The youth labour market: from education to work before and after the global financial crisis

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This article examines labour market outcomes for teenagers and young adults before and after the Global Financial Crisis (GFC). Using labour market activity calendar data I analyse two cohorts of young people—a pre-GFC cohort and a post-GFC cohort—over the period from 2001 to 2016. A life course approach (sequence analysis) is used to track education-to-work transitions over this period. Optimal matching methods and cluster analysis are used to subdivide the cohorts into three distinctive categories. These form the basis for further analysis, including regression modelling.

The key issue examined is whether labour market outcomes differed between these two cohorts, and, by extension, between the period before and after the GFC. In addition, the categorisation is used to examine issues of long-term marginalisation in the labour market. The main labour market outcomes analysed were gaining employment and conditions of employment, specifically underemployment and casualisation. The article concludes gaining employment significantly deteriorated over this period. Furthermore, while the comparison of GFC cohorts showed no significant differences when it came to underemployment and casualisation, this partly reflected the fact that both of these were already very high among this population of teenagers and young adults.

1 The global financial crisis and the labour market

The global financial crisis

In 2009 at the height of the global financial crisis, French President Sarkozy declared that a 'page had been turned' on the history of 'Anglo-Saxon capitalism' and that the age of deregulation was over (Tooze 2018: 271). A few months earlier, in even more dramatic tones, Australia's leader, Kevin Rudd, declared that 'events of a truly seismic significance' were underway, and surmised that neo-liberalism was now dead (Rudd 2009). Both these inflated assessments appear to have been wide of the mark. Nevertheless, by late 2018, Australia's Reserve Bank governor, Philip Lowe conceded that something rather fundamental had changed in the wake of the GFC.

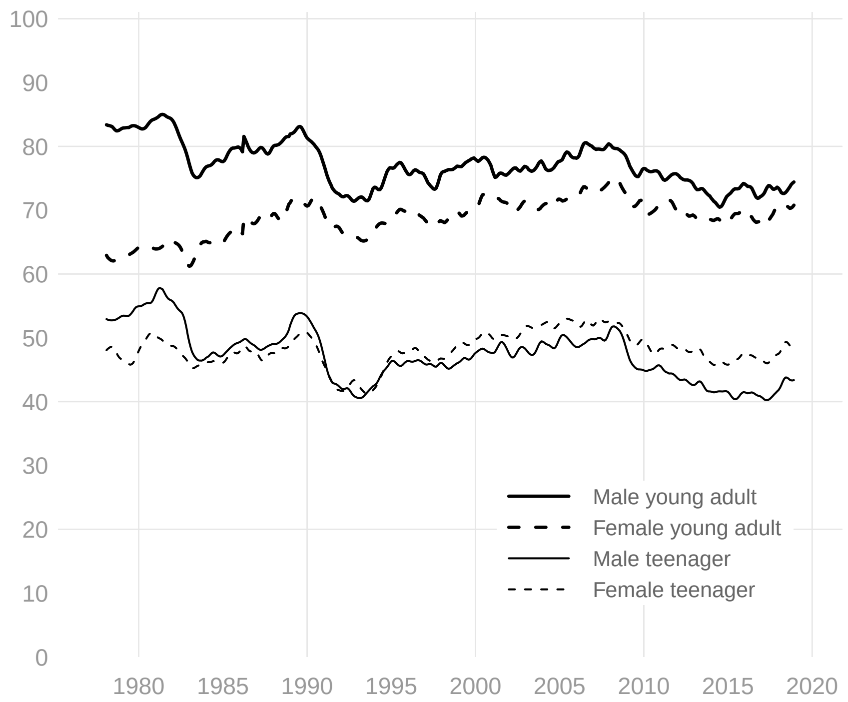
> ... flat real wages [since 2012] are diminishing our sense of shared prosperity ... The diminished trust in the idea that living standards will continue to improve is a major economic, social and political issue. It underlies some of the political changes we are seeing around the world (Lowe 2018: 4:5).

Whether events such as Brexit, the election of Donald Trump and the resurgence of support for right-wing populist parties prove to be 'seismic' awaits the passage of time. Meanwhile, in Australia the persistence of flat wages, high levels of underemployment, subdued capital investment and sluggish consumption by debt-laden households have all combined to render the post-GFC period considerably different to the period which preceded it. What about the youth labour market? Has the GFC marked a watershed in that domain, worsening the employment prospects for teenagers and young adults, or has the long-term downward trajectory in full-time employment for young people largely carried on regardless? This article tackles this question using an innovative methodology (sequence analysis) which tracks the education and labour market states which two cohorts of young people passed through over a seven and a half year period. As well assessing the effects of the GFC, a more enduring concern is also raised: can we identify any particular subgroups who are at greater risk of long-term marginalisation in the labour market?

The youth labour market

The long-term trajectory of the youth labour market has been characterised by a decline in their share of full-time employment. These were the kinds of jobs common in the 1960s which offered young people a 'port-of-entry' into adult working life. While higher levels of school retention, as well as more young people entering tertiary education, have been positive for most young people, the decline in full-time job openings for teenagers and young adults has eliminated career opportunities for a considerable minority. This trajectory began in the late 1970s and early 1980s, when school retention rates rose and employers shed teenage labour in large numbers. This was particularly so for teenage women: 30,000 full-time jobs disappeared during the 1970s, to be replaced by part-time jobs. During the late 1980s, 40,000 clerical jobs for teenage women disappeared. The only substantial growth in teenage employment was part-time casualised service sector jobs, such as cashiers and salesworkers(I. Watson 1994; Sweet 1988). In his overview of this period, Russell Ross observed that despite the addition of one million new jobs to the economy in the mid-1980s, full-time employment among teenagers fell in absolute terms (Ross 1988).

Figure 1: Employment to population ratios (%), teenagers and young adults, Australia 1978 to 2018

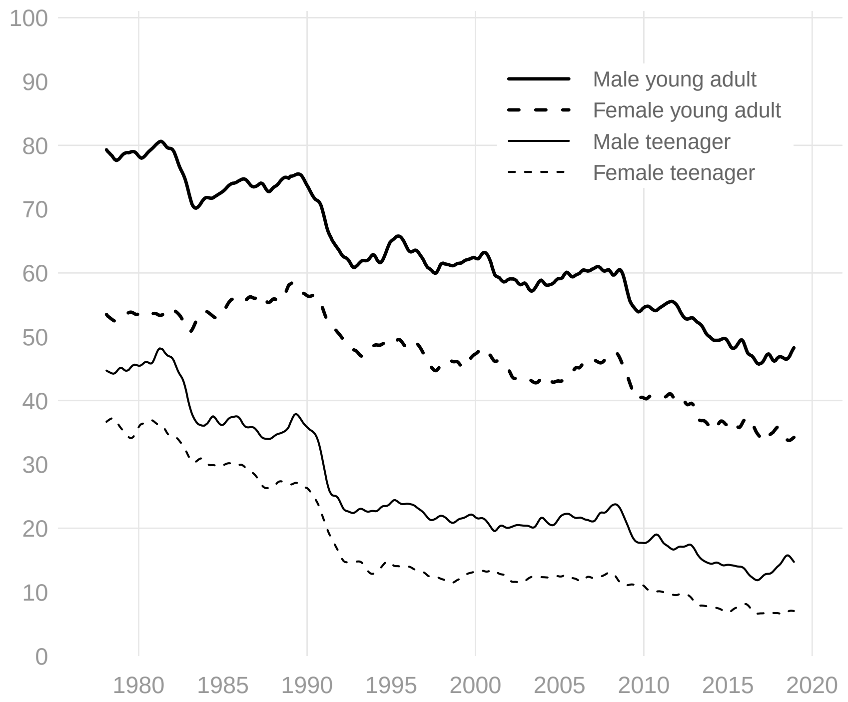


Source: Calculated from ABS *Labour Force Survey*, Cat. No. 6202.0 (6202013.xls and 6202017.xls).

This long term trajectory is shown in Figure 1 which highlights how each recession or severe downturn has seen sharp falls in the employment rates (that is, the employment to population ratio) for both teenagers and young adults (those aged 20 to 24).[1] In the case of young adult men, not only were these falls greater than for young adult women, but the recovery after each downturn was much weaker. Consequently, over the course of the last 40 years the employment rate for young adult men has fallen 10 percentage points, while that for young adult women has risen 8 percentage points. A similar pattern was evident for teenagers, though their employment rates have been substantially lower. Male teenagers have also seen their employment rates fall by 10 percentage points, while the rates for female teenagers have held steady over the period (with more moderate rises and falls).

However, what does appear distinctive about the 2000s is that young men and women both shared in the strong economic growth of the early 2000s—but both also shared in the downturn at the time of the GFC. Both failed to benefit in any substantial way from the Federal Government's fiscal stimulus, and only in the most recent period has there been any signs of possible improvement. In summary, the years 2008–2009 appear to be a significant turning point, with this slide in the employment rate reversing a decade of increasing employment.

Figure 2: Full-time employment to population ratios (%), teenagers and young adults, Australia 1978 to 2018



Source: Calculated from ABS *Labour Force Survey*, Cat. No. 6202.0 (6202013.xls and 6202017.xls).

However, that earlier decade of growth was primarily due to the increased *part-time* employment of young people. When it came to *full-time* employment, the story was uniformly negative. As Figure 2 shows, over the last 40 years full-time employment among teenagers has largely collapsed: for male teenagers the full-time employment rate fell from 45 per cent to 15 per cent, and for female teenagers, from 37 per cent to just 7 per cent. This partly reflected steadily increasing school and higher-education participation and it partly reflected the disappearance of full-time employment opportunities in the teenage labour market. In the case of young adults the decline in full-time employment has also been relentlessly downward. Over the last 40 years, young adult men have seen their full-time employment rate fall from nearly 80 per cent to under 50 per cent; for young adult women the drop—of about 20 percentage points—has been less severe, but only because their starting point was so much lower. Overall, in the case of *full-time* employment, unlike *total* employment, there has been no substantial rebound after each recession or downturn. Compared with total employment, the losses in full-time employment have been steeper with each downturn, and any recovery has been so muted that the long-term trend has continued unabated.

These data are cross-sectional in nature, drawn from the ABS monthly labour force surveys. However, to more fully analyse the education-to-work transition among teenagers and young adults requires longitudinal data (panel data), that is, data collected on the same individuals over time. Fortunately, Australia is blessed with the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which has been tracking the family and working lives of the Australian population for this whole period (from 2001 onward). Before introducing these data, I will outline a methodological approach—sequence analysis—which is ideally suited to examining life course events, such as the labour market histories of young people.

2 Sequence analysis

For many years most life course research drew on retrospective reporting: collecting information about past events or situations recalled by informants during interviews. In recent decades researchers have had access to numerous longitudinal datasets which are based on (mostly) contemporaneous reporting. In the case of Australia, a number of such datasets now exist, with the HILDA survey pre-eminent. In general, longitudinal datasets provide researchers with detailed information over many years on the annual 'states' or situations in which individuals find themselves. In some cases, this is supplemented with more frequent 'calendar' information, usually gathered retrospectively during the survey interview, but sometimes derived from diaries maintained by respondents.

The techniques available for life course analysis include event history analysis and the analysis of transitions between states (see, for example, Allison 1984); survival analysis as well as competing risks and multistate modelling (Martinussen and Scheike 2010; Beyersmann et al. 2012). Sequence analysis is *not* part of this tradition of research, as it largely remains tied to producing descriptive results. These can, however, be incorporated into modelling, as a subsequent stage in the research, and this is the approach taken in this article.

Much of the pioneering work on sequence analysis was conducted in the 1990s by Andrew Abbott and colleagues, and software advances in recent years have spurred further interest in the method.(Abbott and Hrycak 1990; Abbott and Tsay 2000; Blanchard et al. 2014; McVicar and Anyadike-Danes 2002; Aassve et al. 2007; Brzinsky-Fay and Solga 2016). In essence, sequence analysis looks for patterns in the mutually exclusive states which individuals pass through (for example: education / job / unemployed / not in the labour force) and when accumulated over the a sufficiently large number of observations appear quite distinctive. These states are assigned an 'alphabet', for example, EJUN, and the longitudinal calendar data is then recast into such sequences, for example: EEEJJUNNJUJ. When related to young people, such states might represent transitions such as secondary school to work, or secondary school to tertiary education.

While each sequence may often be unique, it is possible to move beyond individual patterns—the specific life-course 'biographies' of individuals— and explore sociological and economic questions about the functioning of the youth labour market. This can be done by transforming the sequences in such a way that *groups of individuals* can be matched according to their 'similarity'. One common method—optimal matching—uses substitution, insertion and deletion of particular states in the sequence to make these transformations. Such operations entail a penalty, that is a cost, which can be summed to provide a single numeric measure of similarity (or dissimilarity) called a 'distance'. To transform EEJJUNNN into EEJJJJJU, for example, might entail a higher cost than transforming the same sequence into EEJJUUNN, thus giving the latter comparison a lower distance score than the former. In other words, the third sequence is closer to the first than the second, and thus the third individual has a greater 'similarity' to the first when it comes it comes to their life course.

Various clustering techniques can then be applied to this distance measure and these allow the researcher to construct discrete categories of individuals based on their similarity. Such categories lend themselves to further analysis, through descriptive statistics and regression modelling, and thereby allow researchers to link these groups of individuals to their personal and social characteristics, as well as to the wider historical and economic context.

3 Data and method

The HILDA labour market activity calendar

The HILDA survey provides one of the best longitudinal datasets in Australia and provides researchers with an extensive range of data items relevant to the labour market. Conducted annually since 2001, it is based on a survey of Australian households carefully sampled to be representative of the Australian population. The survey collects information on the households, and on the individuals living in those households. As with any longitudinal survey, the representativeness of the sample declines since changes in the composition of the broader population may not be reflected in the sample. Over time, the main differences between the HILDA sample and the broader population have related to recent migrants. The survey designers 'refreshed' the sample in 2011 to address divergences like this. (For more on the longitudinal sample design in HILDA see N. Watson 2012).

From a labour market perspective, the HILDA survey collects an annual contemporary 'snapshot' of the education/labour market states (referred to as 'states' for convenience) in which respondents are located. In addition, the survey also collects some retrospective data. Some of these are about states in the interval between annual snapshots, such as previous jobs for those who changed jobs or became unemployed. While this retrospective data is valuable, the information about jobs is not as rich as the annual data. For example, there is no information on earnings or preferred working hours. Both of these snapshots—current jobs and previous jobs—form part of the analysis in this article, supplementing the use of the calendar data.

It is this *calendar data* which forms the core innovation in this article, and to which the sequence analysis is applied. It is based on a labour market activity calendar: a basic listing of the states in which respondents were located at one third of each month during the year. With 16 years of data this means we can (potentially) examine the 576 states which a respondent has passed through. When multiplied across many thousands of individuals, the data management aspects of analysing calendar data can be formidable.

Fortunately, modern software eases this burden and the time delays in processing what can be millions of data records are not onerous.

As well as the data management task, another issue involves the treatment of the 'seams', the windows where the data from two adjacent surveys overlap and provide inconsistent information about what that individual was doing during that 'spell'. Within the HILDA literature the issue of overlapping seams has been raised, but the usage of the calendar data has been quite limited, and thus there are no well-established conventions as to how to resolve some of the seam issues.[2] For the purposes of this analysis, several approaches were tested, and the state distribution plots provided by sequence analysis proved very useful in this testing. The approach which produced the least number of anomalies over the year (in terms of artificial 'spikes') was, not surprisingly, one in which the most recently recalled information was prioritised over the least recent.[3]

Methodology

The key research questions were: did the labour market outcomes of young people substantially differ between the pre-GFC cohort and the post-GFC cohort; and were there any sub-groups (within each cohort) identified by the cluster analysis who were more vulnerable to long-term marginalisation in the labour market? To explore these questions I created two cohorts: one group made up of 16 year olds in 2001/2002 and another group of 16 year olds in 2008/2009.[4] This provided samples of 385 and 400 young people in each cohort and each were followed for 7.5 years.[5]

Eight mutually exclusive categories for describing states were constructed on the basis of the calendar entries for each third of one month. The states (and their 'alphabets') were as follows:

1. Job: jb
2. More than one job: jbs
3. Full-time education: eft
4. Job and full-time education: eftjb
5. Job and part-time education: eptjb
6. Unemployed: une
7. Not in the labour force: nlf
8. Missing: *

The TraMineR package (used with the R statistical software) was applied to these states (for each cohort in turn) to produce a set of sequences, that is, the unique combinations of states for each respondent. These sequences are essentially descriptive in nature but form the building blocks for further analysis. Through simple tabulation they provide useful duration statistics, that is, the length of time spent in different states. More importantly, these sequences can be analysed according to their similarity or dissimilarity, and thus provide a rigorous method for subdividing individuals into meaningful subgroups or categories. Cluster analysis is the statistical device used to form these catgories.

While a number of dissimilarity measures are available, the analysis here made use of an optimal matching (OM) edit distance. This entailed calculating matrices of 'substitution-costs' for each of the cohorts. These matrices were then analysed using hierarchical cluster analysis (the Ward method) which aimed to group these distance measures in meaningful ways. As Figures 3 and 4 show, three clear-cut clusters emerged. Examining what was distinctive about each cluster allowed them to be classified into the three groups:

1. *Working*: where the state distribution plots showed a dominance of work;
2. *Mixed*: where the state distribution plots showed a mix between work, education, unemployment and being outside the labour market;
3. *Education*: where the state distribution plots showed a dominance of full-time education (and within that, a dominance of a job alongside full-time education).

Figures 5 and 6 confirm that these descriptions are accurate summaries of the states which these young people passed through over this period of time (colour versions of these figures are available in the Appendix). For example, looking at the educational category in the pre-GFC cohort (Figure 5) the frequencies for the states of full-time education and the combination of job / full-time education were high among respondents who were aged 16. By the time they reached 21 and 22, the job/full-time education combination was still dominant, but by the age of 23, the job state had become dominant, with job/education as the second most common state. Turning to those in the working category, their states at age 16 were also a mix of job and full-time education, but by age 20 they were overwhelmingly in a job and the educational state hardly featured at all. Finally, those respondents in the mixed category were least likely to have held a job while still at school at 16 or 17. Moreover, as they entered their early twenties, states such as unemployment and not in the labour force (NILF) were nearly as frequent as the job state, though the job/education combination was still dominant.

Figure 3: Hierarchical cluster analysis for pre-GFC cohort

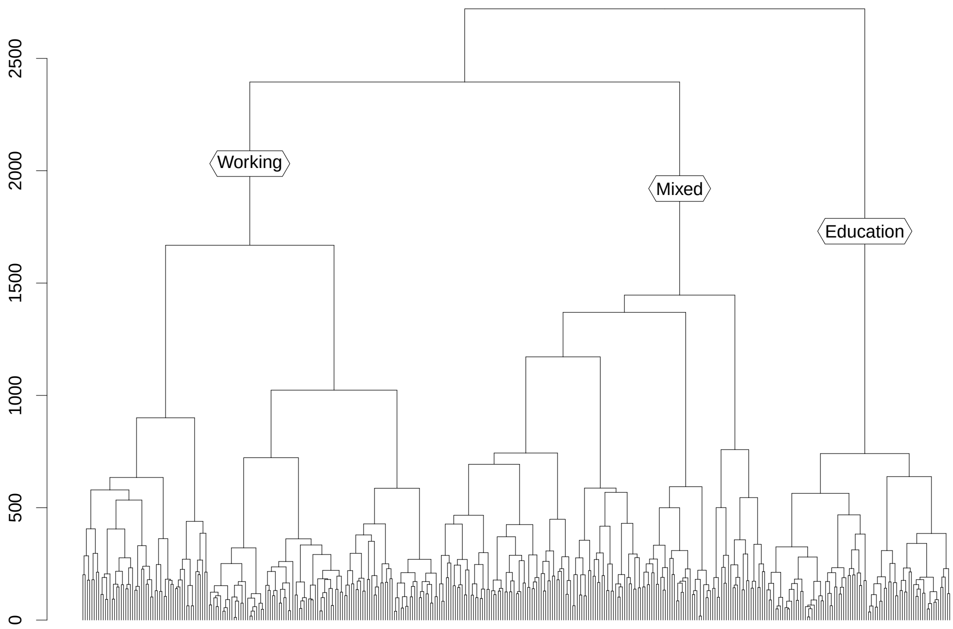


Figure 4: Hierarchical cluster analysis for post-GFC cohort

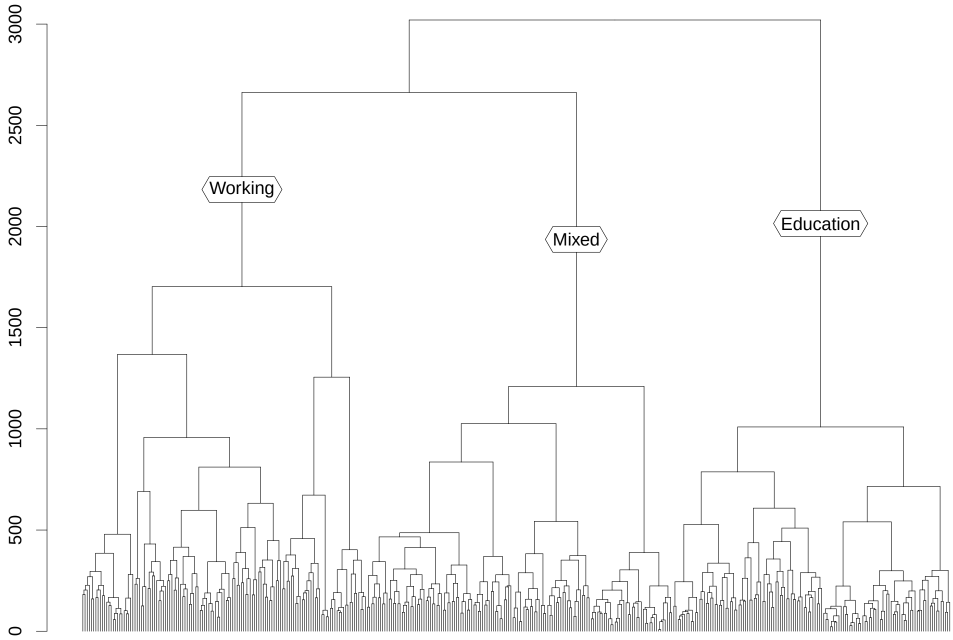


Figure 5: State distribution for pre-GFC cohort

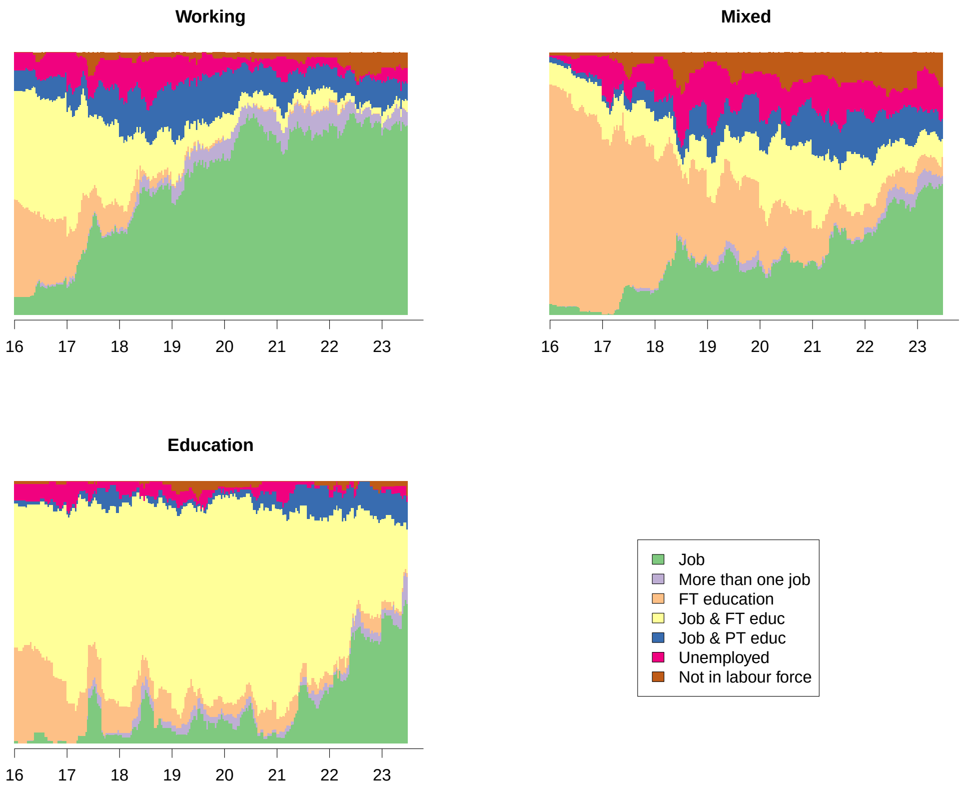
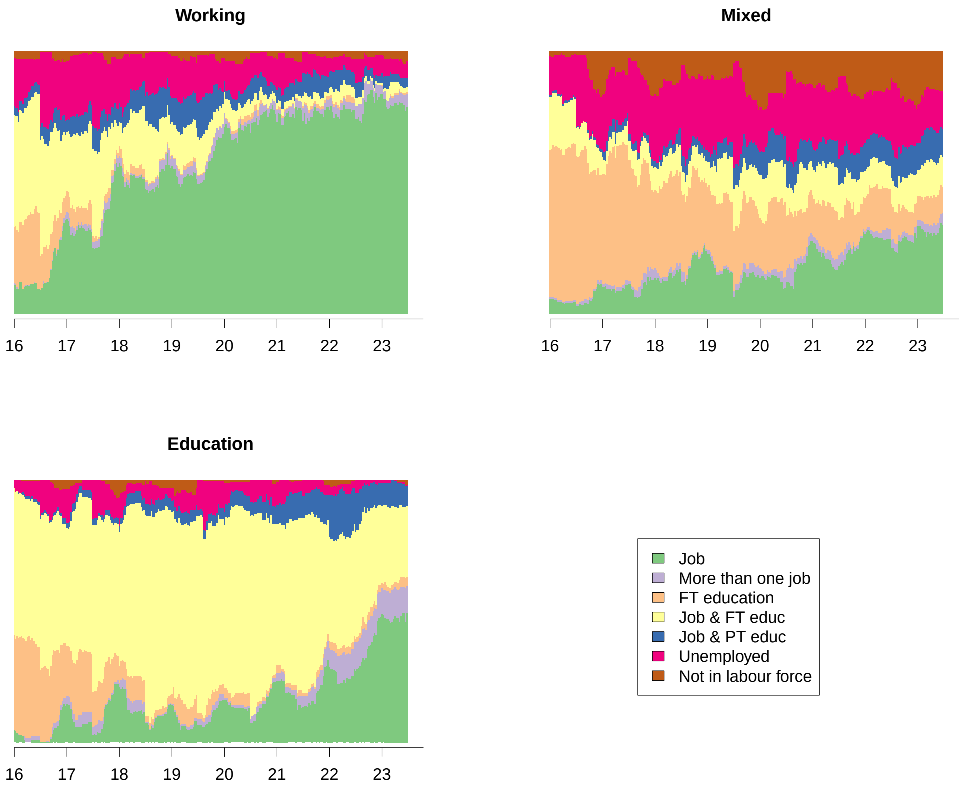


Figure 6: State distribution for post-GFC cohort



4 Descriptive findings

The main differences between the two cohorts lay in greater levels of unemployment and time outside the labour market for the post-GFC cohort. This is confirmed in the duration averages (Table 1), which show that the duration of unemployment was about two thirds greater for the post-GFC cohort. The time spent outside the labour market was also greater by about one third. In addition, full-time education by itself was nearly one quarter lower for the post-GFC cohort, and part-time education while holding a job was about one fifth lower.

Table 1: Average cumulative duration of time in various states, pre GFC and post GFC (months)

Period	jb	jbs	eft	eftjb	eptjb	une	nlf
Pre GFC	25.5	2.3	14.0	21.5	7.5	6.7	3.4
Post GFC	25.9	2.9	10.7	23.4	5.9	11.1	4.6
Difference (months)	0.5	0.5	-3.3	2.0	-1.6	4.4	1.2
Difference (percentage)	1.8	23.2	-23.3	9.1	-21.4	65.3	34.5

Notes: jb = Job, jbs = More than one job, eft = FT education, eftjb = FT education and job, eptjb = PT education and job, une = Unemployed, nlf = Not in labour force
Source: HILDA Release 16.

Table 2: Average cumulative duration of time in various states for each category, pre GFC and post GFC (months)

Categories	jb	jbs	eft	eftjb	eptjb	une	nlf
PRE GFC COHORT							
Working	41.6	3.6	5.9	14.3	9.9	6.2	2.0
Mixed	16.1	1.3	25.4	11.0	6.8	9.1	6.3
Education	11.0	1.8	9.4	53.8	3.9	3.4	1.2
POST GFC COHORT							
Working	47.9	2.7	3.3	13.1	6.1	10.3	1.8
Mixed	13.7	2.7	21.8	9.4	6.2	18.1	11.0
Education	14.2	3.3	7.5	49.2	5.2	4.8	1.2

Notes: jb = Job, jbs = More than one job, eft = FT education, eftjb = FT education and job, eptjb = PT education and job, une = Unemployed, nlf = Not in labour force
Source: HILDA Release 16.

The contrasts between the three cluster categories—working, mixed and education—confirms that the clustering method has indeed produced quite distinct groupings (Table 2). Comparing Tables 1 and 2 highlights how much the grouped results understate the deterioration in the labour market situation for sub-groups, particularly those in the mixed category. While the unemployment averages were 6.7 months (pre-GFC) and 11.1 months (post-GFC) in the grouped data, for those in the mixed category the duration of unemployment was 9.1 months (pre-GFC) and 18.1 months (post-GFC). Similarly, the differences for those outside the labour force were also quite stark: the grouped averages of 3.4 months (pre-GFC) and 4.6 months (post-GFC) contrasted with 6.3 months (pre-GFC) and 11 months (post-GFC) for the mixed group. These contrasts suggest the presence of a subgroup of young people at risk of long-term marginalisation in the labour market: a subgroup within the mixed category. The labour market disadvantage of this category was evident in both periods, but was more severe in the post-GFC period.

There is no doubt that education-to-work transitions can be a rocky road in the 21st century labour market. Despite the advantages of mixing study and work, the prospects for gaining a foothold in the full-time workforce have been steadily declining for decades (see Figure 1). The emergence of the gig-economy and the increasing use of unpaid internships by large organisations may have pushed that goal even further into the distance. The end of each period in this analysis is the age of 23, and by this age we might assume that the transition from education to work has been largely completed for the vast majority of young people. After all, more than 80 per cent reported that they were no longer full-time students by this age. With this in mind, we can examine their labour market destinations as 23 year olds and assess their degree of success in completing this transition. Table 3 summarises these data and shows that 63 per cent of the pre-GFC cohort had gained full-time employment. For the post-GFC cohort, however, the figure was much lower at 47 per cent. Moreover, this contrast was worse for the mixed cluster category: 52 per cent compared with 28 per cent. For the mixed category in the post-GFC cohort, nearly as many young people were working part-time (26 per cent), and even more were either unemployed or marginally attached to the labour force (31 per cent).

How accurate is this summary of these transition outcomes? Indeed, how seriously should we take the gloomy aspects of Table 3, particularly the high levels of unemployment and marginal labour force attachment among the mixed category? After all, some of these young people may have had parenting responsibilities or may have still been studying (keeping in mind that the mixed category still contained some full-time students at the end of the period). To answer this question, multivariate analysis is required, and this task is undertaken in the next section of this article.

Table 3: Labour market destinations (at age 23) of each cohort

	Pre-GFC cohort				Post-GFC cohort			
Destination	**Working**	**Mixed**	**Education**	**Total**	**Working**	**Mixed**	**Education**	**Total**
Employed FT	76	52	60	63	60	28	52	47
Employed PT	11	20	34	19	28	26	39	31
Unemployed	4	8	3	5	9	15	2	9
NILF marg attach	6	10	1	6	2	16	6	8
NILF not marg att	4	11	1	6	2	14	2	6
Total	100	100	100	100	100	100	100	100
n	139	122	73	334	126	123	116	365

Notes: FT = full time, PT = part time, NILF marg attach = Not in labour force marginally attached (ie. willing and available to work given sufficient time to make arrangements), NILF not marg att = Not in labour force and not marginally attached.

5 Multivariate analysis

The results of the sequence analysis not only make for insightful descriptive findings, but they also lend themselves to regression analysis.[6] The first model discussed below asks whether the cluster categories which arise from the sequence analysis are indeed distinctive subgroups of young people. Of greater interest to the concerns of this article are the models which focus on labour market outcomes for these young people at the end of each period, that is, at the age of 23. These models take us beyond the descriptive findings from the last section, and allow us to draw more robust conclusions about the differences between the pre-GFC cohort and the post-GFC cohort, and between the different cluster categories. Finally, a diagnostic model is also fitted to these data to test whether there were any substantial background differences between each cohort. In the absence of such differences it is reasonable to conclude that the comparison between the two cohorts also constitutes a difference between two periods in time. I return to this issue in the discussion section at the end of the article.

The models were all fitted to the pooled data, that is, to both cohorts. In general, this meant that there were 688 observations provided by the two cohorts (327 in the pre-GFC cohort and 361 in the post-GFC cohort). It is important to note that the number of observations in the various models sometimes differed. In some cases this reflected sub-sampling (such as restricting the analysis to those only in employment) and in some cases the 'unit of analysis' changed from the individual at one point in time, to multiple observations of the same individual over time. These differences are noted when each model is discussed and the sample sizes are all shown in the Appendix tables.

Are the cluster categories really distinct?

All of the descriptive statistics, and the visual representations of the sequences and the clusters, suggested that these cluster categories constitute meaningful subgroups. A more robust approach, however, is to model these categories as outcomes in a multinomial logistic regression model. Fitting this model with a broad range of background covariates confirms that these categories differ from each other in non-arbitrary ways. The covariates for this model included those factors which applied at the start of each period, when the respondents were aged 16 as well as two educational variables (highest level of education and age when left school) which reflected their situation when they were aged 23.[7]

The results (coefficients and statistics) for this multinomial logistic regression are shown in Appendix Table A1. Being a multinomial model, one of the dependent categories is omitted (in this case, the educational cluster category) so any particular coefficient for a covariate which is a dummy variable entails a 'double referencing'. It reflects the association between the level of that variable (vis-a-vis the omitted level) to the omitted category in the dependent variable. This 'double referencing' makes coefficients from multinomial logistic regression models awkward to interpret at face value, so the usual convention is to present key findings as predicted probabilities and that is done throughout this analysis (and for the other models which follow).

The modelling did highlight a number of key differences between the cluster categories and five explanatory variables emerged as statistically significant in this model: the GFC cohort, the highest level of education, the age when the individual left school, the mother's occupation and the socio-economic status of the area in which they lived.[8] Predictions for several of these variables are shown in Table 4 (and the predictions for the area's socio-economic status is omitted as no clearly defined patterns are evident). A notable feature of the post-GFC cohort was the reduced probability of being in the working category, a result consistent with the earlier duration descriptive statistics. The mixed category showed no difference between cohorts, while the education category was larger in the post-GFC cohort.

The educational factors are consistent with one would expect, with those undertaking tertiary education firmly located within the education cluster category. Notable also were the large proportions of those with only year 11 level (or below) and those with vocational qualifications in the working cluster category. The strongest occupational patterns (for the respondent's mother) was the association between white / pink collar jobs and being in the working cluster category. Interestingly, respondents with mothers in managerial / professional jobs were more strongly associated with young people in the mixed category than the education category (though it is important to recall that the mixed category really is 'mixed' and contains a significant number who were studying). A similar association was also evident at the other end of the spectrum: respondents with mothers who were not employed (or absent) were also more likely to be in the mixed category.

Table 4: Predicted probabilities (%) for selected variables, cluster categories model

Variable	Working	Mixed	Education
Pre-GFC	42	35	24
Post-GFC	34	36	30
HIGHEST EDUCATIONAL LEVEL			
Postgrad	35	27	37
Tertiary	9	38	53
Vocational	48	33	19
Year 12	40	39	21
Year 11 or below	57	40	3
AGE LEFT SCHOOL			
Left at 16 or before	40	42	18
Left at 17 or 18	40	33	27
Left after 18	14	46	39
MOTHER'S OCCUPATION			
Managerial/professional	29	42	29
White/pink collar	46	26	28
Blue collar	39	35	26
Not employed / not present	31	45	23

Notes: Probabilities (shown as percentages) are average predictive margins for each level of the variable (for each outcome).

Labour market outcomes

Were there significant differences in gaining full-time employment between the pre-GFC cohort and the post-GFC cohort, and did it matter which cluster category individuals belonged to? To answer this question, I fitted a model which took the full sample of individuals and sought to predict whether they were in full-time employment at the age of 23. The findings are discussed below.

Secondly, among those individuals who did find employment, what kinds of jobs were these? Two outcomes were analysed: underemployment and job status (casual part-time, casual full-time, fixed-term contract, permanent part-time and permanent full-time). These two models were fitted to a smaller sample—those in employment at the age of 23—and the findings are discussed below.

1. Gaining full-time employment

Why focus on full-time employment as a key labour market outcome? To understand this strategy we need to review the doubts I raised earlier about the accuracy of the labour market destinations presented in Table 3. I suggested that these data appear to understate the mixing of full-time studying with other labour market states, as well as absences from the labour market because of parenting decisions. For example, about one quarter of the category 'NILF not marginally attached' were full-time students and nearly half were parents. Even for the category of marginal attachment to the labour force, about one third were students and just over one fifth were parents. In particular, the unemployment category appears to be ambiguous: nearly 70 per cent of those unemployed and looking for part-time work were full-time students and 30 per cent were parents. Consequently, drawing definitive conclusions about these labour market states—unemployment and NILF—and directly equating them with 'disadvantage' can be problematic. These 'messy' states may simply be indicative of incomplete education-to-work transitions or they may reflect states of temporary unemployment, as young people attempt to organise their working lives around their other priorities. Consequently, a more useful way to gauge the success of the education-to-work transition is to approach the question from the opposite direction: gaining full-time employment. This would seem to be the best measure for assessing labour market outcomes because it signals that a young person has secured a 'foothold' in the workforce, with the possibility of job security and even a potential career path.

To assess this outcome, a logistic regression model with full-time employment at age 23 was fit to these data. A number of covariates were included in the model: background factors, local unemployment rate, GFC cohort and cluster category. The model results are shown in Appendix Table A2 and the predicted probabilities for a number of key variables are shown in Table 5. A considerable number of these covariates were statistically significant:

cluster category and GFC cohort; sex, and sex interacted with being a parent; full-time student and highest level of education; and the area unemployment rate. It was notable that background factors—such as parent's occupation or the childhood socio-economic area—were not significant.

Because Table 5 focuses on just three key dimensions, it is worth noting in passing some of the other findings. The predicted probability of a young man being in full-time employment was 18 percentage points higher than a young woman (74 per cent to 56 per cent). Moreover, the interaction between sex and parenting was even more stark. For men, being a parent had a negligible effect on full-time employment (74 per cent to 73 per cent), whereas, for women, being a parent made a massive difference: 60 per cent to 9 per cent. Full-time students were also far less likely to be employed full-time than those young people not studying (just 22 per cent compared to 72 per cent).

The findings shown in Table 5 suggests that gaining full-time employment was much harder for the post-GFC cohort, by a margin of 12 percentage points. What role did the business cycle play in this? The pre-GFC cohort certainly confronted more buoyant labour market conditions at the end of their period: the unemployment rate they faced was 4.1 per cent in 2008 and 5.4 per cent in 2009. By contrast, the post-GFC cohort faced unemployment rates of 5.7 per cent and 5.3 per cent in 2015 and 2016. Depending on when they entered their current job, they either faced a shrinking or a growing employment market. Clearly, evaluating the labour market outcomes for each cohort needs to take into account these differences, and this has been done by including the area unemployment rate in the model. In addition, for the predicted probabilities shown in Table 5, the unemployment rate was fixed at 5 per cent across both cohorts. By including the unemployment rate in the model, and then adjusting the predictions in this way, these results partly control for the business cycle.

When it came to their cluster category membership, it was clear that the mixed category fared the worst. Only 61 per cent of the pre-GFC cohort were in full-time employment, while the figure for the post-GFC cohort was only 46 per cent. The respondents' highest level of education (by age 23) was also a notable factor in predicting full-time employment. For both cohorts there was an almost linear relationship between the highest educational level and the probability of being in full-time employment, though the figures for the post-GFC cohort were uniformly weaker across all levels.

Table 5: Predicted probabilities (%) for selected variables, full-time employment model

Variable	Pre-GFC	Post-GFC	All
CLUSTER CATEGORY			
Working	77	65	70
Mixed	61	46	53
Education	72	59	65
HIGHEST EDUCATIONAL LEVEL			
Postgrad	80	68	73
Tertiary	78	66	72
Vocational	73	60	66
Year 12	66	52	59
Year 11 or below	62	47	54
ALL	69	57	

Notes: Probabilities (shown as percentages) are average predictive margins for each level of the variable with the unemployment rate fixed at 5%.

2. Conditions of employment

As well as gaining employment another critical factor in achieving a secure foothold in the workforce involves avoiding underemployment and casualisation. Previous research for workers in general has shown that these factors are associated with poor employment conditions, such as high job turnover and limited access to training (Hall et al. 2000; I. Watson et al. 2003; I. Watson 2013). The next two models examined these two factors and restricted the analysis to only those respondents who were employees and no longer full-time students. These restrictions avoid the plethora of casual jobs which are routinely undertaken by full-time students (at both secondary and tertiary level). Both models used data from across the whole period, rather than just at the end of each period.

The first model investigated what factors were associated with underemployment, and whether the two cohorts differed in this regard. These models were multilevel logistic regression models which included repeated observations on the same individuals (that is, panel data). This sample was thus a subset of the two cohorts, but with a larger number of observations because of the repeated individuals. In the terminology of panel data, the observations were 'jobs' (2,303) and the groups were the individuals (680 persons). The job data were based on the information for the job held at the time of the annual interview.

The results for this model are shown in Table A3 in the Appendix. Again, predicted probabilities are the most useful way to interpret these results and these are shown in Table 6 for those variables which were statistically significant: namely, job status, occupation and sex. Importantly, neither the GFC cohort nor the cluster category variables were statistically significant. Again, the unemployment rate was fixed at 5 per cent to for these predictions.

Table 6 shows that underemployment was overwhelmingly a problem for part-time workers, and this applied to permanent as well as casual employees. Some 62 percent of the former, and 58 per cent of the latter, were underemployed, while the average proportion of underemployed workers was about 30 per cent. A notable feature of the occupational findings was that white collar workers—managers, professionals and clerical workers—were all substantially less likely to be underemployed compared to those in other occupations. The gender difference, while significant, was substantively modest.

Table 6: Predicted probabilities (%) for selected variables, underemployment model

Variable	%	Variable	%
Pre-GFC	30	Managers	22
Post-GFC	32	Professionals	22
Working	32	Technicians / Trades	35
Mixed	30	Community / Personal Serv	35
Education	30	Clerical / Admininstrative	23
Casual PT	62	Sales Workers	33
Casual FT	23	Machine Operators / Drivers	32
Fixed-term	17	Labourers	34
Permanent PT	58	Male	33
Permanent FT	16	Female	29

Notes: Probabilities (shown as percentages) are average predictive margins for each level of the variable with the unemployment rate fixed at 5%.

In summary, Table 6 confirms that neither the two cohorts, nor the cluster categories showed significant differences: all were around 30 per cent. It is important to note that these levels of underemployment were more than twice the levels experienced by the workforce in general—that is, all age groups—and this applied to both part-time and full-time workers. These results suggest that the problem of underemployment was particularly acute among part-time workers in the youth labour market irrespective of cohort or category. The patterns of labour market disadvantage which surface around *gaining* employment—patterns with distinct cleavages around GFC cohort and cluster category—were absent once young people found themselves in employment. Did this uniformity also pertain to casualisation? The next model sought to answer that question.

One aspect to casualisation in the youth labour market is the normal mixing of studying while holding a part-time jobs. As we noted earlier, this is now the dominant mode among young people. However, by restricting the sample in the way outlined earlier (employees who are no longer full-time students), the problem of confounding with 'student jobs' is avoided. The dependent variable for this model was job status: a variable which combined hours worked and job contract. Unlike the underemployment model, the sample included not only the annual jobs held, but also some additional data. These were the previous job held prior to the current job during that annual period. This increased the number of observations (jobs) to 2,836 and the number of groups (individuals) to 710. A multilevel multinomial model was fit to these data: multilevel to take account of the repeated observations; multinomial to deal with the five categories of job status (casual part-time, casual full-time, fixed-term contract, permanent part-time and permanent full-time). The results are shown in Appendix Table A4 and some selected findings are shown in Table 7. As with the earlier models, the area unemployment rate was included as a control in the model, and fixed at 5 per cent for the predictions.

While the GFC cohort was not statistically significant, the cluster category was, with the major differences being employed in part-time casual jobs compared with permanent full-time jobs. Compared with the mixed category, those in the working category were 10 percentage points less likely to be casual part-timers and 13 percentage points more likely to be permanent full-time workers. The education and mixed groups were basically the same. It is well known that occupation and industry are strongly correlated with the casual / permanent contrast, and this applied to the young workers in this analysis (results not shown). Of considerable interest are the results for two demographic variables: sex and age. Even with the controls for occupation and industry—which thus takes into account the gender segmentation in the Australian labour market—the predicted probability of being in casual part-time job for young women was 8 percentage points higher than for men. The findings for age showed one glimmer of hope in a generally bleak landscape: the probabilities of being in casual part-time jobs fell dramatically with increasing age. They dropped from 42 per cent at age 16 to 18 per cent at age 23. Commensurate with this drop was a rise in permanent full-time employment from 28 per cent (at 16) to 47 per cent (at 23).

Table 7: Predicted probabilities (%) for selected variables, job status model

Variable	Cas PT	Cas FT	Fixed	Perm PT	Perm FT
GFC COHORT					
Pre-GFC	23	15	9	7	46
Post-GFC	24	14	11	10	42
CLUSTER CATEGORY					
Working	19	14	9	9	49
Mixed	29	15	11	9	36
Education	29	15	9	9	38
SEX					
Male	19	16	10	7	47
Female	27	12	10	10	41

Notes: FT = full-time; PT = part-time; Fixed = fixed term. Probabilities (shown as percentages) are average predictive margins for each level of the variable with the unemployment rate fixed at 5%.

6 *Discussion*

The descriptive duration statistics (Table 2) suggested that the post-GFC cohort fared much worse in the labour market than did the pre-GFC cohort. This was particularly notable for unemployment and for being outside the labour force, and appeared to affect the mixed category more than the other two. As mentioned earlier, this suggests that a sub-group of that category is likely to constitute a seriously disadvantaged group of young people who may end up marginalised in the labour market for many years to come. They make up the core of that group of teenagers and young adults termed NEETs (neither in employment, education or training) who have become a focus for concern among policy makers in recent decades (McClelland et al. 1998; Dusseldorp Skills Forum 2007). The duration statistics covered the whole transition period (from 16 onward), so a more realistic picture can be gauged by examining their situation at age 23. While this does not represent a completed transition for all young people, it does for the vast majority. Descriptive statistics for labour market outcomes at this age (Table 3) again raised concerns around the prospects for the mixed category. However, closer inspection of these data showed that parenting and mixing study with job searching was a feature of this group of young people. Consequently, to fully examine whether the education-to-work transition was problematic for a subgroup among the mixed category, and to assess whether the post-GFC cohort did fare significantly worse, required a multivariate regression analysis of a more unequivocal labour market outcome, namely, gaining full-time jobs.

The multivariate analysis was also used to examine a number of issues. First, it sought to identify the key background characteristics which distinguished the three cluster categories. Secondly, it examined labour market outcomes: gaining full-time employment (just mentioned) as well as the conditions of employment. Finally, a diagnostic model was fit to the data to examine whether the two cohorts could be equated with the two time periods (this last model is discussed below).

The multinomial logistic regression model predicting cluster category membership confirmed that these categories were not arbitrary, but reflected distinctive characteristics among these individuals. The key background factors were the highest education level attained, the age of leaving school, the mothers' occupation and the socio-economic status of the area. None of these findings were surprising. This model did, however, endorse some of the descriptive findings: namely a lower level of labour market engagement in the post-GFC cohort (that is, a lower probability of being in the working cluster category).

The logistic regression model which predicted gaining full-time employment by the age of 23 did find significant differences between the mixed category and the other two categories, with the former faring much worse. The pre-GFC and post-GFC comparison also showed that the post-GFC cohort fared much worse. Admittedly, the two cohorts faced different stages in the business cycle, but statistically controlling for this by including the area unemployment rate led to the same conclusion.

The next two models examined outcomes related to conditions of employment. The underemployment model reinforced the almost axiomatic association between part-time jobs and underemployment, but also threw light on the important occupational component of this problem. It also highlighted the extent to which the levels of underemployment were considerably higher for young workers than for the workforce as a whole. Most importantly, there were no differences between the GFC cohorts or cluster categories in this model. The job status model also confirmed this absence of a difference between GFC cohorts, but it did find a significant difference between the working category and the mixed and education categories. Both of the latter had much higher rates of part-time casual employment and much lower rates of permanent full-time employment.

These findings raise two important questions. First, to what extent can we regard this comparison between the pre-GFC cohort and the post-GFC cohort as a comparison between the two periods: before 2008–09 and after? After all, we are not comparing the same group of people at two different periods in time. A question like this is a familiar one in the sociological literature: how to untangle the confounding of *period* effects (historical events), *ageing* effects (life cycle) and *cohort* effects (generational aspects). A more detailed discussion of this issue can be found in Glenn (1976), Glenn (1977) and Mason, Karen Oppenheim et al. (1973).

In the analysis conducted here, the ageing effect is partially ruled out, because each group has been matched on this measure (both groups span the 16 to 23 year age range). Nevertheless, year effects and age effects can remain entangled because of year-to-year variability. For example, looking at business conditions highlights an important difference: those in the pre-GFC cohort ended their teenage years in the midst of a mining construction and property boom; those in the post-GFC cohort ended their teenage years in the aftermath of the GFC itself, with an unemployment rate on the rise. However, across each period as a whole the unemployment rates averaged similar levels: 5.2 per cent to 5.3 per cent. In modelling employment conditions where the dependent variables spanned the full periods (the underemployment and casualisation models) these similar average unemployment rates would have applied. Even so, the precise age at which a young person sought a job would have made a difference: an early school leaver, for example, in the first cohort faced an unemployment rate around 6 per cent; the same early school leaver in the second cohort faced an unemployment rate around 5 per cent. Clearly, disentangling the business cycle from these results is a complex task, but the inclusion of statistical controls (in the form of the area unemployment rate) did take account of this problem to some extent.

There still remains the potential confounding between the cohort effect and the period effect, a problem familiar to researchers dealing with ‘treatment effects’. In other words, perhaps there is something about the pre-GFC cohort which is quite different to the post-GFC cohort which makes them more likely to have fared better in the education-to-work transition than their later peers? To test this supposition a logistic regression model was fit to these data to examine whether a broad range of personal and family characteristics were associated with membership of each of the GFC cohorts. These characteristics included sex, migrant background, being the child of a sole parent, the highest level of education, the age when left school, father’s and mother’s occupation, and socio-economic status of the area. Overall, the model was a poor fit to the data, with most of these variables not strongly associated with cohort membership. The results of this model are shown in Appendix Table A5. This poor fit suggests that there were no substantial systematic differences between the two cohorts, a finding consistent with identifying these two cohorts as two time periods.

In this diagnostic model only two variables showed statistically significant differences: father's and mother's occupation.[9] However, the patterns here tended to cancel each other out. For example, compared to the pre-GFC cohort, the post-GFC cohort had fathers who were more likely to work in blue-collar occupations, but less likely to be not employed or not present. Similarly, with the mother's occupation: they were less likely to be not employed or not present; but more likely to be in white or pink collar jobs. When it came to managerial/professional occupations, the cohorts barely differed at all for the father, and only in a minor way for the mother. It is primarily these managerial/professional backgrounds which have been identified as the bearers of 'cultural capital' (Bourdieu and Passeron 1977; Bourdieu 1984) and as just noted, the two cohorts were largely indistinguishable in this regard. Overall, the absence of decisive background factors distinguishing the two cohorts does suggest that it is legitimate to regard the comparison between the two cohorts as a comparison between the two periods. This means that the weaker labour market outcomes for the post-GFC *cohort* were also a sign of a weaker labour market for young people in the post-GFC *period*.

Conclusion

Have the employment prospects of these young people been shaped by long-term structural changes in the youth labour market rather than the abrupt disruption of the GFC and the fluctuations of 21st century business cycles? Certainly, the long-term decline in full-time employment was evident in this analysis, but there is little doubt that the GFC spurred this decline still further. When it came to conditions of employment, specifically underemployment and casualisation, the structural changes were fundamental, and the effects of the GFC negligible. This is largely because the youth labour market has been reshaped over several decades. With permanent full-time jobs making up less than half of all jobs, such beacons of security now constitute an oasis in a desert of insecurity. Part-time jobs, with their elevated levels of underemployment; casual jobs, which ebb and flow with the business cycle; and temporary jobs, with good conditions but with limited prospects; all of these now form the landscape which people in their early twenties must navigate.

It seems fair to conclude that the GFC was indeed a key moment in the further shrinking of that oasis, but it was of less consequence for the surrounding desert, where underemployment and casualisation remained endemic. As for the risk of long-term marginalisation among a subgroup of the mixed category, the results remain unclear. Certainly, the disadvantages of being in that category were evident in a number of ways, but many similarities with the education category meant that definitive results were elusive. This was particularly so for various labour market states, such as unemployment and being outside the labour force. Greater clarity would emerge from further research into the intersection between the labour market activity of young people in their early to mid twenties and those other key aspects of their lives, such as studying, taking 'gap' years, and becoming parents.

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Notes

1. In order to present employment to population ratios for both teenagers and young adults (rather than the combined ratios provided by the ABS), I have calculated the ratios using employment counts. In the case of the numerator, these are trend data; in the case of the denominator, they are original data. These results (for teenagers, where there are comparable ABS estimates) appear to be identical to the published ABS estimates.

2. Studies which have made use of the calendar data include Carroll 2006; Dockery 2004; I. Watson 2008. A comprehensive study of the seam effects in HILDA has been undertaken by Nicole Watson, see N. Watson 2009.

3. In other words, where there were discrepancies for particular weeks over the calendar period (which averaged between 14 and 18 months), those weeks closest to the interview date were accepted ahead of those weeks furthest away. While this does not eliminate all the potential sources of recall error, it does minimise some of the memory and telescoping problems outlined by Nicole Watson which attach to retrospective reporting (N. Watson 2009: 2–3). In her modelling of the sources of misclassification error in the HILDA calendar data, Nicole Watson found that for young people the most likely mistakes related to spells not in the labour force (N. Watson 2009: 18). For researchers using *Stata*, a new command by Hannes Kröger can facilitate the management of seams. See Kröger 2015.

4. The calendar data covering 16 waves of the HILDA survey were converted to sequences suitable for sequence analysis using the TraMineR package in R. The subsequent analysis was also conducted using a combination of TraMineR and the cluster package (R Core Team 2017; Gabadinho et al. 2011; Gabadinho et al. 2010; Maechler et al. 2017).

5. A two year period was chosen to maximise sample size and to take account of young people turning 16 at different times during the year. This meant potentially 270 observations on each individual, though some individuals had fewer observations. The decision rule for inclusion in the scope of the analysis was to select individuals who were present for at least 5 waves of an 8 wave period. Unlike some statistical procedures which discard missing data, sequence analysis can incorporate missing periods in a sequence. These missing periods may be due to non-response for the data items or non-response to the survey. In the case of the latter, absence from the survey and re-entry can in itself be informative.

6. The models discussed below were fitted using Stata Release 15. All models were tested for over-fitting using split sample methods. Predictions and discussion in the text focused on those variables which were consistently statistically significant, and those variable which were of central interest, namely, GFC cohort and cluster category. The results shown in the Appendix tables are for the full sample models.

7. Note that whether the respondent was still a full-time student was included in the model, not for explanatory purposes, but as a control. It was highly significant, as expected since it was strongly correlated with being in the education category.

8. In some cases where information was missing on the parents' occupation (as reported by the respondent), information was derived from the household data on the occupations held by the parents when the respondent was 16.

9. As mentioned all models were tested for over-fitting using split sample validation methods. In the case of the diagnostic model, some samples showed a statistical difference for the sole parent variable, but only the two parental occupational variables were consistently significant. Moreover, the sole parent variable was not statistically significant in the earlier model which predicted full-time employment outcomes.

Appendix

Table A1: Multinomial logistic regression: cluster categories

	Working category			Mixed category		
Variable	**Coef**	**SE**	**P**	**Coef**	**SE**	**P**
Post-GFC	-0.682	0.260	0.01	-0.352	0.244	0.15
Female	-0.391	0.246	0.11	-0.299	0.228	0.19
Child of sole parent	0.359	0.318	0.26	0.150	0.293	0.61
Migrant	-0.196	0.485	0.69	0.077	0.397	0.85
FT student	-1.818	0.359	0.00	-0.520	0.270	0.05
HIGHEST EDUCATIONAL LEVEL						
Postgrad	-3.381	1.199	0.01	-3.103	1.192	0.01
Tertiary	-5.294	1.091	0.00	-3.254	1.064	0.00
Vocational	-2.134	1.063	0.04	-2.074	1.069	0.05
Year 12	-2.493	1.056	0.02	-2.024	1.060	0.06
AGE LEFT SCHOOL						
Left at 16 or before	2.509	0.692	0.00	1.103	0.566	0.05
Left at 17 or 18	1.917	0.504	0.00	0.321	0.352	0.36
FATHER'S OCCUPATION						
Managerial/professional	-0.360	0.464	0.44	-0.578	0.417	0.17
White/pink collar	0.273	0.524	0.60	0.099	0.486	0.84
Blue collar	0.364	0.478	0.45	-0.073	0.444	0.87
MOTHER'S OCCUPATION						
Managerial/professional	-0.415	0.410	0.31	-0.376	0.367	0.31
White/pink collar	0.315	0.397	0.43	-0.721	0.375	0.05
Blue collar	0.113	0.502	0.82	-0.404	0.464	0.38
GEOGRAPHICAL LOCATION						
Melbourne	0.096	0.402	0.81	-0.119	0.365	0.74
Other cities	-0.087	0.397	0.83	-0.126	0.364	0.73
Outside cities	0.223	0.370	0.55	0.125	0.341	0.71
SEIFA DECILE						
Lowest decile	1.070	0.671	0.11	1.329	0.619	0.03
2nd decile	1.263	0.608	0.04	1.074	0.560	0.06
3rd decile	1.282	0.594	0.03	0.845	0.543	0.12
4th decile	0.770	0.633	0.22	0.648	0.567	0.25
6th decile	1.154	0.601	0.06	0.898	0.543	0.10
7th decile	0.144	0.539	0.79	-0.338	0.499	0.50
8th decile	0.818	0.547	0.14	-0.226	0.520	0.67
9th decile	0.060	0.529	0.91	-0.250	0.462	0.59
Highest decile	0.605	0.577	0.29	-0.031	0.501	0.95
Intercept	1.383	1.321	0.29	3.174	1.240	0.01

Notes: Coef = coefficient; SE = standard error; P = P-value (95% level). SEIFA = ABS socio-economic indicators for areas.

Population: all observations. Omitted dependent variable: Education cluster category. Omitted independent variables: Before GFC; Male; Not child of sole parent; Not a migrant; Year 11; Left after 18; Not employed; Not employed; Sydney; 5th decile.

No. obs = 688; Log likelihood = -587.811; Pseudo R-squared = 0.216.

Table A2: Logistic regression: full-time employment at age 23

Variable	Coefficient	SE	P-value
Post-GFC	-0.853	0.228	0.00
Area unemployment rate	-0.264	0.110	0.02
Migrant	0.167	0.365	0.65
Female	-0.923	0.212	0.00
Child of sole parent	0.033	0.254	0.90
FT student	-2.841	0.332	0.00
Has parental responsibilities	-0.064	0.615	0.92
Female by Has parental responsibilities	-3.458	0.911	0.00
HIGHEST LEVEL EDUCATION			
Postgrad	1.430	0.679	0.04
Tertiary	1.282	0.420	0.00
Vocational	0.858	0.360	0.02
Year 12	0.327	0.355	0.36
AGE LEFT SCHOOL			
Left at 16 or before	-0.358	0.463	0.44
Left at 17 or 18	0.312	0.368	0.40
FATHER'S OCCUPATION			
Managerial/professional	0.413	0.350	0.24
White/pink collar	0.407	0.387	0.29
Blue collar	0.509	0.344	0.14
MOTHERS'S OCCUPATION			
Managerial/professional	0.157	0.321	0.62
White/pink collar	0.376	0.306	0.22
Blue collar	0.697	0.385	0.07
SEIFA DECILE			
Lowest decile	-0.177	0.461	0.70
2nd decile	0.328	0.463	0.48
3rd decile	0.283	0.464	0.54
4th decile	1.236	0.535	0.02
6th decile	0.053	0.466	0.91
7th decile	0.143	0.442	0.75
8th decile	0.429	0.480	0.37
9th decile	0.243	0.435	0.58
Highest decile	-0.125	0.477	0.79
CLUSTER CATEGORY			
Mixed	-1.159	0.246	0.00
Education	-0.386	0.302	0.20
Intercept	1.905	0.880	0.03

Notes: SE = standard error; FT = full-time; PT = part-time. SEIFA = ABS socio-economic indicators for areas.
Population: All observations. Dependent variable is being in full-time employment at age 23.
Omitted independent variables: Not a migrant; Male; Not child of sole parent; Not FT student; No parental responsibilities; Male with no parental responsibilities; Year 11; Left after 18; Not employed; Not employed; 5th decile; Working category.
No. obs = 688; Log likelihood = -323.052; Pseudo R-squared = 0.318.

Table A3: Multilevel logistic regression: underemployment

Variable	Coefficient	SE	P-value
Post-GFC	0.183	0.162	0.26
Area unemployment rate	-0.030	0.064	0.64
Job tenure	-0.038	0.043	0.38
Age	-0.051	0.035	0.15
Female	-0.341	0.178	0.06
Migrant	-0.082	0.320	0.80
AGE LEFT SCHOOL			
Left at 16 or before	-0.549	0.380	0.15
Left at 17 or 18	-0.250	0.341	0.47
JOB STATUS			
Casual PT	2.731	0.202	0.00
Casual FT	0.537	0.208	0.01
Fixed-term	0.090	0.236	0.70
Permanent PT	2.481	0.240	0.00
OCCUPATION			
Professionals	-0.055	0.441	0.90
Technicians / Trades	0.935	0.385	0.01
Community / Personal Serv	0.958	0.388	0.01
Clerical / Admininstrative	0.072	0.399	0.86
Sales Workers	0.836	0.373	0.03
Machine Operators / Drivers	0.711	0.459	0.12
Labourers	0.866	0.388	0.03
INDUSTRY			
Manufacturing	0.763	0.435	0.08
Utilities / construction	0.611	0.431	0.16
Retail	0.788	0.425	0.06
Wholesale / Transport	0.952	0.455	0.04
Accommodation / Food	0.776	0.419	0.06
Inform / Finance / Real estate	0.878	0.510	0.09
Professional etc Services	0.343	0.515	0.51
Administrative Services	0.403	0.528	0.45
Public Administration	1.131	0.502	0.02
Education / Training	0.300	0.539	0.58
Health Care / Social Assistance	0.716	0.467	0.12
Arts etc / Other Services	0.476	0.450	0.29
CLUSTER CATEGORY			
Working	0.133	0.217	0.54
Mixed	0.024	0.235	0.92
Intercept	-1.887	1.051	0.07
SD of panel level variance	1.094	0.112	
Rho	0.267	0.040	

Notes: SE = standard error; SD = standard deviation; FT = full-time; PT = part-time. Population: Employees who were not full-time students. Rho is proportion of total variance attributed to panel (ie. subject) variance. Note that a shortened version of ANZSIC is used for industry. Omitted independent variables: Before GFC; Male; Not a migrant; Left after 18; Permanent FT; Managers; Agriculture / mining; Education category.
No. obs = 2301 in 680 groups (ie. subjects); Log likelihood = -1094.017; LR test that rho=0 = 63 and P-value for LR test = 0.000 (test comparing the panel data with pooled data).

Table A4: Multilevel multinomial logistic regression: job status

	Casual PT		Casual FT		Fixed-term		Perm PT	
Variable	**Coef**	**P**	**Coef**	**P**	**Coef**	**P**	**Coef**	**P**
Post-GFC	0.220	0.299	0.038	0.839	0.398	0.026	0.478	0.029
Age	-0.322	0.000	-0.111	0.004	-0.157	0.000	-0.057	0.242
Area unemployment rate	0.184	0.015	0.094	0.194	0.122	0.090	0.006	0.945
Female	0.866	0.000	0.067	0.745	0.228	0.232	0.727	0.002
Migrant	0.227	0.580	0.130	0.723	-0.802	0.061	0.443	0.253
AGE LEFT SCHOOL								
Left at 16 or before	-0.512	0.298	-0.129	0.769	-0.979	0.012	-0.015	0.976
Left at 17 or 18	-0.133	0.762	0.034	0.932	-0.443	0.192	0.073	0.872
OCCUPATION								
Professionals	2.321	0.001	0.552	0.302	0.825	0.037	0.267	0.611
Technicians / Trades	2.461	0.000	1.122	0.016	1.032	0.006	0.285	0.585
Community / Personal Serv	4.703	0.000	2.857	0.000	1.012	0.014	1.495	0.002
Clerical / Admininstrative	2.457	0.000	1.191	0.012	0.474	0.215	0.556	0.248
Sales Workers	4.270	0.000	2.239	0.000	0.829	0.036	2.497	0.000
Machine Operators / Drivers	4.183	0.000	2.708	0.000	0.331	0.537	1.437	0.026
Labourers	5.319	0.000	3.003	0.000	0.176	0.706	2.295	0.000
INDUSTRY								
Manufacturing	0.074	0.881	-0.616	0.101	-0.298	0.504	-0.075	0.913
Utilities / construction	-0.261	0.599	-0.769	0.036	-0.942	0.033	-0.838	0.260
Retail	1.414	0.003	-0.973	0.015	-0.477	0.304	0.604	0.348
Wholesale / Transport	0.693	0.176	-0.780	0.058	-0.789	0.138	0.389	0.573
Accommodation / Food	2.461	0.000	0.438	0.258	-0.472	0.335	1.847	0.004
Inform / Finance / Real estate	0.557	0.323	-1.788	0.001	-0.523	0.293	-0.227	0.762
Professional etc Services	0.652	0.256	-0.912	0.063	-0.604	0.209	0.543	0.449
Administrative Services	0.902	0.104	-0.216	0.629	-0.148	0.778	0.309	0.682
Public Administration	-1.126	0.113	-1.455	0.004	0.307	0.518	-0.670	0.440
Education / Training	1.355	0.021	-0.608	0.265	0.787	0.120	1.681	0.022
Health Care / Social Assistance	0.587	0.272	-0.895	0.047	-0.237	0.624	1.212	0.073
Arts etc / Other Services	0.848	0.088	-1.050	0.013	-0.419	0.358	0.317	0.646
CLUSTER CATEGORY								
Working	-1.182	0.000	-0.591	0.024	-0.413	0.075	-0.578	0.040
Mixed	0.096	0.745	0.082	0.770	0.299	0.225	0.142	0.643
Random intercept	1.000	1.000	0.694	0.000	0.505	0.000	0.674	0.000
Model constant	0.756	0.556	0.005	0.996	1.533	0.185	-2.616	0.068

Notes: FT = full-time; PT = part-time; Coef = Coefficient; P = P-value (95% level).

Population: Employes who were not full-time students. Model fitted using generalized structural equation command. Omitted dependent variable is permanent FT. Note that a shortened version of ANZSIC is used for industry. Omitted independent variables: Before GFC; Male; Not a migrant; Left after 18; Managers; Agriculture / mining; Sydney; Education category.

No. obs = 2836 in 710 groups (ie. subjects); Log likelihood = -3258.569; Subject level variance = 3.367. Note that random intercept is constrained to 1 for the first outcome.

Table A5: Logistic regression: cohort membership

Variable	Coefficient	SE	P-value
Area unemployment rate	1.069	0.116	0.00
Female	-0.089	0.183	0.63
Migrant	-0.616	0.342	0.07
Child of sole parent	0.574	0.237	0.01
HIGHEST LEVEL EDUCATION			
Postgrad	1.712	0.670	0.01
Tertiary	0.605	0.377	0.11
Vocational	0.357	0.341	0.29
Year 12	0.243	0.341	0.48
AGE LEFT SCHOOL			
Left at 16 or before	-0.271	0.429	0.53
Left at 17 or 18	-0.232	0.339	0.49
FATHER'S OCCUPATION			
Managerial/professional	1.170	0.337	0.00
White/pink collar	1.301	0.377	0.00
Blue collar	1.660	0.330	0.00
MOTHERS'S OCCUPATION			
Managerial/professional	0.627	0.295	0.03
White/pink collar	0.881	0.279	0.00
Blue collar	0.425	0.348	0.22
SEIFA DECILE			
Lowest decile	-0.056	0.444	0.90
2nd decile	-0.045	0.431	0.92
3rd decile	0.050	0.430	0.91
4th decile	0.727	0.476	0.13
6th decile	0.357	0.444	0.42
7th decile	-0.149	0.420	0.72
8th decile	0.179	0.431	0.68
9th decile	-0.059	0.409	0.89
Highest decile	0.590	0.435	0.17
Intercept	-7.533	0.923	0.00

Notes: SE = standard error; FT = full-time; PT = part-time. SEIFA = ABS socio-economic indicators for areas.
Population: All observations. Dependent variable is membership of the post-GFC cohort.
Omitted independent variables: Male; Not a migrant; Not child of sole parent; Year 11; Left after 18; Not employed; Not employed; 5th decile.
No. obs = 688; Log likelihood = -373.876; Pseudo R-squared = 0.215.

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