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Climbing the jobs ladder slower: Young people in a weak labour market

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Catherine de Fontenay
Bryn Lampe
Jessica Nugent
Patrick Jomini

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Publications enquiries

Media, Publications and Web, phone: (03) 9653 2244 or email: mpw@pc.gov.au

The Productivity Commission

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Further information on the Productivity Commission can be obtained from the Commission's website (www.pc.gov.au).

Foreword

Economists often talk of the economic 'cycle', but the terminology can mislead. Although downturns are often short-lived, their effects can be long-lasting for some groups and individuals.

This is particularly true in that most human of interactions, the labour market.

This paper investigates labour market scarring that might have occurred over the period 2008 to 2018 — specifically whether young people entering the labour market during and following the GFC had a harder transition into employment than those entering earlier, and whether that experience could have longer term impacts on the labour market outcomes for this cohort.

We show that from 2008 to 2018, young people had more difficulty getting jobs in the occupations they aspired to. And if they started in a less attractive occupation, it was even harder than before 2008 to climb the occupation ladder. This suggests that poor initial opportunities could have serious long-term consequences.

The data used pre-dates the COVID-19 recession, but the paper's findings are of heightened salience in our present circumstances. Many young people have experienced unemployment recently, and are likely to face a reduced set of job opportunities as a result of the recession. This scarring could last some time. Also, while some young people might choose to pursue further study, and return to the job market when conditions are more favourable, this paper suggests that, if labour markets continue to be weak, additional education can lead to a mismatch between existing job opportunities and aspirations.

This staff working paper can be seen as part of the Productivity Commission's research output on trends in incomes. After exploring recent trends in the distribution of incomes in Rising inequality? A stocktake of the evidence, the Commission has pursued a number of avenues to investigate trends in the earnings of young people.

The paper was originally prepared for presentation at the Reserve Bank of Australia's Annual Conference to be held in April 2020. The COVID-19 pandemic interrupted the conference, but the central issue at the heart of the analysis, the scarring effects on young people of poor labour-market outcomes, has become even more relevant.

The authors are grateful to Jeff Borland and Bob Gregory, staff at the Australian Treasury and Ken Quach, Mabel Andalón, Melisa Bubonya, Marco Hatt, James Thiris, Henry Williams and other colleagues within the Productivity Commission for stimulating discussions and insightful contributions.

Michael Brennan

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Abbreviations and explanations

ABS	Australian Bureau of Statistics
AME	Average Marginal Effect
ANU	Australian National University
ANZSCO	Australian and New Zealand Standard Classification of Occupations
AUSEI06	Australian Socioeconomic Index 2006
BLS	(US) Bureau of Labor Statistics
GFC	Global Financial Crisis
HILDA	Household Income and Labour Dynamics in Australia
PC	Productivity Commission
PDF	Probability Density Function
SIH	Survey of Income and Housing
VET	Vocational Education and Training

Climbing the jobs ladder slower: Young people in a weak labour market

Abstract

The 2008 Global Financial Crisis (GFC) and the end of the mining boom ushered in a downturn in the Australian labour market. Even though past downturns were marked by high unemployment, the unemployment rate post-GFC recovered quickly and remained low until the COVID-19 crisis in 2020. Instead, the weak labour market post-2008 was reflected in slow wage rate growth and in job seekers finding part-time work or work in less attractive firms or occupations (PC 2020). These trends were particularly noticeable for young people. Workers aged 20-34 experienced nearly zero growth in real wage rates from 2008 to 2018, and workers aged 15-24 experienced a large decline in full-time work and an increase in part-time work (PC 2020).

The Australian labour market proved to be flexible in absorbing workers from 2008 until the COVID-19 crisis (perhaps because the downturn was mild, prior to COVID-19). This suggests that the unemployment rate may no longer be useful as the primary measure of the health of the job market. Instead, more attention must be devoted to the *types* of jobs available.

Using data from the Household Income and Labour Dynamics in Australia (HILDA) dataset, we show that young people found work in 'lower-scored' occupations after the GFC (using a score developed by the ANU that connects a person's education with thei earning potential). Controlling for education, we found that occupational scores declined between 2001 and 2018. Likewise, the cohort that graduated between 2013 and 2015 obtained work in lower-scored occupations than earlier cohorts.

This decline in average occupational score hides significant heterogeneity in outcomes. Some young workers found very high-scored occupations, while more were 'unlucky' — obtaining work in occupations whose score was well below what one would have predicted in earlier years. Was this temporary? Were some of these unlucky young workers able to work their way back to their desired occupation over the following years?

We examine this question through the lens of Markov transitions, looking at transitions across the quartiles of the occupational score distribution. We examine transition rates for young Australians who graduated between 2001 and 2015. The likelihood of transitioning to better outcomes is low, and worsened slightly over this period, suggesting that poor initial outcomes can have long-term effects on one's occupation.

Introduction

The Global Financial Crisis (GFC), followed by the slowing of the mining boom, ushered in a weak labour market. These macroeconomic shocks weakend labour demand, while higher participation rates and increases in educational attainment greatly increased supply, particularly for high-skilled jobs (PC 2020).

Notably, however, the weak labour market from 2008 to 2019 was not marked by a high unemployment rate. The unemployment rate did jump two percentage points in 2008-2009, but it then remained steady and did not return to its higher pre-2001 levels until the COVID-19 crisis. This is in contrast to past downturns, such as the 1991 recession, during which unemployment was high. The Australian labour market proved flexible in absorbing workers from 2008 to 2018, possibly because the effects of the GFC were not severe in Australia.

Evidence suggests that labour markets adjusted through mechanisms other than unemployment. For example, we show that full-time employment declined and part-time employment increased among workers aged 15-34 (young people) (PC 2020). Given that young people are often seeking their first job, or changing jobs, this statistic may speak to what types of jobs are being created. Some authors have argued that the rise in part-time work implies that the unemployment rate has lost its relevance as a measure of labour market health (Borland 2020). Another adjustment mechanism is wage rates: workers aged 20-34 experienced nearly zero wage rate growth from 2008 to 2018 (PC 2020), in part because of lower starting wages. Also, more young workers are now working in small firms, which pay lower wages (PC 2020).

One key adjustment mechanism is the choice of occupation. We examine the occupations of young people after they graduate, using data from the Household Income and Labour Dynamics in Australia (HILDA) survey from 2001 to 2018 and occupational scores developed by McMillan, Beavis and Jones (2009).[1] We find that the average occupational score increased in Australia; however, educational attainment also increased over the period. When we control for workers' characteristics, including education, we find that the average occupational score for recent graduates declined from 2008 to 2018, suggesting that labour demand did not adjust to the mix of skills in the market. Occupational scores by education level continued to decline until 2018. In the first four years after leaving education, we find, the latest cohorts (2010–2012 and 2013–2015) had the worst outcomes for occupational scores. Extending the analysis to six years yields similar results.

This decline in predicted occupational scores masks significant heterogeneity in outcomes. Some young workers are in very high-scored occupations, while many others have been 'unlucky' — obtaining work in occupations with an occupational score well below what one

1 These occupational scores are a socioeconomic index that connects a person's education with their earning potential. The index provides researchers with a 'means of assigning sociologically meaningful occupational status scores to data coded in accordance with the official occupational classifications of the Australian Bureau of Statistics (ABS).' (McMillan, Beavis and Jones 2009). The index allows us to connect a person's occupation with a quantifiable, continuous, measure.

would have predicted in earlier years. A natural follow-up question is whether some unlucky young workers were able to work their way back to their desired occupation over the next few years. A lower starting point is not necessarily a problem if young workers can improve their occupational score relatively quickly. If workers can 'catch up' then the burden of a weak labour market could be shared by many, but the effects would not be permanent. If, instead, the effects are permanent, this could lead to a phenomenon called 'scarring'.

'Scarring' occurs when workers who experience a negative shock in the labour market suffer long-term consequences. This negative shock could be a spell of unemployment (Arulampalam, Gregg and Gregory 2001; Knights, Harris and Loundes 2002), or it could be a spell of underemployment or low-wage work (Buddelmeyer, Lee and Wooden 2010; Chalmers and Hill 2007; Fok, Scutella and Wilkins 2015; Fouarge and Muffels 2009; Mosthaf 2014).[2] More recent work on scarring has considered the 'quality' of jobs. It is possible that holding a job that does not fully use one's skills can raise the probability of unemployment or reduce future wage rate growth (Guvenen et al. 2020; Mavromaras, Sloane and Wei 2015; Naidoo, Packard and Auwalin 2015).[3] And a negative shock today can lead to holding lower-scored occupations in the future. For instance, Kahn (2010) found that in the United States, cohorts that graduated when unemployment was high were in lower-scored occupations (and that this effect had not disappeared after 10 years).[4]

We examine the question of scarring through the lens of Markov transitions. We undertake discrete-time Markov chain analysis of transitions between quartiles of the distribution of occupational scores, controlling for demographic characteristics. This is the first paper to apply Markov analysis to occupational scores. We examine transition rates for young Australians who graduated between 2001 and 2015.

We see no evidence of improved likelihood of transitioning to better outcomes, suggesting that poor initial outcomes are likely to have long-term effects on one's occupation. If anything, when we examine young graduates between 2013 and 2015, people who found work in lower quartiles of the score distribution were more likely to remain in those quartiles

2 Some authors have coined the term 'wage scarring' to mean the possibility that a long spell of unemployment today could lead to lower wage rates in the future (Arulampalam 2001). And the earnings of graduates who enter the labour market in a recession are lower than those of other cohorts (Altonji, Kahn and Speer 2016). This reduction in wage rates can last as long as 10 years (Oreopoulos, von Wachter and Heisz 2012).

3 Other authors who look at occupational scores include: Sicherman (1991) — who started a literature that looked at the occupational mobility of over-educated and over-skilled people — and Ralston et al. (2016) — who looked at whether persistent unemployment leads to occupational scarring. Unlike our paper, these papers are not concerned with scarring effects that might be specific to downturns.

4 Although Kahn (2010) shows that the effects of a downturn on occupational scores can endure, it is not clear whether the negative effect was from longer job tenure or from getting caught on a low-skilled job trajectory: Kahn also found that workers who graduated in a downturn were less likely to change jobs. It is important to examine subsequent transitions because the primary mechanism through which workers increase their wages is moving to better-paying employers (Berge 2018, Deutscher 2019). For young workers, these moves are particularly important because young workers have the largest wage rate gains and losses associated with moves up and down the occupational ladder (Forsythe 2019).

compared with earlier cohorts. Thus, young people who obtained a lower-scored job in the post-2008 weak labour market are likely to remain on a low-scored job trajectory.

There is no evidence that employers are now more willing to consider an applicant from a lower-scored occupation, taking into account that some high-skill workers may have been unlucky. This may be because the labour market is still weak, and there are many high-skill applicants among recent graduates. Also, it could be that occupational mobility will recover when the labour market finally improves (which would now be well after the COVID-19 crisis). But the fact that the weak labour market lasted for a decade means that many young workers will face long-term scarring.

The rest of the paper proceeds as follows: in section 1, we show that the post-2008 weak labour market translated into lower wages for new workers and more part-time work. In section 2, we turn to occupational scores, and show that in the weak labour market people looking for work accepted lower-scored occupations. We compare cohorts to show that outcomes worsened. Section 3 undertakes a Markov analysis of the transitions between quartiles of the occupation distribution to show that the transitions did not improve.

The weak labour market is not reflected in employment rates

The weak labour market after the GFC

Beginning in 2007, the GFC had a relatively mild impact on Australia when compared to other countries. For instance, some reports suggest that economic activity and nominal wage growth in Australia had recovered by 2011 (Stewart, Stanford and Hardy 2018, p. 7). The increase in unemployment was smaller in Australia than in other countries — unemployment in Australia increased from 4.3 per cent in December 2007 to 5.8 per cent by mid-2009, while in the United States unemployment increased from 5 per cent to 9.5 per cent over the same period (ABS 2020; BLS 2020).

The end of the mining investment boom — during which the size of the mining sector increased from 2 per cent of GDP in 2003 to 8 per cent in 2013 — may have also contributed to the subsequent weak labour market. One estimate shows that the mining investment boom contributed to a 6 per cent increase in real wage rates, and a 1.25 percentage point decrease in the unemployment rate, relative to the counterfactual (Downes, Hanslow and Tulip 2014, p. 1). As the investment phase wound down rapidly after 2012, the less labour-intensive resource production phase began, and there was a sharp reduction in labour demand from this sector (Davis, McCarthy and Bridges 2016).[5]

5 However, Davis, McCarthy and Bridges (2016) point out that after the end of the boom, low interest rates and the depreciation of the exchange rate supported labour demand in other sectors. This suggests that the end of the mining investment boom may have had limited effects on labour demand.

In response to these events, the Australian economy experienced a relative slowdown. Real GDP growth slowed from 3.3 per cent per annum between 2001 and 2008 to 2.6 per cent between 2009 and 2018 (World Bank 2020). There may have been a short-term imbalance between labour demand and labour supply (PC 2020). Labour demand slowed after the GFC and the mining investment boom. At the same time, increased participation rates for women aged over 25 and people aged 55 and over increased supply. Further, a sharp increase in the number of graduates (PC 2019) led to greater competition for skilled jobs.

Employment outcomes after the GFC

We analyse data from the Household Income and Labour Dynamics in Australia (HILDA) survey from 2001 to 2018. HILDA is a large-scale, longitudinal survey of Australian households. Our cleaned dataset includes about 1800 people aged 20-24, 2400 people aged 25-34, and 6400 people aged 35-64 in each year.[6]

We study the extent of adjustment via employment and (hourly) wage rates, controlling for changes to the characteristics of the population (such as increased education). We do this by including year dummies in a regression model to identify how employment and wage rates evolve over time. One challenge is that wages may vary because the composition of the pool of employed persons varies over time, partly based on characteristics that are unobservable to researchers. We can mitigate this issue with a standard Heckman two-step regression (Heckman 1979).

In the Heckman estimation, we first estimate an employment equation, predicting the likelihood that an individual is employed. Next, using information from the first step, a wage equation corrects for any selection bias that might arise from the fact that wage rates are only observed for people who participate in employment. The exclusion restrictions (variables assumed to affect employment but not wages) are the ratio of children aged under 15 to people aged over 15 in the household, and that ratio interacted with the person's gender.[7]

We estimate employment outcomes (full-time or part-time) for people aged 20-34, and separately estimate outcomes for people aged 35-64 for comparison. This gives additional flexibility to the estimated coefficients in case the age groups face different labour market conditions. Importantly, we include year dummies in both regressions to account for

6 We omit people aged 15-19 because HILDA over-estimates their employment to population ratio. Comparisons between the employment rate of people aged 15-19 in HILDA and the ABS labour force survey are presented in appendix A.

7 We perform sensitivity tests (1) using the ratio of children aged under 15 to people aged over 15 in the household, and that ratio interacted with the person's gender; (2) using the number of children of the potential wage-earner and whether the individual is married as alternative exclusion restrictions; (3) breaking the probit estimation into two samples (2001-2007, the period of high wage growth, and 2008-2018, the period of slow wage growth) and then running one combined wage regression with the Mills ratio calculated for each sample separately; and (4) using selected demographic coefficients interacted with the year dummies. We find similar results for the year dummies in each specification. See appendix A for full specifications.

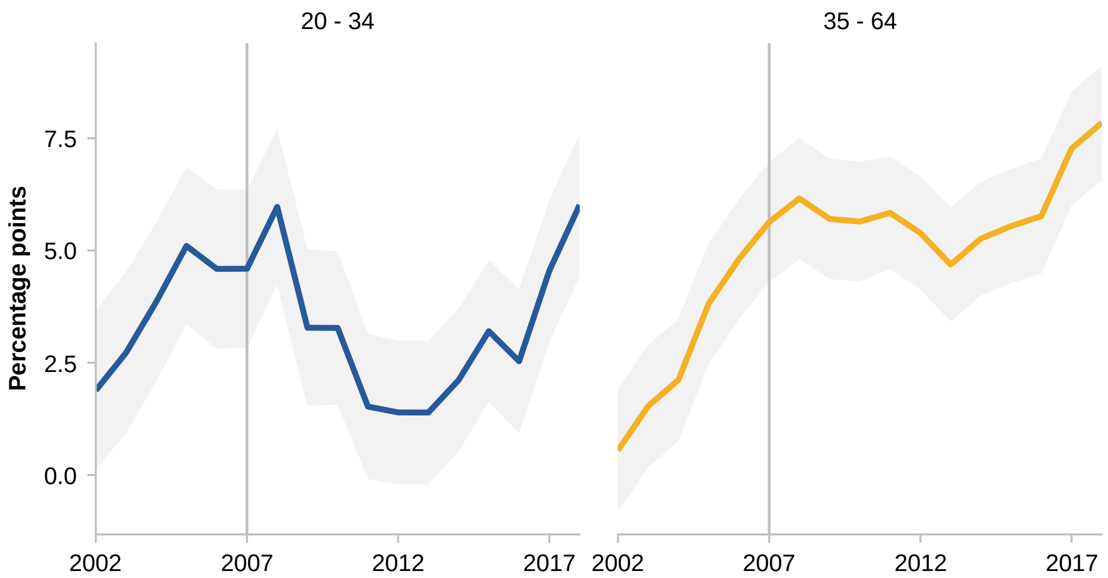
economy-wide or business-cycle changes that might affect the labour market. We report the year dummies graphically, with full regression results in appendix A.

We define the wage rate to be the natural logarithm of average weekly earnings in all jobs divided by hours usually worked per week, for both full- and part-time workers, and drop wage rates below $5 per hour and above $300 per hour.

We find that the probability of employment for people aged 20-34 fell after 2008, but recovered by 2017 (figure 1). For people aged 35-64, the probability of employment stalled relative to the period of high growth before 2008, but recovered after 2015. (In contrast to younger people, there was no appreciable decline in their probability of employment.)

Figure 1 **Employment for people aged 20–34 recovered after five years**

Average marginal effect of year on probability of employment relative to 2001 for people aged 20-34 and 35-64, 2002–2018[a,b,c,d]



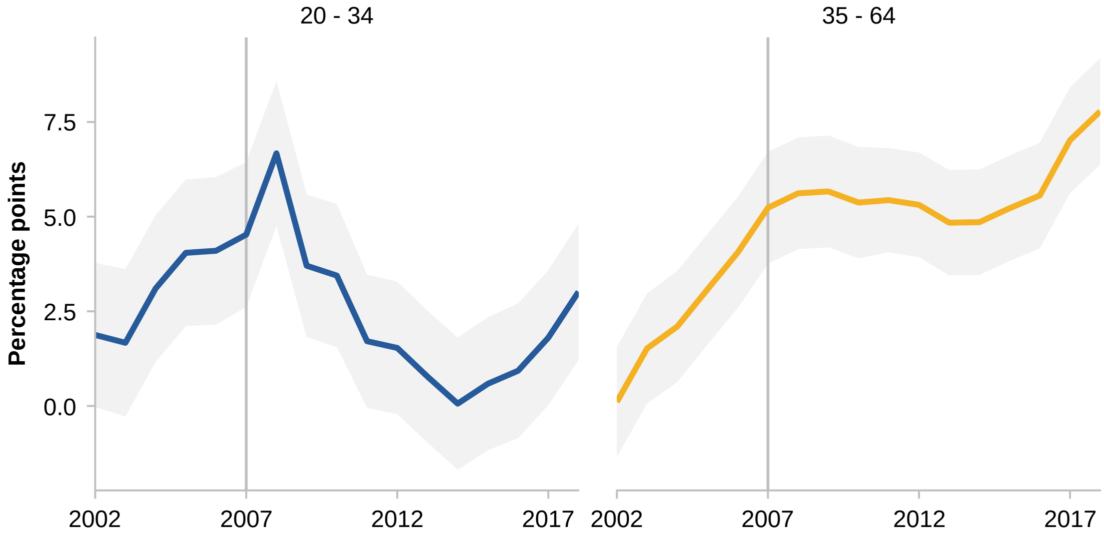
[a] The area shaded represents the 95 per cent confidence interval. [b] Standard errors are clustered by individual. [c] The average marginal effect jumps by about 2 percentage points for people aged 20-34 in 2002. This could be because the employment to population ratio is over-estimated in HILDA for younger people, when compared to the ABS labour force survey. Despite this, the trends in the employment to population ratio remain similar between HILDA and the ABS labour force survey (appendix A). [d] The vertical line represents the start of the GFC.

Data source: Commission estimates based on HILDA data.

However, the recovery appears to be driven by an increase in part-time employment. Full-time employment of people aged 20-34 fell between 2008 and 2014 and did not recover to 2008 levels (figure 2). Thus, if we think of part-time and full-time as crude measures of job quality, we see a decline in the quality of jobs for people aged 20-34.

Figure 2 **The recovery of young people's employment was not driven by full-time employment**

Average marginal effect of year on probability of full-time employment relative to 2001 for people aged 20 to 34 and 35 to 64, 2002–2018[a,b,c]



[a] The area shaded represents the 95 per cent confidence. [b] Standard errors are clustered by individual. [c] The vertical line represents the start of the GFC.

Data source: Commission estimates based on HILDA data.

Full-time employment has been in long-term decline since the 1980s for people aged 20-24, coinciding with them spending more time in education. That decline paused briefly during the boom (from 2001 to 2008). That said, the decline in full-time employment after 2008 occurred primarily for people aged 15-24 who were *not* studying (PC 2020), which suggests that it was driven by a weak labour market rather than by a preference for more education.

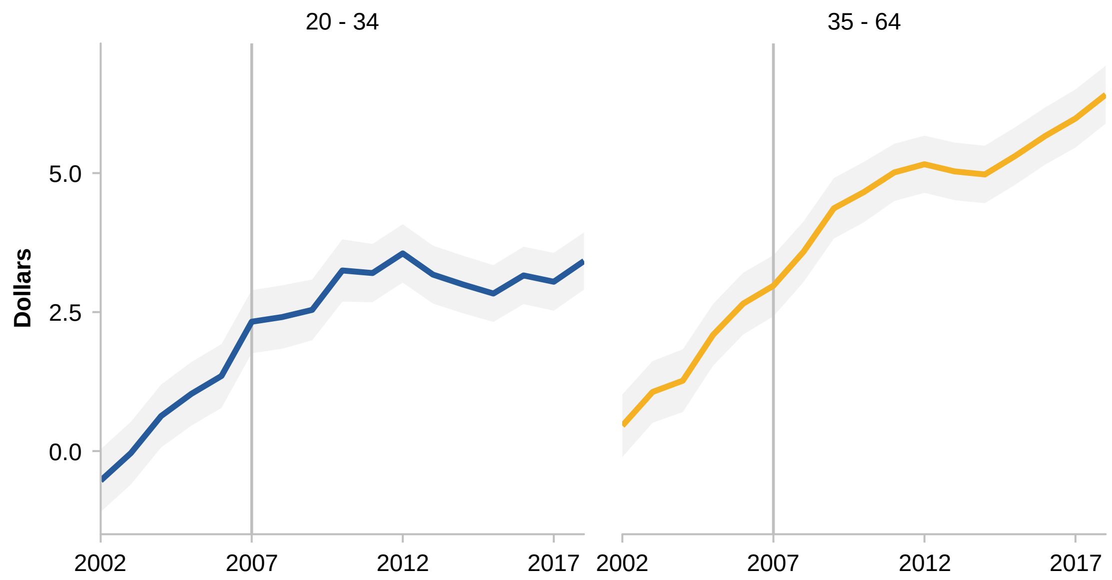
Wage rates after the GFC

Looking at young people's wage rates paints a bleaker picture. Figure 3 presents the Heckman wage equation by showing the evolution of the coefficients on the year dummy variables; they show how predicted wage rates evolve over time (full results in appendix A).

For workers aged 35-64, some flattening of wage rates occurred between 2010 and 2015, but growth resumed between 2015 and 2018 (figure 3). This result is confirmed with aggregate data from HILDA and the ABS Survey of Income and Housing (SIH) (PC 2020). Much more striking is the flattening of the wage rate profile for people aged 20-34. In real terms, growth in wage rates for workers aged 20-34 (based on the year dummies) averaged 1.46 per cent per annum before the GFC, slowed to 0.86 per cent per annum until 2012 and declined by 0.08 per cent per annum afterwards. This is compared with growth in wage rates for workers aged 35-64 (based on the year dummies) that averaged 1.7 per cent per annum before the GFC, 1.36 per cent per annum until 2012 and 0.62 per cent afterwards.

Figure 3 **Wage rate growth for young workers slowed after 2007**

Marginal effects of year on wages relative to 2001 for workers aged 20-34 and 35-64, 2002–2018, transformed to dollar values[a,b,c,d]



a The estimated coefficient was transformed into dollars by $(e^{\hat{\beta}} - 1) * e^{\ln(wage\ rate\ in\ 2001)}$. **b** Shaded area represents the 95 per cent confidence interval. **c** Standard errors are clustered at the individual level. **d** The vertical line represents the start of the GFC.

Data source: Commission estimates based on HILDA data.

Different wage rates for young people and people aged 35-64 likely arise from differing labour market experience of people staying in a job versus people seeking a job.[8] Kalb and Meekes (2019, p. 1) showed that, for workers who remain in their job for a year or more, wage growth is actually faster for younger workers than for older workers; so wage growth on the job is not part of the explanation. Young workers are more likely to be looking for work, as they join the labour force, and they are more likely to change jobs than older workers (Deutscher 2019, p. 5).

In a mild slowdown, the share of workers retrenched is small. Also, since wage rates are generally 'sticky', wage rates for workers remaining with a firm are unlikely to decline. But if firms want to hire fewer new workers — causing labour demand to fall short of labour supply — people looking for work are likely to obtain lower starting wage rates due to their reduced bargaining power. At the same time, it is likely that some people looking for work will accept roles in less desirable firms, or outside of their desired occupation. And as shown above, workers aged under 35 are less likely to secure full-time work. Section 2 will show that young people looking for work have also seen a decline in their 'occupational scores'.

8 One telling piece of evidence is that when we compare young people looking for jobs with older people looking for jobs, outcomes are more comparable. For example, long-term unemployment was similar for all age groups after 2008 (PC 2020). And Kalb and Meekes (2019, p. 20) suggested that when we compare incumbents, outcomes are comparable between young and old.

The weak labour market is reflected in occupational scores

An introduction to occupational scores

We have identified that average wages grew more slowly for young people in 2008–2018 than in 2001–2008. Given that wages were growing in existing jobs, stagnating average wages implies that wages for new job offers were lower.

In some firms, new hires may have been offered lower starting wages than earlier hires. However, it is also possible that young people found themselves in different roles. Faced with a tighter job market and fewer new positions, young people may have had to move ‘down the jobs ladder’ (Haldane 2019) and accept jobs in less attractive occupations. Young people with tertiary qualifications may in turn be pushing other young people further down the ladder. Towards the bottom of the jobs ladder, there may be more flexibility to add additional part-time or casual workers and more flexibility in setting wages; this could explain why unemployment has not risen more. We have already seen evidence that people aged 20-24 were more likely to work part-time in the 2008–2018 period than before 2008, and part-time work is one rough measure of job quality.

Here we focus on occupations. We explore whether occupational downgrading was a major source of labour market adjustment from 2008 to 2018. To do this, we use a 0-100 scale of occupational scores developed in 2006 by researchers at the Australian National University, based on the ABS occupation classification. Broadly, the occupational score is a function of the average education required for an occupation and the average earnings in that occupation — for example, neurosurgery has a high score. Table 1 shows an example of occupational scores. The occupational scale has been used extensively; see McMillan, Beavis and Jones (2009) for more information on the development and use of the scale.

We use the 2006 scores to analyse the entire 2001–2018 sample period. An occupation has the same score throughout the sample period, even if the average level of education or the earnings in an occupation changed over the period. Keeping the scores constant allows us to see if there was a change in the occupations that young people were able to find work in.

The resulting scores can be thought of as being ordered along an occupational ladder (in a rough sense). It is worth bearing in mind that individual job seekers have their own preferences and, of course, the occupational score is not the only important characteristic of a job. However, if we see a significant decline in occupational scores for young workers over time, it is likely to reflect an involuntary worsening of their employment outcomes.

Table 1 **Examples of occupational scores**

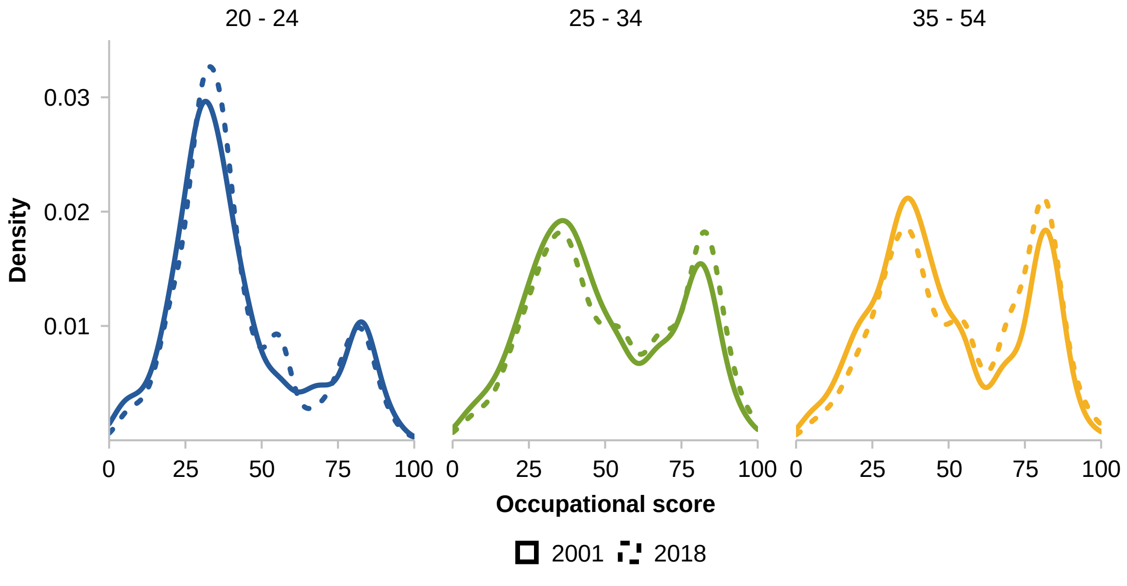
Occupation	*Score*
Medical practitioners	100.0
Natural and physical science professionals	85.6
Assorted managers (including education managers, policy and planning managers, and other specialist managers)	78.6
Arts professionals; fashion, industrial and jewellery designers; graphic and web designers, and illustrators	67.0
Cafe workers, hotel service managers, other hospitality workers	37.0
Storepersons, shelf fillers	20.8

Source: McMillan, Beavis and Jones (2009).

Figure 4 plots the empirical probability density functions (PDFs) of occupational scores in 2001 and 2018. The most noticeable feature of the occupation distributions is that they are bimodal (i.e. with two peaks) for all age groups. This bimodal shape is possibly the result of 'job polarisation' over the past few decades, which has reduced the number of jobs in the middle of the distribution. The first peak is much higher for younger workers aged 20-24, possibly because some of them held low-wage jobs during their studies. Given how few people are in the middle of the distribution, one implication is that some of these young people are likely to move a long way up in the distribution over the course of their life. We will analyse where young people move in the occupation distribution in section 3.

Figure 4 **Workers aged 25-54 are in higher-scored occupations in 2018**

Empirical probability density functions (PDFs) of occupational scores



Data source: Commission estimates based on HILDA data.

When we look at how the distribution has changed over time, the overall direction of change seems promising. High-scored occupations were more likely in 2018 than in 2001, both for young workers and for over-35s. Workers aged 25-34 and 35-54 were more likely to be in higher-scored occupations in 2018 than in 2001. The picture is more nuanced for workers aged 20-24: they were more likely to be in mid-score occupations than in low-scored occupations relative to 2001. (A relatively small number of workers aged 20-24 were in high-scored occupations, but the number was even smaller by 2018.)

Breaking the period down allows us to see the pattern more clearly (figure 5). The early period (before 2008) had relatively favourable market conditions, and this is reflected in the occupation distribution. If we compare 2001 to 2010, scores improved noticeably for 25-34 year olds and 35-54 year olds. Under-25s experienced a slight decline in high-scored occupations (perhaps because young workers were staying in school longer) and an increase in the bottom and middle of the distribution. In contrast, between 2010 and 2015 the likelihood of being in higher-scored occupations declined for all workers under 35; the decline was particularly sharp for 20-24 year olds, but they also experienced a recovery from 2015 to 2018. Workers aged 25-34 were mildly worse off in terms of occupational score in 2015 than in 2010, and there was a very slight recovery after 2015. In stark contrast, for each period shown, the proportion of workers aged 35-54 in high-scored occupations increased. It appears that young people's occupational outcomes were more sensitive to market conditions.

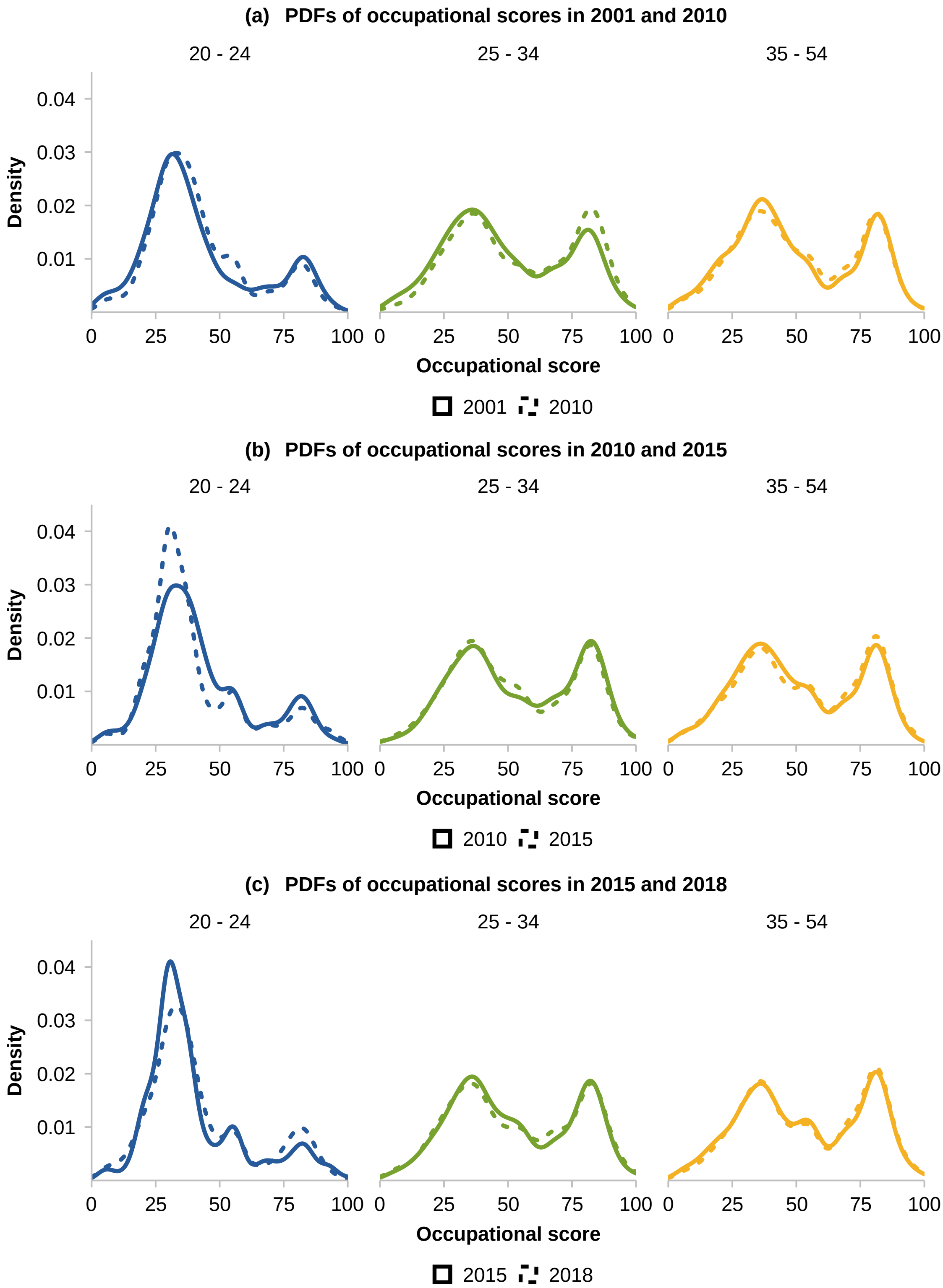
We now turn to consider how occupational outcomes changed for a worker of a given education level. Average educational attainment increased steadily over the past 20 years (PC 2019), and the mix of occupations is shifting towards those with higher education requirements (figure 4). However, the increased supply of graduates might worsen the prospects of the average graduate. In the next graphs, we examine outcomes for graduates of different ages. Graduates include people with a vocational education qualification (VET)[9], identified as 'sub-bachelor', and people with a bachelor or post-graduate qualification.

Once we control for education, a gloomier picture emerges — the distribution of occupations for graduates under 35 worsened (figure 6). Young people aged 25-34 with bachelor degrees are substantially worse off in 2018 than in 2001, particularly in their likelihood of securing a high-scored occupation. Outcomes have slightly worsened for other groups with bachelor's degrees. Outcomes for people aged 20-24 have slightly deteriorated, but mostly at the very low-score end of the distribution, while outcomes are also worse for people aged 35-54 in the middle and low-score end of the distribution.

9 VET courses are generally offered outside of the high school curriculum, but can include both high school and post-high school students. This study focuses on graduates aged 20-34, who are generally post-high school students.

Figure 5 **Workers aged 20-34 were more likely to be in lower-scored occupations during the weak labour market in 2010–2015**

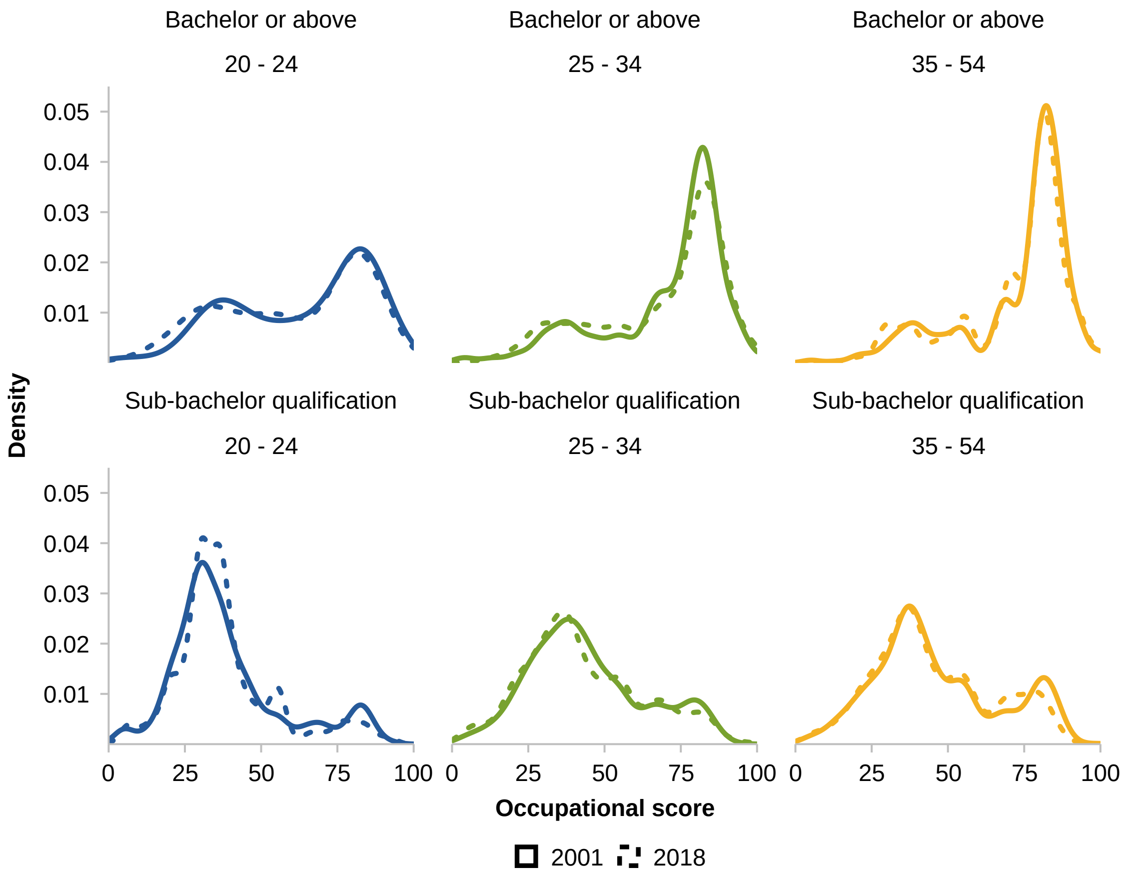
Empirical probability density functions (PDF) of occupational scores



Data source: Commission estimates based on HILDA data.

Figure 6 **Graduates under 35 are more likely to be in lower-scored occupations in 2018**

Empirical probability density functions (PDF) of occupational scores



Data source: Commission estimates based on HILDA data.

This is consistent with the growth in the supply of skilled people exceeding the growth in demand for those skills, resulting in increased competition for high-scored occupations.[10] The growth in the number of jobs in higher-scored occupations was not large enough to absorb the increased supply of highly educated workers. A person looking for a high-scored occupation in 2018 may have faced a more competitive labour market, and therefore was more likely to end up in a lower-scored occupation than they would have in 2001. Note, however, that 35-54 year olds in high-scored occupations appear to have been shielded from competition, maybe by virtue of incumbency: there is no noticeable decline in their occupational scores.

10 Changes to which jobs require a qualification ('credential creep') can artificially change this distribution. Coelli and Wilkins (2009) showed that credential creep did occur in an earlier period (1981 to 2004) and that this may have supressed estimates of women's wage growth by 6 percentage points. The main changes to credentials outlined in Coelli and Wilkins (2009) were the re-classification of existing nursing and teaching qualifications to bachelor degrees. This could have the effect shown in the 'Bachelor or above' category in figure 6 (shifting the PDF to the left).

As workers move down the 'jobs ladder', there is more competition in lower-scored occupations. This may explain why occupational scores have also declined for sub-bachelor qualifications. When we turn to people with sub-bachelor qualifications, the probability of obtaining a high-scored occupation declined for all groups. And for young people aged 20-24, the decline in average occupational score was substantial.

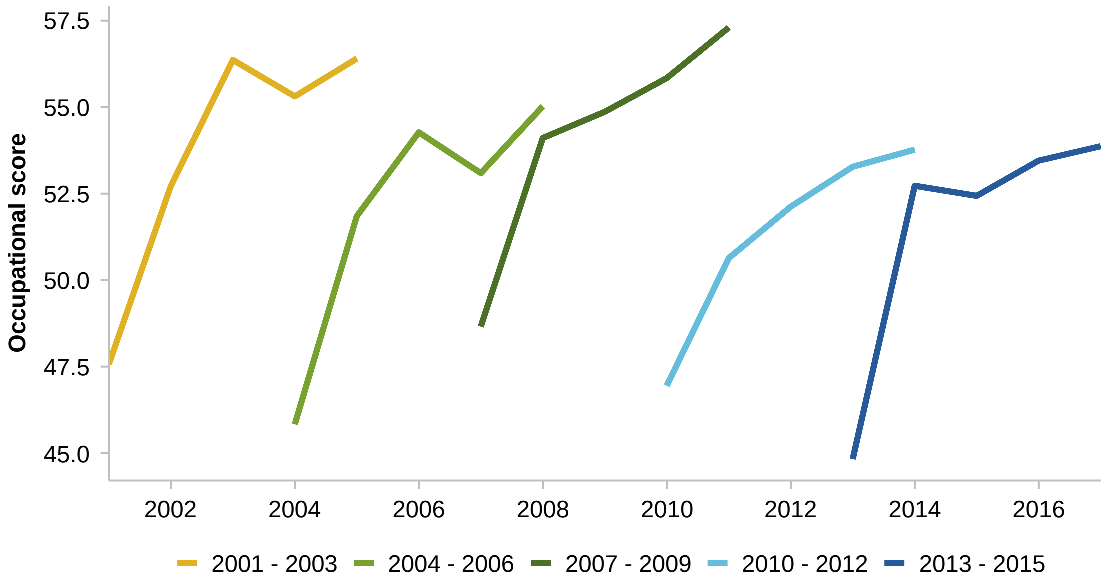
It is true that graduates took longer to find their first graduate job after 2008 (Pennington and Stanford 2019, p. 58).[11] This delay could look like a step 'down the jobs ladder' on a static occupational score distribution for young workers, if they held a casual job while searching for a graduate job. In section 3 we consider transitions between occupations, to understand whether the decline in occupations could be explained by the delay in finding one's first job.

Raw occupational scores by graduation cohort

Before we turn to econometric results, we graph the average occupational score of each graduation cohort from 2001 to 2015 (figure 7). While the results are noisy, they confirm that average occupational score did not increase, even though educational attainment increased. As a result, young graduates towards the end of the period were accepting lower-scored occupations than earlier graduates with a comparable level of educational attainment.

Figure 7 **Occupational scores for graduates have not improved**

Average occupational score, first five years[a] after graduation, 2001–2018



[a] That is, years 0, 1 ,2 ,3 and 4.

Data source: Commission estimates based on HILDA data.

[11] The number of bachelor's degree graduates in full-time employment as a percentage of people available to work full-time hours steadily increased from the late 1990s until 2008 and then fell to its lowest rate in 17 years in 2014 (Pennington and Stanford 2019, p. 58).

Regressions: occupational score by year and graduation cohort

We now turn to econometric specifications to control for educational attainment and other demographics. We begin by estimating an equation for the occupational score of graduates, controlling for economic conditions in each year by including year dummies. This is similar to the classic Mincer equation, but rather than considering wage outcomes, the outcome of interest is occupational score.

$$y_{i,t} = \lambda_t \alpha_1 + e_i \alpha_2 + \boldsymbol{x_{i,t}} \alpha_3 + \varepsilon_{i,t} \quad (1)$$

Where $y_{i,t}$ is the occupational score of individual i at time t. The regression also includes dummies for each year, λ_t, a series of dummies for the years of experience of the worker, e_i, and other individual characteristics, $\boldsymbol{x_{i,t}}$. We restrict the sample to workers under the age of 35 in their graduation year and the first four years after graduation. We measure their experience as the number of years since their graduation. We report the full regression results in appendix B and present coefficients for the year dummies and the experience dummies (figure 8).

As expected, the results show some evidence that the average occupational score declined over time once we control for education, particularly after about 2010. That said, the 95 per cent confidence interval is wide, so we fail to reject the hypothesis that the point estimates for the year dummies are different from one another.[12]

Occupational scores tend to jump several points in the first year after graduation, and then stabilise. This may suggest that many young workers have not yet found their permanent occupation in the first year after leaving school or tertiary education.

We now look at the experience of each cohort in more detail. This regression is, in effect, the results of figure 8, but with controls for graduate cohort characteristics. We estimate the following occupational score regression:

$$y_{i,g,t} = \lambda_t \alpha_1 + c_g \alpha_2 + e_i c_g \alpha_3 + e_i^2 c_g \alpha_4 + \boldsymbol{x_{i,t}} \alpha_5 + \varepsilon_{i,t} \quad (2)$$

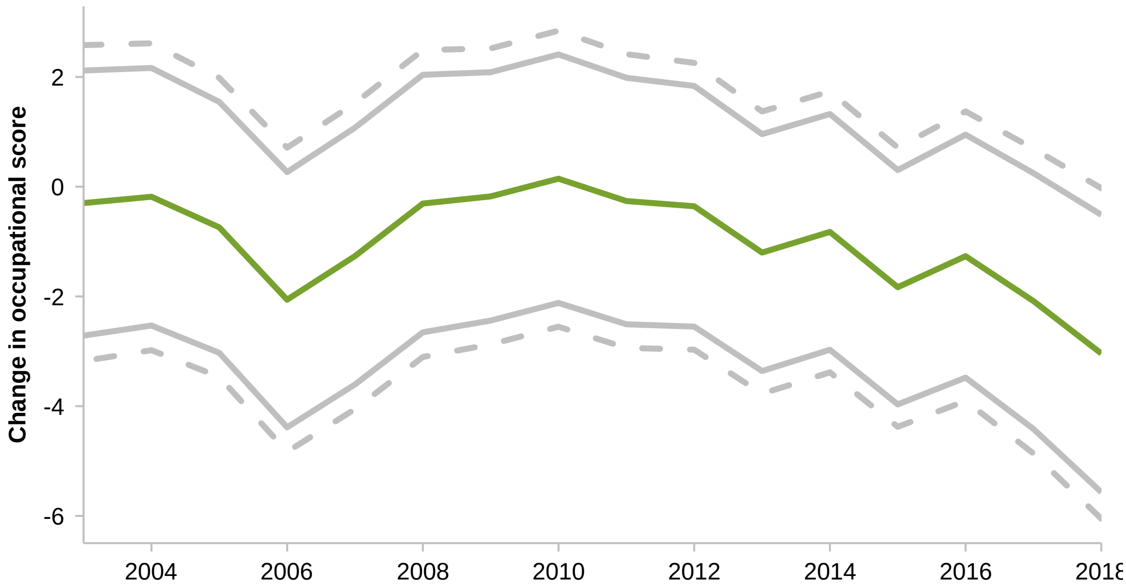
Where $y_{i,g,t}$ is the occupational score of individual i, in graduation cohort g, at time t. In addition to the year dummies and demographic characteristics from the previous regression, we now have cohort effects. Experience is included as a continuous variable in this specification and we fit a quadratic term in experience for each cohort. We restrict the sample to workers under the age of 35, in the first four years since they finished their education. And then we estimate the same regression with six years of experience rather than four, which requires us to leave out the 2013–2015 cohort.

[12] The 95 per cent confidence interval is wide, so we fail to reject the null that any particular point estimate is different from another at the 5 per cent level. However, the test statistic of the one-sided hypothesis test $H_0: \hat{\alpha}_{2010} \leq \hat{\alpha}_{2018}$ and $H_1: \hat{\alpha}_{2010} > \hat{\alpha}_{2018}$ is 1.54. This means the null is rejected at the 10 per cent level and we can be 90 per cent confident that $\hat{\alpha}_{2018}$ is below $\hat{\alpha}_{2010}$.

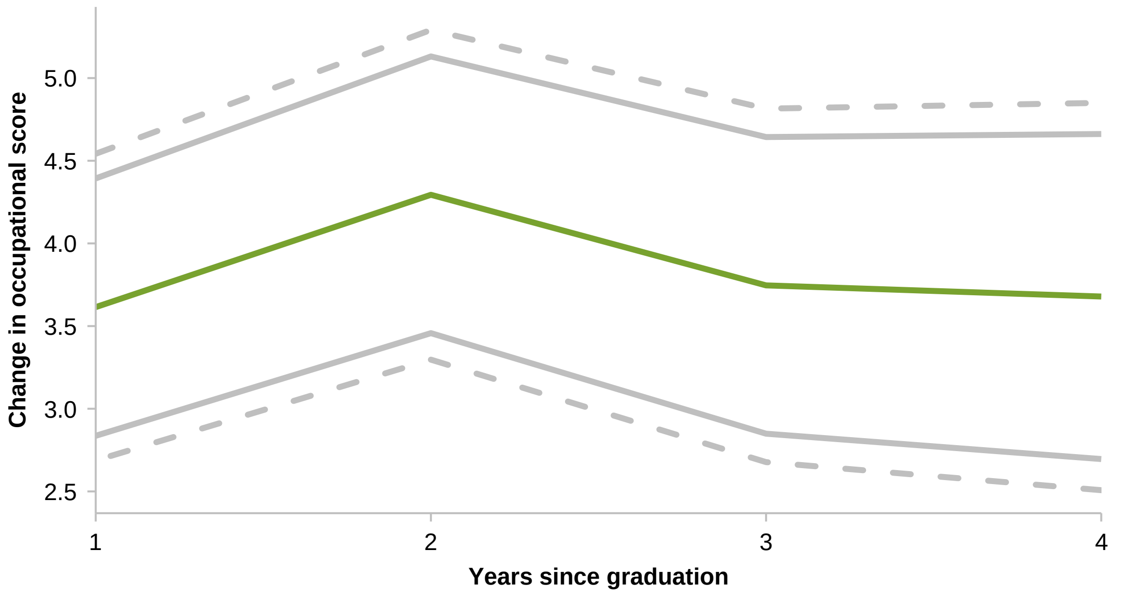
Figure 8 **Declining trend in occupational score after about 2010**

Plot of time dummies[a] and experience variable[b] from regression (1)

(a) Time dummy coefficients



(b) Experience (years since graduation) dummy coefficients



[a] Change is relative to 2002. [b] Change is relative to graduation year. [c] Confidence intervals are reported in grey at the 95 per cent (dashed) and 90 per cent (solid) level.

Data source: Commission estimates based on HILDA data.

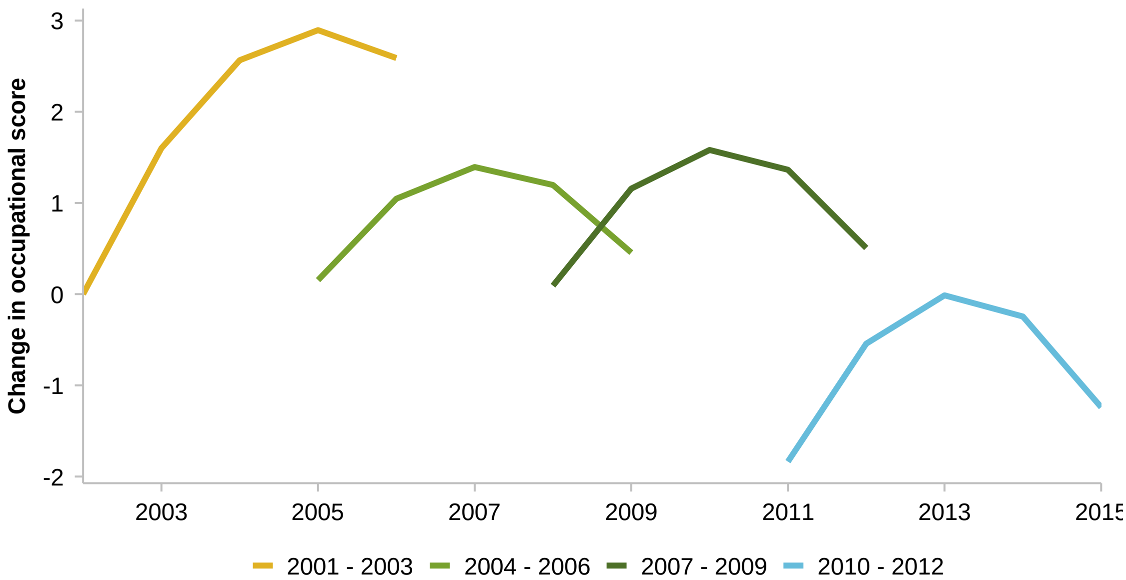
As before, the parameters on year dummies decline over time, with a slight dip in about 2006. Figure 9 plots the graduation cohort effects for four years of data and six years of data, with the full regression results in appendix B.

Figure 9 **Longer-term cohort effects do not show improvement**

Plot of the quadratic function in experience[a] from regression (2)

(a) Shorter-term cohort effects (0 to 4 years after graduation)

(b) Longer-term cohort effects (0 to 6 years after graduation)



[a] That is, $c_a\hat{\alpha}_2 + e_i c_a\hat{\alpha}_3 + e_i^2 c_a\hat{\alpha}_4$ is plotted for each cohort.

Data source: Commission estimates based on HILDA data.

The path of each graduate cohort follows the general pattern observed in the year effects from regression (1), with graduate outcomes worsening from about 2010. When we extend the analysis to include more years of experience, the last cohort in the sample (2010–2012) appears to experience the worst occupational score outcomes. Compared with the three previous cohorts, the 2010–2012 cohort begins at a low occupational score and the occupational score does not grow quickly with experience, which suggests that the average score may be declining. (Including cubic experience terms yields similar results of a decline for the 2010–2012 cohort.)

These results are supported with cross-sectional regressions of occupational scores one year and four years after graduation on a matched sample that uses 2001–2003 graduates as a control group (further details in section 3). The matched results show that the 2013–2015 graduate cohort occupational score was 3.96 (p-value 0.07) points lower than the 2001–2003 cohort one year after graduation and 3.83 (p-value 0.125) points lower four years after graduation. The 2007–2009 cohort had scores better than the 2001–2003 cohort, while all other cohorts fared worse than the 2001–2003 cohort (although most of the differences are not statistically significant, with the exception of the 2013–2015 cohort outcome one year after graduation). Full results are in appendix B.

Changes in the labour market from year to year can mean that a particular graduate year are more likely to start in a lower-scored occupation after they graduate. Conditions in subsequent years can then also affect mobility in the first few years of a graduate's career. Figures 7 and 9 show both of these effects, with some graduate years starting at a lower average occupational score and some graduate years climbing more slowly. For instance, after controlling for observables, the 2013–2015 graduates had a lower average occupational score one year after graduation while the 2010–2012 graduates' experience function was almost flat (figure 9).

The results show that recent cohorts of graduates have experienced a significant decline in their average occupational score, and that outcomes over the first six years continue to be poor. However, outcomes for the 2013–2015 cohort (figure 9) are intriguing: while this cohort appears to begin at a much lower occupational score than earlier cohorts, their score rises very quickly. (The pattern is there in the raw data in figure 7 as well, although it is less pronounced.) Is it possible that later cohorts start with lower initial occupation scores, but those low scores are offset by higher mobility of the affected workers? To answer this question we turn to Markov analysis to consider how young workers move through the occupation distribution.[13]

The weak labour market is reflected in low occupational mobility

The above analysis focuses on changes in average occupational outcomes. However, the average masks considerable heterogeneity, as revealed in the bimodal distribution of occupations. In addition to understanding outcomes at any point in time, we want to

[13] The Markov analysis cannot differentiate between people who take longer to find their desired job (and stay in their previous part-time job while searching) and people who find a job in a lower-scored occupation. However, the Markov assumption means that, conditional on a person's current occupation, we can see if subsequent transitions might be compensating for a known decrease in occupational score.

understand how people move through the distribution over time. How much upward mobility is there in occupations? If more people start at low occupational scores in the later period, are more of them likely to subsequently move up in the distribution more quickly?

We analyse Markov transitions between quartiles in the occupational score distribution to understand how much mobility there is in occupations. Over this whole period, transitions between quartiles are relatively uncommon, as one would expect (recall that the average occupational score stabilises quickly after graduation). But a decline in average occupational score for later cohorts implies that there are more 'unlucky' workers than in earlier years. (The 'unlucky' are young workers whose occupational score is far lower than we would have predicted from their characteristics in earlier generations.) As the number of 'unlucky' young workers increases over time, one might expect some corresponding improvement in upward transitions. If employers are aware that a larger share of workers in lower-scored occupations are 'unlucky', they should be more willing to try out a worker who is currently in a lower-scored occupation. And on the worker side, if an 'unlucky' worker is to recover from their 'bad luck' they must improve their upward transitions compared with other workers.

Markov analysis of occupations

This paper uses a discrete-time Markov chain analysis (Craig and Sendi 2002) on an unmatched (figure 10) and then a matched (figure 11) sample. For the matched sample, we separate young people into one control group (people who graduated from 2001 to 2003) and four treatment groups (people who graduated from 2004 to 2006, 2007 to 2009, 2010 to 2012 and 2013 to 2014[14]) based on their last observed graduation date. (As before, we include both university and VET graduates.)

Occupational transitions are observed for the four years after graduation — that is, someone who graduated in 2007 is observed between 2008 and 2011. Four years might seem too short a time to observe transitions post-graduation, but there is a trade-off between the number of cohorts that can be compared and the length of time for which each cohort can be observed.[15]

For both samples, the distribution is cut into quartiles based on the unmatched distribution of occupational scores for young people who graduated in 2001–2003. The probability of transitions between these quartiles is estimated. The Markov chain analysis, therefore, measures how quickly graduates after 2003 moved up or down the occupational score quartiles. Figure 10 shows the raw transition probabilities, not adjusted for any differences in demographics between different cohorts. Figure 11 shows the difference in transition

14 We omit graduates from 2015 to ensure all graduates in the final cohort have four years' worth of transitions.

15 To include the 2013–2014 cohort, it is necessary to restrict transitions to the four years after graduation for all other cohorts. Although excluding this cohort would increase the timeframe other cohorts could be observed for, it would restrict the ability to assess whether there has been a recovery in transitions.

probabilities between the treatment and control groups, where the transitions of the control group have been weighted by the matching weights.

Using genetic matching[16] (Diamond and Sekhon 2013; Ho et al. 2011; Sekhon 2011), graduates are matched on observables at their year of graduation. This process develops four different control groups of 2001–2003 graduates — one for each of the treatment groups.

The extent to which this procedure provides valid comparisons of the transitions between the treatment and control groups depends on whether the conditional independence assumption is satisfied and whether there is any omitted variable bias. If these assumptions are violated, then the changes in transitions are in part due to graduation cohort and in part due to differences in the unobserved characteristics.[17] Given that education and other labour market characteristics will affect one's likely occupation, it is particularly important to control for these characteristics. In general, the matching procedure improves the balance of the sample (although, our sample was relatively balanced before matching took place). Further, the graduation cohorts for which there is statistically significant variation in occupational score one year after graduation have higher Rosenbaum scores — suggesting that they are less sensitive to unobserved heterogeneity.[18] The full set of matching characteristics along with balance plots and Rosenbaum bounds is presented in appendix C.

Figure 11 shows the changes in transition probabilities across the different time periods. These changes in transition probabilities are estimated while controlling for demographic and educational differences between the 2001–2003 cohort and the subsequent cohorts.

Graduates are very likely to stay within their occupational score quartile

Figure 10 suggests that, over the sample period, about 75 per cent of young people remained within the same occupational quartile each year. This could reflect the fact that quartiles are a relatively coarse measure of the distribution, or that job-to-job transitions were relatively infrequent over the period. Deutscher (2019, p. 5) estimated job switching rates of about 20 per cent per annum for people in their early 20s. In that context, our estimate of mobility

[16] Genetic matching is an iterative algorithm that checks propensity scores. It improves them using a combination of propensity score and Mahalanobis distance matching (Diamond and Sekhon, 2013).

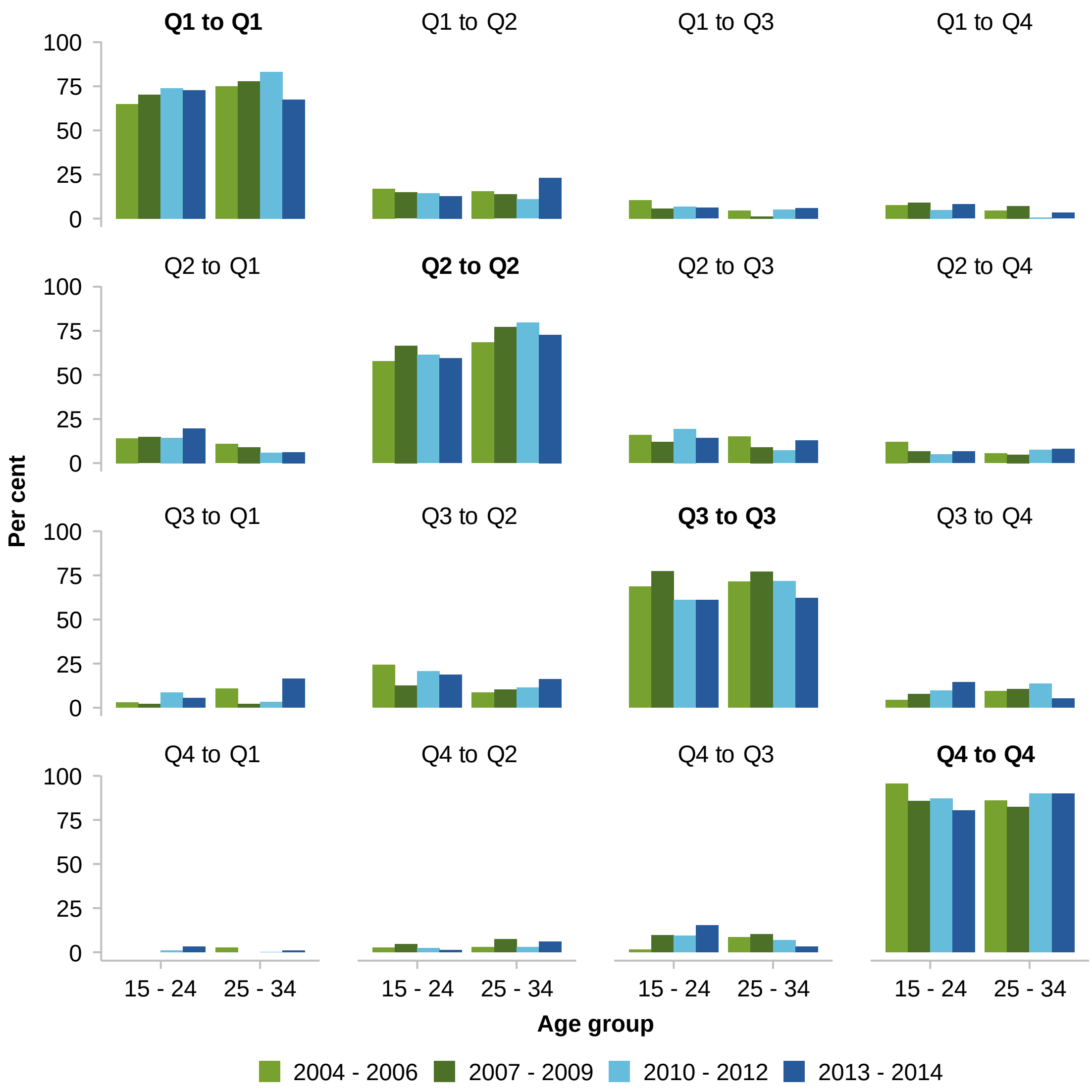
[17] There is an inherent tension between matching, which assumes there are no omitted variables, and the Heckman analysis, which assumes there are. For instance, the Heckman methodology assumes there is a selection effect into employment that introduces bias into the estimates in the wage equation. This selection can change over time, as changes to labour market conditions might mean more people accept job offers. For the matching procedure, this might mean graduates who face better labour market conditions, would be more likely to participate in the job market after graduation. Proxies for skill and the likelihood of participation must be included in the matching to reduce any selection bias. We use experience, experience squared and degree type at graduation to partly control for skill; and the unemployment rate in the local government area and the proportion of life spent unemployed to control for their likelihood of participation.

[18] The assumption of conditional independence (conditional on matching characteristics) was checked by comparing the absolute standardised mean differences of the covariates. And the sensitivity of matching to unobserved heterogeneity can be assessed using Rosenbaum's bounds. These are presented in Appendix B.

is relatively high: about a 25 per cent probability, each year, that a young person moves to an occupation in a different quartile. This suggests that quartiles are not too coarse.

Figure 10 **Young people are likely to stay in the same occupation quartile**

Probability of transition between occupation quartiles each year[a], unmatched sample



[a] The occupation quartile in each year of the four years after graduation was recorded and then year to year transitions were pooled across the four-year period. [b] Transitions weighted by HILDA's representative person weights.

Data source: Commission estimates based on HILDA data.

Young people who graduated after 2007 were less likely to move out of the lower two quartiles when compared with graduates from 2004–2006 (figure 10) and 2001–2003 (figure 11 (1)). And the lower quartiles did not show large upward movement as the economy recovered by 2017–2018. This could imply scarring for young graduates in 2010–2012 and 2013–2014. They may find themselves in lower-scored occupations (which usually imply lower wage growth) over the long term.[19]

Figure 11 allows us to compare transition probabilities in each year with transitions in 2001–2003 for a comparable cohort. The effects of the weak labour market after the GFC are noticeable. Relative to the period before the GFC, young people aged 15-24 are now more likely to remain in the bottom (first) quartile of the occupation distribution. It is concerning that they are also more likely to move from the second quartile to the bottom quartile: between 5 and 10 percentage points more likely (figure 11 (2)).

Young workers aged 25-34 are more likely to remain in the second quartile (figure 11 (1)). They are also more likely to move from the third quartile into the lower two quartiles (figure 11 (2)) and less likely to move up from the second or third quartiles (figure 11 (3)). These results suggest that the recession not only made it more likely that young people would find a low-scored occupation, but more likely that they would remain in low-scored occupations.

Now we focus on the transitions later in the dataset — the 2013–2014 cohort's transitions. We compare them to earlier cohorts.

The most striking feature of these Markov transitions is that not much improvement takes place for that last cohort. Transitions between quartiles look very similar for people graduating in 2007–2009 and for people graduating in 2013–2014, even though the 2013–2014 graduates are transitioning during a recovery. Even though there is a sizeable decrease in the probability of a 25-34 year old remaining in the lowest occupation quartile — that probability is 15 percentage points lower — many of those transitions are to the second quartile (figure 12). Meanwhile, there is a 5 to 15 percentage point decrease in the probability of moving from the second quartile to higher quartiles. People aged 15-24 from the 2013-2014 cohort were less likely to transition from the bottom quartile than they were in the previous cohort.

The lack of improvement in mobility has serious implications: if young people looking for work after 2010 had to accept lower-quartile jobs because of the state of the economy, there is little sign that they were able to move out of these lower quartiles in the following years. There is no indication that employers have adjusted for the fact that the lower quartiles now include many promising but unlucky young workers, and are prepared to give them a chance. This may be because in a weak labour market, employers still face an excess supply of recent graduates and school leavers from which to choose.

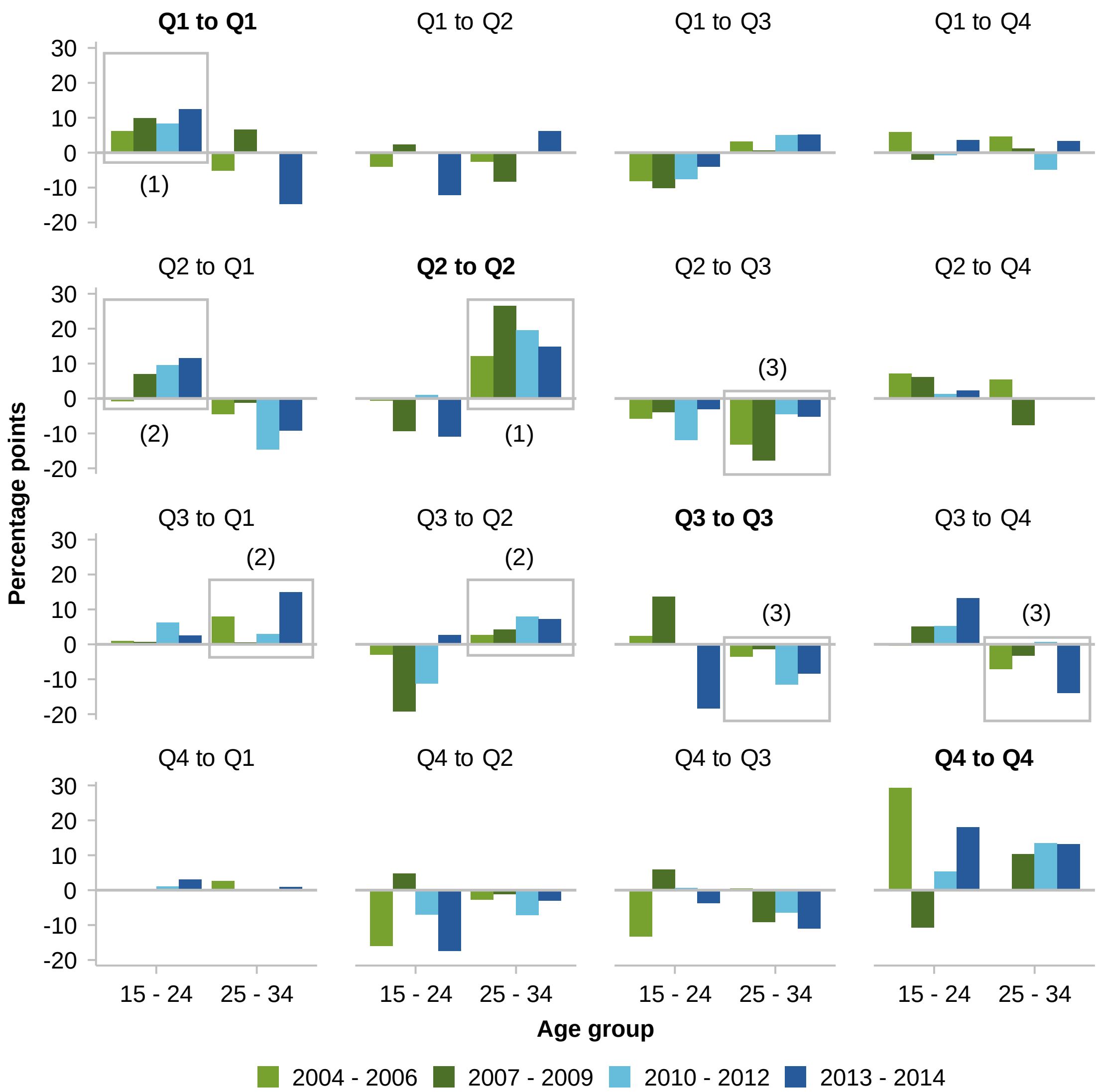
A longer time horizon is needed to draw firm conclusions. In particular, we cannot be certain whether there is a lack of mobility because the labour market is weak, or if it is a feature of

[19] Relatedly, Storesletten, Telmer and Yaron (2004) found that cohorts who live through more downturns can have larger dispersions in their labour income.

the Australian labour market. Low mobility between quartiles throughout the sample period may suggest that immobility is a feature of the market. But, likewise, we see a small decline in mobility just as the occupational scores worsen. At the least, it is safe to say that we are not seeing strong signs that young workers can easily move out of lower-scored occupations, if they face a more difficult market at the time of graduation.

Figure 11 **Young people are more likely to stay in occupations in the two bottom quartiles of occupational score**

Changes in the probability of transition between occupation quartiles each year[a], comparisons between treatment and matched control groups



[a] Graduates in each time period were matched with graduates from 2001 to 2003. Their occupation quartile in each year of the four years after graduation was recorded and then transitions were pooled across the four years. [b] The change in probability is the difference between the two weighted transition matrices for the treated and control groups. [c] The treated transitions are weighted by HILDA's representative person weights. [d] The control transitions are weighted by matching weights and HILDA's representative person weights.

Data source: Commission estimates based on HILDA data.

These results are corroborated by Markov analysis of the transitions between unemployment, being out of the labour force, part-time work, and full-time work (appendix B). We do not see any strong increase in the transitions from part-time work to full-time work after 2008. Again, these results suggest that unlucky young workers who fail to secure full-time work in a weak labour market do not find it easier to move from part-time work.

Conclusion

This paper has shown that the weak labour market from 2008 to 2018 is reflected primarily in young workers finding lower-scored occupations and earning lower wage rates than earlier generations. Movement down the jobs ladder has negative implications for the lifetime earnings of those young workers, and possibly for their work satisfaction. It also has implications for young people with low educational attainment, as they face competition from young people with more education. Some young people were pushed 'off the ladder', as indicated by the rise in long-run unemployment (PC 2020). But the fact that the unemployment rate did not rise sharply suggests that certain segments of the labour market had more flexibility to absorb additional workers, possibly at lower wages. The increase in part-time employment and decline in full-time employment among people aged under 25 may be a related phenomenon (PC 2020).

Our results show that there is some potential for long-term effects from the weak labour market of 2008 to 2018. We show that young workers looking for work after the GFC experienced a dip in the occupational score of the jobs they secured. With Markov analysis, we are able to show that there was no large increase in upward movements; there is no evidence that young people who took lower-scored jobs found better jobs in the recovery. The absence of those upward transitions suggests that the generation who sought work during the 2008–2018 weak labour market faced worse long-term career prospects than their predecessors.

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Appendix A

Six models are presented below, five different Heckman specifications and one OLS. Each models uses the exclusion restrictions of ‘household child ratio’ and ‘household child ratio x gender’ unless specified otherwise.

The six probit specifications for people aged 20-34 and 35-64 are:

1. baseline specification
2. sensitivity test with exclusion restrictions of number of ‘children’ and ‘married’
3. sensitivity test with additional exclusion restrictions of selected variables interacted with the year dummies
4. sensitivity test with restricted sample based on two periods:
   a. sample split for years 2001–2007
   b. sample split for years 2007–2018 (the overlap of 2007 allows for consistent comparison of the year dummies across the samples.)
5. sensitivity test predicting full-time employment, with the exclusion restriction of ‘household child ratio’.

The six wage specifications for people aged 20-34 and 35-64 are:

1. baseline specification
2. sensitivity test with exclusion restrictions of ‘number of children’ and ‘married’
3. sensitivity test with additional exclusion restrictions of ‘household child ratio’, ‘household child ratio x gender’, and selected variables interacted with the year dummies
4. sensitivity test with whole sample using probit specification (4a) and (4b) to calculate the inverse Mills ratio for each period separately (4a was used for 2007)
5. sensitivity test predicting full-time employment with exclusion restrictions of ‘household child ratio’ and ‘household child ratio x female wage-earner’
6. OLS regression.

Heckman regression results: employment equation

Table A.1 **Probability of Employment – people aged 35-64**

Probit estimation results, first stage Heckman results

	(1)	*(2)*	*(3)*	*(4a)*	*(4b)*	*(5)*
	employed	employed	employed	employed	employed	employed (full-time)
2002	0.021	0.020	0.030	0.020		0.004
	(0.027)	(0.027)	(0.060)	(0.027)		(0.026)
2003	0.069**	0.068**	0.188***	0.066**		0.053**
	(0.028)	(0.028)	(0.062)	(0.028)		(0.026)
2004	0.092***	0.095***	0.199***	0.089***		0.073***
	(0.028)	(0.028)	(0.063)	(0.028)		(0.026)
2005	0.164***	0.165***	0.244***	0.163***		0.108***
	(0.028)	(0.028)	(0.064)	(0.028)		(0.026)
2006	0.210***	0.216***	0.343***	0.208***		0.142***
	(0.028)	(0.028)	(0.065)	(0.029)		(0.026)
2007	0.249***	0.257***	0.418***	0.248***		0.184***
	(0.029)	(0.029)	(0.066)	(0.029)		(0.027)
2008	0.272***	0.282***	0.422***		0.023	0.197***
	(0.029)	(0.029)	(0.066)		(0.030)	(0.027)
2009	0.253***	0.259***	0.412***		0.003	0.199***
	(0.029)	(0.029)	(0.066)		(0.030)	(0.026)
2010	0.248***	0.253***	0.403***		-0.002	0.189***
	(0.028)	(0.028)	(0.066)		(0.030)	(0.026)
2011	0.259***	0.266***	0.379***		0.006	0.191***
	(0.026)	(0.026)	(0.062)		(0.028)	(0.025)
2012	0.235***	0.247***	0.431***		-0.016	0.187***
	(0.026)	(0.026)	(0.062)		(0.028)	(0.025)
2013	0.208***	0.218***	0.381***		-0.044	0.170***
	(0.026)	(0.026)	(0.063)		(0.028)	(0.025)
2014	0.233***	0.247***	0.408***		-0.019	0.170***
	(0.027)	(0.027)	(0.063)		(0.028)	(0.025)
2015	0.241***	0.256***	0.447***		-0.011	0.183***
	(0.027)	(0.027)	(0.064)		(0.028)	(0.025)
2016	0.249***	0.262***	0.459***		-0.004	0.195***
	(0.027)	(0.027)	(0.065)		(0.029)	(0.025)
2017	0.314***	0.327***	0.542***		0.062**	0.247***
	(0.027)	(0.027)	(0.066)		(0.029)	(0.025)
2018	0.339***	0.349***	0.579***		0.087***	0.275***
	(0.027)	(0.027)	(0.068)		(0.029)	(0.025)

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Table A.1 (continued)

	(1)	(2)	(3)	(4a)	(4b)	(5)
	employed	employed	employed	employed	employed	employed (full-time)
Age	0.224***	0.146***	0.223***	0.232***	0.228***	0.186***
	(0.008)	(0.008)	(0.008)	(0.013)	(0.009)	(0.008)
Age squared/100	-0.346***	-0.267***	-0.346***	-0.357***	-0.350***	-0.298***
	(0.008)	(0.008)	(0.008)	(0.013)	(0.009)	(0.008)
Experience	0.099***	0.115***	0.099***	0.102***	0.098***	0.095***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Experience squared/100	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University degree	0.587***	0.598***	0.765***	0.665***	0.546***	0.490***
	(0.013)	(0.013)	(0.055)	(0.022)	(0.016)	(0.012)
Diploma or certificate	0.246***	0.238***	0.227***	0.245***	0.241***	0.249***
	(0.012)	(0.012)	(0.047)	(0.019)	(0.015)	(0.011)
High school	0.210***	0.197***	0.302***	0.244***	0.187***	0.195***
	(0.017)	(0.017)	(0.065)	(0.027)	(0.020)	(0.016)
In full-time study	-0.821***	-0.849***	-0.908***	-0.821***	-0.810***	-0.843***
	(0.037)	(0.036)	(0.141)	(0.060)	(0.045)	(0.041)
VIC	0.022*	0.015	0.024*	-0.001	0.044***	-0.054***
	(0.013)	(0.013)	(0.013)	(0.021)	(0.015)	(0.011)
QLD	-0.006	-0.000	-0.005	-0.046**	0.024	0.052***
	(0.013)	(0.013)	(0.013)	(0.023)	(0.016)	(0.012)
SA	-0.065***	-0.068***	-0.065***	-0.146***	-0.021	-0.146***
	(0.017)	(0.017)	(0.017)	(0.029)	(0.021)	(0.016)
WA	0.005	0.006	0.006	-0.046	0.037*	-0.038**
	(0.018)	(0.018)	(0.018)	(0.029)	(0.021)	(0.016)
TAS	0.057**	0.049*	0.058**	-0.055	0.119***	-0.075***
	(0.028)	(0.028)	(0.028)	(0.045)	(0.034)	(0.026)
NT	0.595***	0.578***	0.597***	0.532***	0.617***	0.542***
	(0.068)	(0.067)	(0.068)	(0.117)	(0.080)	(0.052)
ACT	0.032	0.005	0.032	0.200***	-0.033	0.126***
	(0.035)	(0.035)	(0.035)	(0.062)	(0.041)	(0.031)
Lives in regional area	-0.097***	-0.097***	-0.003	-0.079***	-0.111***	-0.142***
	(0.010)	(0.010)	(0.040)	(0.017)	(0.012)	(0.010)
Indigenous	-0.112***	-0.122***	-0.113***	-0.113*	-0.100***	-0.008
	(0.033)	(0.032)	(0.033)	(0.059)	(0.038)	(0.033)
Female	0.216***	0.026**	0.347***	0.193***	0.223***	-0.769***
	(0.012)	(0.011)	(0.040)	(0.021)	(0.014)	(0.009)
Proportion of life spent unemployed	-1.182***	-1.090***	-1.183***	-1.273***	-1.105***	-1.759***
	(0.066)	(0.066)	(0.066)	(0.113)	(0.078)	(0.075)
Not English speaking	-0.118***	-0.111***	-0.115***	-0.268***	-0.028*	0.046***
	(0.014)	(0.014)	(0.014)	(0.022)	(0.017)	(0.013)

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Table A.1 (continued)

	(1)	(2)	(3)	(4a)	(4b)	(5)
	employed	employed	employed	employed	employed	employed (full-time)
Married	0.090***		0.090***	0.139***	0.066***	-0.034***
	(0.011)		(0.011)	(0.018)	(0.013)	(0.010)
Intercept	-4.487***	-2.739***	-4.606***	-4.520***	-4.397***	-3.555***
	(0.180)	(0.189)	(0.184)	(0.303)	(0.217)	(0.171)
Exclusion restrictions:						
Child ratio	0.119***		0.122***	0.063**	0.139***	-0.342***
	(0.016)		(0.016)	(0.025)	(0.020)	(0.009)
Child ratio x female	-0.519***		-0.523***	-0.488***	-0.533***	
	(0.019)		(0.019)	(0.030)	(0.023)	
Married		0.146***				
		(0.011)				
Number of kids aged 0 to 4		-0.346***				
		(0.011)				
Number of kids aged 5 to 14		-0.051***				
		(0.006)				
Number of kids aged 15 to 24		0.137***				
		(0.007)				
Year x degree type	No	No	Yes	No	No	No
Year x lives in regional area	No	No	Yes	No	No	No
Year x in full-time study	No	No	Yes	No	No	No
Year x female	No	No	Yes	No	No	No
N	115 217	115 217	115 217	40 519	80 245	115 217
Log likelihood	-46 906	-46 817	-46 829	-16 847	-32 053	-57 386
AIC	93 895.470	93 718.445	93 945.768	33 754.151	64 176.399	114 852.858

Source: Commission estimates based on HILDA data

Table A.2 **Probability of Employment – people aged 20-34**

Probit estimation results, first stage Heckman results

	(1)	*(2)*	*(3)*	*(4a)*	*(4b)*	*(5)*
	employed	employed	employed	employed	employed	employed (full-time)
2002	0.087**	0.088**	0.154	0.078*		0.070*
	(0.040)	(0.041)	(0.098)	(0.040)		(0.037)
2003	0.123***	0.115***	0.148	0.111***		0.063*
	(0.041)	(0.042)	(0.101)	(0.041)		(0.037)
2004	0.193***	0.180***	0.395***	0.177***		0.117***
	(0.042)	(0.042)	(0.106)	(0.042)		(0.038)
2005	0.253***	0.240***	0.358***	0.236***		0.153***
	(0.043)	(0.043)	(0.108)	(0.042)		(0.038)
2006	0.230***	0.221***	0.386***	0.214***		0.156***
	(0.042)	(0.043)	(0.108)	(0.042)		(0.038)
2007	0.224***	0.232***	0.367***	0.208***		0.172***
	(0.042)	(0.043)	(0.109)	(0.042)		(0.038)
2008	0.298***	0.308***	0.402***		0.073	0.257***
	(0.043)	(0.044)	(0.110)		(0.046)	(0.038)
2009	0.158***	0.175***	0.251**		-0.066	0.140***
	(0.041)	(0.041)	(0.105)		(0.044)	(0.037)
2010	0.157***	0.173***	0.209**		-0.067	0.130***
	(0.040)	(0.041)	(0.102)		(0.044)	(0.037)
2011	0.073**	0.107***	0.201**		-0.151***	0.064*
	(0.037)	(0.038)	(0.095)		(0.041)	(0.034)
2012	0.068*	0.099***	0.007		-0.155***	0.057*
	(0.037)	(0.037)	(0.093)		(0.040)	(0.034)
2013	0.068*	0.095**	0.081		-0.157***	0.029
	(0.037)	(0.037)	(0.094)		(0.040)	(0.034)
2014	0.101***	0.124***	0.138		-0.123***	0.002
	(0.037)	(0.037)	(0.094)		(0.040)	(0.034)
2015	0.153***	0.166***	0.089		-0.070*	0.022
	(0.037)	(0.037)	(0.096)		(0.041)	(0.034)
2016	0.117***	0.126***	0.104		-0.105***	0.035
	(0.037)	(0.037)	(0.098)		(0.041)	(0.034)
2017	0.226***	0.230***	0.249**		0.006	0.068**
	(0.038)	(0.038)	(0.100)		(0.041)	(0.034)
2018	0.295***	0.295***	0.410***		0.075*	0.114***
	(0.038)	(0.039)	(0.103)		(0.042)	(0.034)

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Table A.2 (continued)

	(1)	(2)	(3)	(4a)	(4b)	(5)
	employed	employed	employed	employed	employed	employed (full-time)
Age	-0.312***	-0.286***	-0.312***	-0.240***	-0.342***	0.051**
	(0.024)	(0.024)	(0.024)	(0.042)	(0.028)	(0.022)
Age squared/100	0.360***	0.260***	0.361***	0.252***	0.407***	-0.255***
	(0.044)	(0.045)	(0.044)	(0.078)	(0.053)	(0.041)
Experience	0.303***	0.320***	0.304***	0.233***	0.332***	0.213***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)
Experience squared/100	-0.009***	-0.008***	-0.009***	-0.006***	-0.010***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
University degree	0.838***	1.000***	0.974***	0.847***	0.822***	0.674***
	(0.023)	(0.024)	(0.084)	(0.039)	(0.028)	(0.021)
Diploma or certificate	0.418***	0.478***	0.484***	0.440***	0.406***	0.371***
	(0.020)	(0.020)	(0.075)	(0.033)	(0.024)	(0.019)
High school	0.416***	0.497***	0.457***	0.417***	0.416***	0.234***
	(0.020)	(0.020)	(0.076)	(0.034)	(0.025)	(0.019)
In full-time study	-0.522***	-0.548***	-0.670***	-0.620***	-0.481***	-1.443***
	(0.020)	(0.020)	(0.091)	(0.039)	(0.023)	(0.022)
VIC	0.041**	0.044**	0.040**	0.069**	0.026	-0.021
	(0.018)	(0.018)	(0.018)	(0.032)	(0.021)	(0.016)
QLD	-0.105***	-0.125***	-0.105***	-0.035	-0.133***	-0.039**
	(0.019)	(0.019)	(0.019)	(0.033)	(0.022)	(0.017)
SA	-0.049**	-0.078***	-0.052**	-0.023	-0.069**	-0.135***
	(0.025)	(0.025)	(0.025)	(0.044)	(0.029)	(0.022)
WA	-0.125***	-0.136***	-0.126***	-0.092**	-0.135***	-0.069***
	(0.025)	(0.025)	(0.025)	(0.042)	(0.030)	(0.022)
TAS	0.069*	0.051	0.066*	0.036	0.083*	-0.090**
	(0.040)	(0.040)	(0.040)	(0.069)	(0.047)	(0.037)
NT	0.286***	0.279***	0.284***	0.523***	0.193**	0.397***
	(0.074)	(0.074)	(0.075)	(0.149)	(0.083)	(0.063)
ACT	0.088*	0.080*	0.086*	-0.044	0.114**	0.117***
	(0.048)	(0.048)	(0.048)	(0.085)	(0.056)	(0.040)
Lives in regional area	-0.053***	-0.065***	-0.087	-0.064**	-0.053***	-0.046***
	(0.015)	(0.015)	(0.060)	(0.027)	(0.018)	(0.014)
Indigenous	-0.196***	-0.214***	-0.196***	-0.237***	-0.167***	-0.156***
	(0.032)	(0.032)	(0.032)	(0.066)	(0.036)	(0.033)
Female	-0.232***	-0.425***	-0.194***	-0.275***	-0.220***	-0.850***
	(0.016)	(0.014)	(0.057)	(0.029)	(0.019)	(0.012)
Proportion of life spent unemployed	-1.402***	-1.254***	-1.404***	-1.289***	-1.407***	-1.636***
	(0.048)	(0.049)	(0.048)	(0.088)	(0.057)	(0.054)
Not English speaking	0.021	0.066***	0.020	-0.098***	0.081***	0.019
	(0.023)	(0.023)	(0.023)	(0.038)	(0.028)	(0.021)

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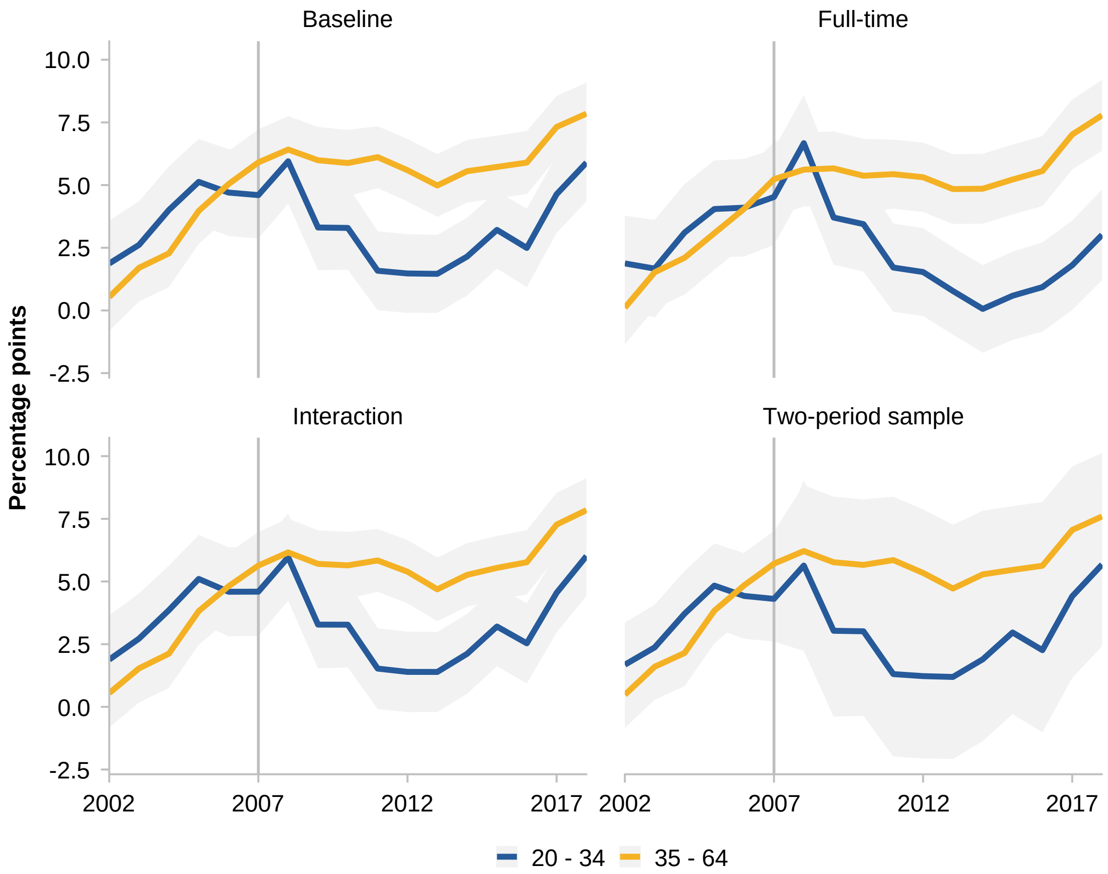
Table A.2 (continued)

	(1)	(2)	(3)	(4a)	(4b)	(5)
	employed	employed	employed	employed	employed	employed (full-time)
Married	-0.083***		-0.082***	-0.136***	-0.057***	0.136***
	(0.015)		(0.015)	(0.026)	(0.018)	(0.013)
Intercept	5.045***	4.886***	5.003***	4.264***	5.596***	0.011
	(0.315)	(0.318)	(0.321)	(0.556)	(0.370)	(0.291)
Exclusion restrictions:						
Child ratio	-0.066***		-0.066***	-0.112***	-0.055*	-0.683***
	(0.023)		(0.024)	(0.040)	(0.028)	(0.014)
Child ratio x female	-0.543***		-0.543***	-0.512***	-0.543***	
	(0.027)		(0.027)	(0.046)	(0.032)	
Married		0.158***				
		(0.016)				
Number of kids aged 0 to 4		-0.550***				
		(0.010)				
Number of kids aged 5 to 14		0.011				
		(0.012)				
Number of kids aged 15 to 24		0.248***				
		(0.077)				
Year x degree type	No	No	Yes	No	No	No
Year x lives in regional area	No	No	Yes	No	No	No
Year x in full-time study	No	No	Yes	No	No	No
Year x female	No	No	Yes	No	No	No
N	64 971	64 971	64 971	20 712	47 129	64 971
Log likelihood	-23 459	-22 902	-23 408	-7 560.896	-16 830	-30 192
AIC	47 001.486	45 888.407	47 102.602	15 181.792	33 730.756	60 465.867

Source: Commission estimates based on HILDA data

Figure A.1 **Comparison of specifications (1), (3), (4a) and (4b) and (5)**

Average marginal effect of year on the probability of employment



[a] The two-period sample the combines the results from (4a) and (4b). The AME in the two-period graph was calculated by adding the value of the AME at 2007 from regression (4a) to the AME of each year dummy from regression (4b).

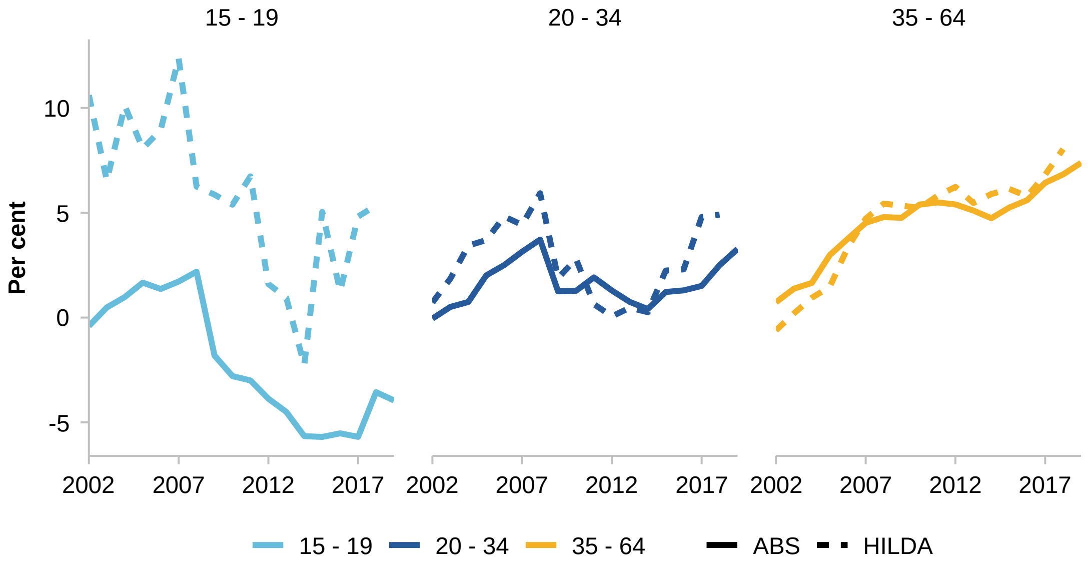
Data source: Commission estimates based on HILDA data

The regressions omit workers aged 15-19

The sample of workers aged 15-19 is not well represented when HILDA is compared with equivalent ABS data (figure A.2). The regressions omit workers aged 15-19 because of this discrepancy.

Figure A.2 **HILDA data overestimates employment of people aged 15-19**

Change in employment to population rate above 2001 level, 2002-2018



Data sources: Commission estimates based on HILDA data and ABS (Labour Force, detailed, Mar 2020, cat. no. 6291.0.55.001)

Heckman regression results: wage equation

Table A.3 **ln(wage) regression – people aged 35-64**

Linear wage rate estimation results, second stage Heckman results

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	ln(wage)	ln(wage)	ln(wage)	ln(wage)	ln(wage) (full-time)	ln(wage) (OLS)
2002	0.016*	0.016*	0.016*	0.016*	0.016	0.015
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2003	0.038***	0.038***	0.038***	0.037***	0.040***	0.034***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2004	0.045***	0.045***	0.045***	0.044***	0.048***	0.040***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2005	0.075***	0.076***	0.074***	0.073***	0.077***	0.066***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2006	0.095***	0.097***	0.094***	0.093***	0.098***	0.084***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
2007	0.106***	0.109***	0.106***	0.104***	0.112***	0.093***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
2008	0.128***	0.131***	0.127***	0.125***	0.133***	0.114***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
2009	0.156***	0.159***	0.155***	0.153***	0.162***	0.143***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
2010	0.166***	0.169***	0.166***	0.163***	0.172***	0.153***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
2011	0.179***	0.182***	0.178***	0.176***	0.184***	0.165***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2012	0.184***	0.187***	0.183***	0.181***	0.190***	0.171***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2013	0.179***	0.182***	0.179***	0.177***	0.185***	0.168***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2014	0.177***	0.181***	0.177***	0.175***	0.182***	0.164***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2015	0.189***	0.193***	0.189***	0.186***	0.195***	0.176***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2016	0.202***	0.205***	0.201***	0.199***	0.208***	0.188***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2017	0.214***	0.217***	0.213***	0.210***	0.221***	0.196***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
2018	0.229***	0.233***	0.228***	0.225***	0.237***	0.211***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)

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Table A.3 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(wage)	ln(wage)	ln(wage)	ln(wage)	ln(wage) (full-time)	ln(wage) (OLS)
Age	0.005	0.009***	0.004	0.002	0.012***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age squared/100	-0.016***	-0.023***	-0.015***	-0.013***	-0.028***	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Experience	0.020***	0.021***	0.020***	0.019***	0.024***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience squared/100	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University degree	0.460***	0.469***	0.458***	0.454***	0.479***	0.428***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
Diploma or certificate	0.133***	0.136***	0.133***	0.131***	0.144***	0.120***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
High school	0.126***	0.128***	0.126***	0.124***	0.135***	0.114***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
In full-time study	-0.047***	-0.064***	-0.044**	-0.037**	-0.087***	0.006
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
VIC	-0.045***	-0.045***	-0.045***	-0.045***	-0.050***	-0.046***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
QLD	-0.039***	-0.040***	-0.039***	-0.039***	-0.034***	-0.039***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
SA	-0.096***	-0.097***	-0.096***	-0.095***	-0.106***	-0.093***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
WA	0.017***	0.016***	0.017***	0.017***	0.014**	0.017***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
TAS	-0.027***	-0.028***	-0.027***	-0.028***	-0.036***	-0.030***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
NT	0.119***	0.121***	0.118***	0.115***	0.139***	0.097***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ACT	0.122***	0.127***	0.122***	0.123***	0.132***	0.120***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Lives in regional area	-0.111***	-0.109***	-0.111***	-0.110***	-0.120***	-0.106***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Indigenous	0.050***	0.042***	0.050***	0.051***	0.054***	0.057***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)
Female	-0.122***	-0.125***	-0.122***	-0.122***	-0.190***	-0.125***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
Proportion of life spent unemployed	-0.866***	-0.944***	-0.863***	-0.852***	-0.940***	-0.793***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.029)
Not English speaking	-0.102***	-0.099***	-0.102***	-0.101***	-0.091***	-0.098***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

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Table A.3 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(wage)	ln(wage)	ln(wage)	ln(wage)	ln(wage) (full-time)	ln(wage) (OLS)
Married	0.064***		0.064***	0.063***	0.052***	0.058***
	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)
Intercept	2.970***	2.914***	2.987***	3.035***	2.761***	3.337***
	(0.075)	(0.075)	(0.075)	(0.074)	(0.077)	(0.062)
Mills ratio coefficient (rho * sigma)	0.138***	0.167***	0.131***	0.114***	0.168***	
	(0.016)	(0.015)	(0.015)	(0.015)	(0.013)	
N	83 586	83 586	83 586	83 586	83 586	83 586
R-squared	0.218	0.216	0.218	0.218	0.219	0.217
F-statistic	597.243	606.286	597.121	596.672	600.083	610.421

Source: Commission estimates based on HILDA data

Table A.4 **ln(wage) regression – people aged 20-34**

Linear wage rate estimation results, second stage Heckman results

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(wage)	ln(wage)	ln(wage)	ln(wage)	ln(wage) (full-time)	ln(wage) (OLS)
2002	-0.021*	-0.017	-0.021*	-0.021*	-0.020*	-0.021*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2003	-0.001	0.004	-0.001	-0.002	-0.000	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2004	0.025**	0.034***	0.025**	0.025**	0.027**	0.025**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2005	0.040***	0.052***	0.040***	0.040***	0.043***	0.041***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2006	0.053***	0.064***	0.053***	0.053***	0.056***	0.053***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2007	0.091***	0.104***	0.091***	0.091***	0.094***	0.091***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2008	0.095***	0.110***	0.094***	0.094***	0.099***	0.095***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2009	0.100***	0.109***	0.100***	0.099***	0.102***	0.100***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
2010	0.127***	0.139***	0.127***	0.127***	0.130***	0.128***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)

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Table A.4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(wage)	ln(wage)	ln(wage)	ln(wage)	ln(wage) (full-time)	ln(wage) (OLS)
2011	0.126***	0.133***	0.126***	0.125***	0.127***	0.126***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2012	0.139***	0.147***	0.139***	0.139***	0.141***	0.140***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2013	0.124***	0.132***	0.124***	0.124***	0.125***	0.125***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2014	0.117***	0.125***	0.117***	0.117***	0.118***	0.118***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2015	0.111***	0.122***	0.111***	0.111***	0.112***	0.111***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2016	0.124***	0.133***	0.124***	0.124***	0.125***	0.124***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2017	0.119***	0.133***	0.119***	0.119***	0.121***	0.120***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
2018	0.134***	0.149***	0.134***	0.134***	0.136***	0.134***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	0.023***	0.015**	0.023***	0.023***	0.023***	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age squared/100	-0.017	-0.013	-0.017	-0.017	-0.021*	-0.016
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Experience	0.026***	0.042***	0.025***	0.025***	0.030***	0.026***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Experience squared/100	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University degree	0.268***	0.313***	0.268***	0.267***	0.283***	0.269***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.006)
Diploma or certificate	0.064***	0.087***	0.064***	0.063***	0.071***	0.064***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
High school	0.059***	0.080***	0.058***	0.058***	0.064***	0.059***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
In full-time study	-0.002	-0.034***	-0.001	-0.001	-0.029***	-0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.006)
VIC	-0.049***	-0.046***	-0.049***	-0.049***	-0.048***	-0.049***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

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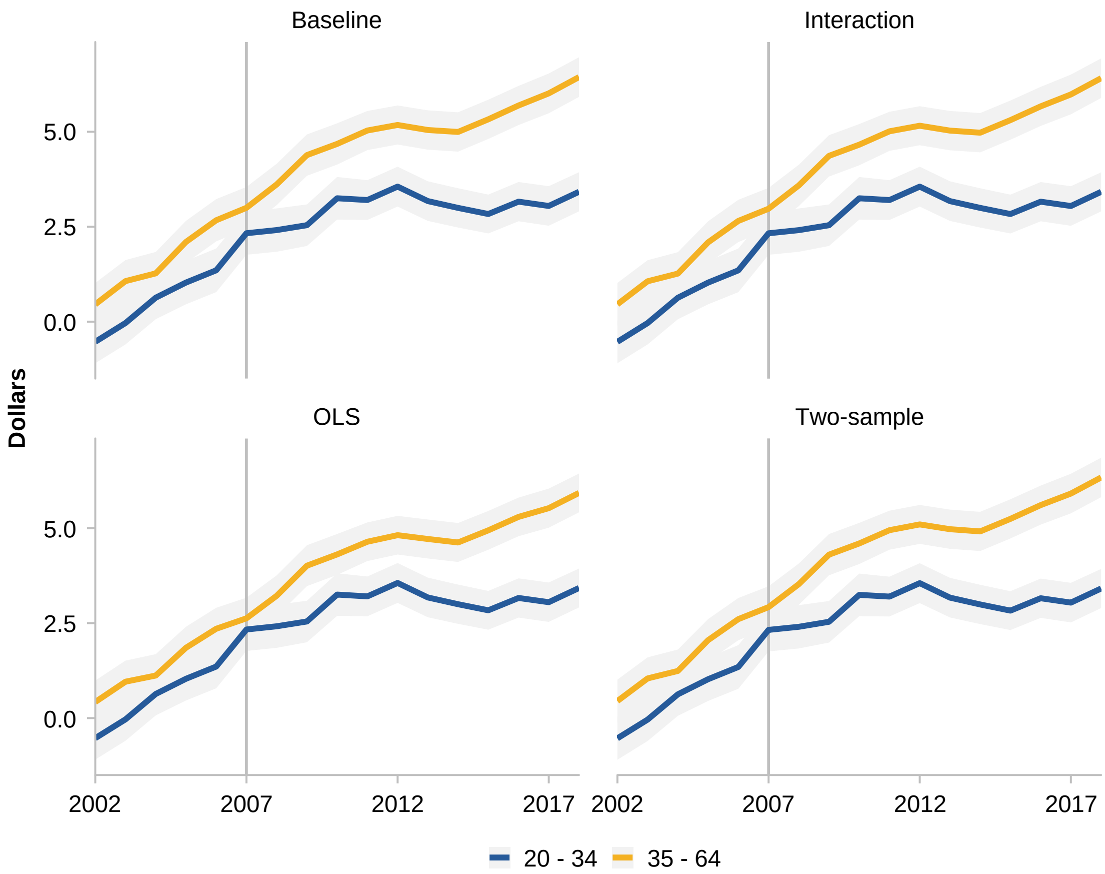
Table A.4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(wage)	ln(wage)	ln(wage)	ln(wage)	ln(wage) (full-time)	ln(wage) (OLS)
QLD	-0.036***	-0.038***	-0.036***	-0.036***	-0.037***	-0.036***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
SA	-0.052***	-0.052***	-0.052***	-0.052***	-0.054***	-0.052***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
WA	0.035***	0.031***	0.035***	0.035***	0.034***	0.035***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
TAS	-0.056***	-0.053***	-0.056***	-0.056***	-0.057***	-0.056***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
NT	0.068***	0.076***	0.068***	0.068***	0.073***	0.068***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
ACT	0.072***	0.077***	0.072***	0.072***	0.073***	0.072***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lives in regional area	-0.047***	-0.047***	-0.047***	-0.047***	-0.049***	-0.047***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Indigenous	0.008	-0.005	0.008	0.008	0.004	0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Female	-0.071***	-0.086***	-0.071***	-0.071***	-0.085***	-0.072***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Proportion of life spent unemployed	-0.327***	-0.431***	-0.326***	-0.325***	-0.356***	-0.328***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)
Not English speaking	-0.047***	-0.045***	-0.047***	-0.048***	-0.046***	-0.047***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Married	0.058***		0.058***	0.058***	0.059***	0.058***
	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)
Intercept	2.556***	2.625***	2.555***	2.551***	2.541***	2.560***
	(0.090)	(0.089)	(0.090)	(0.090)	(0.088)	(0.088)
Mills ratio coefficient (rho * sigma)	-0.002	0.128***	-0.003	-0.006	0.029***	
	(0.013)	(0.012)	(0.013)	(0.013)	(0.008)	
N	50 893	50 893	50 893	50 893	50 893	50 893
R-squared	0.203	0.201	0.203	0.203	0.203	0.203
F-statistic	331.668	335.717	331.669	331.673	332.047	340.402

Source: Commission estimates based on HILDA data

Figure A.3 **Comparison of specifications (1), (3), (4) and (6)**

Coefficients of year dummies transformed to dollars



Data source: Commission estimates based on HILDA data

Appendix B

Occupational regressions

The following tables present the full occupational regression results. Five different specifications are presented below:

1. $y_{i,g,t} = \lambda_t \alpha_1 + e_i \alpha_2 + \boldsymbol{x_{i,t}\alpha} + \varepsilon_{i,t}$

2. $y_{i,g,t} = \lambda_t \alpha_1 + e_i c_g \alpha_2 + \boldsymbol{x_{i,t}\alpha} + \varepsilon_{i,t}$

3. $y_{i,g,t} = \lambda_t \alpha_1 + c_g \alpha_2 + e_i c_g \alpha_3 + \boldsymbol{x_{i,t}\alpha} + \varepsilon_{i,t}$

4. $y_{i,g,t} = \lambda_t \alpha_1 + c_g \alpha_2 + e_i c_g \alpha_3 + e_i^2 c_g \alpha_4 + \boldsymbol{x_{i,t}\alpha} + \varepsilon_{i,t}$

5. $y_{i,g,t} = \lambda_t \alpha_1 + c_g \alpha_2 + e_i c_g \alpha_3 + e_i^2 c_g \alpha_4 + e_i^3 c_g \alpha_5 + \boldsymbol{x_{i,t}\alpha} + \varepsilon_{i,t}$

Where $y_{i,g,t}$ is the occupational score of individual i, λ_t are year dummies, e_i is experience (years since graduation), and c_g are graduation cohort dummies. e_i is a continuous variable in regression (2) to (5) but a series of dummies in regression (1).

Table B.1 **Occupational score regressions, 0 to 4 years after graduation**

	Dependent variable: occupational score				
	(1)	(2)	(3)	(4)	(5)
Years since graduation * Graduation cohort:					
2001 - 2003		0.683 ***	0.277	2.651 *	1.917
		(0.254)	(0.584)	(1.425)	(2.551)
2004 – 2006		0.079	-0.338	2.710 **	6.749 ***
		(0.232)	(0.483)	(1.142)	(2.163)
2007 – 2009		0.923 ***	0.376	3.152 ***	6.320 ***
		(0.225)	(0.477)	(1.152)	(2.229)
2010 – 2012		1.397 ***	0.303	1.485	2.607
		(0.217)	(0.416)	(1.014)	(1.910)
2013 - 2015		1.746 ***	1.814 ***	4.675 ***	7.725 ***
		(0.409)	(0.410)	(0.888)	(1.688)
Years since graduation squared * Graduation cohort:					
2001 - 2003				-0.490	0.115
				(0.315)	(1.610)
2004 – 2006				-0.769 ***	-3.729 ***
				(0.267)	(1.381)
2007 – 2009				-0.743 ***	-3.012 **
				(0.266)	(1.422)
2010 – 2012				-0.276	-1.044
				(0.232)	(1.213)
2013 - 2015				-0.825 ***	-3.084 ***
				(0.217)	(1.086)
Years since graduation cubed * Graduation cohort:					
2001 - 2003					-0.105
					(0.270)
2004 – 2006					0.505 **
					(0.231)
2007 – 2009					0.385
					(0.237)
2010 – 2012					0.130
					(0.203)
2013 - 2015					0.386 **
					(0.182)

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Table B.1 (continued)

	Dependent variable: occupational score				
	(1)	(2)	(3)	(4)	(5)
Years since graduation:					
1	3.615 ***				
	(0.473)				
2	4.294 ***				
	(0.509)				
3	3.746 ***				
	(0.545)				
4	3.679 ***				
	(0.598)				
Graduation cohort:					
2001 - 2003			-1.003	0.054	-0.320
			(1.790)	(2.016)	(2.024)
2004 – 2006			-2.123	-0.743	-1.232
			(2.428)	(2.536)	(2.548)
2007 – 2009			-3.229	-1.430	-1.657
			(2.837)	(2.918)	(2.925)
2010 – 2012			-7.325 **	-5.881 *	-6.203 *
			(3.095)	(3.177)	(3.183)
2013 - 2015			-1.003	0.054	-0.320
			(1.790)	(2.016)	(2.024)
2003	-0.298	0.313	0.457	-0.058	-0.055
	(1.469)	(1.470)	(1.481)	(1.501)	(1.503)
2004	-0.183	0.809	1.440	0.131	0.211
	(1.427)	(1.432)	(1.722)	(1.873)	(1.873)
2005	-0.741	0.363	1.383	-0.438	-0.837
	(1.390)	(1.399)	(2.004)	(2.118)	(2.137)
2006	-2.060	-0.724	0.574	-1.528	-1.885
	(1.414)	(1.426)	(2.193)	(2.272)	(2.287)
2007	-1.265	0.319	2.048	-0.172	-0.180
	(1.423)	(1.441)	(2.385)	(2.460)	(2.461)
2008	-0.307	1.355	3.558	1.477	1.495
	(1.427)	(1.459)	(2.598)	(2.639)	(2.647)
2009	-0.177	1.242	3.724	1.633	1.601
	(1.376)	(1.399)	(2.652)	(2.692)	(2.697)
2010	0.145	1.037	4.014	1.884	1.768
	(1.377)	(1.398)	(2.792)	(2.846)	(2.848)
2011	-0.262	-0.064	3.531	1.669	1.749
	(1.366)	(1.395)	(2.960)	(2.992)	(2.997)
2012	-0.357	-0.296	3.670	1.997	2.003
	(1.333)	(1.350)	(3.013)	(3.041)	(3.045)

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Table B.1 (continued)

	Dependent variable: occupational score				
	(1)	(2)	(3)	(4)	(5)
2013	-1.201	-1.207	4.272	2.625	2.541
	(1.306)	(1.340)	(3.200)	(3.238)	(3.242)
2014	-0.824	-1.147	5.521 *	3.475	3.253
	(1.306)	(1.340)	(3.200)	(3.238)	(3.242)
2015	-1.832	-2.373 *	4.670	2.389	2.199
	(1.298)	(1.359)	(3.253)	(3.284)	(3.287)
2016	-1.266	-2.087	5.064	2.514	2.415
	(1.346)	(1.503)	(3.328)	(3.363)	(3.364)
2017	-2.085	-4.113 **	2.895	1.165	1.434
	(1.417)	(1.812)	(3.462)	(3.479)	(3.483)
2018	-3.040 **	-6.343 ***	0.627	0.037	0.300
	(1.537)	(2.059)	(3.594)	(3.607)	(3.611)
Aged 25 – 34	11.505 ***	11.423 ***	11.442 ***	11.545 ***	11.553 ***
	(0.373)	(0.374)	(0.374)	(0.373)	(0.373)
Lives in regional area	-3.125 ***	-3.116 ***	-3.110 ***	-3.107 ***	-3.111 ***
	(0.405)	(0.405)	(0.405)	(0.405)	(0.405)
Lives in remote area	-2.715 **	-2.740 **	-2.782 **	-2.763 **	-2.751 **
	(1.282)	(1.284)	(1.284)	(1.282)	(1.282)
NSW	-0.906	-0.977	-0.901	-0.902	-0.904
	(1.027)	(1.029)	(1.029)	(1.028)	(1.028)
NT	-1.141	-1.170	-1.087	-1.103	-1.150
	(1.825)	(1.827)	(1.827)	(1.825)	(1.825)
Qld	-0.725	-0.855	-0.810	-0.788	-0.770
	(1.050)	(1.052)	(1.052)	(1.051)	(1.051)
SA	-2.882 **	-3.039 **	-2.971 **	-2.925 **	-2.918 **
	(1.187)	(1.189)	(1.189)	(1.188)	(1.188)
Tas	0.398	0.331	0.361	0.384	0.403
	(1.558)	(1.559)	(1.560)	(1.558)	(1.558)
Vic	-3.427 ***	-3.524 ***	-3.499 ***	-3.495 ***	-3.490 ***
	(1.041)	(1.042)	(1.042)	(1.041)	(1.041)
WA	-1.769	-1.871 *	-1.804	-1.803	-1.800
	(1.101)	(1.103)	(1.103)	(1.102)	(1.102)
Speaks English:					
Not well	-12.881	-11.689	-12.437	-14.046	-14.549
	(19.731)	(19.754)	(19.751)	(19.730)	(19.727)
Very well	10.870	11.434	10.934	9.794	9.327
	(19.269)	(19.291)	(19.287)	(19.266)	(19.262)
Well	1.239	1.843	1.393	0.242	-0.179
	(19.300)	(19.323)	(19.319)	(19.297)	(19.293)
Degree at graduation: University	19.694 ***	19.766 ***	19.761 ***	19.726 ***	19.713***
	(0.371)	(0.371)	(0.371)	(0.371)	(0.371)

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Table B.1 (continued)

	Dependent variable: occupational score				
	(1)	(2)	(3)	(4)	(5)
Degree at graduation: Other	-0.543 **	-0.537 **	-0.527 **	-0.534 **	-0.526 **
	(0.247)	(0.247)	(0.247)	(0.247)	(0.247)
Unemployment in statistical region	-0.543 **	-0.537 **	-0.527 **	-0.534 **	-0.526 **
	(0.247)	(0.247)	(0.247)	(0.247)	(0.247)
Proportion of life spent unemployed	-21.018 ***	-20.845 ***	-20.919 ***	-21.040 ***	-21.100 ***
	(1.492)	(1.493)	(1.494)	(1.492)	(1.492)
Number of kids aged 0-4	-0.668 *	-0.679 *	-0.677 *	-0.661 *	-0.662 *
	(0.357)	(0.357)	(0.357)	(0.357)	(0.357)
Number of kids aged 5-14	-2.651 ***	-2.607 ***	-2.616 ***	-2.671 ***	-2.663 ***
	(0.385)	(0.386)	(0.386)	(0.385)	(0.385)
Number of kids aged 15-24	-4.185	-4.279	-4.384	-4.390	-4.345
	(2.757)	(2.761)	(2.762)	(2.759)	(2.758)
Married	3.519 ***	3.514 ***	3.506 ***	3.505 ***	3.513 ***
	(0.369)	(0.370)	(0.370)	(0.370)	(0.370)
Indigenous	-1.683	-1.729 *	-1.695	-1.718	-1.733 *
	(1.048)	(1.050)	(1.050)	(1.048)	(1.048)
Born in an English speaking country	-0.437	-0.418	-0.422	-0.465	-0.455
	(0.632)	(0.633)	(0.633)	(0.632)	(0.632)
female	3.899 ***	3.923 ***	3.911 ***	3.905 ***	3.898 ***
	(0.329)	(0.330)	(0.330)	(0.329)	(0.329)
N	14311	14311	14311	14311	14311
R squared	0.323	0.322	0.322	0.324	0.325
F- statistic	154.866	150.383	138.404	126.633	116.182

a. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Source: Commission estimates based on HILDA data.

Table B.2 Occupational score regressions, 0 to 6 years after graduation

	Dependent variable: occupational score		
	(3)	(4)	(5)
Years since graduation * Graduation cohort:			
2001 - 2003	-0.507	1.918 *	2.877
	(0.409)	(1.063)	(1.799)
2004 – 2006	-0.555	1.165	4.336 ***
	(0.339)	(0.829)	(1.473)
2007 – 2009	-0.397	1.385 *	5.189 ***
	(0.326)	(0.821)	(1.476)
2010 – 2012	0.211	1.675 **	1.861
	(0.368)	(0.768)	(1.324)
Years since graduation squared * Graduation cohort:			
2001 - 2003		-0.318 **	-0.690
		(0.156)	(0.713)
2004 – 2006		-0.272 **	-1.790 ***
		(0.128)	(0.610)
2007 – 2009		-0.320 **	-2.206 ***
		(0.129)	(0.613)
2010 – 2012		-0.381 ***	-0.459
		(0.134)	(0.574)
Years since graduation cubed * Graduation cohort:			
2001 - 2003			0.039
			(0.079)
2004 – 2006			0.173 **
			(0.068)
2007 – 2009			0.220 ***
			(0.069)
2010 – 2012			0.011
Graduation cohort:			(0.066)
2001 - 2003	-2.442	0.154	-0.041
	(1.503)	(1.955)	(1.997)
2004 – 2006	-3.114	0.093	-0.445
	(2.167)	(2.459)	(2.478)
2007 – 2009	-5.565 **	-1.837	-1.801
	(2.564)	(2.764)	(2.784)
2010 – 2012	-2.442	0.154	-0.041
	(1.503)	(1.955)	(1.997)
2003	0.605	-0.038	-0.182
	(1.458)	(1.477)	(1.485)
2004	2.111	-0.026	-0.216
	(1.598)	(1.820)	(1.854)
2005	2.456	-0.532	-1.030
	(1.797)	(2.084)	(2.092)

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Table B.2 (continued)

	Dependent variable: occupational score		
	(3)	(4)	(5)
2006	1.795	-1.650	-2.286
	(1.975)	(2.243)	(2.256)
2007	2.655	-1.011	-1.487
	(2.181)	(2.416)	(2.427)
2008	4.183 *	0.408	0.107
	(2.361)	(2.556)	(2.557)
2009	5.225 **	1.337	1.134
	(2.428)	(2.594)	(2.602)
2010	5.520 **	1.523	1.222
	(2.579)	(2.729)	(2.734)
2011	5.798 **	1.804	1.877
	(2.695)	(2.830)	(2.829)
2012	6.138 **	2.260	2.515
	(2.770)	(2.882)	(2.886)
2013	6.829 **	2.835	3.036
	(2.868)	(2.971)	(2.978)
2014	7.498 **	3.817	3.808
	(2.986)	(3.081)	(3.080)
2015	6.586 **	3.795	3.441
	(3.143)	(3.207)	(3.222)
2016	5.266	3.969	3.737
	(3.377)	(3.418)	(3.434)
2017	5.319	5.534	5.145
	(3.580)	(3.657)	(3.658)
2018	6.515 *	8.364 **	7.764 *
	(3.872)	(4.042)	(4.067)
Aged 25 – 34	10.919 ***	10.991 ***	11.064 ***
	(0.402)	(0.402)	(0.402)
Lives in regional area	-3.160 ***	-3.157 ***	-3.163 ***
	(0.431)	(0.431)	(0.430)
Lives in remote area	-2.025	-2.060 *	-2.019
	(1.237)	(1.236)	(1.235)
NSW	-0.504	-0.518	-0.551
	(1.150)	(1.149)	(1.148)
NT	0.824	0.821	0.736
	(1.870)	(1.868)	(1.867)
Qld	-1.463	-1.478	-1.501
	(1.145)	(1.145)	(1.144)

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Table B.2 (continued)

	Dependent variable: occupational score		
	(3)	(4)	(5)
SA	-1.762	-1.748	-1.765
	(1.294)	(1.293)	(1.292)
Tas	2.455	2.420	2.372
	(1.699)	(1.697)	(1.696)
Vic	-3.247 ***	-3.295 ***	-3.321 ***
	(1.150)	(1.150)	(1.149)
WA	-2.803 **	-2.850 **	-2.871 **
	(1.190)	(1.189)	(1.188)
Speaks English:	23.823 ***	24.223 ***	24.390 ***
Not well	(4.549)	(4.546)	(4.543)
	14.079 ***	14.378 ***	14.512 ***
Very well	(4.741)	(4.737)	(4.735)
	-1.762	-1.748	-1.765
Well	(1.294)	(1.293)	(1.292)
	2.455	2.420	2.372
Degree at graduation			
University	20.559 ***	20.511 ***	20.498 ***
	(0.395)	(0.395)	(0.395)
Other	0.456	0.518	0.549
	(0.475)	(0.475)	(0.474)
Unemployment in statistical region	-0.934 ***	-0.953 ***	-0.949 ***
	(0.275)	(0.275)	(0.274)
Proportion of life spent unemployed	-26.895 ***	-27.009 ***	-27.100 ***
	(1.713)	(1.711)	(1.711)
Number of kids aged 0-4	-0.093	-0.036	-0.035
	(0.355)	(0.355)	(0.355)
Number of kids aged 5-14	-2.406 ***	-2.437 ***	-2.460 ***
	(0.399)	(0.399)	(0.399)
Number of kids aged 15-24	-2.809	-2.945	-2.943
	(2.702)	(2.700)	(2.698)
Married	3.729 ***	3.680 ***	3.687 ***
	(0.388)	(0.388)	(0.388)
Indigenous	-1.667	-1.599	-1.567
	(1.151)	(1.150)	(1.150)
Born in an English speaking country	-0.616	-0.637	-0.651
	(0.678)	(0.678)	(0.677)
female	3.485 ***	3.474 ***	3.476 ***
	(0.347)	(0.347)	(0.347)

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Table B.2 (continued)

	Dependent variable: occupational score		
	(3)	(4)	(5)
Intercept	20.460 ***	19.541 ***	19.164 ***
	(4.884)	(4.889)	(4.896)
N	12 567	12 567	12 567
R squared	0.346	0.347	0.348
F statistic	143.781	133.105	123.742

a. *** p < 0.01; ** p < 0.05; * p < 0.1.

Source: Commission estimates based on HILDA survey data.

Matching analysis

Matching variables

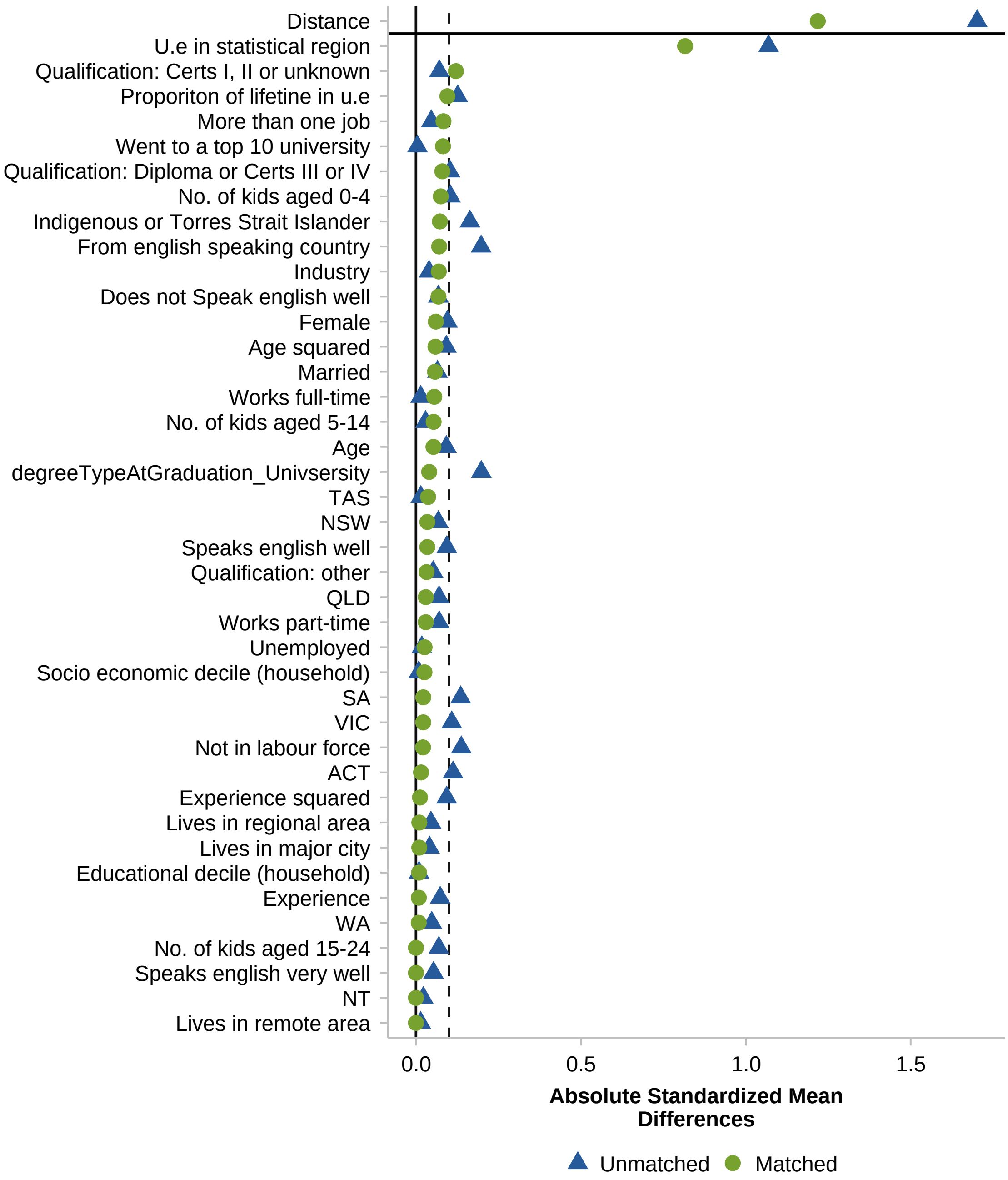
Table B.3 **Variables used in matching procedure**

Demographics	*Labour market*	*Education*	*Family life*
Age and Age squared	Experience and experience squared	Education decile of household (as continuous variable)	Number of kids aged 0-4
Indigenous or Torres Strait Islander status	Unemployment in statistical region (household level)	Degree type at graduation (university, VET III and IV, VET I and II, other)	Number of kids aged 5-14
Gender	Proportion of life spent unemployed	Went to a top 10 university (Times 2020 rankings)	Number of kids aged 15-24
From an English speaking country	Work multiple jobs		Married
Lives in major city, regional area or remote area	Employment type (full-time, part-time, not in labour force, unemployed, employed but usual hours unknown)		
State of residence	Industry (as continuous variable)		
Socioeconomic decile of statistical region (household level) (as continuous variable)			
English proficiency (Very well, well, not well)			

Balance tests

Figure B.1 **2004–2006 graduates**

Love plots of absolute standardised mean differences before and after genetic matching procedure.

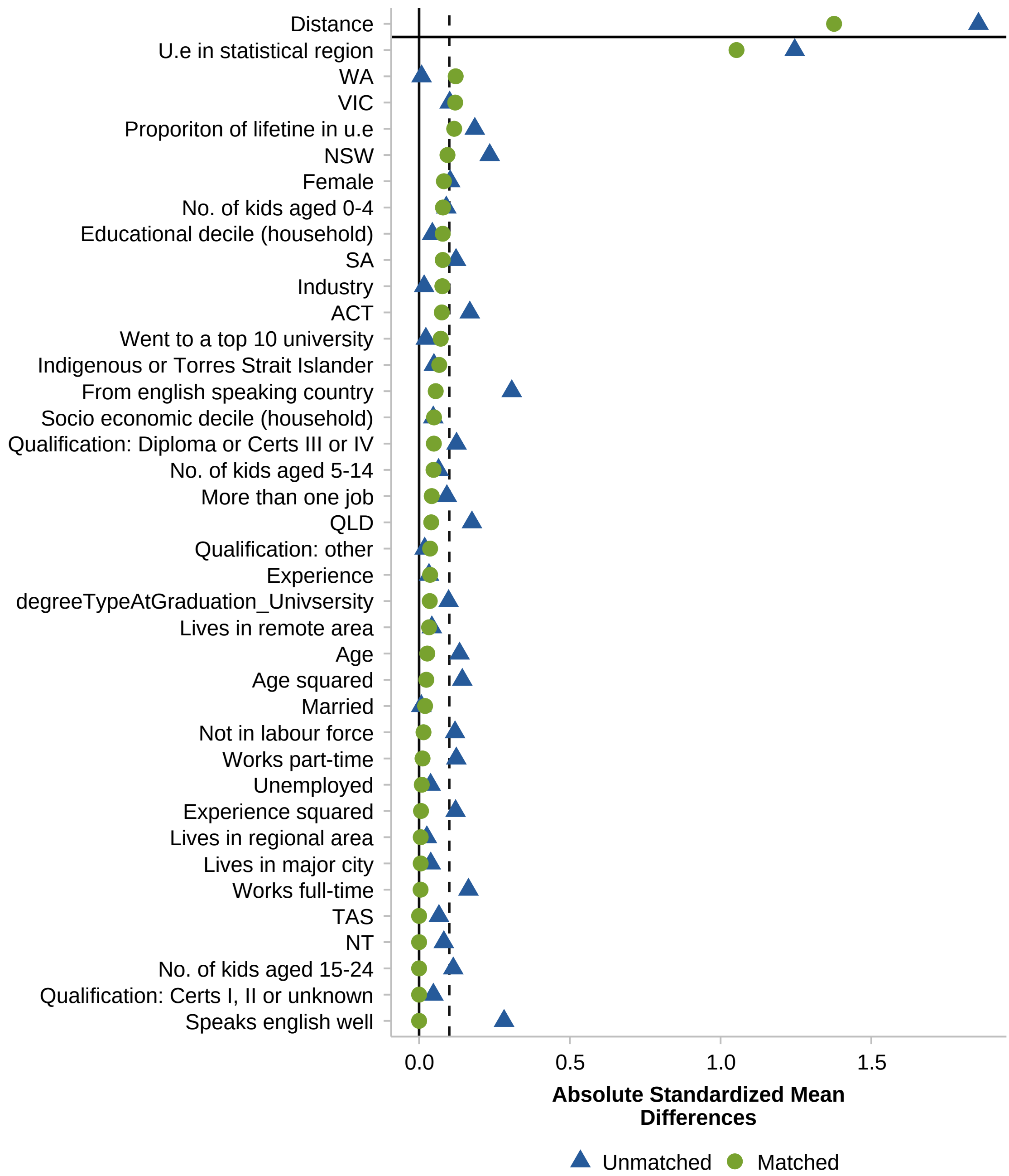


[a] Cut-off value = 0.1 (dotted line). The closer to zero, the better the balance of the sample is on these observables. Distance measures the overall balance of the sample.

Data source: Commission estimates based on HILDA data

Figure B.2 **2007–2009 graduates**

Love plots of Absolute standardised means before and after genetic matching procedure.



[a] Cut-off value = 0.1 (dotted line). The closer to zero, the better the balance of the sample is on these observables. Distance measures the overall balance of the sample.

Data source: Commission estimates based on HILDA data

Figure B.3 **2010–2012 graduates**

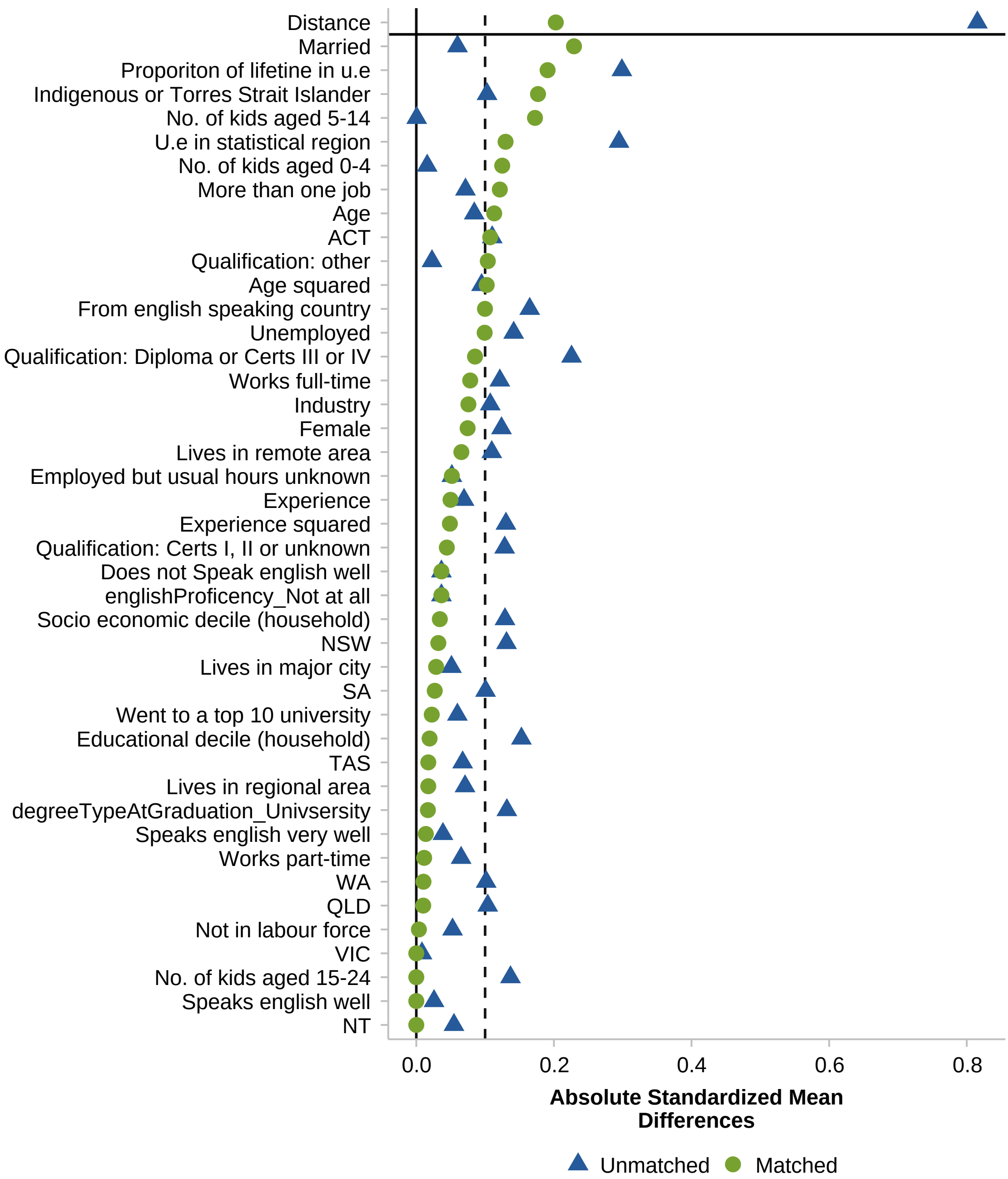
Love plots of Absolute standardised means before and after genetic matching procedure.

a Cut-off value = 0.1 (dotted line). The closer to zero, the better the balance of the sample is on these observables. Distance measures the overall balance of the sample.

Data source: Commission estimates based on HILDA data

Figure B.4 **2013–2015 graduates**

Love plots of Absolute standardised means before and after genetic matching procedure.



[a] Cut-off value = 0.1 (dotted line). The closer to zero, the better the balance of the sample is on these observables. Distance measures the overall balance of the sample.

Data source: Commission estimates based on HILDA data

Sensitivity analysis: Rosenbaum bounds

The following table represents sensitivity tests that test how sensitive significant results are to unobserved heterogeneity. To get these values, the following procedure is followed:

1. Each graduate cohort is matched to the 2001–2003 cohort using genetic matching

2. The occupational score one and then four years after graduation is estimated via regression

$$y_{i,g,t} = T_g\alpha_1 + \boldsymbol{x_{i,t}}\alpha + \varepsilon_{i,t}$$

   Where $y_{i,g,t}$ is the occupational score either 1 or 4 years after graduation, T_g is an indicator for treatment group and $\boldsymbol{x_{i,t}}$ are the control variables used to match.

3. The Rosenbaum bounds are calculated for each regression in (2) (Keele 2014; Rosenbaum 1987, 2002).

The value of gamma in the Rosenbaum tests is interpreted as the tipping point beyond which we cannot be reject that the results are driven by unobserved heterogeneity. For instance, if gamma is 1.1 then to attribute a higher occupational score to an unobserved covariate rather than to the treatment, that unobserved covariate would need to increase the odds ratio of treatment by a factor of 1.1. It tests how sensitive a test that rejects the null is to unobserved heterogeneity. The results that are statistically significant or close to statistically significant have gamma values between 1.2 and 1.5, which means the odds ratio would need to be increased by 20-50 per cent before the null cannot be rejected.

Table B.4 **Sensitivity analysis of matching results**

Average treatment effect on the treated and Rosenbaum bounds for the matched sample of each graduate cohort.

Cohort and years after graduation		*Regression results*			*Rosenbaum Sensitivity Test for Wilcoxon Signed Rank P-Value*			*Rosenbaum Sensitivity Test for Hodges-Lehmann Point Estimate*	
	ATT	Standard error	P-value	Gamma	Lower	Upper	Gamma	Lower	Upper
2004–2006, 1yr	-2.97	2.35	0.21	1.0	0.17	0.17	1.1	-2.25	0.05
2004–2006, 4yr	-2.01	2.56	0.43	1.0	0.16	0.16	1.1	-2.25	0.05
2007–2009, 1yr	3.94	2.50	0.11	1.3	0.00	0.17	1.5	-0.55	10.05
2007–2009, 4yr	2.19	2.63	0.40	1.3	0.00	0.1735	1.5	-0.55	10.05
2010–2012, 1yr	-1.28	2.14	0.55	1.0	0.18	0.18	1.1	-2.05	0.15
2010–2012, 4yr	-1.74	2.41	0.47	1.0	0.18	0.18	1.1	-2.05	0.15
2013–2013, 1yr	-3.96*	2.23	0.08	1.3	0.00	0.13	1.4	-7.95	0.75
2013–2013, 4yr	-3.83	2.49	0.12	1.2	0.00	0.13	1.4	-7.95	0.75

Source: Commission estimates based on HILDA data.

Markov analysis: occupational transitions

Table B.5 **Markov transition matrices: workers aged 15–24**

Row: quartile from *Column: quartile to*	*0 –25%*	*26–50%*	*51–75%*	*76–100%*
		Graduated from 2004 to 2006		
0–25%	0.649	0.169	0.104	0.078
26–50%	0.141	0.578	0.160	0.122
51–75%	0.029	0.242	0.687	0.043
76–100%	0.000	0.028	0.016	0.956
		Graduated from 2007 to 2009		
0–25%	0.702	0.149	0.058	0.092
26–50%	0.148	0.666	0.120	0.067
51–75%	0.022	0.126	0.774	0.077
76–100%	0.000	0.047	0.096	0.857
		Graduated from 2010 to 2012		
0–25%	0.740	0.144	0.068	0.049
26–50%	0.144	0.613	0.194	0.049
51–75%	0.086	0.205	0.612	0.097
76–100%	0.011	0.024	0.095	0.870
		Graduated from 2013 to 2014		
0–25%	0.729	0.128	0.062	0.081
26–50%	0.197	0.594	0.142	0.067
51–75%	0.056	0.187	0.611	0.146
76–100%	0.031	0.012	0.152	0.804

Source: Commission estimates based on HILDA survey data.

Table B.6 **Markov transition matrices: workers aged 25–34**

Row: quartile from *Column: quartile to*	*0 –25%*	*26–50%*	*51–75%*	*76–100%*
		Graduated from 2004 to 2006		
0–25%	0.751	0.156	0.047	0.047
26–50%	0.109	0.684	0.151	0.055
51–75%	0.108	0.085	0.714	0.093
76–100%	0.027	0.029	0.084	0.860
		Graduated from 2007 to 2009		
0–25%	0.779	0.137	0.013	0.070
26–50%	0.091	0.771	0.090	0.048
51–75%	0.022	0.102	0.771	0.105
76–100%	0.000	0.074	0.103	0.824
		Graduated from 2010 to 2012		
0–25%	0.833	0.109	0.051	0.008
26–50%	0.059	0.796	0.071	0.074
51–75%	0.034	0.114	0.718	0.135
76–100%	0.002	0.029	0.068	0.901
		Graduated from 2013 to 2014		
0–25%	0.674	0.232	0.061	0.033
26–50%	0.063	0.728	0.129	0.080
51–75%	0.165	0.161	0.623	0.051
76–100%	0.009	0.059	0.032	0.900

Source: Commission estimates based on HILDA survey data.

Table B.7 **Markov transition matrices, change from 2001–2003: workers aged 15–24**

Row: quartile from *Column: quartile to*	*0 –25%*	*26–50%*	*51–75%*	*76–100%*
		Graduated from 2004 to 2006		
0–25%	0.063	-0.040	-0.082	0.060
26–50%	-0.007	-0.006	-0.058	0.072
51–75%	0.010	-0.030	0.023	-0.003
76–100%	0.000	-0.161	-0.133	0.294
		Graduated from 2007 to 2009		
0–25%	0.100	0.023	-0.102	-0.021
26–50%	0.070	-0.093	-0.039	0.062
51–75%	0.006	-0.192	0.136	0.050
76–100%	0.000	0.047	0.059	-0.107
		Graduated from 2010 to 2012		
0–25%	0.083	-0.001	-0.075	-0.007
26–50%	0.096	0.010	-0.119	0.013
51–75%	0.062	-0.113	-0.001	0.052
76–100%	0.011	-0.070	0.007	0.053
		Graduated from 2013 to 2014		
0–25%	0.125	-0.121	-0.041	0.037
26–50%	0.116	-0.108	-0.030	0.022
51–75%	0.025	0.026	-0.183	0.132
76–100%	0.031	-0.174	-0.037	0.180

Source: Commission estimates based on HILDA survey data.

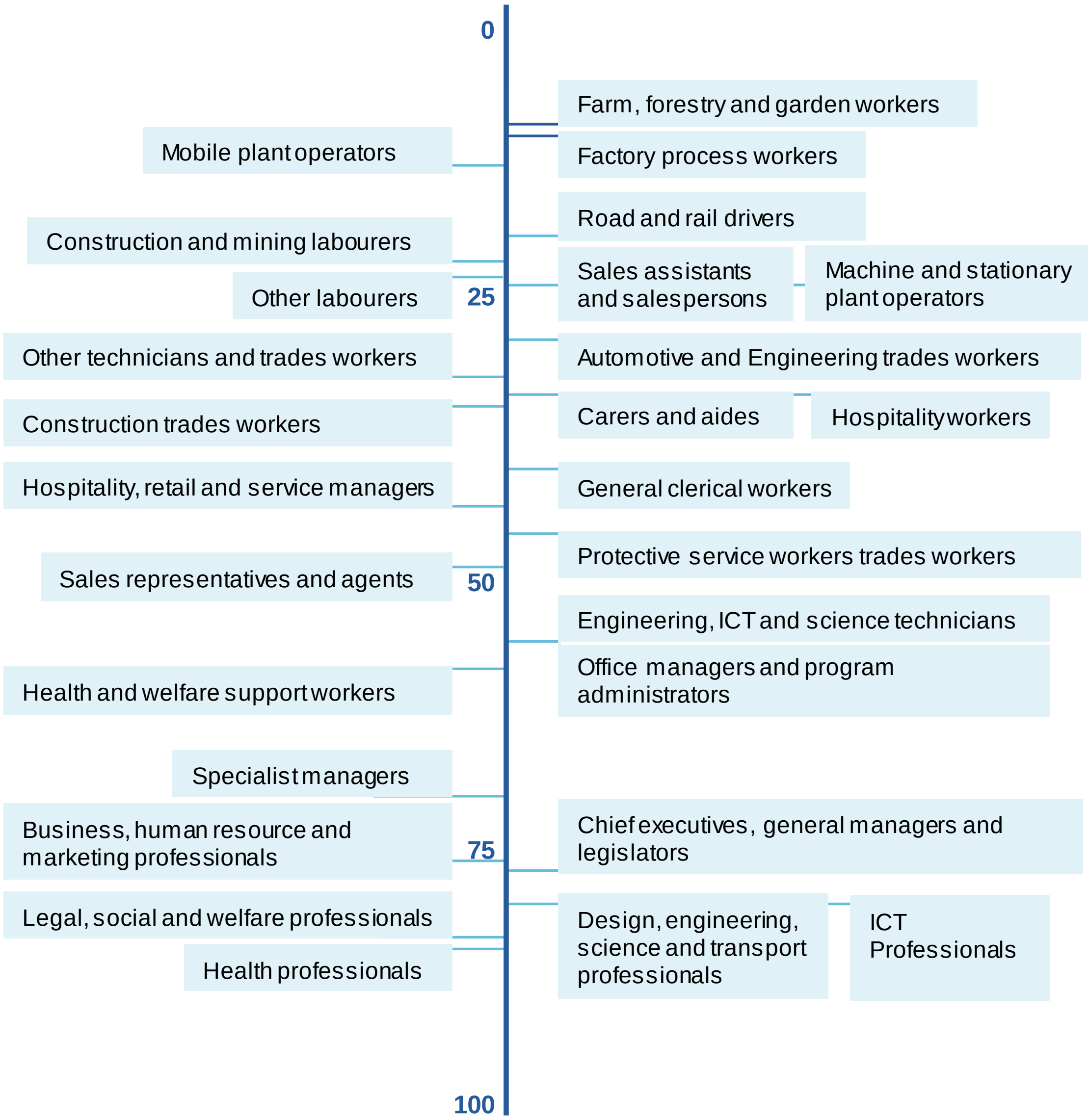
Table B.8 **Markov transition matrices, change from 2001–2003: workers aged 25–34**

Row: quartile from *Column: quartile to*	*0 –25%*	*26–50%*	*51–75%*	*76–100%*
		Graduated from 2004 to 2006		
0–25%	-0.052	-0.026	0.032	0.047
26–50%	-0.044	0.121	-0.132	0.055
51–75%	0.079	0.027	-0.035	-0.071
76–100%	0.027	-0.028	0.004	-0.003
		Graduated from 2007 to 2009		
0–25%	0.066	-0.084	0.006	0.012
26–50%	-0.012	0.265	-0.177	-0.076
51–75%	0.004	0.041	-0.014	-0.032
76–100%	0.000	-0.012	-0.091	0.103
		Graduated from 2010 to 2012		
0–25%	0.000	-0.002	0.051	-0.049
26–50%	-0.147	0.195	-0.045	-0.004
51–75%	0.029	0.079	-0.114	0.006
76–100%	0.002	-0.072	-0.065	0.135
		Graduated from 2013 to 2014		
0–25%	-0.148	0.062	0.052	0.033
26–50%	-0.092	0.148	-0.053	-0.004
51–75%	0.150	0.072	-0.083	-0.139
76–100%	0.009	-0.030	-0.110	0.131

Source: Commission estimates based on HILDA survey data.

Occupational scale

Figure B.5 **Mapping ANZSCO 2-digit level to AUSEI06**



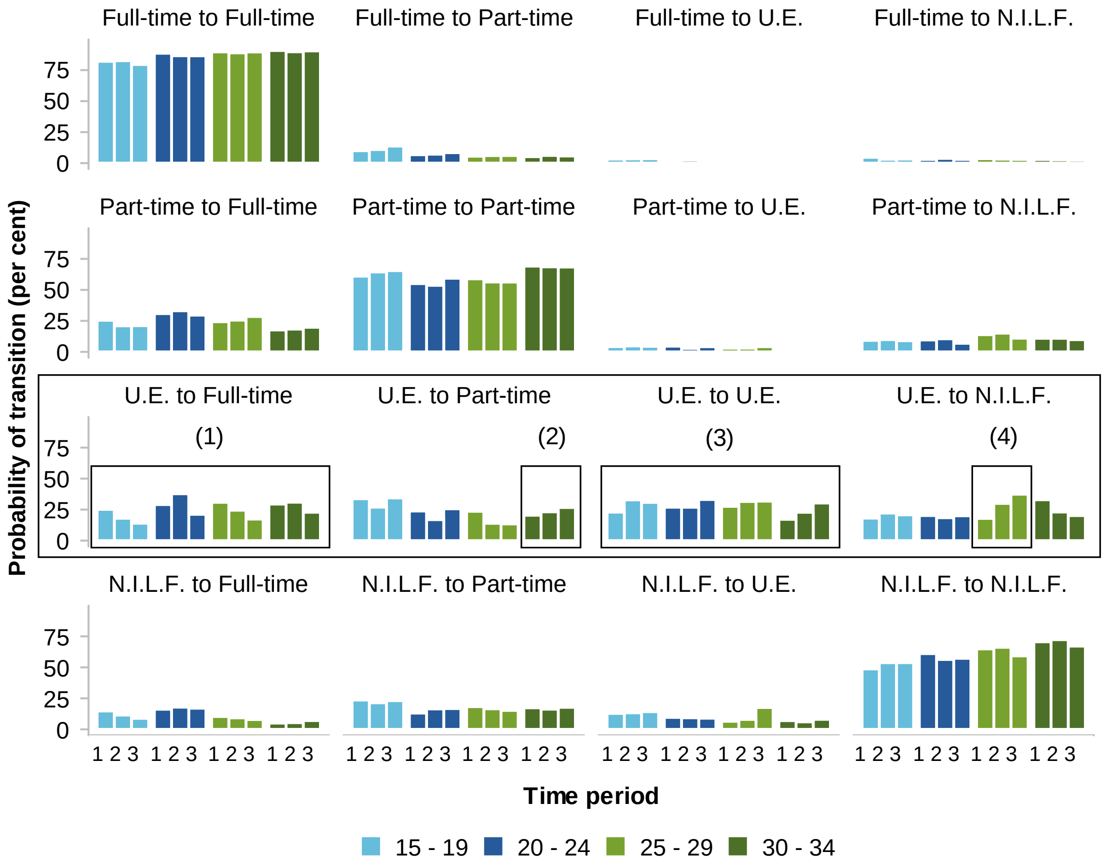
Data sources: ABS (ANZSCO, Australian and New Zealand Standard Classifications of Occupations, first edition, revision 1, Jun 2009, cat. no 1220.0) and McMillian Beavis and Jones (2009) (ANZSCO sub-major group conversion files).

Markov analysis: transitions from unemployment and part-time work

We consider four employment states: full-time employed, part-time employed, unemployed, and not in the labour force (NILF). We estimate the probability of transitioning between states, with the maintained assumption that the transition probabilities are Markov (i.e. the probability of transitioning from one state to another is not dependent on the past history of the individual). In figure B.2, we graph how those transition probabilities have evolved over time. Figure B.2 restricts the transition probabilities to be identical across all individuals, as a starting point.

Figure B.6 **The probability of transitions from unemployment to better states declined**

Discrete-time Markov transition probabilities (per cent) between employment states for periods 1. 2001–2006, 2. 2007–2012 and 3. 2013–2018



Data source: Commission estimates based on HILDA data.

We consider transition probabilities over three distinct periods — 2001–2006, 2007–2012 and 2013–2018 — for people who were within each five-year age group at the start of each period.[20] The individuals we follow are fixed within each period, so people not observed in the starting year of each period (2001, 2007 and 2013) do not enter into the sample.

In line with the rise in long-run unemployment we find that unemployment became a ‘stickier’ state. The probability of remaining in unemployment increased slightly in later periods than in former periods for young people of all ages (figure B.2(3)). They were also less likely to transition from unemployment to full-time work (figure B.3(1)).

The likelihood of a ‘low-pay no-pay cycle’ (a phenomenon discussed in Fok et al. (2015)) has also increased. This is because the likelihood of transitioning from part-time work into full-time work has not markedly improved, while part-time work has become more common.

The other important result is that we do not find any significant increase in the transitions from part-time work to full-time work in the last period considered. It does not appear that unlucky young people who find themselves in part-time work during the slowdown are not being identified and hired by firms as the economy improves.