Bridges or traps? Casualisation and labour market transitions in Australia

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Abstract

In this article [1] I re-examine the familiar debate on whether casual jobs represent a 'bridge' into permanent employment, or a 'trap' which keeps workers locked into ongoing casualised work or joblessness. My analysis looks at the labour market destinations of casual workers over time, making use of the HILDA data for the period 2001 to 2009. The novelty of my approach is two-fold. I examine an extensive range of individual, locality and job characteristics to assess which of these are most strongly associated with various labour market destinations. Secondly, I conduct the analysis using longitudinal panel data, in which I make use of random intercepts multinomial logit panel models to estimate various conditional predicted probabilities for these destinations.

The findings show that as far as individual characteristics are concerned, age and years in paid employment matter a great deal, while education matters much less. Increasing age leads to worse outcomes, more years in paid employment lead to better outcomes, and increased levels of educational qualification have only a modest link to better outcomes. In regard to locality, the more disadvantaged the area, the more likely that casual jobs will persist, transitions to permanent jobs will diminish and transitions to joblessness increase. In regard to the jobs themselves, casualisation persists in those industries where casual density is high, where organisations are small, where the work is part-time, and where skills development is limited. These findings suggest that systemic influences count for a great deal, while human capital elements count for much less. I conclude that the very nature of casual jobs is itself responsible for perpetuating casualised employment.

1 Introduction

The vast majority of new jobs created in Australia during the 1990s were casual jobs (Borland et al. 2001), a phenomenon which left labour market researchers divided in their assessments of the labour market. Some argued that the growth of casual employed showed the Australian labour market had become more 'flexible', something they regarded as desirable (Wooden 2001; Wooden and Warren 2004). Others argued that it represented a growing polarisation in the labour market between 'good' jobs—those with permanency—and 'bad' jobs. From this perspective, casual jobs were seen as poor quality jobs, insecure, poorly paid and with little long term prospects for career advancement (Watson et al. 2003; Burgess and Campbell 1998*b*; Burgess and Campbell 1998*a*). As Chalmers and Waddoups (2007: 2) observed, the growth of casual employment raised the prospect of creating a large pool of 'second-class industrial citizens'.

Within this debate an interesting set of metaphors have arisen. While the defenders of labour market casualisation sometimes concede that the jobs are of poor quality, they suggest that they play an important bridging role, providing stepping stones for the unemployed to re-enter the labour market. On the other hand, the critics of casualisation suggest that such bridges are illusory and that most casuals stayed trapped in a cycle of job churning.

The Australian literature is somewhat ambiguous in arbitrating between these two positions. The early study by Burgess and Campbell (1998*a*) concluded that for job seekers casual jobs did not serve as a bridge. Looking at the mid 1990s SEUP data,[2] Burgess and Campbell (1998*a*) found that casual jobs did not lead to permanent jobs and they argued that 'casual employment is just another form of exclusion and precariousness that encompasses unemployment and income deprivation' (Burgess and Campbell 1998*a*: 48). Also using the SEUP data Chalmers and Kalb (2001) concluded on a more positive note. They examined the length of time it took to transition from unemployment to permanent employment, and whether taking a casual job shortened that time. They concluded that it did for some jobseekers, and that casual jobs might be a 'promising path' to permanent jobs for some jobseekers. However, they also noted that there was a large amount of variability in the outcomes, and considerable proportions of jobseekers remained stuck in either unemployment or casual employment.

With access to more recent data—in the form of the HILDA survey—a number of researchers have returned to the question. Chalmers and Waddoups (2007) used four waves of HILDA data to apply survival analysis to casual employment. They found that people's duration in casual jobs was associated with the length of their job tenure and with whether the job was part-time. Their overall judgement on the bridge / trap question was, however, inconclusive.

Also using the HILDA data, and also using survival analysis, Mitchell and Welters concluded in a more negative vein. They showed that structural factors, such as industry location, firm size and locality played an important role in whether workers found themselves trapped in casual jobs (Mitchell and Welters 2008). In a later study, which examined duration dependence in casual jobs, the authors concluded that 'casual employment does lock in workers, which is in line with findings from studies that cannot find conclusive evidence that casual employment functions as a stepping stone towards non-casual employment' (Welters and Mitchell 2009: 11).

A different econometric approach, which modelled employment transitions between different labour market states, was undertaken by Buddelmeyer and Wooden (2011), also using the HILDA data. They found more positive results for casual jobs, although this depended on gender. They concluded, in the case of men, that workers were 'better off accepting casual work rather than remaining unemployed'. For women, however, 'we find that unemployment has the edge over casual employment when it comes to enhancing the probability of permanent employment 1 year onwards' (Buddelmeyer and Wooden 2011: 128).

Comparing the different approaches taken by Buddelmeyer and Wooden (2011) vis-a-vis Mitchell and Welters (2008) is particularly illuminating. Buddelmeyer and Wooden (2011) used a series of dynamic, multinomial logit panel models with random intercepts to estimate transition probabilities between various labour market states over adjacent years.[3] These states were a set of comprehensive destinations—which included self-employment, unemployment and not in the labour force (NILF) as well as the casual, fixed-term and permanent categories. By comparing all labour market transitions, the authors were able to construct the counter-factual: 'what would have happened to persons working in non-standard jobs had they been in a different labor market state instead' (Buddelmeyer and Wooden 2011: 116). The random intercepts specification allowed them to control for unobserved heterogeneity. As is well known, heterogeneity effects are common in labour market processes. These might be educational, motivational or skill characteristics of the worker or contextual aspects of their location. Some of these can be controlled for explicitly—such as educational attainment—but others are not measurable. Incorporating random intercepts into the modelling allows researchers to control for these unobserved effects.

There is a serious downside to the approach taken by Buddelmeyer and Wooden (2011), one which the studies by Mitchell and Welters explicitly target. While there are some measures of locality included, the majority of the regressors in these models of labour market transitions are individual characteristics: things like educational background, age, years in paid employment, marital status, presence of children. The inclusion of the lagged employment state (and the original employment state) are the only regressors which capture systemic aspects of the labour market situation which are not reducible to these individual characteristics, but they are not explicitly identified as would be the case were they included as specific regressors. The authors' preference for this approach is partly philosophical and partly statistical. The perspective behind the Buddelmeyer and Wooden (2011) approach is overwhelmingly supply-side neo-classical economics, a framework which is based on methodological individualism. When it comes to their statistical approach, the authors are restricted in their options because their regressors must be chosen from those common to all labour market states. Important job characteristics are available in the HILDA data, but only for those respondents who were employees at the time of the interview.[4]

By way of contrast, Mitchell and Welters (2008: 5) argue for an analysis which incorporates both individual and systemic influences, an approach which takes account of local labour market conditions and the level of macroeconomic activity. They are able to do this because their philosophical perspective alerts them to the wider structural settings in which labour market outcomes occur, and because their method is based on survival analysis for those currently employed in casual jobs. They thus have access to a wide range of job characteristics from which to fashion their regressors. The downside to their approach, inherent in using survival analysis, is that they can only model non-casual outcomes as a single category, that is, as an exit from casual employment.

In the analysis which follows, I pursue the emphasis on systemic influences but I also consider all possible labour market outcomes. In this respect, my approach 'bridges' these two divergent methodologies. Like Buddelmeyer and Wooden (2011) I estimate transition probabilities using multinomial logit panel models with random intercepts. While I examine *all* possible labour market outcomes, *the subjects for this analysis are those individuals currently working in casual jobs*. In this way, like Mitchell and Welters I am able to draw upon a wider range of systemic influences in choosing my regressors, particularly the characteristics of the casual jobs. Unlike Buddelmeyer and Wooden (2011) I do not model all labour market transitions since I do not examine how individuals who are unemployed, permanent employees, or self-employed fare. In this respect, I am not considering the counterfactual, of how the same person might have fared had they been a permanent worker, for example, instead of a casual.

The question this analysis asks is thus: in what labour market situation does a male (female) casual (fixed-term) worker find themselves in the following year? How does this relate to their demographic characteristics (age, education, years in paid employment, health); to the locality where they live (the unemployment rate, the socio-economic characteristics); and to the casual or fixed-term job itself (hours, pay, industry, organisational size)? Many of the regressors used for this analysis are common in most labour market studies, but the richness of the HILDA data also allow for some quite unique variables to be included. These include the effects of social support networks and the skills opportunities which jobs offer. Most importantly, the HILDA data allow the researcher to distinguish between casual and fixed-term employees, and this proves to be a fundamental distinction in this subject area.

2 Data and analysis

The HILDA survey is a household-based longitudinal survey covering a broad range of social and economic questions which has been conducted annually since 2001 (for more details, see `http://www.melbourneinstitute.com/hilda/`). Respondents aged 15 or over living in the sampled households are surveyed each year (called a 'wave'), generally in the latter half of the year, and respond to both interviewer-administered questionnaires and a self-completion questionnaire. There are a set of core questions which remain the same every year, thereby allowing for a valuable accumulation of consistent data on the same individual over time. New subjects are recruited into the survey from two sources: existing members of a household may turn 15, or new members may enter a household (for example, through marriage).

The data for this analysis come from 9 waves of the HILDA survey, spanning the period 2001 to 2009. I work with four subsets of the data: male and female casual employees and male and female employees on fixed-term contracts. While the categories casual and fixed-term employee are often merged in labour market studies—due to a reliance on the ABS definition of a casual which is based on leave entitlements—it is possible with the HILDA data to separate the two categories because a question is included which explicitly asks interviewees how they are employed. Research over the last decade using this distinction has emphasised its importance, with the situation of fixed-term employees being quite different to that of casuals (see, for example, Wooden and Warren 2003). An obvious, and very important difference, is that fixed-term employees are dominated by management and professional occupations while casual jobs are dominated by sales and labouring occupations.

A further restriction on the population studied here is that the age range of the subjects spans 15 to 64 and excludes full-time students in the current year and in the subsequent year. The exclusion of students is crucial, since a considerable proportion of casual jobs are held by students whose working situation usually changes abruptly once they graduate. A casual job in hospitality, for example, is usually very transitory for a full-time student studying accountancy or teaching.

A person's current labour market state—either casual or fixed-term—is the basis for defining each population, and the regressors are ones which are available for that current situation. The full list of regressors is shown in the tables in the appendix. The outcome variable is the labour market state *in the following year*. This is composed of six categories: permanent, casual, fixed-term, self-employment, unemployment and not in the labour force (NILF).

The use of a lead-variable (ie. the situation the following year) reduces the sample to 8 waves of data, and the other restrictions mentioned above further reduce the sample size: 2,731 observations for male casuals; 4,725 for female casuals; 1,849 for male fixed-term employees; and 2,008 for female fixed-term employees. Transition outcomes are not normally distributed but follow an extreme value type 1 (EV1) distribution, which makes fitting a multinomial logit model (MNL) the appropriate estimation strategy.[5]

With longitudinal data, such as the HILDA survey panel data, the modelling needs to accommodate repeated observations on the same individual. The appropriate model for this is a random intercepts MNL model in which the probability of observing an outcome j is conditional on observed characteristics X_{it} and unobserved individual effects α_i. The former vary over time and between individuals, the latter vary between individuals, but are time invariant. The notation for this model (Haan and Uhlendorff 2006: 230) is as follows:

$$Pr(j|\mathrm{X}_{it}, \alpha_i) = \frac{exp(\mathrm{X}_{it}\beta_j + \alpha_{ij})}{\sum_{k=1}^{J} exp(\mathrm{X}_{it}\beta_k + \alpha_{ik})}$$

Here j represents one of the possible outcomes, i is the individual, and t represents the time period, that is, the wave in which is the individual is observed. In the analysis for this article, j is actually j_{t+1} and reflects the fact that the outcome is for the following year. The unit of analysis is an 'occasion', which is nested within an individual person. The unobserved individual effects, α_i can be modelled as random intercepts and while they do not (by definition) have parameters, their variability can be estimated (this is shown as the standard deviation of the random intercept in the modelling results in the appendix).

Models such as these are referred to as mixed MNL models or multi-level MNL models depending on the discipline (Gelman and Hill 2007; Pinheiro and Bates 2004; Skrondal and Rabe-Hesketh 2004) and they require particular estimation procedures. For this analysis maximum simulated likelihood (MSL) estimation is used.[6] When it comes to interpretation, the MNL coefficients for each of the observed characteristics, that is, the covariates X_{it} for each of the $J-1$ outcomes, can be presented as raw estimates or as relative risk ratios (RRRs). The tables in the appendix show the raw estimates, but for ease of interpretation, predicted probabilities are much more intuitive. A common presentation device is to set all the values of the regressors, apart from the variable of interest, to their mean value, and to allow the variable of interest to alternate between set values. There are two common methods in using this approach: *predictions at the mean* and *mean predictions* (sometimes called 'the method of recycled predictions')[7]. The latter approach is taken in this article.

3 Results

The unconditional probabilities for each of the labour market destinations for the four populations are shown in Table 1. The destinations are for the following year, and are shown in the vertical rows. The percentages shown here suggest that duration dependence—that is, being stuck in the same situation—is very high for casuals but weaker for fixed-term employees. Amongst casuals, nearly half of males, and more than half of females, remain casuals the following year. In the case of fixed-term employees, the fraction who remain fixed-term is closer to two-fifths. Fixed-term employees have much better odds of becoming permanents: 48 per cent for male fixed-term employees and 44 per cent for females. By contrast, among casuals the proportions who become permanents are just 28 per cent and 21 per cent. These are, nevertheless, higher proportions than those who become jobless: 13 per cent of male casuals end up either unemployed or outside the labour force; the equivalent figure for females is 15 per cent, with most of these leaving the labour force.

Table 1: Unconditional transition probabilities: destinations in following year for each population

	Casuals		Fixed-term	
	Male	Female	Male	Female
Permanent	28	21	48	44
Casual	48	54	5	8
Fixed-term	5	5	39	38
Self-employed	6	4	4	3
Unemployed	6	3	2	2
NILF	7	12	3	5
Total	100	100	100	100
Sample size:	2,792	4,815	2,006	2,118

Notes: Unweighted data. All waves of data. Includes repeated observations. Note that the sample sizes for estimation are slightly smaller than these numbers because of missing observations for some of the covariates.

One can see why researchers regard the bridge / trap debate as inconclusive. On the one hand, permanent destinations outweigh jobless destinations, particularly for male casuals. On the other hand, poor labour market outcomes—in the form of remaining casual or becoming jobless—considerably outweigh good labour market outcomes. However, if the purpose of the research exercise is more than just drawing up a crude balance sheet then these unconditional probabilities are not very informative in themselves. If the research goal is to actually understand the dynamics, and the generative mechanisms, within casual labour markets, then conditional probabilities are what really matter. We need to know not only which individuals—in terms of personal characteristics—stay locked in casual employment, but what kinds of jobs and what kinds of localities consistently reproduce casualised work.

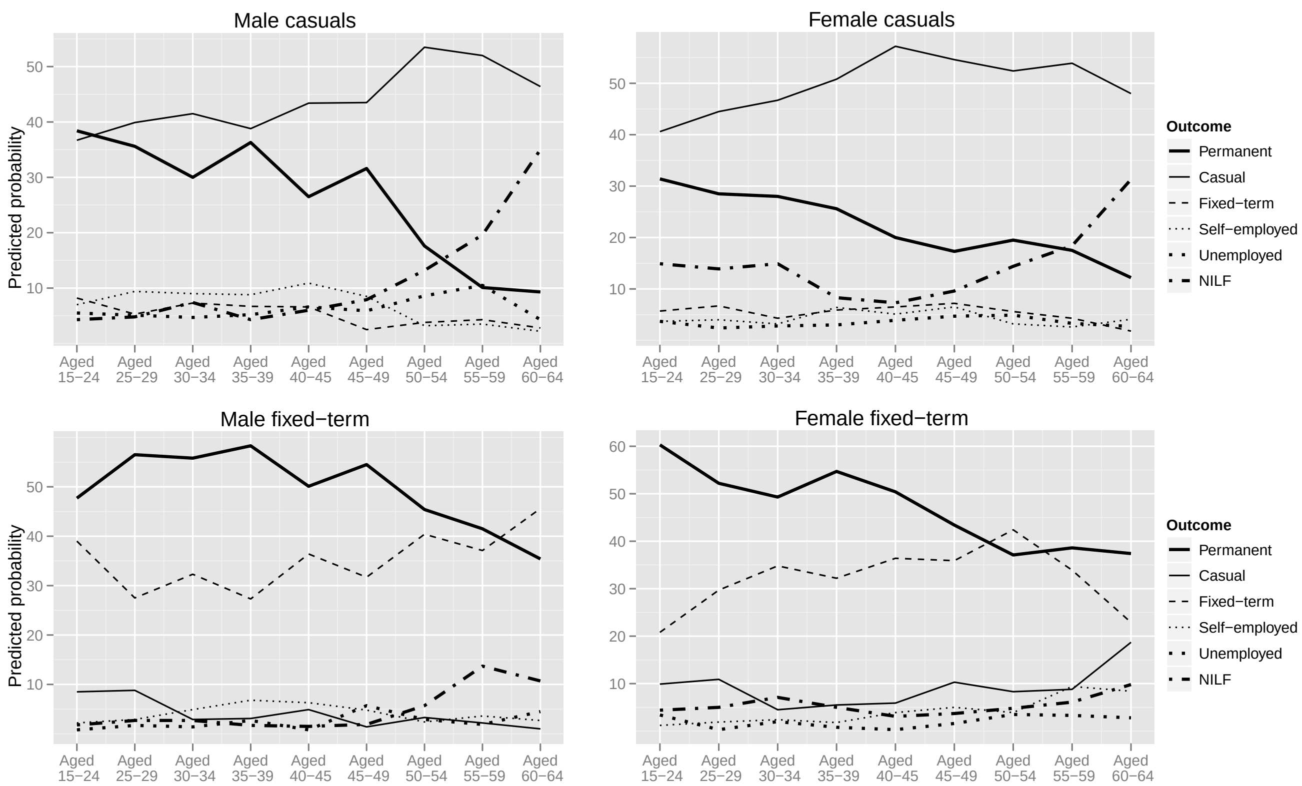
In this respect, the most important findings about individuals from this analysis are that age and years in paid employment matter a great deal, while education matters much less. Increasing age leads to worse outcomes, more years in paid employment lead to better outcomes, and increased levels of educational qualification have only a modest link to better outcomes. In regard to locality, the more disadvantaged the area, the more likely that casual jobs will persist, transitions to permanent jobs will diminish and transitions to joblessness increase. In regard to the jobs themselves, casualisation persists in those industries where casual density is high, where organisations are small, where the work is part-time, and where skills development is limited. In summary, systemic influences count for a great deal, while human capital elements count for much less.

In the discussion which follows I often refer to 'joblessness' as an outcome, a categorisation where unemployment and not in the labour force (NILF) are lumped together. While for women, the NILF category can be a unique destination given the gendered nature of unpaid domestic labour and caring work, for men in the working age population used in this study (keeping in mind the exclusion of full-time students) the NILF category often masks hidden unemployment or forced early retirement. In this respect, this category of 'jobless' is quite a reasonable measure of the lack of employment opportunities for this population.

3.1 Age, years in paid employment and education

The effect of age is shown as a series of line plots in Figure 1. All present the same sobering story that movement into permanent jobs falls with age, particularly once workers reach their mid forties. For male casuals, the fall (as a trend line) is modest until the mid forties, but then drops sharply. For female casuals, it is a steady downhill slide from their twenties.

Figure 1: Predicted probabilities of labour market status for age groups (%)



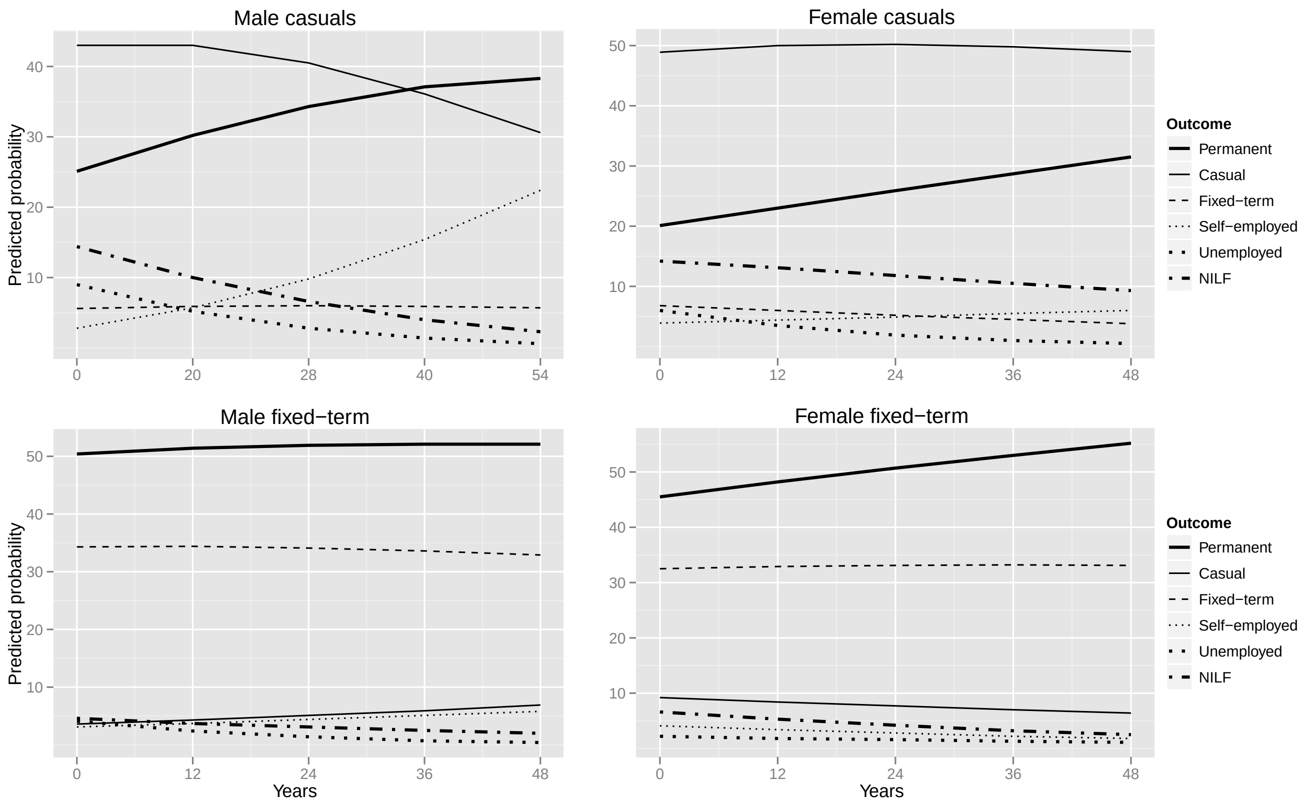
Male fixed-term workers fare somewhat better, with the fall (again, as a trend line) quite slight until the mid forties, but then a sharp drop sets in. Female fixed-term workers resemble their casual counterparts in that the downhill slide (as a trend line) is steadily downward from their twenties onwards.

The other destinations show considerable variation. For male casuals, casual destinations continue to rise with age, right through into the fifties. Unemployment rises during the late forties, but it is movement outside the labour force which takes off dramatically when male casuals enter their fifties. For female casuals, casual destinations stop rising after they reach their forties, and the same pattern as for men is evident with the NILF outcomes.

Male fixed-term workers are inclined to stay in that labour market state over the life course, with no (trend) decline evident. This is not the case for women, whose fixed-term job destinations begin to decline once they reach their fifties. While male fixed-term workers have virtually no movement into casual jobs, for female fixed-term workers this destination actually increases towards the end of their working lives.

The results for years of paid employment are also shown as a series of line plots in Figure 2.[8] With the exception of male fixed-term employees, these plots show a steady increase in permanent destinations for those workers with longer years of paid employment behind them. They also show some other interesting variations. For male casuals, casual employment falls as a likely destination and self-employment becomes much more likely. Jobless outcomes also decline for workers with a longer history of paid employment, though these effects are confined to casuals.

Figure 2: Predicted probabilities of labour market status for years in paid employment (%)



Among male casuals, job tenure has no impact on their employment destinations, nor on their prospects of avoiding joblessness (Table 2). For women, however, the impact is considerable. Longer job tenure in their current casual job considerably increases their prospects of employment and reduces their prospects of being unemployed. But when it comes to staying employed, job tenure actually increases the prospects of remaining casual rather than moving into permanent employment. Whereas a female casual with one year's job tenure has odds of about 1.3 (23 per cent to 17 per cent) of staying casual rather than becoming permanent, once that job tenure stretches out to four years, the odds have more than doubled (51 per cent to 24 per cent).

Table 2: Predicted probabilities of labour market status by job tenure for casuals (%)

	Male					Female				
	Under 1 yr	One yr	Two yr	Three yrs	Four yrs	Under 1 yr	One yr	Two yr	Three yrs	Four yrs
Permanent	30	30	30	30	30	11	17	22	24	24
Casual	44	44	44	44	44	13	23	35	44	51
Fixed-term	6	6	6	6	6	4	5	6	6	6
Self-employed	7	7	7	7	7	2	3	4	4	5
Unemployed	6	6	6	5	5	63	40	21	8	3
NILF	7	7	8	8	8	8	11	13	13	13

Notes: Because of the nature of their contracts, job tenure is not included as a regressor for fixed-term employees.

The results for educational qualifications are shown in Table 3. For male casuals, a degree does indeed confer an advantage in attaining permanency, particularly vis-a-vis early school leavers. But the advantage is slight if the comparison is with those holding Certificates III/IV. Moreover, holders of a diploma (or advanced diploma) are no better off than early school leavers. Compared with others kinds of qualifications, degree-holding does make it more likely that male casuals will move on to fixed-term jobs. Finally, degree holding does make it less likely that male casuals end up jobless.

Table 3: Predicted probabilities of labour market status by highest educational level (%)

	Male					Female				
	Degree†	Dip/Adv Dip	Yr 12	Cert III/IV	Yr 11‡	Degree†	Dip/Adv Dip	Yr 12	Cert III/IV	Yr 11‡
Casuals										
Permanent	36	26	30	32	27	22	20	26	24	24
Casual	37	41	46	41	48	45	50	50	50	52
Fixed-term	12	6	7	5	4	10	9	4	6	4
Self-employed	6	11	5	10	4	6	6	5	5	3
Unemployed	4	8	4	5	7	3	2	4	3	4
NILF	6	9	9	8	8	14	12	11	12	13
Fixed-term										
Permanent	43	50	60	59	55	47	50	54	52	50
Casual	4	5	2	4	8	7	10	8	9	9
Fixed-term	46	31	29	28	25	36	28	29	31	30
Self-employed	5	5	3	4	4	3	4	3	3	2
Unemployed	1	2	2	2	2	2	3	2	2	1
NILF	1	6	3	3	7	5	5	5	3	7

Notes: † includes those with post-graduate degrees. ‡ includes Certificate I/II and those with less than Year 11.

In the case of female casuals, the results are much weaker. Degrees do not confer any advantage in attaining permanency, though they do make it slightly more likely that incumbents will move on to fixed-term employment. There is no association between degrees and destinations outside the labour force.

For workers on fixed-term contracts the results are similar. The best prospects for permanency are found among Year 12 graduates and Certificate III/IV, rather than those with higher qualifications. Among males, degrees holders are just as likely to stay fixed-term as to gain permanency, though for females permanency is more likely than continuing as fixed-term. It's important to keep in mind that many fixed-term employees are working as professionals so the association between continuity and degree holding is not particularly informative.

3.2 Job characteristics

Industry has been defined according to its casual or fixed-term density. The notes below Table 4 show which industry divisions have been allocated to which category, with the general rule being that *low* density refers to below average levels of casualisation / fixed-term employment, *moderate* refers to about average, and *high* refers to considerably above average. Table 4 shows that those industries with high density have the worst outcomes for permanency, particularly for fixed-term employees. The likelihood of staying a casual increases steadily with density for males and jumps suddenly for females in high density industries. Among male fixed-term employees remaining in that category increases as one moves from low to moderate density, while for female fixed-term employees the jump is again from moderate density to high density.

Table 4: Predicted probabilities of labour market status by industry density (%)

	Male			Female		
	Low density†	Moderate density‡	High density⋆	Low density◇	Moderate density♯	High density∗
Casuals						
Permanent	32	29	27	24	25	22
Casual	40	45	49	49	46	54
Fixed-term	6	6	6	7	6	4
Self-employed	7	6	6	4	6	4
Unemployed	6	6	6	3	4	3
NILF	9	8	7	12	13	13
Fixed-term						
Permanent	56	48	50	52	54	43
Casual	4	5	6	8	7	9
Fixed-term	30	37	37	29	28	39
Self-employed	5	4	2	4	3	2
Unemployed	2	2	2	3	2	1
NILF	3	4	3	4	5	5

Notes: † defined as: Mining; Manufacturing; Electricity, Gas, Water and Waste Services; Construction; Wholesale Trade; Information Media and Telecommunications; Financial and Insurance Services; Rental, Hiring and Real Estate Services; Professional, Scientific and Technical Services; Public Administration and Safety; Other Services.
‡ defined as: Agriculture, Forestry and Fishing; Transport, Postal and Warehousing; Education and Training; Health Care and Social Assistance.
⋆ defined as: Retail Trade; Accommodation and Food Services; Administrative and Support Services; Arts and Recreation Services.
◇ defined as: Agriculture, Forestry and Fishing; Mining; Electricity, Gas, Water and Waste Services; Construction; Financial and Insurance Services; Professional, Scientific and Technical Services; Public Administration and Safety; Education and Training; Health Care and Social Assistance.
♯ defined as: Manufacturing; Wholesale Trade; Transport, Postal and Warehousing; Information Media and Telecommunications; Rental, Hiring and Real Estate Services; Administrative and Support Services; Other Services.
∗ defined as: Retail Trade; Accommodation and Food Services; Arts and Recreation Services.

The results for earnings quintiles suggest little variation in outcome. When it comes to organisational size, the results suggest that male casuals have better prospects for permanency if they work for large organisations. However, among female casuals their destination patterns do not differ according to organisational size. On the other hand, among female fixed-term employees, being employed in a large organisation does favour permanency.

The results for hours of work are dramatic. As Table 5 shows, the prospects of a full-time casual gaining permanent employment in the following year are nearly 10 percentage points higher than for a part-time casual. This applies to both men and women. Among male fixed-term employees, the advantage conferred on full-timers is even higher: 17 percentage points. Vulnerability to subsequent joblessness is also higher among part-time casuals, particularly men. Some 17 per cent of male part-time casuals face this prospect compared to 11 per cent of male full-time casuals.

Table 5: Predicted probabilities of labour market status by hours of work (%)

	Casuals				Fixed-term			
	Male		Female		Male		Female	
	Full-time	Part-time	Full-time	Part-time	Full-time	Part-time	Full-time	Part-time
Permanent	34	25	31	22	53	36	52	43
Casual	42	46	45	51	4	14	6	13
Fixed-term	7	5	7	6	35	32	34	32
Self-employed	6	8	5	5	4	10	3	3
Unemployed	6	6	3	4	2	5	2	2
NILF	5	11	9	13	3	4	4	6

One of the more common criticisms levelled at casual jobs is that they are often 'dead-end' jobs. While not necessarily boring or repetitive, 'dead-end' jobs lead nowhere because they offer no prospects for a worker to enlarge their capacities. One useful measure of this is the question in the HILDA self-completion questionnaire which asked respondents about their opportunity to learn new skills in a job. For male casuals the skills content of the job does have implications for its incumbent. As one moves along the scale measuring this potential, the probability of attaining permanency in the following year rises steadily. At the same time, the probability of staying in a casual job, or ending up outside the labour force, also declines. The results are similar for women, but weaker in strength. By way of contrast, the potential skills of fixed-term jobs is largely irrelevant because fixed-term jobs are already relatively high in skills content.

3.3 Aspects of locality

As well as the characteristics of the job, an individual's locality also makes a difference. Areas with higher unemployment rates provide fewer employment opportunities for local residents. Such areas are also characterised by greater levels of social disadvantage in a broader sense. The higher an area's unemployment rate (on a standardised scale) the worse are the prospects of gaining permanent employment. This applies to both males and females, and to both casuals and fixed-term employees. Instead, staying a casual, or staying fixed-term, is much more likely in these areas.

A more direct measure of social disadvantage can be found in the SEIFA indices which measure the economic resources of households at an area level (things like income, expenditure, assets, dwelling size).[9] These indices are also associated with labour market outcomes, though these effects are almost exclusively confined to casuals. As one moves to higher levels of the SEIFA index (again on a standardised scale), the probability of staying in a casual job drops, and the probability of moving into a permanent job increases. This association is stronger for women than for men in terms of moving to permanency, but stronger for men than for women in terms of escaping casual jobs.

The social support networks in which people live also shape their labour market prospects.[10] This can happen at a personal level, in the sense that support and encouragement can assist with confidence. It can happen in practical ways in that job openings are mediated through personal networks. In a more general sense, such networks are also an indicator of the depth of social capital in neighbourhoods. The modelling showed that male casuals, in particular, benefit from social support networks, with their probability of moving to permanent jobs being higher with greater degrees of social support. Their likelihood of remaining casual, or becoming jobless, also declines with more social support. For female casuals the effect is much weaker, as it is with female fixed-term employees.

3.4 Cumulative effects

Many of the factors considered in the exposition above do not operate in isolation. While regression analysis is useful for gauging the *net effect* of a particular factor of interest, in practice the situation is more likely to be cumulative. This can be illustrated with cameos, where a number of factors are combined in their more likely combinations and a combined probability calculated. This is done in Table 6 which illustrates the impact of locality and job characteristics. It does this by combining the three measures of locality just discussed and highlighting the difference by contrasting 'unfavourable' and 'favourable' combinations of factors. In other words, comparing a locality with a high unemployment rate, low SEIFA score and low social support networks, with a locality with the opposite characteristics. In the real world, the contrast will not be this stark, but the contrast illustrated here shows what the 'outer boundaries' are likely to be. The same contrast is done with job characteristics: a job with part-time hours, in a small organisation, at the lowest level of pay and with low opportunities for skill, is contrasted with its opposite.

Table 6: Predicted probabilities of labour market status for contrasting cameos (%)

	Casuals				Fixed-term			
	Male		Female		Male		Female	
	Unfav	Fav	Unfav	Fav	Unfav	Fav	Unfav	Fav
Locality								
Permanent	21	36	13	34	44	57	35	58
Casual	55	32	58	41	3	5	19	4
Fixed-term	3	10	4	6	33	33	36	27
Self-employed	3	13	4	6	8	2	6	2
Unemployed	8	3	7	2	3	1	1	2
NILF	11	6	14	11	9	1	3	6
Job characteristics								
Permanent	16	37	14	34	30	53	34	48
Casual	48	42	54	43	28	2	20	7
Fixed-term	4	8	1	11	22	35	29	33
Self-employed	11	4	8	4	15	4	11	4
Unemployed	7	4	4	2	1	1	1	3
NILF	14	4	18	7	4	4	5	4

Notes: Unfav = unfavourable combination of factors; fav = favourable combination of factors.
For locality, unfavourable means high unemployment rate, low SEIFA index and low social support score. Favourable means the opposite. For job characteristics, unfavourable means part-time hours, working in a small organisation, being in the bottom earnings quintile, and having the lowest opportunity to learn new skills. Favourable means the opposite.

As the top panel in Table 6 shows, the prospects for permanency among male casuals jump from 21 per cent to 36 per cent as one moves from an 'unfavourable' to 'favourable' locality and among female casuals the increase is even greater, from 13 per cent to 34 per cent. Not only are prospects for casualisation greater in the 'unfavourable' localities, but joblessness is also much more likely: 19 per cent for male casuals and 21 per cent for female casuals. The equivalent figures are about half this in the 'favourable' localities. Fixed-term employment departs from this pattern. While there is a similar contrast in terms of permanency (but weaker in strength), there is no change in the fixed-term outcome among males. Only among women does the fixed-term destination fall as one moves from 'unfavourable' to 'favourable' localities.

The results of the cameo for job characteristics also illustrate a sharp difference between 'unfavourable' and 'favourable' combinations. Those male casuals in 'unfavourable' jobs have only a 16 per cent probability in the following year of gaining permanency in employment and a 21 per cent probability of ending up jobless. Self-employment—possibility a form of hidden unemployment—is also more likely for this group. By contrast, male casuals in 'favourable' jobs have a 37 per cent probability of getting permanent jobs and only an 8 per cent probability of joblessness. The pattern for female casuals in 'unfavourable' jobs closely follows that of the male pattern, though with self-employment less likely and remaining in casual jobs somewhat higher.

As with the locality cameo, fixed-term employees also depart from the pattern found with casuals. Certainly their prospects for permanency increase as one moves from the 'unfavourable' to the 'favourable' category, but their likelihood of remaining fixed-term in the following year actually *increases*, whereas among casuals continuation in that category falls. What seems to be happening is that the other destination categories—ending up in casual jobs or in self-employment—fall away as one moves from the 'unfavourable' to the 'favourable' combination of job factors. These findings are consistent with the fact that fixed-term employment is dominated by professional and managerial jobs.

3.5 Conclusion

These various results defy an easy human capital explanation and suggest a difficult conundrum for conventional analysis. On the one hand, increasing age reduces the prospects of good outcomes, such as permanency, and makes it more likely casuals will either stay casual, or enter joblessness. At the same time, years in paid employment have the opposite effect. Ordinarily, the latter is conceptualised as 'experience' in a human capital framework, and is often operationalised by the recourse to age (when no other direct measure is available.) Here they have opposite effects, and are not correlated at all. At the same time, education, the other key human capital variable, has an impact on improving good outcomes only for male casuals, and only at certain levels.

Overall, the education results fly in the face of current policy wisdom which entreats young people to stay in the education system as long as possible. While further education may reduce the prospects of initially entering casual employment—something not analysed in this current research—it only has limited value in helping people escape casual employment.

One explanation for these intriguing results lies in reconceptualising casualised labour markets, and recognising that they exist as a secondary labour market in their own right, with their own dynamics and their own internal system of regulation. One unspoken convention in the labour market is that by a certain age, 'good workers' will have settled into a career path and their increasing maturity will see them consolidating the advantages of incumbency, such as higher earnings and promotions. But for casual workers this axiom does not apply: to be in a casual job in one's mature years signals 'failure'. As many retrenched workers have found—and the workforce laid off by the clothing maker Bonds exemplify this—such a judgment may apply even if the current casual job was preceded by decades of permanent employment. In other words, *the casual job itself turns age into a liability*.

On the other hand, years in paid employment ('experience') is definitely an asset. The reason this does not correspond to increasing age is because it actually represents continuity of employment. Extended periods of casual employment usually mean an intermittent labour market history, with periods in and out of joblessness. Such a history makes gaining a permanent job much harder, because the work-based networks which assist such a transition are continually disrupted by such intermittency. Even if the prior employment was in casual work, the continuity makes a difference. Earlier modelling work (not shown in this article) suggested that the lagged-employment state also made a difference to the employment state in the following year. In other words, those casuals who had been employed in the prior year, whether casual or permanent, had better prospects in the following year than those who had been jobless. It is patterns like these which lie behind the adage 'any job is better than unemployment', a sentiment which lies behind the welfare-to-work policies of many neo-liberal governments. The point that it illustrates, in this analysis, is that continuing attachment to employment is a major asset, but that *by their very nature, casual jobs constantly undermine this attachment*. For many workers, particularly women who have left the labour market to undertake parenting, the only prospects for re-entry into jobs is via casual employment, particularly if they seek part-time hours. The intermittency here is based on transitions between such casual jobs and the NILF category, rather than cycling through unemployment. Clearly, greater opportunities for permanent part-time employment would help break this intermittency.

As noted earlier, job tenure had no appreciable influence on the results. In human capital terms, years in *employment* represent 'general experience and skills' whereas *job* tenure represents 'firm specific experience and skills'. Clearly, in casualised labour markets a worker's job tenure record may have no value to employers, if value is measured in terms of granting permanency. That such transitions are meant to happen lies behind the notion that casual jobs can provide probationary periods for employees. Yet here we see casuals kept on indefinitely, but with no progression to permanency. They have presumably passed their 'probation', but their career prospects have not improved. The most likely explanation lies in the nature of the job: these are the casual jobs which are not intended to ever become permanent jobs. Keeping a reservoir of casual jobs is clearly part of the employment strategies of many firms.

The results for hours of work exemplify the commodification of labour power which is implicit in the casual labour market. Labour market researchers often despair at the layperson's loose use of language when 'casual' and 'part-time' are used interchangeably. For researchers, these represent two separate dimensions: mode of engagement and working hours. Yet the layperson's view is probably closer to the reality that the two are really interchangeable. With the easy availability of *permanent part-time* work a rarity, anyone seeking part-time hours must usually make do with accepting a casual job. From the employer side, seeking part-time workers generally means seeking casual employees. Not only is this 'flexible' employment strategy focussed on buying smallish chunks of labour power, but it also aims to buy the ability to turn such labour power on and off with ease.

In terms of the bridge / trap debate, the unconditional probabilities outlined at the beginning of this section suggest that the conclusion drawn depends on how one evaluates the labour market outcomes. The bridge metaphor weighs up permanent outcomes against the avoidance of joblessness: more casuals end up in permanent jobs than jobless. By contrast, the trap metaphor emphasises the patterns of continuing casualisation and intermittent joblessness experienced by most casual workers. In looking at the conditional probabilities, on the other hand, it is clear that the characteristics of casuals jobs, in themselves, are a major factor in perpetuating this kind of work. It seems reasonable to conclude that casual jobs do indeed operate as labour market traps, and they are actually crafted to do so.

Appendix tables

Table 7: Model estimates and standard errors (in parentheses) for male casuals

Variable	Permanent		Fixed-term		Self-employed		Unemployed		NILF	
	Outcome in following year (base: casual)									
Aged 15-24	0.651	(0.302)	0.631	(0.619)	-0.634	(0.709)	-0.040	(0.498)	-0.289	(0.564)
Aged 25-29	0.435	(0.286)	-0.073	(0.598)	-0.187	(0.647)	-0.217	(0.504)	-0.224	(0.574)
Aged 30-34	0.208	(0.266)	0.238	(0.529)	-0.281	(0.574)	-0.336	(0.500)	0.289	(0.542)
Aged 35-39	0.505	(0.238)	0.275	(0.481)	-0.295	(0.506)	-0.164	(0.482)	-0.337	(0.576)
Aged 45-49	0.161	(0.255)	-1.117	(0.666)	-0.400	(0.499)	-0.119	(0.537)	0.335	(0.562)
Aged 50-54	-0.737	(0.307)	-1.013	(0.636)	-2.095	(0.703)	0.122	(0.602)	0.755	(0.605)
Aged 55-59	-1.317	(0.366)	-0.937	(0.716)	-1.878	(0.747)	0.421	(0.669)	1.393	(0.645)
Aged 60-64	-1.292	(0.422)	-1.351	(0.847)	-2.163	(0.898)	-0.505	(0.973)	2.500	(0.719)
Degree or above	0.521	(0.220)	1.037	(0.394)	0.370	(0.566)	0.132	(0.480)	-0.264	(0.434)
Adv dip/diploma	-0.049	(0.279)	-0.040	(0.546)	1.372	(0.636)	0.890	(0.489)	0.192	(0.515)
Cert III/IV	0.181	(0.180)	-0.220	(0.373)	1.260	(0.472)	0.349	(0.355)	-0.004	(0.359)
Cert I/II, Year 11 <	-0.184	(0.165)	-0.591	(0.346)	-0.156	(0.454)	0.619	(0.300)	-0.151	(0.323)
Years in paid employment	0.543	(0.344)	0.290	(0.725)	2.000	(0.845)	-1.355	(0.559)	-1.272	(0.550)
Years of job tenure	-0.028	(0.138)	0.297	(0.227)	0.008	(0.259)	-0.697	(0.439)	0.496	(0.183)
Long-term health prob	-0.227	(0.142)	-0.071	(0.290)	0.014	(0.311)	-0.105	(0.263)	0.960	(0.239)
SEIFA of local area	0.196	(0.117)	0.415	(0.234)	0.475	(0.279)	-0.268	(0.228)	0.322	(0.230)
Local unemployment rate	-0.203	(0.111)	-0.227	(0.226)	-0.767	(0.285)	-0.099	(0.211)	0.207	(0.217)
Level of social support	0.242	(0.109)	0.534	(0.239)	0.104	(0.264)	-0.122	(0.187)	-0.055	(0.211)
Learn new skills in job	0.335	(0.121)	0.227	(0.245)	-0.134	(0.286)	0.230	(0.231)	-0.379	(0.234)
Part-time hours	-0.515	(0.120)	-0.725	(0.247)	0.536	(0.283)	-0.020	(0.219)	0.972	(0.257)
Bottom earnings quintile	0.067	(0.158)	0.194	(0.324)	-0.333	(0.373)	0.329	(0.285)	0.464	(0.313)
Second earnings quintile	0.051	(0.150)	-0.325	(0.337)	-0.586	(0.359)	-0.122	(0.295)	0.249	(0.314)
Fourth earnings quintile	-0.038	(0.182)	0.604	(0.346)	-0.386	(0.411)	-0.258	(0.389)	0.162	(0.373)
Top earnings quintile	-0.375	(0.197)	-0.057	(0.381)	-0.105	(0.413)	-0.463	(0.427)	0.197	(0.384)
Industry: mod density	-0.244	(0.137)	-0.130	(0.278)	-0.276	(0.319)	-0.139	(0.255)	-0.183	(0.261)
Industry: high density	-0.411	(0.140)	-0.263	(0.285)	-0.575	(0.332)	-0.276	(0.256)	-0.577	(0.269)
Small organisation	-0.198	(0.117)	-0.268	(0.242)	1.645	(0.299)	0.133	(0.212)	0.453	(0.225)
Intercept	-0.012	(0.265)	-2.274	(0.594)	-3.951	(0.840)	-3.023	(0.583)	-3.910	(0.723)
SD random effects	0.851	(0.122)	1.803	(0.391)	2.251	(0.548)	1.285	(0.415)	1.755	(0.447)
Correlations*	Fixed	Self	Un	NILF						
Permanent by	-0.85	0.12	-0.32	-0.41						
Fixed-term by		-0.61	-0.01	0.02						
Self-emp by			0.27	0.68						
Unemp by				0.07						
No. observations†	2,731									
No. 'groups'‡	1,434									
Log likelihood	-3397									
LR chi-squared	2994									
McFadden Pseudo $R^2\star$	0.31									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws. Note that all the continuous regressors have been fitted as standardised values (see the discussion in the footnote text on page 20), including those whose predicted probabilities were presented as years (eg. paid employment, job tenure.)

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ As is well known, pseudo R-squared is not analogous to R-squared in linear regression, and is regarded as uninformative by some authors (Long 1997: 102). Others see value in the McFadden version and have established an empirical mapping between the two measures. In this context, a pseudo R-squared of 0.3 for a MNL model is equal to approximately 0.6 for a linear regression model and indicates 'a decent model fit' (Hensher et al. 2005: 338).

Omitted categories: Aged 40–44; Year 12; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Male casuals aged 15 to 64, excluding full-time students.

Table 8: Model estimates and standard errors (in parentheses) for female casuals

Variable	Permanent		Fixed-term		Self-employed		Unemployed		NILF	
	Outcome in following year (base: casual)									
Aged 15-24	0.932	(0.226)	0.303	(0.375)	0.059	(0.487)	0.308	(0.453)	1.161	(0.276)
Aged 25-29	0.715	(0.222)	0.372	(0.359)	0.064	(0.453)	-0.321	(0.504)	0.989	(0.268)
Aged 30-34	0.627	(0.197)	-0.216	(0.350)	-0.260	(0.410)	-0.180	(0.456)	0.992	(0.242)
Aged 35-39	0.430	(0.173)	0.051	(0.293)	0.433	(0.323)	-0.181	(0.408)	0.285	(0.234)
Aged 45-49	-0.113	(0.174)	0.194	(0.272)	0.386	(0.323)	0.292	(0.389)	0.373	(0.233)
Aged 50-54	0.062	(0.205)	-0.064	(0.346)	-0.413	(0.439)	0.405	(0.472)	0.823	(0.248)
Aged 55-59	-0.100	(0.245)	-0.403	(0.443)	-0.636	(0.552)	-0.128	(0.612)	1.060	(0.277)
Aged 60-64	-0.393	(0.343)	-1.172	(0.795)	0.108	(0.640)	-0.267	(0.925)	1.823	(0.325)
Sep/div/widowed	0.048	(0.151)	0.186	(0.248)	-0.712	(0.348)	0.646	(0.310)	-0.152	(0.175)
Never married	0.131	(0.141)	0.024	(0.237)	-0.575	(0.329)	0.055	(0.289)	-0.631	(0.180)
One child 0-4 years old	-0.008	(0.144)	-0.301	(0.264)	0.330	(0.282)	-0.184	(0.328)	0.599	(0.158)
Two or more child 0-4	-0.186	(0.240)	-0.223	(0.420)	0.745	(0.406)	0.045	(0.533)	0.505	(0.248)
Degree or above	-0.060	(0.166)	1.195	(0.273)	0.547	(0.331)	-0.115	(0.391)	0.398	(0.200)
Adv dip/diploma	-0.229	(0.206)	0.942	(0.325)	0.377	(0.394)	-0.540	(0.530)	0.118	(0.248)
Cert III/IV	-0.057	(0.157)	0.386	(0.285)	0.089	(0.332)	-0.195	(0.332)	0.082	(0.192)
Cert I/II, Year 11 <	-0.144	(0.136)	-0.205	(0.268)	-0.449	(0.296)	0.046	(0.277)	0.131	(0.163)
Born ESB	0.276	(0.176)	-0.227	(0.320)	-0.100	(0.369)	0.216	(0.410)	-0.000	(0.217)
Born NESB	0.099	(0.166)	-0.592	(0.318)	0.183	(0.319)	-0.279	(0.403)	0.457	(0.183)
Years in paid employment	0.251	(0.174)	-0.283	(0.293)	0.213	(0.350)	-1.255	(0.374)	-0.208	(0.183)
Years of job tenure	-0.190	(0.109)	-0.290	(0.184)	-0.088	(0.212)	-1.856	(0.526)	-0.247	(0.129)
Long-term health prob	-0.038	(0.122)	0.111	(0.209)	0.110	(0.256)	0.364	(0.242)	0.319	(0.136)
SEIFA of local area	0.289	(0.102)	-0.105	(0.172)	0.315	(0.210)	0.054	(0.224)	-0.085	(0.121)
Local unemployment rate	-0.317	(0.095)	-0.126	(0.165)	-0.239	(0.197)	0.153	(0.206)	-0.115	(0.111)
Level of social support	0.143	(0.091)	0.330	(0.173)	-0.042	(0.185)	-0.350	(0.176)	-0.010	(0.107)
Learn new skills in job	0.275	(0.099)	0.301	(0.174)	-0.107	(0.209)	0.210	(0.219)	-0.178	(0.118)
Part-time hours	-0.583	(0.120)	-0.456	(0.200)	-0.259	(0.276)	0.052	(0.273)	0.208	(0.172)
Bottom earnings quintile	-0.169	(0.130)	-0.467	(0.220)	0.520	(0.282)	0.775	(0.306)	0.086	(0.152)
Second earnings quintile	-0.046	(0.127)	-0.878	(0.239)	-0.217	(0.301)	0.447	(0.314)	-0.139	(0.157)
Fourth earnings quintile	0.118	(0.153)	-0.444	(0.258)	0.312	(0.339)	0.199	(0.410)	-0.127	(0.198)
Top earnings quintile	-0.250	(0.176)	-0.618	(0.264)	0.539	(0.336)	-0.502	(0.534)	-0.125	(0.207)
Industry: mod density	0.080	(0.127)	-0.210	(0.220)	0.445	(0.249)	0.284	(0.280)	0.152	(0.150)
Industry: high density	-0.236	(0.117)	-0.858	(0.220)	-0.218	(0.255)	-0.122	(0.259)	-0.116	(0.140)
Small organisation	-0.178	(0.100)	-0.941	(0.209)	0.955	(0.199)	-0.316	(0.220)	0.286	(0.114)
Intercept	-0.536	(0.229)	-1.488	(0.388)	-3.737	(0.561)	-4.506	(0.704)	-2.752	(0.321)
SD random effects	0.989	(0.107)	1.248	(0.363)	1.751	(0.312)	1.523	(0.935)	0.951	(0.439)
Correlations*	Fixed	Self	Un	NILF						
Permanent by	-0.51	-0.22	-0.04	-0.39						
Fixed-term by		0.86	0.23	0.88						
Self-emp by			-0.16	0.77						
Unemp by				0.03						
No. observations†	4,725									
No. 'groups'‡	2,192									
Log likelihood	-5710									
LR chi-squared	5512									
McFadden Pseudo $R^2\star$	0.33									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws.

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ See note to Table 7.

Omitted categories: Aged 40–44; Married/defacto; No children 0–4 years old; Year 12; Born in Australia; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Female casuals aged 15 to 64, excluding full-time students.

Table 9: Model estimates and standard errors (in parentheses) for male fixed-term

	Outcome in following year (base: fixed-term)									
Variable	Casual		Permanent		Self-employed		Unemployed		NILF	
Aged 15-24	0.547	(0.863)	-0.175	(0.417)	-1.238	(0.850)	-0.106	(1.362)	3.461	(11.644)
Aged 25-29	1.022	(0.740)	0.520	(0.376)	-0.479	(0.755)	1.159	(1.273)	11.706	(11.895)
Aged 30-34	-0.489	(0.691)	0.321	(0.324)	-0.130	(0.609)	0.716	(1.278)	11.428	(12.514)
Aged 35-39	-0.169	(0.593)	0.601	(0.293)	0.480	(0.512)	1.706	(1.172)	3.050	(8.888)
Aged 45-49	-1.207	(0.779)	0.320	(0.299)	-0.113	(0.562)	2.386	(1.189)	5.038	(9.329)
Aged 50-54	-0.592	(0.739)	-0.291	(0.355)	-1.130	(0.757)	1.293	(1.393)	27.115	(22.325)
Aged 55-59	-0.933	(0.904)	-0.334	(0.421)	-0.411	(0.819)	1.061	(1.634)	49.166	(37.844)
Aged 60-64	-2.002	(1.233)	-0.821	(0.596)	-1.041	(1.113)	1.759	(1.855)	42.284	(36.055)
Degree or above	-0.012	(0.538)	-1.045	(0.262)	-0.162	(0.561)	-1.032	(0.736)	-16.570	(14.737)
Adv dip/diploma	0.823	(0.675)	-0.383	(0.336)	0.420	(0.677)	0.097	(0.907)	15.910	(12.901)
Cert III/IV	0.679	(0.509)	0.011	(0.254)	0.130	(0.538)	0.051	(0.672)	-0.880	(4.971)
Cert I/II, Year 11 <	1.495	(0.530)	0.002	(0.281)	0.486	(0.575)	-0.080	(0.788)	20.039	(11.621)
Years in paid employment	0.433	(0.883)	0.050	(0.396)	0.342	(0.782)	-1.313	(0.916)	-9.165	(8.925)
Years of job tenure	-0.125	(0.364)	0.579	(0.168)	-0.010	(0.334)	0.141	(0.521)	-3.604	(4.787)
Long-term health prob	0.549	(0.378)	0.079	(0.208)	0.842	(0.375)	0.800	(0.549)	16.367	(9.079)
SEIFA of local area	-0.395	(0.315)	-0.057	(0.163)	0.040	(0.331)	0.305	(0.483)	-9.279	(7.443)
Local unemployment rate	-0.285	(0.293)	-0.198	(0.145)	0.271	(0.294)	0.068	(0.445)	2.052	(2.379)
Level of social support	0.157	(0.286)	-0.007	(0.143)	-0.623	(0.290)	-0.877	(0.386)	-12.220	(6.561)
Learn new skills in job	-0.178	(0.297)	-0.133	(0.160)	-0.401	(0.309)	-0.164	(0.489)	-1.874	(3.132)
Part-time hours	1.887	(0.452)	-0.506	(0.294)	1.434	(0.473)	1.740	(0.649)	3.862	(3.165)
Bottom earnings quintile	-0.254	(0.482)	-0.297	(0.278)	0.908	(0.598)	0.268	(0.816)	11.271	(7.196)
Second earnings quintile	-0.563	(0.467)	0.037	(0.242)	0.737	(0.542)	0.372	(0.684)	-14.937	(10.465)
Fourth earnings quintile	-0.688	(0.469)	-0.000	(0.221)	0.370	(0.546)	-0.343	(0.722)	6.308	(6.344)
Top earnings quintile	-0.499	(0.426)	-0.331	(0.219)	0.729	(0.515)	-0.333	(0.673)	12.452	(11.098)
Industry: mod density	0.123	(0.385)	-0.467	(0.191)	-0.463	(0.378)	-0.201	(0.528)	7.385	(6.064)
Industry: high density	0.266	(0.439)	-0.402	(0.220)	-1.274	(0.517)	-0.434	(0.655)	3.809	(8.927)
Small organisation	0.991	(0.364)	0.257	(0.213)	1.139	(0.365)	-1.656	(1.081)	-6.018	(5.645)
Intercept	-3.410	(1.017)	1.182	(0.365)	-3.148	(0.962)	-4.495	(1.587)	-106.572	(66.904)
SD random effects	1.269	(0.506)	1.301	(0.144)	1.448	(0.652)	1.647	(0.861)	41.451	(20.460)
Correlations*	Perm	Self	Un	NILF						
Casual by	-0.07	0.52	0.80	-0.01						
Permanent by		-0.20	-0.38	0.32						
Self-emp by			0.09	-0.67						
Unemp by				0.12						
No. observations†	1,849									
No. 'groups'‡	1,104									
Log likelihood	-1891									
LR chi-squared	2843									
McFadden Pseudo R^2⋆	0.43									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws.

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ See note to Table 7.

Omitted categories: Aged 40–44; Year 12; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Male fixed-term employees aged 15 to 64, excluding full-time students.

Table 10: Model estimates and standard errors (in parentheses) for female fixed-term

Variable	Outcome in following year (base: fixed-term)									
	Casual		Permanent		Self-employed		Unemployed		NILF	
Aged 15-24	1.312	(0.595)	0.937	(0.367)	-0.619	(0.998)	3.122	(1.263)	1.024	(0.661)
Aged 25-29	1.035	(0.525)	0.284	(0.314)	-0.667	(0.810)	0.257	(1.523)	0.695	(0.555)
Aged 30-34	-0.335	(0.575)	0.022	(0.293)	-0.525	(0.761)	1.964	(1.206)	0.956	(0.501)
Aged 35-39	0.048	(0.459)	0.257	(0.250)	-0.727	(0.714)	1.043	(1.267)	0.645	(0.462)
Aged 45-49	0.706	(0.410)	-0.182	(0.245)	0.298	(0.632)	1.666	(1.147)	0.195	(0.492)
Aged 50-54	0.196	(0.508)	-0.622	(0.303)	-0.300	(0.784)	2.278	(1.160)	0.248	(0.557)
Aged 55-59	0.516	(0.641)	-0.221	(0.392)	1.289	(0.857)	2.544	(1.326)	0.864	(0.682)
Aged 60-64	2.020	(0.831)	0.217	(0.588)	1.598	(1.268)	2.805	(1.675)	1.771	(0.858)
Sep/div/widowed	0.309	(0.356)	0.080	(0.221)	-1.048	(0.667)	1.076	(0.529)	-0.037	(0.388)
Never married	0.662	(0.335)	0.081	(0.203)	-1.309	(0.669)	-0.059	(0.538)	-0.899	(0.428)
One child 0-4 years old	-0.727	(0.555)	0.390	(0.272)	1.617	(0.617)	0.207	(0.829)	0.776	(0.394)
Two or more child 0-4	-49.855	(0.000)	0.446	(0.465)	-0.228	(1.292)	0.780	(1.246)	1.178	(0.601)
Degree or above	-0.362	(0.410)	-0.491	(0.246)	-0.079	(0.646)	-0.487	(0.614)	-0.365	(0.423)
Adv dip/diploma	0.419	(0.496)	-0.056	(0.312)	0.427	(0.755)	0.335	(0.740)	-0.015	(0.539)
Cert III/IV	0.045	(0.459)	-0.152	(0.283)	0.092	(0.725)	-0.133	(0.633)	-0.547	(0.527)
Cert I/II, Year 11 <	0.195	(0.451)	-0.166	(0.280)	-0.408	(0.727)	-0.470	(0.664)	0.339	(0.455)
Born ESB	-0.419	(0.410)	-0.333	(0.240)	-1.121	(0.686)	-0.343	(0.638)	-0.224	(0.401)
Born NESB	0.247	(0.467)	0.324	(0.285)	0.212	(0.623)	-0.775	(1.087)	0.524	(0.449)
Years in paid employment	-0.211	(0.464)	0.109	(0.290)	-0.501	(0.637)	-0.378	(0.716)	-0.517	(0.466)
Years of job tenure	-0.067	(0.267)	0.435	(0.161)	-0.189	(0.494)	-0.710	(0.620)	0.146	(0.287)
Long-term health prob	0.424	(0.295)	0.182	(0.192)	-0.422	(0.600)	0.409	(0.469)	0.794	(0.310)
SEIFA of local area	-0.399	(0.252)	-0.002	(0.155)	0.211	(0.408)	0.096	(0.430)	-0.032	(0.265)
Local unemployment rate	0.139	(0.251)	-0.415	(0.145)	-0.257	(0.399)	-0.533	(0.409)	-0.430	(0.260)
Level of social support	-0.350	(0.212)	-0.015	(0.137)	-0.746	(0.322)	-0.150	(0.348)	0.034	(0.254)
Learn new skills in job	-0.061	(0.246)	-0.248	(0.147)	-1.102	(0.374)	0.211	(0.412)	-0.486	(0.249)
Part-time hours	1.136	(0.273)	-0.203	(0.161)	-0.120	(0.414)	0.383	(0.420)	0.378	(0.270)
Bottom earnings quintile	0.205	(0.397)	0.281	(0.252)	0.616	(0.665)	1.749	(0.711)	0.320	(0.479)
Second earnings quintile	0.028	(0.343)	0.570	(0.198)	0.486	(0.620)	1.438	(0.666)	0.479	(0.381)
Fourth earnings quintile	-0.111	(0.329)	-0.062	(0.185)	0.226	(0.614)	0.994	(0.667)	0.425	(0.353)
Top earnings quintile	0.433	(0.362)	-0.082	(0.216)	1.348	(0.567)	0.987	(0.747)	0.613	(0.378)
Industry: mod density	-0.020	(0.331)	0.093	(0.200)	-0.308	(0.482)	-0.273	(0.477)	0.049	(0.361)
Industry: high density	-0.100	(0.350)	-0.682	(0.211)	-1.357	(0.556)	-1.342	(0.564)	-0.291	(0.368)
Small organisation	0.609	(0.320)	-0.135	(0.209)	1.628	(0.424)	-0.786	(0.617)	-0.381	(0.389)
Intercept	-3.313	(0.780)	0.875	(0.344)	-3.147	(1.058)	-5.623	(1.444)	-2.996	(0.699)
SD random effects	1.604	(0.358)	1.322	(0.274)	2.156	(0.512)	1.234	(0.572)	1.209	(0.372)
Correlations*	Perm	Self	Un	NILF						
Casual by	-0.33	0.17	0.62	0.52						
Permanent by		0.86	0.52	0.63						
Self-emp by			0.87	0.93						
Unemp by				0.99						
No. observations†	2,008									
No. 'groups'‡	1,205									
Log likelihood	-2297									
LR chi-squared	2885									
McFadden Pseudo R^2⋆	0.39									

Notes: Random intercept multinomial logit model with estimation by maximum simulated likelihood (MSL) estimation using 250 Halton draws.

SD random effects = standard deviation of the random effects.

∗ correlations of the random intercepts.

† 'occasions', that is, individuals by years. ‡ separate individuals.

⋆ See note to Table 7.

Omitted categories: Aged 40–44; Married/defacto; No children 0–4 years old; Year 12; Born in Australia; No long-term health condition; Full-time hours; Middle earnings quintile; Industry: low density; Large organisation.

Source: HILDA Release 9.

Population: Female fixed-term employees aged 15 to 64, excluding full-time students.

Notes

1. I'd like to thank Hielke Buddelmeyer for generously making available his unpublished modeling results and computer code. This article benefited from the feedback of a number of people and I'd like to thank: Caroline Alcorso, Grant Belchamber, Murray Goot, Humphrey McQueen, Frank Stilwell, and two anonymous referees. An earlier version of this article was presented at the 2012 CofFEE Conference, Newcastle.

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2. The ABS Survey of Employment and Unemployment Patterns, conducted between 1994 and 1997 as part of the data collection to accompany the Commonwealth Government's *Working Nation* program.

3. An earlier analysis by the Productivity Commission (Productivity Commission 2006) also used a multinomial logit approach to model transitions out of casual employment. While it also used HILDA data, it did not make use of panel data methods, such as those used by Buddelmeyer and Wooden (2011) and also used in this article. The Productivity Commission study used only three waves of the HILDA survey and 'stacked' the cross-sectional data to increase the number of observations. While the authors took account of the clustering among repeated observations, their method did not deal with the issue of unobserved heterogeneity, the core advantage of random effects modelling.

4. While there is some information collected on the previous job held by persons not currently employed, it is not comparable to the full set of data items for those currently employed.

5. As Hensher et al. (2005: 84) note, the differences between the normal and the EV1 distribution become important when there are a large number of alternatives, as is the case in this study.

6. For a good introduction to MSL see the special issue of the *Stata Journal* Vol.6, No.2. (2006) which is devoted to this topic. The random intercept MNL models used in this study have been estimated using the *NLOGIT* software which is part of *LIMDEP* (Greene 2007). 250 Halton draws were used for this analysis. The remainder of the analysis for this article has has been conducted in *R* with the plots produced by *ggplot2* (R Development Core Team 2011; Wickham 2009).

7. Also called the 'method of predictive margins'. See *Stata Version 12 Manual* [R] mlogit postestimation, p. 1225.

8. All the continuous measures in this analysis have used standardised scales, following the approach advocated by Gelman and Hill (2007: 56–57). This approach has advantages in modelling the data and interpreting the coefficients. In the case of this line plot, the results have been converted back into years for presentation purposes.

9. SEIFA: 'socio-economic indicators for areas' are constructed by the ABS and based on the 2001 Census.

10. Social support is based on a summation of the questions about friendship, loneliness and access to personal support in the HILDA Self Completion Questionnaire. The final score was standardised for this scale.

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