimate the impact of the age, period and cohort variables on the Australian gender wage gap and isolate the APC effects from traditional human capital effects. Our results suggest that age is a significant predictor of the gender wage gap. Moreover, if period effects are not controlled for, age and cohort effects on wages are likely to be overestimated in Mincer-type earnings functions. The results also show that period effects contribute less to women's wage rates than to men's, meaning the gender wage gap is more likely to worsen from year-to-year changes in the socio-economic environment. Finally, the paper reveals no significant wage gains across female birth cohorts in Australia as recent female cohorts are not performing better than their male counterparts.

It is noteworthy that even after controlling for both APC variables and education and tenure, the age effect remains significant whereas the cohort effect has disappeared both for male wages and for male-female wage differences. This result contrasts with some of the previous studies that have ignored such controls and thus found significant effects of birth cohorts on these wages (e.g., Beaudry and Green 2000; Abe 2010). This finding has implications for studies utilising Mincer type equations for different purposes without properly addressing the APC problem, such as estimating the life-cycle wage inequality, since they can also be over- or under-estimated. The study also provides some policy suggestions based on the findings.

The rest of the paper is organized as follows. The next section introduces APC analysis, explains how it is useful for wages and reviews how it has been used in the past. Section 3 lays out the empirical strategy. Section 4 and 5 describe the data and empirical evidence, respectively. Finally, section 6 concludes.

2 Age, Period, Cohort Effects and Wages

2.1 The Basic APC Model

Researchers from different branches of social and human sciences have long been attempting to differentiate the individual effects of age, period and cohort on some outcome variable of interest for developing an understanding of that particular outcome. The result has been the advancement of age-period-cohort (APC) analysis, which traditionally results in the simultaneous quantification of age, period, and cohort effects from a single statistical equation (Luo 2013a). In APC analysis, age effects represent changes within individuals as they become older, which can be both biological and social. Period effects reflect developments occurring over time that affect all age groups at the same time (Yang and Land 2013). In contrast, cohort effects refer to changes that occur to a group because of being exposed to a specific event at a specific period, such as birth or marriage during a particular time. A birth cohort, which is formed of the individuals born within a given year or some other period, constitutes the most studied unit of analysis in social sciences (Glenn 2005; Yang and Land 2013).

To the extent that age, period and cohort represent different sets of socio-economic and environmental relationships, studies that distinguish their differences will continue to be valuable for analytic purposes (Yang and Land 2013). In the labour market, disentangling the effects of age, period and cohort from each other therefore is crucial for developing a proper understanding of the pay gap between different groups as it helps to identify the individual and social mechanism working behind it.

2.2 Age Effects

Men and women differ from each other in health and aging, which originates from biological as well as from behavioural and lifestyle choices (Oksuzyan et al. 2008; Dennerstein et al. 1998). Although poor health decreases the probability of participation in the labour market for both men and women, it is the old and especially the elderly females who observe the greatest fall in the participation rate (Cai 2010; Cai and Kalb 2006). It is also reasonable to assume that part of the health problems of working women would not be reflected in any kind of health assessment despite having implications for productivity and wages. As Jäckle and Himmler (2010) have found in Germany, better health status leads to higher wages for males, but for women, it mainly affects their participation rate and not the wages.

The aging process also comes for women as a source of greater anxiety (Barrett and Rohr 2008) and lower self-esteem (McMullin and Cairney 2004). Older women are also more vulnerable regarding body shape and body image than older men (Ferraro et al. 2008). Works on non-cognitive skills and labour market performance (e.g., Santos-Pinto 2012; de Araujo and Lagos 2013; Fortin 2008; Mueller and Plug 2006) have established that the difference in personality traits along these lines can contribute to the wage gap. One of the channels through which this relationship may operate is through the effects of personality traits on individual productivity (Cubel et al. 2016), and thus labour demand. There may also be greater demand from employers for workers with particular job attributes, while those attributes may be connected with certain individual traits (Cobb-Clark and Tan 2011).

The physical and psychological aspects of ageing are also challenging for older women because of the views that society generally holds regarding women and ageing. For example, some studies (e.g., Hawkins 1996) have shown that men generally hold a more negative view of elderly women than women do, although opposite results are also available (e.g., Barrett and Rohr 2008). In the labour market, however, there is multiple evidence of the prevalence of negative attitudes towards older workers (e.g., Bendick, Brown, and Wall 1999; Bendick, Jackson, and Romero 1996; Gringart, Helmes, and Speelman 2005; Farber, Silverman, and Wachter 2016), with considerable evidence of elderly women workers being the most discriminated against (e.g., Neumark, Burn, and Button 2019; Gringart and Helmes 2001).

2.3 Period Effects

In the labour market, the period effect may especially arise from technical progress or other labour market variables (Heckman and Robb 1985). The impact of technological advances on wages can be both positive and negative. As argued by Acemoglu (1998), technological change can be skill-replacing and skill-complementary. If the economy observes a rise in the supply of skilled graduates while the technology is constant, there will be a fall in the education premium and wages of those graduates. On the other hand, if the technological change is designed to complement those skills, the college premium and wage inequality will observe a rise. In addition, technological change has different proliferation rates in different sectors (Gould, Moav, and Weinberg 2001). Now if there is significant gender segregation by industry and sectors (see, for example, Coelli 2014; Coelli and Borland 2016), technological progress can disproportionately affect the wages of the male or the female workers, and worsen or improve the gender wage gap.

The unemployment rate is one of the key variables that have been frequently used in the literature to represent the period effect (e.g., Berger 1985; Dohmen et al. 2017). A higher unemployment rate is associated with a lower male-female employment gap since the economic downturn in the past has been found to influence mainly the male employment rate (Gharehgozli and Atal 2020). The decline of male-dominated industries or the increase of the supply of male labour force participation rate as a result of the worsening of the economic and household financial situation also affects the relative demand of male and female labour (Şahin, Song, and Hobijn 2010; Gharehgozli and Atal 2020). The unemployment rate can also act as a substitute for overall economic conditions (Dohmen et al. 2017).

The period effect also represents the legislative and attitudinal improvements that reduce gender and other forms of discrimination (Goldin and Mitchell 2017). For example, when minimum wage rates are increased, workers at the bottom of the wage distribution start to receive comparatively higher wages. Since it is women who generally work at the bottom, minimum wage laws are more likely to benefit them disproportionately, and thus could diminish the overall gender wage gap (Hallward-Driemeier, Rijkers, and Waxman 2017). Gender discrimination and equal pay laws may also improve the gender wage gap, although at the cost of a lower employment rate (Neumark and Stock 2006). However, it is possible for some anti-discrimination laws to produce the opposite result sometimes as they may actually improve the employment status of men more than that of women, the age discrimination laws of the United States being one such example (McLaughlin 2020).

2.4 Cohort Effects

Cohort effects are usually observed in the labour market when the large size of some birth cohort later leads to greater labour supply from the cohort, and therefore, suppresses the wage rates for those born in that particular cohort (Topel 1997). In the case of the gender wage gap, the impact of cohort size can be observed if cohort size affects the proportion of women entering the labour market and if male and female labour are imperfect substitutes. Several empirical studies have already established that the size of one's birth cohort is inversely related to his or her wage rates (e.g., Welch 1979; Berger 1985; Macunovich 1999). The effect of cohort size on male-female wage differential, however, has been scarcely documented. Katz and Murphy (1992) is one exception who considered the possibility of changes in the relative supply of female workers affecting the male-female wage gap in the United States but found not much evidence.

An educational boom within a cohort can also lead to cohort effects. Since education can be considered to be essentially fixed when a cohort enters the job market, the cohort that has a comparatively fewer number of educated workers will experience a relatively different composition of returns than that that is observed for the average cohort (Card and DiNardo 2002). In general, the wage gap will observe a fall because of the improvement in the educational status of women compared to men if the labour market is gender-segregated and both genders are imperfect substitutes. For example, Card and Lemieux (2001) have demonstrated that the rise in the college-high school wage differential in the United States, the United Kingdom and Canada in the past can partly be attributed to the lower supply of the college-educated labour force. Previously, Katz and Murphy (1992) have also shown that the changes in the relative supply of college-educated students can predict the movement of the college-high school wage gap for the United States between 1963 and 1987. The authors, however, found that movement in the rate of growth of relative labour supply did not have any significant effects on male-female wage gap.

Yet another source of cohort effects on the gender wage gap could be the preparedness of younger females for performing more challenging tasks in the labour market (Blau and Kahn 2000). Workers in predominantly male occupations and industries receive comparatively higher wages than female-dominated ones (Macpherson and Hirsch 1995; Ransom and Oaxaca 2010). As recent cohorts of women are better prepared, they are more suited to enter the male-dominated industries and affect the wage premia traditionally enjoyed by men. There is already some evidence that sex segregation is declining in the labour market in a range of countries (e.g., Gallen, Lesner, and Vejlin 2019; Blau and Kahn 2017; Blau, Brummund, and Liu 2013). The Australian labour market, however, remains one of the most heavily gender-segregated along the occupational and industrial lines. For example, despite the ups and downs within different sub-categories of occupation, there were no significant changes in segregation levels over the last two decades (WGEA 2019).

2.5 This Paper's Age Period Cohort Effects

The separation of age, period and cohort effects thus can exclusively portray a parsimonious picture of the influence of a complex set of socio-economic, historical and environmental factors (Yang and Land 2013). The power of such an approach, however, has remained largely ignored in the economic literature, especially in labour market research. First, the previous work has mainly focused on the determination of either age effects (e.g., Tyrowicz, Velde, and Staveren 2018; Erosa, Fuster, and Restuccia 2016; Wu 2007) or cohort effects (e.g., Card and Lemieux 2001; Beaudry and Green 2000; Fortin 2019; Macunovich 1999), while period effects have remained virtually unexplored. Second, some of the previous research has completely ignored the identification problem by disregarding one of the effects altogether (e.g., Erosa, Fuster, and Restuccia 2016; Wu 2007; Macunovich 1999). Furthermore, many previous works have grouped successive cohorts or ages into one broad category to estimate of age or cohort effects (e.g., Card and Lemieux 2001; Fortin 2019; Juhn and McCue 2017). Such grouping is also an imperfect method of estimating the true effects as the estimates may change depending on how many cohorts or ages are included in one category. Even when some researchers explicitly mentioned the identification issue, either they did not attempt to address the problem or the approach they adopted still did not solve it (e.g., Tyrowicz, Velde, and Staveren 2018; Beaudry and Green 2000; Chatterjee, Singh, and Stone 2016).

The above trend is also true for Australian labour market research, including the literature which is dealing with the male-female wage differential. Apart from neglecting the APC issue, previous works on the gender wage gap in Australia have also been limited in scope as they dealt with only full-time workers (e.g., Daly et al. 2006; Chzhen, Mumford, and Nicodemo 2013; Johnston and Lee 2012), full-time managerial workers (Watson 2010), private sector employees (e.g., Chzhen, Mumford, and Nicodemo 2013; Meng 2004; Meng and Meurs 2004), married couples (e.g., Flinn, Todd, and Zhang 2018), limited time span (e.g., Miller 2005; Kee 2006; Risse, Farrell, and Fry 2018; Daly et al. 2006; Chzhen, Mumford, and Nicodemo 2013; Eastough and Miller 2004; Meng 2004; Meng and Meurs 2004; Flinn, Todd, and Zhang 2018), or an older time period (e.g., Coelli 2014; Cobb-Clark and Tan 2011; Johnston and Lee 2012; Daly et al. 2006; Barón and Cobb-Clark 2010; Chzhen, Mumford, and Nicodemo 2013; Eastough and Miller 2004; Watson 2010; Meng 2004; Meng and Meurs 2004). Since the number of workers involved in part-time and full-time employment varies between men and women, excluding part-time workers from the sample has the possibility of distorting both the true size and composition of the male and female workforce (Risse, Farrell, and Fry 2018). Similarly, the coverage of only old- or limited-time span fails to take account of the recent trends, while attention to specific groups only provides a partial picture.

3 Empirical Approach

3.1 Econometric Model Specification

We begin the empirical analysis by extending a Mincer-type earnings function with the age, period and cohort variables resulting in the following wage function:

$$y_{it} = \boldsymbol{\beta}_A A_{it} + \boldsymbol{\beta}_P P_t + \boldsymbol{\beta}_C C_i + \boldsymbol{\beta}_F F_i + \boldsymbol{\beta}_{AF} A_{it} F_i + \boldsymbol{\beta}_{PF} P_t F_i + \boldsymbol{\beta}_{CF} C_i F_i + \mathbf{Z}_i \boldsymbol{\gamma} + \mathbf{X}_{\text{it}} \boldsymbol{\beta} + \boldsymbol{W}_i + \varepsilon_{it} \quad (1)$$

where y_{it} is the log of the hourly real wage for individual i in year t. A_{it}, P_t, C_i, and F_i are the dummy variables representing age, period, cohort, and female, respectively. The vector of all time-varying regressors other than age is denoted by $\mathbf{X}_{it}$. On the other hand, $\mathbf{Z}_i$ is the set of time-constant observed variables excluding cohort and gender and $\mathbf{W}_i$ contains the unobserved heterogeneity or individual effect and a constant term. In equation (1), age, period and cohort effects for men are represented by $\boldsymbol{\beta}_A$, $\boldsymbol{\beta}_P$ and $\boldsymbol{\beta}_C$, respectively. In contrast, the differential impact of the same effects on women are respectively represented by $\boldsymbol{\beta}_{AF}$, $\boldsymbol{\beta}_{PF}$ and $\boldsymbol{\beta}_{CF}$. While the age effect is expected to worsen the gender wage gap, the cohort effect is supposed to be positive for smaller and recent cohorts. The period effect can run in both directions, depending on the influence of the forces working behind it.

3.2 APC identification Strategy

Popular methods to resolve the APC identification issue can be grouped into two categories, both of which have major weaknesses. One of the first proposed solutions is to assume that only two from age, period and cohort are relevant for a particular problem. However, this is a rather strong theoretical assumption to make, which does not hold in many situations including the present one (Winship and Harding 2008). Another widely used approach is to make one or more identifying constraints on the regression parameters, such as the one that the coefficients of the first two cohorts are equal (Yang and Land 2013). Such constraints can sometimes be implicit, which is observed for the more recent intrinsic estimator (IE) method (Luo 2013b). A major problem with this second approach is that it depends on the number of age, period, and cohort categories that are considered in the study or produces significantly different results based on the choice of constraints (Jürges 2003; Luo 2013a).[1]

In this study, we therefore apply the proxy variable method to replace at least one of the age, period, or cohort effects and thus solve the identification problem. The reasons are the following. First, as pointed out by Glenn (1976), the solutions to the APC problem can never be found in statistical manoeuvring alone, and therefore, they should come from theories. the proxies can

[1] See Dohmen et al. (2017) and Luo et al. (2016) for empirical evidence of some of the most serious limitations of these approaches.

be selected on theoretical grounds. In our case, we have discussed how past economic literature relates different variables to the age, period and cohorts effects in wages in the second section (e.g., Card and Lemieux 2001; Berger 1985). Our proxies are chosen based on these discussions. Second, since age, period, and cohort effects act as a summary measure of the influences of different factors on a variable of interest (Hobcraft, Menken, and Preston 1985), the use of those factors directly as proxy variables not only solves the identification problem, but also provides valuable information about the underlying forces at work. The knowledge that the unemployment rate is negatively related to the gender wage gap is certainly more useful to policymakers than knowing that there is evidence of period effects. Additionally, our use of proxy variable is also different from previous similar works in that we utilize multiple proxies to represent a single effect and thus attempt to fully measure the APC effects it is proxying, rather than employing a single proxy variable per each effect (e.g., Dohmen et al. 2017; Euwals, Knoef, and Vuuren 2011).

A range of proxy variables are used in this paper to replace the period (P_t) or the cohort (C_i) dummies at one time.[2] Since a good proxy has to be context-specific, and hence labour market related for this study, changes in the economic conditions are proxied by the unemployment rate in case of period effects (see Nientker and Alessie 2019; Kapteyn, Alessie, and Lusardi 2005 for further discussion). Technological progress is measured by the ratio of information technology net capital stock to the net capital stock, as was one in Kelly (2007). Finally, since two significant federal level anti-discriminatory legislation were passed between 2001 and 2018 (i.e., Age Discrimination Act 2004 and Fair Work Act 2009), two dummy variables are used to reflect such changes in the legal environment. The proxy variables for cohort effects, on the other hand, include the size of a person's birth cohort and the educational level of that particular

[2] Since the age effect is associated with psychological variables like maturity, it is extremely difficult to find or develop appropriate proxy variables for it (Heckman and Robb 1985; Black, Tseng, and Wilkins 2010).

birth cohort, i.e., the ratio of workers with post-senior secondary education to the total number of workers in each year.

3.3 Estimation Strategy

The study uses the correlated random effects (CRE) model to estimate Equation (1). The pooled ordinary least squares (OLS) method is not suitable for the present study as it neglects the panel nature of the data. The fixed effects (FE) method, on the other hand, cannot estimate the coefficients of time-constant variables. The random effects (RE) procedure instead relies on the assumption that the unobserved time-constant variables are not correlated with the explanatory variables, which is too restrictive in many applications. For example, in the present case, ability and motivation are two such unobserved individual characteristics that influence an individual's education level and work experience (Breunig, Hasan, and Salehin 2013).

The CRE model overcomes all the above issues, and therefore is applied as the estimator of choice in this study. The CRE approach assumes that $\boldsymbol{W}_i$ in equation (1) is correlated with the time-varying regressors in the following manner:

$$\boldsymbol{W}_i = \overline{\boldsymbol{R}}_i\boldsymbol{\delta} + u_i \tag{2}$$

where $\mathbf{R}_i$ is the set of all time-varying characteristics and is assumed to be uncorrelated with u_i.[3] Substituting equation (2) into (1) gives

$$y_{it} = \boldsymbol{\beta}_A A_{it} + \boldsymbol{\beta}_P P_t + \boldsymbol{\beta}_C C_i + \boldsymbol{\beta}_F F_i + \boldsymbol{\beta}_{AF} A_{it} F_i + \boldsymbol{\beta}_{PF} P_t F_i + \boldsymbol{\beta}_{CF} C_i F_i + \mathbf{Z}_i\boldsymbol{\gamma} + \mathbf{X}_{\mathrm{it}}\boldsymbol{\beta} + \overline{\boldsymbol{R}}_i\boldsymbol{\delta} + u_i + \varepsilon_{it} \tag{3}$$

where $(u_i + \varepsilon_{it})$ is the composite error term. By including the means of the time-varying variables (e.g., occupational tenure and age), the CRE approach can estimate the coefficients

[3] More specifically, $\overline{\mathbf{R}}_i$ contains $\overline{\mathbf{X}}_i$, the mean value of individual age and the interaction of mean individual age and the female dummy.

of time-constant covariates while allowing for arbitrary correlation between unmeasured heterogeneity and the observed explanatory variables (Joshi and Wooldridge 2019).

3.4 Employment Selection and weights

To addresses the possibility of the presence of selection bias in panel data, we employ the parametric correction procedure proposed by Wooldridge (1995) and Semykina and Wooldridge (2010). The method is similar to Heckman's two-step estimation but involves the estimation of a probit selection equation for each survey year. The estimated selection component, i.e., the Inverse Mills Ratio (IMR), is then added to the estimating wage model to solve the self-selection problem.

Following Mulligan and Rubinstein (2008), we employ the interaction between the number of children aged 0–4 years and marital status of the respondent as an additional variable in the employment selection equation. We also use the presence of children between 5 and 9 years of age for the same purpose. These are the variables that are assumed to affect the employment status but not the wage rate. Additionally, the employment equation also includes marital status, age, educational status, health status, place of birth and geographic remoteness. All estimation is conducted without sampling weights, using cluster robust standard errors at the individual level.[4]

4 Data and Descriptive Statistics

This study uses data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey funded by the Department of Social Services and Melbourne Institute of Applied Economic and Social Research (2020). It is a nationally representative panel study of Australian households. The present study incorporates employs the first 18 waves of the survey, which was conducted between 2001 and 2018. In addition, data on net capital stock, information

[4] See Appendix B for explanation.

technology net capital stock and consumer price index are sourced from the Australian Bureau of Statistics (ABS 2018a, 2019).

For this study, our sample consists of all the respondents aged between 25 and 54, inclusive. The labour force participation rate is higher among the 25-54 age bracket (RBA 2018). The decision to study this age group helps to concentrate on individuals who have the highest levels of attachment to the labour market (Bourguignon, Ferreira, and Menéndez 2007). Since part-time work is more prevalent among female workers at 16.2 percent compared to male workers at 5.4 percent (WGEA 2018), both full-time and part-time employees are included in the sample. The sample, however, excludes employers, employees of their own businesses, the self-employed, family workers and students. These restrictions largely overcome the complications arising from the continuity of education, arrangements made for future retirement, and dishonest reporting of earnings, thus producing a relatively homogeneous sample (Christofides, Polycarpou, and Vrachimis 2013). It also excludes observations for which data was refused, unknown or not provided on employment status and working hours. The resulting estimation sample consists of 58,839 men and 67,594 women, with a total of 126,433 observations from 47 birth cohorts (born from 1947 to 1993).

Table 1 reports the summary statistics of the variables used in this study. The definitions of the variables are provided in Appendix Table A1. As can be seen from Table 1, women perform significantly worse than men in terms of a range of employment-related outcomes. For example, women on average receive lower wages than men and have shorter tenure both in terms of involvement in current occupation and with current employer. Women also fall behind men when it comes to employment rates and full-time employment. As expected, the occupational and industry proliferation of men and women significantly varies from each other as certain jobs and sectors are traditionally male-dominated (e.g., machinery operator and driver and mining). In the sample, women are less likely to pursue a certificate course. On the other hand,

Table 1 Summary Statistics

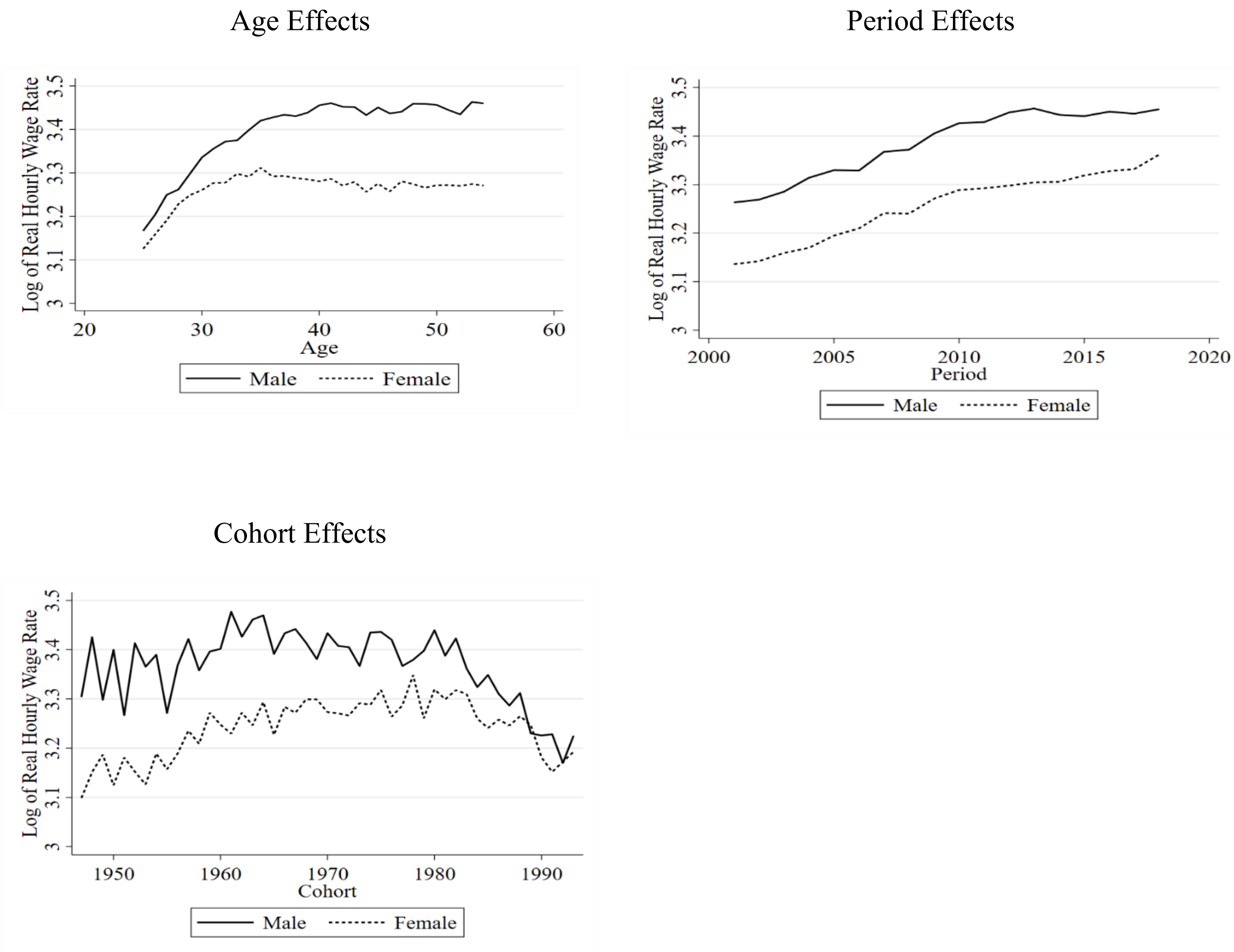
Variables	Men Mean	Men Std. dev.	Women Mean	Women Std. dev.	Men-women mean difference
Real hourly wage (log)	3.39	0.47	3.26	0.43	0.130***
Real hourly wage (raw)	33.22	17.90	28.83	17.91	4.387***
Age	39.07	8.66	39.43	8.64	-0.367***
Number of children 0–4 years	0.29	0.60	0.30	0.61	-0.011***
Tenure: occupation	9.25	8.59	8.29	8.15	0.961***
Tenure: employer	6.85	7.41	6.13	6.57	0.718***
Birth: Australia	0.79	0.41	0.79	0.41	0.007***
Married	0.73	0.45	0.73	0.44	-0.004
Children 0–4 years	0.22	0.41	0.23	0.42	-0.011***
Children 5–9 years	0.20	0.40	0.23	0.42	-0.035***
Geographic remoteness	0.12	0.33	0.12	0.33	0.002
University	0.27	0.45	0.33	0.47	-0.056***
Advanced diploma and diploma	0.09	0.29	0.11	0.31	-0.015***
Certificate III and IV	0.30	0.46	0.17	0.38	0.131***
Year 12	0.13	0.33	0.14	0.35	-0.017***
Year 11 or below	0.20	0.40	0.25	0.43	-0.043***
Health condition	0.21	0.40	0.21	0.41	-0.003
Employed	0.87	0.34	0.72	0.45	0.148***
Full-time employment	0.81	0.40	0.41	0.49	0.392***
Casual employment	0.13	0.34	0.21	0.41	-0.074***
Union member	0.28	0.45	0.29	0.45	-0.011***
Private sector	0.73	0.44	0.54	0.50	0.192***
Firm size less than 5	0.08	0.28	0.08	0.28	0.000
Firm size 5-19	0.25	0.43	0.24	0.43	0.001
Firm size 20-99	0.30	0.46	0.31	0.46	-0.014***
Firm size 100 or more	0.37	0.48	0.36	0.48	0.013***
Manager	0.16	0.37	0.10	0.29	0.067***
Professional	0.23	0.42	0.33	0.47	-0.098***
Technician/trades	0.20	0.40	0.04	0.19	0.165***
Community/personal	0.06	0.24	0.14	0.35	-0.080***
Clerical/administrative	0.08	0.28	0.24	0.43	-0.155***
Sales	0.04	0.20	0.08	0.27	-0.036***
Machinery/driver	0.12	0.33	0.01	0.11	0.110***
Labourer	0.09	0.29	0.06	0.25	0.028***
Agriculture/forestry	0.02	0.15	0.01	0.09	0.016***
Mining	0.04	0.19	0.01	0.08	0.032***
Manufacturing	0.15	0.36	0.05	0.21	0.101***
Electricity/gas	0.02	0.14	0.01	0.07	0.014***
Construction	0.10	0.30	0.01	0.12	0.088***
Wholesale trade	0.05	0.22	0.02	0.15	0.025***
Retail trade	0.06	0.24	0.09	0.29	-0.030***
Accommodation/food	0.03	0.17	0.05	0.21	-0.018***
Transport/postal	0.07	0.26	0.02	0.15	0.051***
Information media	0.03	0.16	0.02	0.15	0.004***
Financial/insurance	0.04	0.20	0.05	0.22	-0.010***
Rental/hiring	0.01	0.11	0.02	0.12	-0.004***
Professional/scientific	0.08	0.27	0.07	0.26	0.008***
Administrative/support	0.02	0.14	0.03	0.17	-0.010***
Public administration	0.10	0.30	0.08	0.26	0.027***
Education/training	0.06	0.24	0.18	0.38	-0.117***
Health care	0.07	0.26	0.26	0.44	-0.193***

Notes: *** and ** denote significance at the 1% and 5% level, respectively.
Source: Authors' calculation based on HILDA Survey data.

union membership and casual work are more prevalent among them. They are on average older and are more likely to have children. In terms of marital status, health condition and geographic remoteness, however, there is no significant difference between the two groups.

Figure 1 shows the average male and female hourly wage rate for each age, period and cohort for our sample. The three charts in Figure 1 show three different trends when it comes to the movement of the gender wage gap. The hourly gender wage gap increased with age, decreased by cohort but remained constant from 2001 to 2018.

Figure 1. Male-Female Wage Rate by Age, Period and Cohort



5 Results

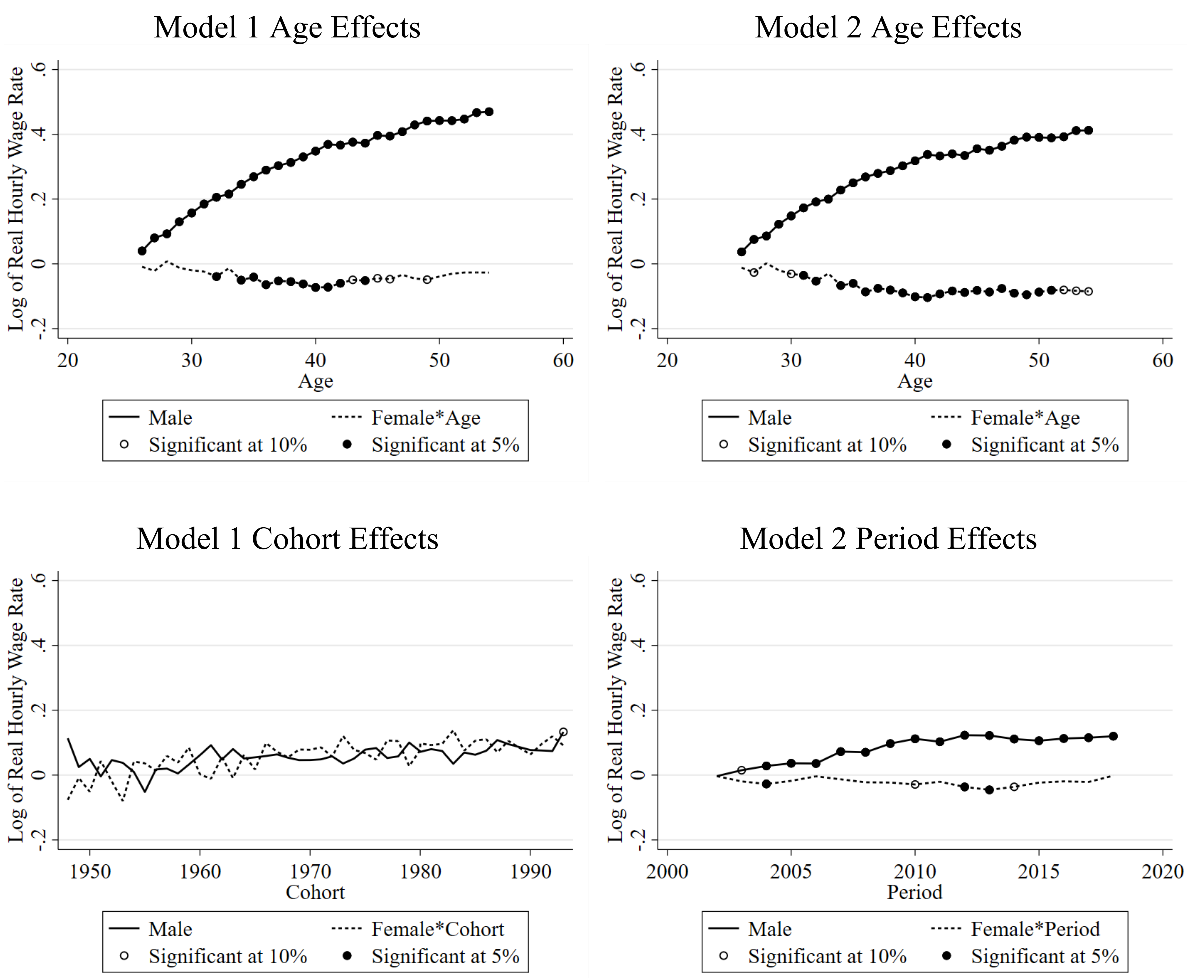
We consider six different specifications of equation (3) in our analysis. Models 1 and 2 are our main models. In Model 1, we replace period dummies with our year proxy variables to solve the linearity problem. In Model 2, we employ cohort proxies instead of cohort dummies for the same purpose.[5] This alternate use of period and cohort proxies enables us to gain a better empirical perspective about our estimates and the adequacy of the proxy variables. The estimated coefficients of the age, period and cohort dummies from models 1 and 2 for every year are presented in Figure 2.[6] As the figure shows, the interaction dummies between women workers and different ages are mostly significant in both the models. On the other hand, despite the presence of positive period effects overall, 3 out of 17 interaction dummies between female workers and period dummies are significant at the 5 percent level in Model 2. Finally, for cohort effects, none of the dummy variables are found to be statistically significant at the 5 percent level of significance in model 1.

The results from our main models suggest that the age effect is a significant predictor of the male-female wage gap in Australia, even after controlling for period effects and labour market experience, education, health, and cohort status of the respondents. It is also reasonable to say that period effects also play some meaningful role in the determination of the gender wage gap by relatively suppressing the female wage rate compared to the male rate. However, in contrast to the age and period effects, the impact of cohort effects on wages is found to be inconsequential in Australia, both for the overall wages as well as for the gender difference in wage rates.

[5] That is, in equation (3), P_t = period proxies and C_i = cohort proxies for Models 1 and 2, respectively. Other variables remain the same.

[6] Note that we get age, period, and cohort effects for every year when we use the dummy variables to represent them. When we use the proxy variables to replace them, we get the average estimates of these effects, which is provided in Table 2.

Figure 3 Age, Period and Cohort Effects: Results from Models 1 and 2

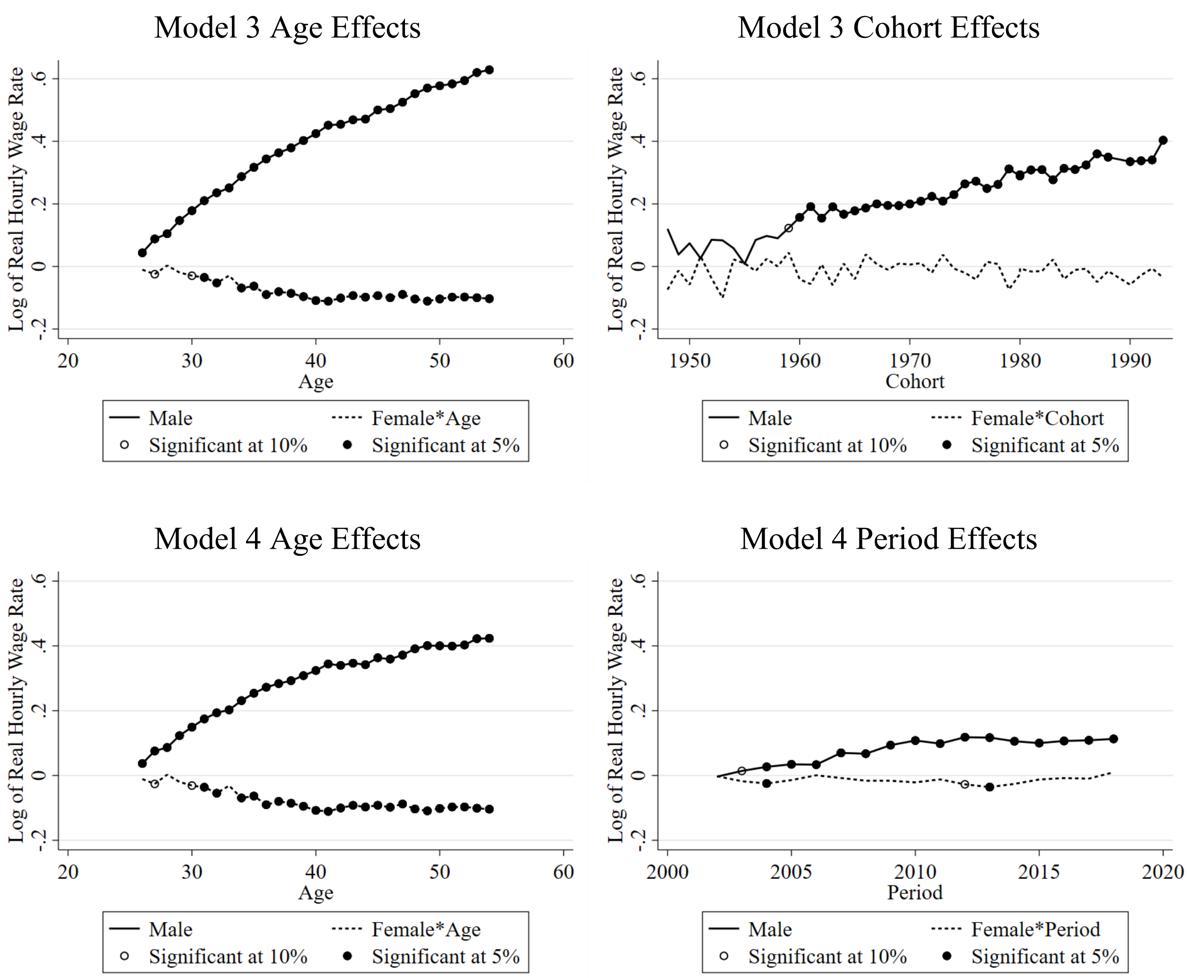


In the next two specifications, we exclude year and cohort variables, respectively, from equation (3). Therefore, Model 3 considers the impact of only age and birth cohort on the gender wage gap as it keeps the period effect out of the analysis. In contrast, Model 4 includes age and period effects, but disregards the cohort effect. These two specifications allow us to understand the consequences of not controlling for all three of age, period and cohort effects in such an analysis.[7] Figure 3 presents the estimated impact of the age, period and cohort dummies. The results show that there are significant cohort effects on wages when year effects are dropped out entirely. Furthermore, average age and cohort effects are now overestimated by about 7.77

[7] That is, for Models 4 and 5, we drop P_t and C_i, respectively from equation (3). Other variables remain the same.

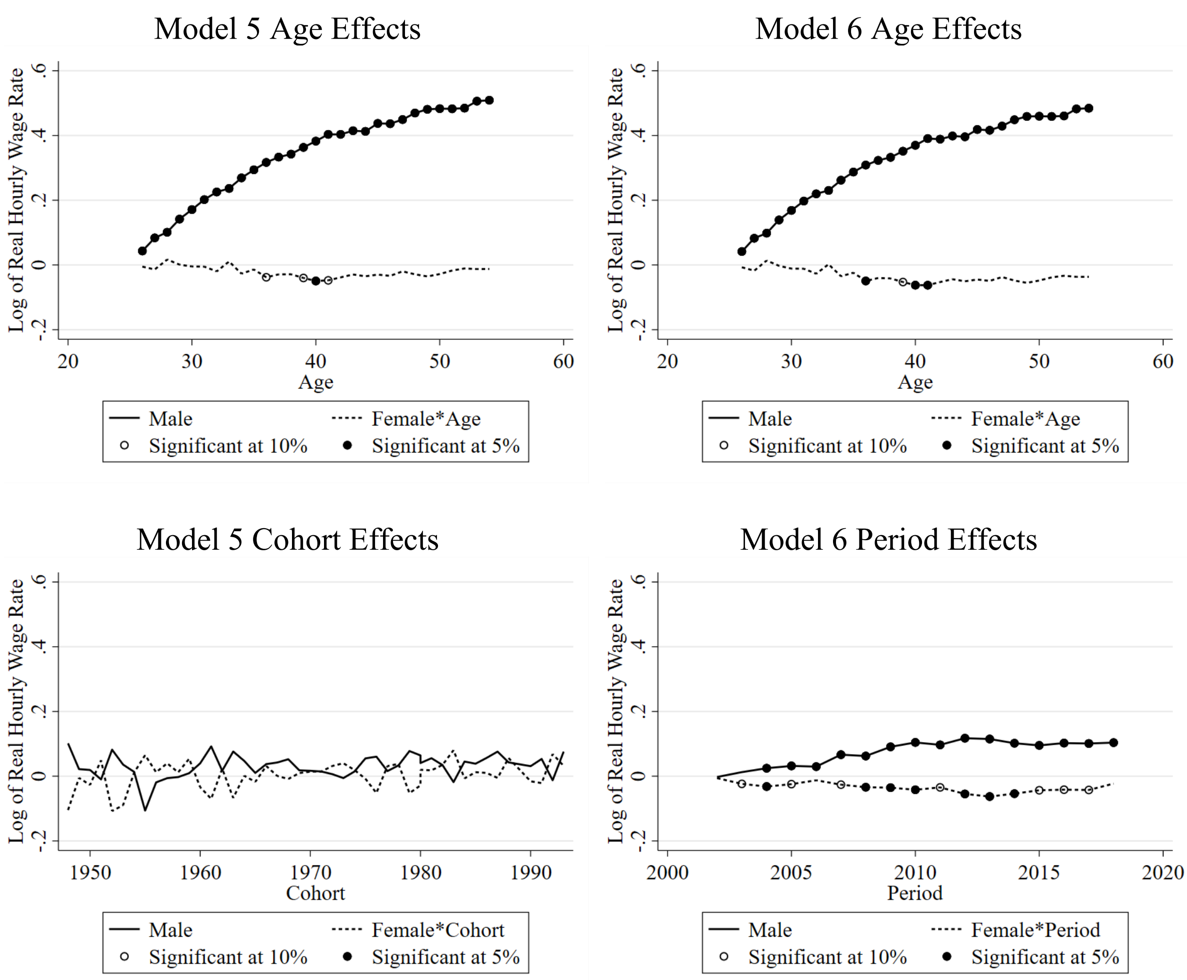
and 15.34 percentage points, respectively for the male employees. A greater number of dummy variables representing the interaction between women and age are now also statistically significant. On the other hand, we see no major impact of the absence of the cohort variables on our estimates.

Figure 4 Age, Period and Cohort Effects: Results from Models 3 and 4



Our final two models estimate equation (3) without the job-related control variables. Model 5, therefore, contains age and cohort dummies with period proxy variables, but no job characteristics of the respondents. Similarly, Model 6 excludes the job-related variables, but this time represents the APC variables by age and period dummies and cohort proxies.[8] Models 5 and 6 thus take into consideration the possibility that the correlation between the cohort effect and the job-related control variables might be the reason for its being absence effects in our previous models. The resulting estimates of the age, period and cohort dummy variables are displayed in Figure 4. As the figure shows, the cohort effect still remains insignificant even without the job-related control variables. Therefore, it appears that the job-related characteristics are not responsible for the lack of cohort effects in Models 1 to 4.

Figure 5 Age, Period and Cohort Effects: Results from Models 5 and 6



[8] In Models 5 and 6, P_t = period proxies and C_i = cohort proxies, respectively. Furthermore, both these models exclude job related control variables from $\mathbf{X}_{it}$ of equation (3). Other variables remain the same.

The regression coefficients of the proxy and the control variables from all six specifications and the model fit statistics are reported in Table 2. It is noticeable that cohort size, cohort educational level and their interaction with female dummy have failed to achieve statistical significance in all the models while several period proxies are significant in Models 2 and 6. On the other hand, Age Discrimination Act and Fair Work Act dummy variables show a significant positive relationship with wage rates in Model (1) and (5). The unemployment rate and the interaction of women and the Fair Work Act dummy, on the other hand, are negatively related to wage rates in both models. Since the net of the anti-discrimination laws, in general, have been positive, it can be said that they have been successful in improving the wage rates of Australian workers. However, the same cannot be said for their effect on the Australian gender wage gap. Finally, the coefficients of the inverse mills ratio (IMR) are negative and significant in all the models, implying that unobservable factors that increase the probability of working reduce the wage rate.

Table 2 Regression coefficients of the period and cohort proxies and the control variables

Variables	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
Constant	2.7248***	2.7202***	2.4737***	2.7157***	3.0643***	3.0091***
Married	0.0133**	0.0136**	0.0124**	0.0133**	0.0118**	0.0118**
Children 0–4 years	0.0211***	0.0201***	0.0244***	0.0204***	0.0372***	0.0370***
Birth: Australia	0.0146**	0.0128**	0.0119*	0.0127**	0.0522***	0.0501***
Geographic remoteness	0.0072	0.0076	0.0090	0.0077	0.0039	0.0046
University	0.0963***	0.0975***	0.0944***	0.0970***	0.0993***	0.0996***
Advanced diploma and diploma	0.0363*	0.0374*	0.0351*	0.0371*	0.0296	0.0299
Certificate III and IV	0.0092	0.0099	0.0086	0.0096	0.0023	0.0023
Year 12	0.0254	0.0252	0.0269	0.0253	0.0232	0.0224
Health condition	0.0100	0.0089	0.0158*	0.0095	0.0134	0.0133
Tenure: occupation	0.0046***	0.0046***	0.0046***	0.0046***		
Tenure squared: occupation	-0.0001***	-0.0001***	-0.0001***	-0.0001***		
Tenure: employer	0.0023***	0.0023***	0.0022***	0.0023***		
Tenure squared: employer	-0.0001*	-0.0001*	-0.0000*	-0.0000*		
Full-time employment	-0.1027***	-0.1026***	-0.1024***	-0.1024***		
Casual employment	0.0459***	0.0457***	0.0453***	0.0457***		
Union member	0.0280***	0.0282***	0.0283***	0.0282***		
Private sector	-0.0164***	-0.0166***	-0.0166***	-0.0166***		
Firm size 5-19	0.0272***	0.0272***	0.0277***	0.0272***		

Firm size 20-49	0.0467***	0.0469***	0.0474***	0.0468***		
Firm size 100 or more	0.0815***	0.0816***	0.0827***	0.0816***		
Manager	0.0733***	0.0737***	0.0738***	0.0737***		
Professional	0.0626***	0.0623***	0.0631***	0.0623***		
Technician/trades	0.0371***	0.0378***	0.0372***	0.0377***		
Community/personal	-0.0057	-0.0054	-0.0060	-0.0054		
Clerical/administrative	0.0403***	0.0402***	0.0411***	0.0401***		
Sales	-0.0005	-0.0002	0.0003	-0.0002		
Machinery/driver	0.0205**	0.0208**	0.0204**	0.0208**		
Agriculture/forestry	-0.0133	-0.0133	-0.0167	-0.0132		
Mining	0.1738***	0.1718***	0.1749***	0.1719***		
Manufacturing	0.0487***	0.0479***	0.0481***	0.0480***		
Electricity/gas	0.0914***	0.0897***	0.0923***	0.0897***		
Construction	0.0829***	0.0817***	0.0845***	0.0818***		
Wholesale trade	0.0234*	0.0224*	0.0234*	0.0225*		
Retail trade	-0.0222*	-0.0231*	-0.0214*	-0.0230*		
Accommodation/food	-0.0330**	-0.0341**	-0.0325**	-0.0339**		
Transport/postal	0.0434***	0.0423***	0.0431***	0.0424***		
Information media	0.0545***	0.0536***	0.0551***	0.0538***		
Financial/insurance	0.0717***	0.0695***	0.0728***	0.0696***		
Rental/hiring	-0.0169	-0.0179	-0.0164	-0.0178		
Professional/scientific	0.0425***	0.0408***	0.0433***	0.0409***		
Administrative/support	0.0177	0.0161	0.0188	0.0162		
Public administration	0.0773***	0.0761***	0.0777***	0.0761***		
Education/training	0.0368**	0.0359**	0.0368**	0.0359**		
Health care	0.0259**	0.0248**	0.0252**	0.0248**		
IMR	-0.0442**	-0.0406*	-0.0588***	-0.0420**	-0.0504**	-0.0494**
Female	-0.1901	-0.1553**	-0.0877	-0.1012*	-0.0549	-0.0258
Age discrimination Act	0.0188***				0.0156**	
Female*Age Discrimination Act	-0.0150				-0.0131	
Fair work Act	0.0579***				0.0639***	
Female*Fair Work Act	-0.0244***				-0.0262***	
Technological developments	0.0002				0.0001	
Female*Technological developments	-0.0005				-0.0004	
Unemployment rate	-0.0108***				-0.0123***	
Female*Unemployment rate	0.0019				0.0040	
Cohort size		0.0350				0.0120
Female*Cohort size		0.0165				0.0052
Cohort educational level		-0.0538				-0.0128
Female*Cohort educational level		0.0156				0.0001
Age (m)	-0.0102***	-0.0101***	-0.0096***	-0.0100***	-0.0078***	-0.0076***
Female*Age (m)	0.0026	0.0025	0.0023	0.0026	-0.0018	-0.0018
Married (m)	0.0419***	0.0421***	0.0408***	0.0424***	0.0741***	0.0738***
Children 0–4 years (m)	0.0538***	0.0542***	0.0545***	0.0539***	0.0524***	0.0518***
Geographic remoteness (m)	-0.0038	-0.0056	-0.0064	-0.0058	-0.0568***	-0.0596***
University (m)	0.0516**	0.0522**	0.0491*	0.0519**	0.2883***	0.2893***
Advanced diploma and diploma (m)	0.0347	0.0348	0.0321	0.0349	0.1713***	0.1711***
Certificate III and IV (m)	0.0247	0.0243	0.0215	0.0239	0.1012***	0.1006***
Year 12 (m)	0.0227	0.0239	0.0192	0.0237	0.1071***	0.1082***
Health condition (m)	-0.0736***	-0.0735***	-0.0741***	-0.0737***	-0.1296***	-0.1298***

Tenure: occupation (m)	0.0107***	0.0107***	0.0107***	0.0109***		
Tenure squared: occupation (m)	-0.0002***	-0.0002***	-0.0002***	-0.0002***		
Tenure: employer (m)	-0.0018	-0.0021	-0.0017	-0.0023		
Tenure squared: employer (m)	0.0000	0.0001	0.0000	0.0001		
Full-time employment (m)	0.0829***	0.0813***	0.0829***	0.0797***		
Casual employment (m)	-0.0112	-0.0129	-0.0113	-0.0130		
Union member (m)	0.0439***	0.0431***	0.0427***	0.0434***		
Private sector (m)	0.0457***	0.0469***	0.0461***	0.0463***		
Firm size 5-19 (m)	0.0354**	0.0352**	0.0357**	0.0350**		
Firm size 20-99 (m)	0.0701***	0.0712***	0.0705***	0.0709***		
Firm size 100 or more (m)	0.1439***	0.1456***	0.1445***	0.1452***		
Manager (m)	0.3593***	0.3601***	0.3604***	0.3604***		
Professional (m)	0.2771***	0.2787***	0.2782***	0.2784***		
Technician/trades (m)	0.1255***	0.1258***	0.1269***	0.1259***		
Community/personal (m)	0.1149***	0.1152***	0.1158***	0.1153***		
Clerical/administrative (m)	0.0983***	0.0987***	0.0984***	0.0986***		
Sales (m)	0.1553***	0.1563***	0.1553***	0.1561***		
Machinery/driver (m)	0.0015	0.0010	0.0018	0.0012		
Agriculture/forestry (m)	-0.1503***	-0.1559***	-0.1504***	-0.1542***		
Mining (m)	0.3536***	0.3544***	0.3524***	0.3553***		
Manufacturing (m)	0.0428*	0.0425*	0.0421*	0.0437*		
Electricity/gas (m)	0.2146***	0.2137***	0.2117***	0.2134***		
Construction (m)	0.1840***	0.1866***	0.1832***	0.1874***		
Wholesale trade (m)	0.0921***	0.0927***	0.0922***	0.0938***		
Retail trade (m)	-0.0604**	-0.0602**	-0.0615**	-0.0594**		
Accommodation/food (m)	-0.0534*	-0.0510*	-0.0544*	-0.0510*		
Transport/postal (m)	0.1096***	0.1116***	0.1103***	0.1127***		
Information media (m)	0.0966***	0.0988***	0.0967***	0.0998***		
Financial/insurance (m)	0.1629***	0.1667***	0.1624***	0.1681***		
Rental/hiring (m)	0.1375***	0.1377***	0.1363***	0.1388***		
Professional/scientific (m)	0.1241***	0.1270***	0.1234***	0.1274***		
Administrative/support (m)	0.0414	0.0405	0.0401	0.0418		
Public administration (m)	0.1396***	0.1432***	0.1414***	0.1438***		
Education/training (m)	-0.0278	-0.0273	-0.0280	-0.0270		
Health care (m)	0.0427*	0.0437*	0.0427*	0.0442*		
R-squared	0.3929	0.3906	0.3911	0.3905	0.2287	0.2245
Wald χ^2	16395***	16013***	16230***	15984***	7146***	6981***
ρ	0.5236	0.5255	0.5246	0.5257	0.5258	0.5990
N	90212	90212	90212	90212	90212	90212

Notes: ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Time-averaged means are indicated by (m). Cluster robust standard errors are used in the analysis.
Source: Authors' calculation based on HILDA Survey data.

In our main models, the coefficients of education and industry variables have reasonable signs. Individuals who are better educated, who work in larger firms or certain occupations (e.g., managerial and professional positions) are expected to receive significantly higher wages.

Similarly, union membership and longer tenure lead to better wage rates. A higher wage rate is also observed for married and Australian-born employees. For other variables, when the values are considered in combination with the coefficients of their mean values (which gives the difference between the estimated between- and within-cluster effects), their signs and significance levels are more or less in line with previous Australian research (e.g., Risse, Farrell, and Fry 2018; Cai and Waddoups 2011; Eastough and Miller 2004).

Questions may arise about the suitability of our chosen proxy variables, especially of the cohort proxies as they are insignificant and have shown no major influence on the estimates in Model (4). As Models 1 and 2 are not the unrestricted versions of Models 3 and 4 and vice versa, there is no direct way to assess the validity of the proxies used. However, it is to be noticed here that model (1) has considered the effects of birth cohort by directly including cohort dummies instead of cohort proxy variables. Still, model (1) has found no significant cohort effects on wages or the wage gap. Furthermore, the significance level of the year and cohort proxies in Table 2 also supports the same conclusion. Therefore, the absence of the cohort effect in the present case can be considered to be suggestive of its true significance, rather than the outcome of poor proxy variable selection.

In the end, it, therefore, can be said that the gender wage gap between male and female workers has been widening with age in Australia. Similarly, there is some evidence of the impact of period effects on the gender pay gap. Cohort effects, however, have no effect on the determination of the gender wage gap in the country. This finding regarding age effects corroborates similar studies performed in Australia and other countries (e.g., Tyrowicz, Velde, and Staveren 2018; Erosa, Fuster, and Restuccia 2016; Wu 2007; Chatterjee, Singh, and Stone 2016). It comes in face of the possibility that age effects may turn out to be lacking in the analysis when the experience variable (in this case, tenure) is also included because of the presence of a high correlation between the two (Adamchik and Bedi 2000). On the other hand, the finding that no cohort effects exist on the Australian gender wage gap contradicts its significant role (both positive and negative) in the determination of gender wage gap in previous such studies performed elsewhere (e.g., Abe 2010; Naur and Smith 2002; Tyrowicz, Velde, and Staveren 2018). A range of explanations for our age-related findings are already provided in Section 2. The insignificant cohort effects in our results, on the other hand, may indicate that cohorts are perfect substitutes for one another. This result aligns with Card and Lemieux (2001) who suggest the wage gap can be fully captured by age and period effects and that cohort effects cannot be expected to play any role.

6 Conclusion

This paper evaluates the impact of age, period and birth cohort on the Australian gender wage gap for the period 2001-2018. Despite the narrowing of the human capital gap between men and women and improvements in the legal framework, the gender wage gap in Australia and many countries has refused to follow the same trend. The age, period and birth cohort effects can help explain the persistence or divergence of this pay gap and provide important guidelines. However, separating these effects from one another is a difficult task because of the linear dependence that exists between the three.

This paper addresses this identification problem by developing appropriate proxies and employing suitable panel data techniques. Like previous studies, this study reveals that age is a significant predictor of the gender wage gap in Australia. The estimated period effects also show a further diverging role in the male-female wage difference. However, as opposed to prior expectations, the paper finds no significant influence of cohort effects on wages or the wage gap. Differences in other standard variables (e.g., education and experience) are found to play their respective roles as usual. Additionally, the paper finds evidence that not-including period effects can result in significant cohort effects or overestimation of the age and cohort effects on wages. This implies that the application of Mincer type equations for certain purposes, such as estimating the wage gap over the life cycle or across cohorts, can lead to over- or under-estimation of the parameters if the APC problem is ignored.

The findings of the paper also have some policy implications. First, if the gender wage gap increases with age, economic conditions would be more unfavourable for women at retirement age and particularly for single female households. Any successful policy of redistributing earnings across age groups, therefore, needs such intersectionality of age and gender into consideration. Second, although the legal framework is expected to be an effective way of reducing the gender wage gap, the negative dummies representing the interaction between the Fair Work Act and women show that some of these changes are actually worsening the gender pay gap problem in Australia. Such results establish the validity of some of the previous criticisms (e.g., Charlesworth and Macdonald 2015, 2014) directed towards the way policies and laws have been introduced and integrated to promote gender equality in the country. Third, policymakers need to be more attentive to the effects of yearly changes in the socio-economic conditions since estimated period effects show a further diverging role in the male-female wage gap. Finally, since eliminating the educational difference between the genders is not proving to be enough for ensuring wage gains for younger female cohorts compared to their male counterparts, policy measures need to be broadened in Australia if they are to reduce the wage gap for recent cohorts. For example, actions may be required to eliminate gender differences in occupation and industry-related special skills, access and opportunities. Furthermore, future research should carry out a detailed investigation into the ageing process of the genders, the work-related human capital acquisition of women, and the effective administration and enforcement of various labour laws to develop a better understanding of the relationship between age, period and cohort variables and the gender wage gap

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References

Abe, Yukiko. 2010. "Equal Employment Opportunity Law and the gender wage gap in Japan: A cohort analysis." *Journal of Asian Economics* 21 (2):142–155.

ABS. 2018a. 5204.0 - Australian System of National Accounts, 2017-18 (Table 63, Table 69). Australian Bureau of Statistics (ABS). Available at https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5204.02017-18?OpenDocument [Accessed January 31, 2020].

ABS. 2018b. Gender Indicators, Australia, Sep 2018. Canberra: Australian Bureau of Statistics (ABS). Available at https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/4125.0~Sep%202018~Main%20Features~In%20This%20Issue%20~1 [Accessed at August 7, 2019].

ABS. 2019. 6401.0 - Consumer Price Index, Australia, Sep 2019 (Table 1). Available at https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6401.0Sep%202019?OpenDocument [Accessed October 09, 2019]. Australian Bureau of Statistics (ABS).

Acemoglu, Daron. 1998. "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *Quarterly Journal of Economics, Volume 113, Issue 4, November 1998* 113 (4):1055–1089.

Adamchik, Vera A., and Arjun S. Bedi. 2000. "Wage differentials between the public and the private sectors: evidence from an economy in transition." *Labour Economics* 7 (2):203–224.

Barón, Juan D., and Deborah A. Cobb-Clark. 2010. "Occupational Segregation and the Gender Wage Gap in Private- and Public-Sector Employment: A Distributional Analysis." *Economic Record* 86 (273):227–246.

Barrett, Anne E., and Carmen Von Rohr. 2008. "Gendered Perceptions of Aging: An Examination of College Students." *International Journal of Aging and Human Development* 67 (4):359–386.

Beaudry, Paul, and David A. Green. 2000. "Cohort patterns in Canadian earnings: assessing the role of skill premia in inequality trends." *Cohort patterns in Canadian earnings: assessing the role of skill premia in inequality trends* 33 (4):907–936.

Bendick, Marc, Lauren E. Brown, and Kennington Wall. 1999. "No Foot in the Door: An Experimental Study of Employment Discrimination Against Older Workers." *Journal of Aging & Social Policy* 10 (4):5–23.

Bendick, Marc, Charles W. Jackson, and J. Horacio Romero. 1996. "Employment Discrimination Against Older Workers: An Experimental Study of Hiring Practices." *Journal of Aging & Social Policy* 8 (4):25–46.

Berger, Mark C. 1985. "The Effect of Cohort Size on Earnings Growth: A Reexamination of the Evidence." *Journal of Political Economy* 93 (3):561–573.

Black, David, Yi-Ping Tseng, and Roger Wilkins. 2010. "The Decline in Male Employment in Australia: A Cohort Analysis." *Australian Economic Papers* 49 (3):180–199.

Blau, Francine D., Peter Brummund, and Albert Yung-Hsu Liu. 2013. "Trends in Occupational Segregation by Gender 1970–2009: Adjusting for the Impact of Changes in the Occupational Coding System." *Demography* 50:471–492.

Blau, Francine D., and Lawrence M. Kahn. 2000. "Gender Differences in Pay." *Journal of Economic Perspectives* 14 (4):75–99.

Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature* 55 (3):789–865.

Bourguignon, François, Francisco H. G. Ferreira, and Marta Menéndez. 2007. "Inequality of Opportunity in Brazil." *Review of Income and Wealth* 53 (4):585–618.

Breunig, Robert, Syed Hasan, and Mosfequs Salehin. 2013. "The Immigrant Wage Gap and Assimilation in Australia: Does Unobserved Heterogeneity Matter?" *Economic Record* 89 (287):490–507.

Buddelmeyer, Hielke, Wang-Sheng Lee, and Mark Wooden. 2010. "Low-Paid Employment and Unemployment Dynamics in Australia." *Economic Record* 86 (272):28–48.

Byrnes, Andrew. 2013. "The implementation of the CEDAW in Australia: success, trials, tribulations and continuing struggle." In *Women's Human Rights: CEDAW in International, Regional and National Law*, edited by Anne Hellum and Henriette Sinding Aasen, 323–357. Cambridge, UK: Cambridge University Press.

Cai, Lixin. 2010. "The relationship between health and labour force participation: Evidence from a panel data simultaneous equation model." *Labour Economics* 17 (1):77–90.

Cai, Lixin, and Guyonne Kalb. 2006. "Health status and labour force participation: evidence from Australia." *Health Economics* 15 (3):241–261.

Cai, Lixin, and C. Jeffrey Waddoups. 2011. "Union Wage Effects in Australia: Evidence from Panel Data." *British Journal of Industrial Relations* 49 (s2):s279–s305.

Card, David, and John E. DiNardo. 2002. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics* 20 (4):733–783.

Card, David, and Thomas Lemieux. 2001. "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *Quarterly Journal of Economics* 116 (2):705–746.

Charlesworth, Sara, and Fiona Macdonald. 2014. "Women, work and industrial relations in Australia in 2013." *Journal of Industrial Relations* 56 (3):381–396.

Charlesworth, Sara, and Fiona Macdonald. 2015. "Australia's gender pay equity legislation: how new, how different, what prospects?" *Cambridge Journal of Economics* 39 (2):421–440.

Chatterjee, Arpita, Aarti Singh, and Tahlee Stone. 2016. "Understanding Wage Inequality in Australia." *Economic Record* 92 (298):348–360.

Christofides, Louis N., Alexandros Polycarpou, and Konstantinos Vrachimis. 2013. "Gender wage gaps, 'sticky floors' and 'glass ceilings' in Europe." *Labour Economics* 21:86–102.

Chzhen, Yekaterina, Karen Mumford, and Catia Nicodemo. 2013. "The Gender Pay Gap in the Australian Private Sector: Is Selection Relevant Across the Earnings Distribution?" *Economic Record* 89 (286):367–381.

Cobb-Clark, Deborah A., and Michelle Tan. 2011. "Noncognitive skills, occupational attainment, and relative wages." *Labour Economics* 18 (1):1–13.

Cobb-Clark, Deborah A. 2012. "That Pesky Problem of Persistent Gender Bias." *Australian Economic Review* 45 (2):211–215.

Coelli, Michael B. 2014. "Occupational Differences and the Australian Gender Wage Gap." *Australian Economic Review* 47 (1): 44–62.

Coelli, Michael, and Jeff Borland. 2016. "Job Polarisation and Earnings Inequality in Australia." *Economic Record* 92 (296):1–27.

Cubel, Maria, Ana Nuevo-Chiquero, Santiago Sanchez-Pages, and Marian Vidal-Fernandez. 2016. "Do Personality Traits Affect Productivity? Evidence from the Laboratory." *Economic Journal* 126 (592):654–681.

Daly, Anne, Xin Meng, Akira Kawaguchi, and Karen Mumford. 2006. "The Gender Wage Gap in Four Countries." *Economic Record* 82 (257):165–176.

de Araujo, Pedro, and Stephen Lagos. 2013. "Self-esteem, education, and wages revisited." *Journal of Economic Psychology* 34:120–132.

Dennerstein, Lorraine, Susan Feldman, Carolyn Murdaugh, Jacques Rossouw, and Sharon Tennstedt. 1998. "Gender and Health Issues in Ageing." *Australasian Journal on Ageing* 17 (s1):19–21.

Department of Social Services and Melbourne Institute of Applied Economic and Social Research. 2020. The Household, Income and Labour Dynamics in Australia (HILDA) Survey, RESTRICTED RELEASE 19 (Waves 1-19), doi:10.26193/0LPD4U. ADA Dataverse, V2.

Dohmen, Thomas, Armin Falk, Bart H. H. Golsteyn, David Huffman, and Uwe Sunde. 2017. "Risk Attitudes Across The Life Course." *Economic Journal* 127 (605):F95–F116.

Eastough, Kristy, and Paul W. Miller. 2004. "The Gender Wage Gap in Paid- and Self-Employment in Australia." *Australian Economic Papers* 43 (3):257–276.

Erosa, Andres, Luisa Fuster, and Diego Restuccia. 2016. "A quantitative theory of the gender gap in wages." *European Economic Review* 85:165–187.

Euwals, Rob, Marike Knoef, and Daniel van Vuuren. 2011. "The trend in female labour force participation: what can be expected for the future?" *Empirical Economics* 40:729–753.

Fagan, Colette, and Jill Rubery. 2018. "Advancing Gender Equality through European Employment Policy: The Impact of the UK's EU Membership and the Risks of Brexit." *Social Policy and Society* 17 (2):297–317.

Farber, Henry S., Dan Silverman, and Till von Wachter. 2016. "Determinants of Callbacks to Job Applications: An Audit Study." *American Economic Review* 106 (5):314–318.

Ferraro, F. Richard, Jennifer J. Muehlenkamp, Ashley Paintner, Kayla Wasson, Tracy Hager, and Fallon Hoverson. 2008. "Aging, Body Image, and Body Shape." *Journal of General Psychology* 135 (4):379–392.

Flinn, Christopher J., Petra E Todd, and Weilong Zhang. 2018. "Personality traits, intra-household allocation and the gender wage gap." *European Economic Review* 109:191–220.

Fortin, Nicole M. 2008. "The Gender Wage Gap among Young Adults in the United States: The Importance of Money versus People." *Journal of Human Resources* 43:884–918.

Fortin, Nicole M. 2019. "Increasing earnings inequality and the gender pay gap in Canada: Prospects for convergence." *Canadian Journal of Economics* 52 (2):407–440.

Gallen, Yana, Rune V. Lesner, and Rune Vejlin. 2019. "The labor market gender gap in Denmark: Sorting out the past 30 years." *Labour Economics* 56:58–67.

Gharehgozli, Orkideh, and Vidya Atal. 2020. "Revisiting the gender wage gap in the United States." *Economic Analysis and Policy* 66:207–216.

Glenn, Norval D. 1976. "Cohort Analysts' Futile Quest: Statistical Attempts to Separate Age, Period and Cohort Effects." *American Sociological Review* 41 (5):900–904.

Glenn, Norval D. 2005. *Cohort Analysis*. 2nd ed. London: Sage Publications.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104 (4):1091–1119.

Goldin, Claudia, and Joshua Mitchell. 2017. "The New Life Cycle of Women's Employment: Disappearing Humps, Sagging Middles, Expanding Tops." *Journal of Economic Perspectives* 31 (1):161–182.

Gould, Eric D., Omer Moav, and Bruce A. Weinberg. 2001. "Precautionary Demand for Education, Inequality, and Technological Progress." *Journal of Economic Growth* 6 (4):285–315.

Gringart, Eyal, and Edward Helmes. 2001. "Age Discrimination in Hiring Practices Against Older Adults in Western Australia: the Case of Accounting Assistants." *Australasian Journal on Ageing* 20 (1):23–28.

Gringart, Eyal, Edward Helmes, and Carig Paul Speelman. 2005. "Exploring Attitudes Toward Older Workers Among Australian Employers." *Journal of Aging & Social Policy* 17 (3):85–103.

Hallward-Driemeier, Mary, Bob Rijkers, and Andrew Waxman. 2017. "Can Minimum Wages Close the Gender Wage Gap? Evidence From Indonesia." *Review of Income and Wealth* 63 (2):310–334.

Hawkins, Michele J. 1996. "College students' attitudes toward elderly persons." *Educational Gerontology* 22:271-279.

Heckman, James, and Richard Robb. 1985. "Using Longitudinal Data to Estimate Age, Period and Cohort Effects in Earnings Equations." In *Cohort Analysis in Social Research: Beyond the Identification Problem*, edited by William M. Mason and Stephen E. Fienberg, 137–150. New York: Springer-Verlag.

Hobcraft, John, Jane Menken, and Samuel Preston. 1985. "Age, Period, and Cohort Effects in Demography: A Review." In *Cohort Analysis in Social Research: Beyond the Identification Problem*, edited by William M. Mason and Stephen E. Fienberg, 89–135. New York: Springer-Verlag.

Jäckle, Robert, and Oliver Himmler. 2010. "Health and Wages: Panel Data Estimates Considering Selection and Endogeneity." *Journal of Human Resources* 45 (2):364–406.

Johnston, David W., and Wang-Sheng Lee. 2012. "Climbing the Job Ladder: New Evidence of Gender Inequity." *Industrial Relations* 51 (1):129–151.

Joshi, Riju, and Jeffrey M. Wooldridge. 2019. "Correlated Random Effects Models with Endogenous Explanatory Variables and Unbalanced Panels." *Annals of Economics and Statistics* 134:243–268.

Juhn, Chinhui, and Kristin McCue. 2017. "Specialization Then and Now: Marriage, Children, and the Gender Earnings Gap across Cohorts." *Journal of Economic Perspectives* 31 (1):183–204.

Jürges, Hendrik. 2003. "Age, Cohort, and the Slump in Job Satisfaction among West German Workers." *Labour* 17 (4):489–518.

Kapteyn, Arie, Rob Alessie, and Annamaria Lusardi. 2005. "Explaining the wealth holdings of different cohorts: Productivity growth and Social Security." *European Economic Review* 49 (5):1361–1391.

Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107 (1):35–78.

Kee, Hiau Joo. 2006. "Glass Ceiling or Sticky Floor? Exploring the Australian Gender Pay Gap." *Economic Record* 82 (259):408–427.

Kelly, Ross. 2007. "Changing Skill Intensity in Australian Industry." *Australian Economic Review* 40 (1):62–79.

Laß, Inga, and Mark Wooden. 2019. "The Structure of the Wage Gap for Temporary Workers: Evidence from Australian Panel Data." *British Journal of Industrial Relations* 57 (3):453–478.

Luo, Liying. 2013a. "Assessing Validity and Application Scope of the Intrinsic Estimator Approach to the Age-Period-Cohort Problem." *Demography* 50 (6):1945–1967.

Luo, Liying. 2013b. "Paradigm Shift in Age-Period-Cohort Analysis: A Response to Yang and Land, O'Brien, Held and Riebler, and Fienberg." *Demography* 50:1985–1988.

Luo, Liying, James Hodges, Christopher Winship, and Daniel Powers. 2016. "The Sensitivity of the Intrinsic Estimator to Coding Schemes: Comment on Yang, Schulhofer-Wohl, Fu, and Land1." *American Journal of Sociology* 122 (3):930–961.

Macpherson, David A., and Barry T. Hirsch. 1995. "Wages and Gender Composition: Why do Women's Jobs Pay Less?" *Journal of Labor Economics* 13 (3):426–471.

Macunovich, Diane J. 1999. "The fortunes of one's birth: Relative cohort size and the youth labor market in the United States." *Journal of Population Economics* 12 (2):215–272.

McLaughlin, Joanne Song. 2020. "Falling Between the Cracks: Discrimination Laws and Older Women." *Labour* 34 (2):215–238.

McMullin, Julie Ann, and John Cairney. 2004. "Self-esteem and the intersection of age, class, and gender." *Journal of Aging Studies* 18 (1):75–90.
Meng, Xin. 2004. "Gender earnings gap: the role of firm specific effects." *Labour Economics* 11:555–573.
Meng, Xin, and Dominique Meurs. 2004. "The gender earnings gap: effects of institutions and firms—a comparative study of French and Australian private firms." *Oxford Economic Papers* 56 (2):189–208.
Miller, Paul W. 2005. "The Role of Gender among Low-Paid and High-Paid Workers." *Australian Economic Review* 38 (4):405–17.
Mueller, Gerrit, and Erik Plug. 2006. "Estimating the Effect of Personality on Male and Female Earnings." *Industrial and Labor Relations Review* 60 (1):3–22.
Mulligan, Casey B., and Yona Rubinstein. 2008. "Selection, Investment, and Women's Relative Wages over Time." *Quarterly Journal of Economics* 123 (3):1061–1110.
Naur, Michèle, and Nina Smith. 2002. "Cohort Effects on the Gender Wage Gap in Denmark." In *Women's Work and Wages*, edited by Inga Persson and Christina Jonung, 122–144. New York: Routledge.
Neumark, David, Ian Burn, and Patrick Button. 2019. "Is It Harder for Older Workers to Find Jobs? New and Improved Evidence from a Field Experiment." *Journal of Political Economy* 127 (2):922–970.
Neumark, David, and Wendy A. Stock. 2006. "The Labor Market Effects of Sex and Race Discrimination Laws." *Economic Inquiry* 44 (3):385–419.
Nientker, Wouter, and Rob Alessie. 2019. "Female Labor Market Participation Across Cohorts: Evidence from the Netherlands." *De Economist* 167:407–433.
O'Reilly, Jacqueline, Mark Smith, Simon Deakin, and Brendan Burchell. 2015. "Equal Pay as a Moving Target: International perspectives on forty-years of addressing the gender pay gap." *Cambridge Journal of Economics* 39 (2):299–317.
OECD. 2017. *The Pursuit of Gender Equality: An Uphill Battle*. Paris: OECD Publishing. Available at https://dx.doi.org/10.1787/9789264281318-en.
OECD. 2018. *Education at a Glance 2018: OECD Indicators*. Paris: OECD Publishing. Available at http://dx.doi.org/10.1787/eag-2018-en.
Oksuzyan, Anna, Knud Juel, James W. Vaupel, and Kaare Christensen. 2008. "Men: good health and high mortality. Sex differences in health and aging." *Aging Clinical and Experimental Research* 20:91–102.
Pike, M. 1982. "Segregation by sex, earnings differentials and equal pay: an application of a job crowding model to UK data " *Applied Economics* 14 (5):503–514.
Ransom, Michael R, and Ronald L. Oaxaca. 2010. "New Market Power Models and Sex Differences in Pay." *Journal of Labor Economics* 28 (2):267–289.
RBA. 2018. Statement on Monetary Policy May 2018. Sydney: Reserve Bank of Australia.
Risse, Leonora, Lisa Farrell, and Tim R. L. Fry. 2018. "Personality and pay: do gender gaps in confidence explain gender gaps in wages?" *Oxford Economic Papers* 70 (4):919–949.
Şahin, Ayşegül, Joseph Song, and Bart Hobijn. 2010. "The Unemployment Gender Gap during the 2007 Recession." *Current Issues in Economics and Finance* 16 (2):1–7.
Santos-Pinto, Luís. 2012. "Labor Market Signaling and Self-Confidence: Wage Compression and the Gender Pay Gap." *Journal of Labor Economics* 30 (4):873–914.
Semykina, Anastasia, and Jeffrey M. Wooldridge. 2010. "Estimating panel data models in the presence of endogeneity and selection." *Journal of Econometrics* 157 (2):375–380.
Topel, Robert H. 1997. "Factor Proportions and Relative Wages: The Supply-Side Determinants of Wage Inequality." *Journal of Economic Perspectives* 11 (2):55–74.
Tyrowicz, Joanna, Lucas van der Velde, and Irene van Staveren. 2018. "Does Age Exacerbate the Gender-Wage Gap? New Method and Evidence From Germany, 1984–2014." *Feminist Economics* 24 (4):108–130.

Watson, Ian. 2010. "Decomposing the Gender Pay Gap in the Australian Managerial Labour Market." *Australian Journal of Labour Economics* 13 (1):49–79.
Welch, Finis. 1979. "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust." *Journal of Political Economy* 87 (5):S65–S97.
WGEA. 2018. Australia's gender equality scorecard: Key findings from the Workplace Gender Equality Agency's 2017-18 reporting data. Workplace Gender Equality Agency (WGEA), Australian Government. Available at https://www.wgea.gov.au/sites/default/files/documents/WGEA_2017-18%20Gender%20Equality%20Scorecard.pdf.
WGEA. 2019. "Gender Segregation in Australia's Workforce." Workplace Gender Equality Agency (WGEA), Australian Government. Available at https://www.wgea.gov.au/data/fact-sheets/gender-segregation-in-australias-workforce, accessed September 29.
Winship, Christopher, and David J. Harding. 2008. "A Mechanism-Based Approach to the Identification of Age–Period–Cohort Models." *Sociological Methods & Research* 36 (3):362–401.
Wooldridge, Jeffrey M. 1995. "Selection corrections for panel data models under conditional mean independence assumptions." *Journal of Econometrics* 68 (1):115–132.
Wu, Huoying. 2007. "Can the Human Capital Approach Explain Life-Cycle Wage Differentials Between Races and Sexes?" *Economic Inquiry* 45 (1):24–39.
Yang, Yang, and Kenneth C. Land. 2013. *Age-Period-Cohort Analysis: New Models, Methods, and Empirical Applications*. New York: Chapman and Hall/CRC.

Appendix A: Definition of Variables

Table A1 Definition of Variables

Variable	Definition
Real wage rate [a]	The logarithm of the real hourly wage earned in the main job (base year 2011-2012)
Age	Age dummies (Base = 25)
Period	Year dummies (Base = 2001)
Cohort	Cohort dummies (Base = 1947)
Female	1 = Yes; 0 = No
Unemployment rate	The unemployment rate in the major statistical region of the person.
Technological developments	Change in the growth of information technology net capital stock to net capital stock; of information technology net capital stock includes computers and peripherals, electrical and electronic equipment, and computer software from all industries in chain volume measures
Age Discrimination Act	1 = If Age Discrimination Act 2004 was enacted; 0 = No
Fair work Act	1 = If Fair Work Act 2009 was enacted; 0 = No
Cohort size	Number of people in one's birth cohort to total number of people in the sample, expressed as a percentage
Cohort educational level	Workers with post-senior secondary education to total workers in the sample expressed as a percentage [b]
Birth: Australia	1 = Yes; 0 = No
Female	1 = Female; 0 = Male
Married	1 = Married or de facto; 0 = No Never married and not de facto, Separated, Divorced or Widowed
Children aged 0–4 years	1 = Yes; 0 = No
Children aged 5–9 years	1 = Yes; 0 = No
Number of children aged 0–4 years	Number of own resident children and resident step/foster/grandchildren without a parent in the household, aged 0-4
Geographic Remoteness	1 = Outer regional, remote, or very remote Australia; 0 = Major city or inner regional Australia
Education [c]:	
University	1 = Yes; 0 = No
Advanced diploma and diploma	1 = Yes; 0 = No
Certificate III and IV	1 = Yes; 0 = No
Year 12	1 = Yes; 0 = No
Year 11 and below	1 = Yes; 0 = No
Health condition	1 = Long term health condition; 0 = No
Employed	1 = Yes; 0 = No
Full-time employment	1 = Yes; 0 = No
Casual	1 = Casual; 0 = Permanent
Union member	1 = Yes, 0 = No
Firm size [d]:	
Firm size 5-19	1 = Yes; 0 = No
Firm size 20-99	1 = Yes; 0 = No
Firm size 100 or more	1 = Yes; 0 = No
Tenure: occupation	Tenure in current occupation in years
Tenure squared: occupation	Tenure in current occupation in years squared/100
Tenure: employer	Tenure with the current employer in years
Tenure squared: employer	Tenure with the current employer in years squared/100
Occupation [e]:	
Manager	1 = Manager, 0 = No
Professional	1 = Professional, 0 = No
Technician/trades	1 = Technician and trades worker, 0 = No
Community/personal	1 = Community and personal service worker, 0 = No
Clerical/administrative	1 = Clerical and administrative worker, 0 = No
Sales	1 = Sales worker, 0 = No
Machinery/driver	1 = Machinery operators and drivers, 0 = No
Industry [f]:	

Agriculture/forestry	1 = Agriculture, forestry and fishing, 0 = No
Mining	1 = Mining, 0 = No
Manufacturing	1 = Manufacturing, 0 = No
Electricity/gas	1 = Electricity, gas, water and waste services, 0 = No
Construction	1 = Construction, 0 = No
Wholesale trade	1 = Wholesale trade, 0 = No
Retail trade	1 = Retail trade, 0 = No
Accommodation/food	1 = Accommodation and food services, 0 = No
Transport/postal	1 = Transport, postal and warehousing, 0 = No
Information media	1 = Information media and telecommunications, 0 = No
Financial/insurance	1 = Financial and insurance services, 0 = No
Rental/hiring	1 = Rental, hiring and real estate services, 0 = No
Professional/scientific	1 = Professional, scientific and technical services, 0 = No
Administrative/support	1 = Administrative and support services, 0 = No
Public administration	1 = Public administration and safety, 0 = No
Education/training	1 = Education and training, 0 = No
Health care	1 = Health care and social assistance, 0 = No

Notes: [(a)] Real wage rate is calculated for people who have a work history of at least one hour per week and earned at least 1$ in that period. The September quarter consumer price index from the Australian Bureau of Statistics has been used to deflate wages to the 2011-12 level. [(b)] This variable can be affected by the change of educational status of some of the respondents for which we have considered the last qualification in our calculation. Restricting the sample to the 25-54 age group is supposed to limit the impact of such changes. [(c, e)] The base category for education dummies is "Year 11 and below," while the same for occupation dummies is "Labourers." [(d)] Firms with less than 5 employees is the base category for the firm size dummies. [(f)] The base category for the industry dummies includes arts and recreation services and other services.

Appendix B: The Issue of Weights

The present study decides not to use weights mainly for three reasons. First, the study is more concerned with testing a theoretical position (i.e., whether age, period and cohort effects contribute to the gender wage gap in Australia). Second, some of the statistical routines used in the present analysis does not support weights. Third, in the case of Australian labour market-related research, studies utilizing both weighted and unweighted approaches have found the inclusion of weights from the HILDA Survey to have a minor, non-trivial, slight, or identical impact on the parameter estimates. That is, the general pattern of results or the conclusions largely remained the same whether weights are used or not (e.g., Laß and Wooden 2019; Coelli 2014; Buddelmeyer, Lee, and Wooden 2010; Chzhen, Mumford, and Nicodemo 2013).