

UNDEREMPLOYMENT AMONG MATURE AGE WORKERS IN AUSTRALIA^{*}

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ABSTRACT

Underemployment is a serious and pervasive problem both in terms of its impact on those individuals affected, and for the economy as a whole. International research has found that those who experience periods of underemployment are more likely to have lower job satisfaction, higher job turnover, poorer mental and physical health and persistently lower earnings. Labour markets with high rates of underemployment are at risk of underutilisation of important skills. This paper explores the patterns of underemployment for mature aged workers in Australia, and seeks in particular to determine the principal factors that contribute to a heightened risk of underemployment. Importantly, our results point to a significant path dependency whereby previous periods of underemployment increase the propensity towards underemployment in the current period.

Keywords: underemployment; labour supply transitions; baby boomers; mature aged workers

JEL classifications: J01, J11 and J21

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This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (the Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either 'FaHCSIA or the Melbourne Institute.

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I. Introduction

Population ageing has been a continuing debate in Australia. Australia Bureau of Statistics (ABS) predicts that the proportion of Australians aged over 65 will grow to more than 20 per cent of the population by 2050, roughly double the current level. This means there will be a declining number of Australians in the labour force and placing ever greater pressure on government resources. A number of solutions to this labour shortage have been put forward and discussed. The Intergenerational Report by Treasury (2010) suggests that an increase in labour market participation rates among mature age Australians may serve as one mechanism to alleviate these burdens. However, understanding mature age labour force participation is complex, with many mature age Australians under-participating or non-participating in the labour market due to various factors.

As a cohort, mature aged workers are relatively vulnerable to periods of involuntary unemployment or underemployment, with previous research suggesting profound differences in both pathways to exit and consequences of exit for this group compared with those who leave the workforce or reduce their attachment by choice (Dorn and Sousa-Poza, 2010; Maes, 2008).

This paper examines labour market transitions for mature age Australians, with a particular focus on those who are under-participating in the labour market. Two key research questions are discussed: first, what are the trajectories leading into and out of underemployment of mature aged workers in Australia? While there have been few studies on underemployment in Australia, such as Wilkins and Wooden (2011), Doiron (2003) etc., none of the studies have carefully examined labour force trajectories leading into and out of this underemployment state. Second, what factors best predict pathways into or out and under-participation in the labour market, and how might one best protect this cohort from underemployment and poor labour market experiences and social outcomes? In addition, the paper also examines the state dependence of underemployment, whether a person who has been underemployed at one particular time is likely to be at risk of underemployed in another time. This paper is the first in Australia to examine underemployment in the context of labour market histories for mature aged workers, and the first to employ hierarchical cluster analysis to identify particular typologies of labour market transitions in this context.

Understanding underemployment is important as underemployment not only may mean lost opportunities for people to fully participate in the labour market and accumulate financial, wealth and personal benefits but also this may create some mental health issue as, not working as many hours as people would have liked may cause distress and depression (Beiser et al., 1993; Johnson and Johnson, 1996) and lower life satisfaction and wellbeing (Feldman and Turnley, 1995; Burke, 1998; Friedland and Price, 2003; Brown et al., 2007; Wilkins, 2007).

Using ten waves of data from the longitudinal HILDA (Household, Income and Labour Dynamics in Australia) survey, the paper tracks a cohort of individuals born between 1951 and 1965, and examines those factors that predict pathways into or out of under-participation in the labour market. Our empirical methods make specific provision for a relationship between previous labour force experiences and current employment outcomes. Hierarchical clustering methods are used to reveal the most common transition patterns prior to and following a period of underemployment. Finally, the paper explores policy options to protect labour market attachment or facilitate labour market re-engagement for this important but often overlooked cohort.

The paper is structured as follows. Following an introduction and a background and motivation, Section 3 examines patterns of underemployment in Australia for our selected cohort using a ten wave longitudinal panel drawn from the HILDA dataset. Section 4 outlines the empirical methodology used to capture the drivers of underemployment among mature aged Australians, with estimation results discussed in Section 5. Finally, Section 6 concludes.

II. *Background and Motivation*

Definition of underemployment

A number of different definitions have been proposed for underemployment. For example, the International Labour Organization (ILO) consider time-related underemployed individuals to fulfil three criteria during the employment reference period (ILO 1998; Hussmanns, 2007).

1. Willing to work additional hours during a reference period; and
2. Available to work additional hours within a specified subsequent period; and
3. Worked less than a threshold relating to working time, to be determined according to 'national circumstances'.

The definition of underemployment adopted in Australia follows this ILO definition time-related underemployment.. The Australian Bureau of Statistics (ABS) underemployment framework uses a threshold of 35 hours in the reference week to differentiate between full-time and part-time work. Similarly in this paper, using HILDA data, defines underemployment as individuals who usually work less than 35 hours per week and would like to work more hours than they currently usually work.¹

Trends and patterns of underemployment

Recent Global Financial Crisis (GFC) 2007-2009, has brought up our attention again towards underemployment rate. Underemployment has been increasingly acknowledged as a measure of underutilisation in the labour market. During the GFC, the unemployment rate in Australia did not rise as much as has been expected during this period, however in terms of the number of hours people worked declined. Underemployment tended to rise during the recession period but only slowly recovered when the macroeconomy has improved. As can be seen in Figure 1, the underemployment rate peaked in August 2009 at 7.9 per cent while the unemployment rate was 5.8 per cent.

The recent Australian Bureau of Statistics (ABS) statistics in August 2012 shows that 7.2 per cent of the labour force was underemployed² with recent (ABS) data showing that the underemployment rate for women in August 2012 was 9.5 per cent compared with 5.4 per cent for men (ABS 2012b), highlighting that the women is likely to be underemployed than men. ABS (2012a) also finds that 60 per cent of 814.700 underemployed part time workers in September 2011 were women.

Nevertheless, the proportion of underemployed part-time males was higher than that for females. While the proportion of male part time employees who were underemployed were 28 per cent, the corresponding proportion for women was 9 percentage points lower.

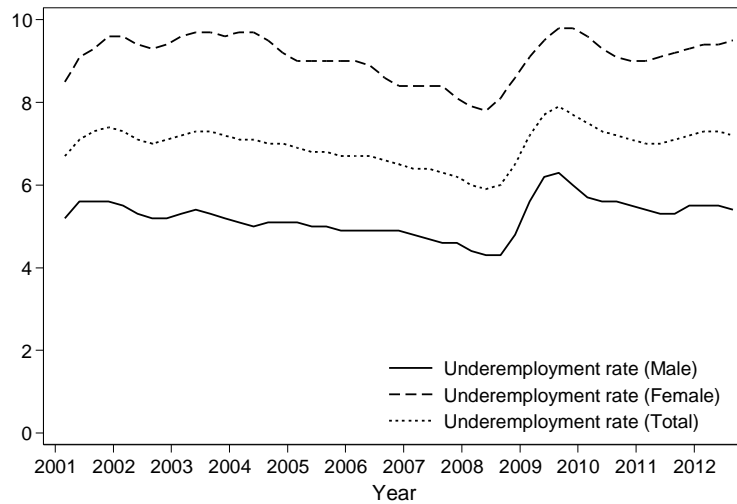
¹ Australian Bureau of Statistics (ABS) defined underemployed workers as either part time workers who would prefer to work more hours and were available to start work with more hours, either in the reference week or in the four weeks following the ABS Labour Force survey or full time workers who worked part time hours in the reference week for economic reasons (such as being stood down or insufficient work being available (ABS 2011). Nevertheless, the statistics collected in the Labour Force Survey since May 2001 only include part-time employees who preferred to work more hours and were available to start work (with those hours) in the reference week or within four weeks.

² Since May 2011, ABS defines underemployment as part-time employees who preferred to work more hours and were available to start work (with those hours) in the reference week or within four weeks. This definition is consistent with the term from ILO.

Underemployment for mature age workers

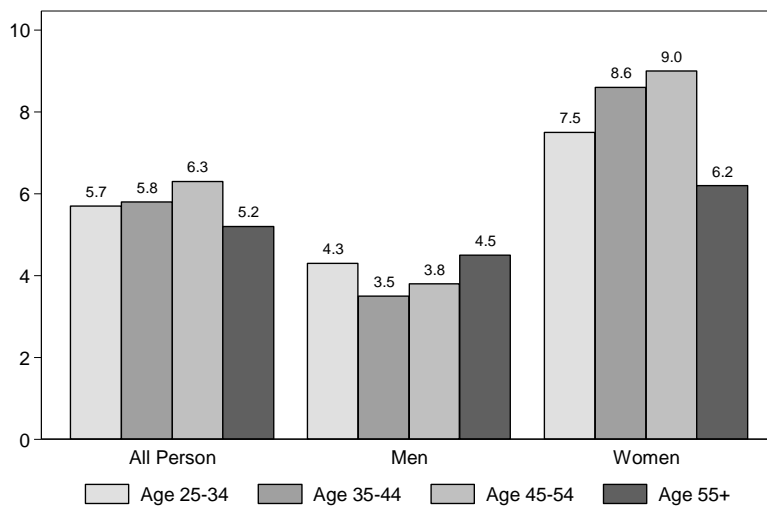
Figure 2 uses ABS data to examine the relationship between underemployment and age for male and female workers in Australia, and reveals significant differences in the pattern of underemployment by age and gender. Underemployment increases clearly with age for women, with the rate of underemployment reaching a high of 9 per cent for women aged between 45 and 55 in August 2012. For men, underemployment is conversely higher at the young age group 25-35 and also for those in the group closer to the retirement age of 55+. Further without gender differentiation, mature older workers, particularly within the age group of 45-54 has experienced higher underemployment rate than the other cohorts.

Figure 1 Trends in Underemployment Rate, 2001-2012



Source: ABS Labour Force Australia, Cat. No 6202.0

Figure 2 Underemployment Rate by Gender and Age, 2012



Source: ABS Labour Force Australia, Cat. No 6202.0

ABS (2012a) discusses that older people also usually experienced a longer duration of underemployment than the younger cohort with 53 per cent of those aged 55 years and over and 45 per cent of those aged 44-54 years were underemployed for one year or more in September 2011.

Determinants of underemployment

Past literature has identified a range of factors considered as determinants of under participation in the labour market. These determinants are closely linked to factors that are considered as barriers for the mature age workers to work. Temple and Adair in the National Seniors report (2012) have indicated some factors, which includes physical illness, injury and disability, discrimination in employment on the basis of age and skill mismatch between supply and demand. Wilkins (2006), has identified personal characteristics associated with underemployment. This includes age, educational attainment, family type, presence of dependent children, place of birth, family background and housing status. For example, in terms of educational attainment, in line with the expectation that people with more human capital is expected to have stronger attachment to labour market, Wilkins (2006) finds that for men, having a diploma degree has reduced the propensity to be underemployed.

Among personal characteristics, migration status comes out as an important factor associated with the likelihood to be underemployed. Wooden (1993) and Flatau et al. (1995) find that immigrants from non-English speaking backgrounds in Australia experience higher underemployment, although for the latter, Flatau et al. (1995) consider underemployment as referring to job mismatch in terms underutilisation of skills and relative pay deprivation. Further, Wilkins (2006) finds some indication that female immigrants are more likely to be underemployed than the native born counterpart although the impact seems to diminish over time.

Madamba and De Jong (1997) and De Jong and Madamba (2001) find similar results among migrants in U.S. that their underemployment rate is greater than the native born Americans. De Jong and Madamba (2001) also argue that the Asian immigrants have experienced a double disadvantage in the US labour market due to their migration and ethnic minority status (although the impact of the later is stronger). Interestingly, Miranti et al. (2010) also find that among partnered workingwomen in Australia, immigrants from other English speaking countries have lower likelihood to work underemployed than the Australian born counterparts.

A few authors (Koeber and Wright 2001; Chan and Steven 2004) suggest that underemployment is likely related to age. Previous research indicates that mature older workers may be vulnerable for underemployment. Gong and Namara (2011) focus on a the 'baby boomer' population and find that just under 25 per cent of population aged 45-64 year old part time workers prefer to work more hours and are likely to experience longer periods of underemployment than younger workers (Spoehr et al. 2009).

Slack and Jensen (2008, 2011) conjecture that the relationship between age and underemployment is curvilinear, with the probability of being underemployed higher at young age ranges, lowest during the prime working age years, but increasing again during the old age cohorts close to the retirement. Wilkins (2006) tests this hypothesis for Australia and finds that across five-year age groups from 15-24 to 55-64, the propensity to be underemployed is lower among 'prime-age' workers than the base category of 15-24 year olds, but higher for the older age of 55-64 for both gender although the impact is not significant. This result carries for both genders.

The impact of health on labour force status among older workers has been discussed substantially in the literature as the workers are getting older, they are also likely to be more prone to health shocks (such as strokes and heart attacks), long term ill health, injury and disability (Bound et al., 1999; Cai and Cong, 2009; Zucchelli, et al., 2012). Most of the literature focuses more on the impact of health on the labour market exit rather than the impact of health on underemployment.

While most of these determinants discussed are from supply side, Wilkins (2006) has also considered the demand side variations, which include location of residence, local labour market characteristics and local socioeconomic characteristics proxied by Socio-Economic Indexes for Areas (SEIFA) decile. Underemployment is found to be affected not only by individual resources or advantage or disadvantage that accumulates over time but also by the nature of the work that is available. For example a report from the Productivity Commission (Abhayaratna et al. 2008) finds that around 36 per cent of part-time workers who could not work more hours and would have liked to work more hours thought that they could not work their preferred hours because of demand-factors, particularly a lack of job vacancies.

Further, Miranti et al. (2010) find that women working in low skilled occupations and those hired on non-permanent contracts are more likely to experience underemployment. It also argues that working women less likely to be underemployed if they live in areas with relatively lower unemployment rates are, even after controlling for a wide range of personal and family characteristics. These findings are in line with those from ABS (2010), which concludes that underemployment is affected by low vacancy rates and lack of skills or experience.

While many factors have been discussed with respect to underemployment, there is limited study on the labour market pathways into and out from underemployment and analyse the potential heterogeneities among underemployed workers. While underemployment can be a transition step to full employment, as argued by Farber(1999), the previous episode(s) of underemployment may increase the likelihood of future underemployment (Wilkins and Wooden, 2011). The analysis is unlikely to be conclusive if not considering both trajectory information and labour market related personal attributes. This paper aims to fill this gap by exploring the impact of both trajectory information and cross-sectional characteristics on underemployment.

III. *Patterns of Underemployment in Australia: HILDA data*

HILDA Dataset

To analyse the patterns of underemployment, we selected HILDA, one of the most popular longitudinal datasets, for our purpose as it explicitly ask for the underemployment information in the survey and covers a wide range of social economic characteristics that are useful for labour market research. This paper uses the first ten waves of HILDA dataset, which is a longitudinal survey conducted annually since 2001. The mature age group is defined as the subpopulation who were born between the year 1951-1965 (aged 35-59 in 2010). The selected sub population includes the ‘baby boomer’ generation in Australia and its neighbouring cohorts.

Table 1 highlights the data filtering process used in this paper. As shown, our sample only includes individuals who were born between 1951-1965, with observed labour market status, valid responses on working hours and employment and who stayed in the survey for at least 5 waves. Among this subset group, there are 975 individuals who experienced underemployment and 2597 without.

Table 1 Data Filtering Process

Criteria	Number of Observations/Individuals
Total number of observations in HILDA (all waves)	177938
Total number of individuals in HILDA (all waves)	28547
Number of individuals born between 1951 and 1965	5404
Number of Individuals with observed labour market status, valid responses on working hours and employment	5038

Number of individuals who stayed in the survey for at least 5 waves with observed labour market activity	3572
Number of individuals with at least one observed underemployment	975
Number of individuals without observed underemployment	2597
Total number of individuals retained	3572
Total number of total observations retained	32925
Total number of observations in labour market	27609
Individuals with observed underemployment transitions	729

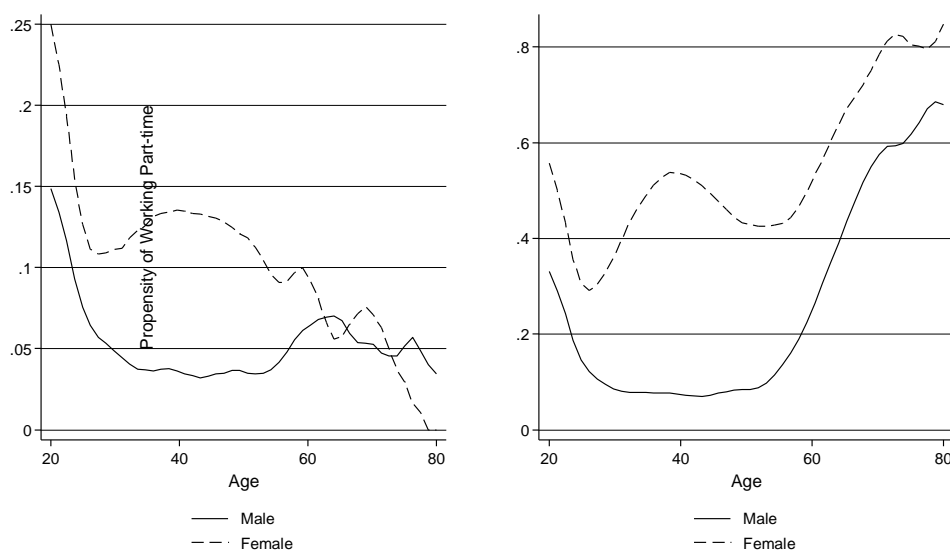
Source: Authors' calculation from HILDA waves 1-10, unit record data

Patterns of underemployment in HILDA

Figure 3 shows that propensity of being underemployed among working population by age (between 20-80) and by gender in HILDA. For women, the propensity of being underemployed is the highest when the women are young in their 20s, although then the chart shows a declining pattern before peaking up again when the women enter the age of 40. This matches with the high propensity of working part time among women which also is peaking up when working women reach the age of 40 which may indicate an age where child-rearing may be easier than it is for them couple years earlier when these women may have just started to have families and have their first child or raise their young children.

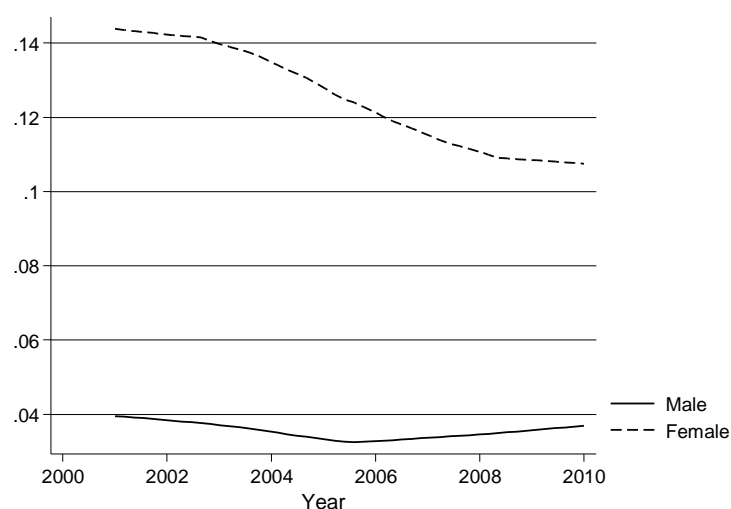
For men, in contrast, after high propensity of being underemployed for youth cohort, the propensity of being underemployed is low for age between 30s and the 50s before it is gradually increasing again when the age is closer to 60. The proportion of underemployment shows a declining pattern after 60 and this coincides with an increasing pattern of part time workers after this age, showing that close to retirement age, these individuals experience some withdrawal from the labour market with working part time and perhaps this is more as a voluntary rather than involuntary choice. The fact that women are more prevalent to underemployment is also shown in Figure 4, that across 10 waves of HILDA, women have double propensity to be underemployed in comparison with men.

Figure 3 Underemployment and Part-time Employment in HILDA among working population



Source: Authors' calculation from HILDA waves 1-10, unit record data

Figure 4 Propensity of being Underemployed among Mature Age Working Population (cohort 1951-1965)



Source: Authors' calculation from HILDA waves 1-10, unit record data

Pathways in and out of Underemployment

To understand the patterns of underemployment, it is important to explore labour supply history for those who experienced underemployment and compare them with the ones without underemployment. This would require us not only looking at the data from a cross-sectional prospective but also from a longitudinal angle. Given that the number of observations is high, and there is a large degree of heterogeneities in potential career paths, we adopt sequence analysis technique³ to explore the patterns among mature age workers.

The analysis treats each individual's observed employment trajectory as a sequence with different labour force status. We can, therefore calculate the distance between each pair of sequence using optimal matching⁴ technique with the assumption that the distance between two labour force statuses is inverse to the transition probability observed in the dataset. As HILDA is an unbalanced dataset, we assume that each missing period has a constant distance to any labour force status⁵. With all distances calculated, it is possible to cluster all sequences into groups according to their distance to explore the patterns in the employment trajectory. Each cluster therefore contains individuals with similar labour force patterns.

Although previous literature have discussed the incidence of underemployment, pathways into and out from underemployment have not been much explored and fully understood. This section will discuss this issue, which is required to better understanding experience of underemployment. For example, we are interested to explore whether there are any distinct pattern of labour force status that characterise the entrance into and out of underemployment.

³ Some calculations and figures involves variants of sequence analysis that has been made thanks to the TraMinR package (Gabadinho et al., 2011)

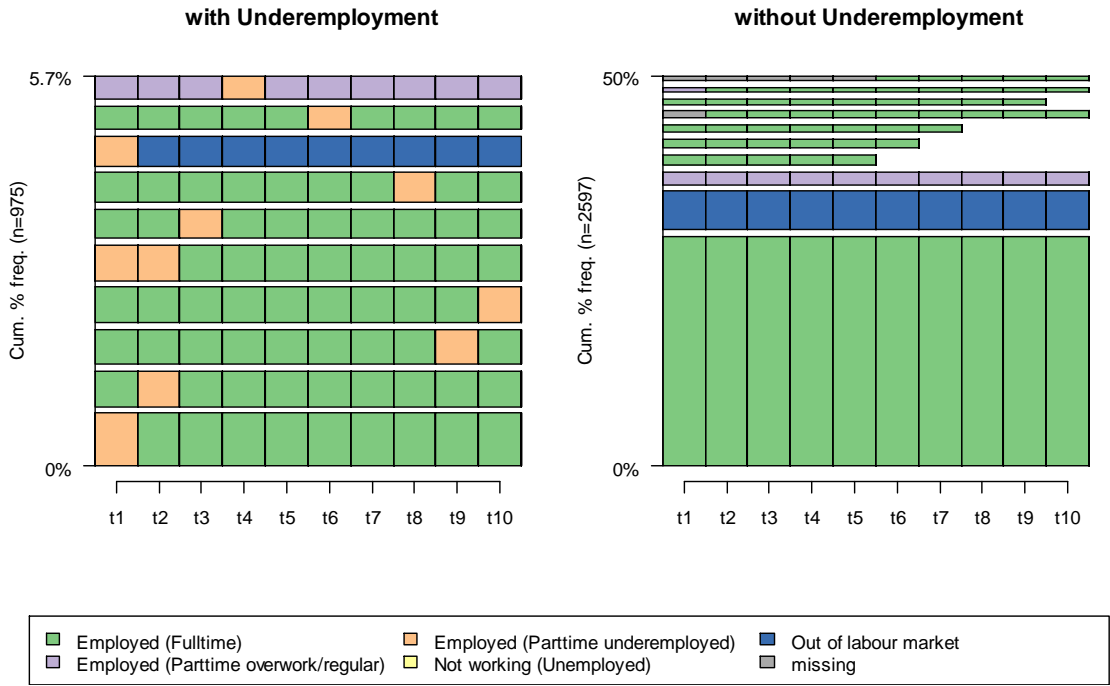
⁴ For a complete description of OM algorithm, please see Abbott *et al.* (2000)

⁵ This is also known as insert/delete cost, which is set to 2 in this analysis.

Figure 5 compares the transition sequences for mature age workers in our sample who experience at least one period of underemployment with their first incidence of underemployment and labour force status prior/after the underemployment are shown versus those who do not experience underemployment (n=2597).

As the clustering here poses no prior assumptions on the patterns or theories as it is purely based on the distance to the most frequent sequences, Figure 5 shows that pathways leading and out of underemployment seem to be dominated by the transition from stable full time job/ stable part-time or out of the labour market. This implies there are limited volatilities in job patterns before and after being underemployed. In details, we can observe that among the top 10 sequences of people who experience underemployment, and covers 5.7 per cent of those who are underemployed, mostly have been working full time in other periods of their life. Within these top 10 sequences also, two other patterns can be observed also are that some underemployed people are not in the labour force or employed part time in the other periods of their life. In contrast, the top 10 sequences of people who do not experience underemployment covering 50 per cent of them mostly work full time and only a few of them who work part time or not in the labour force.

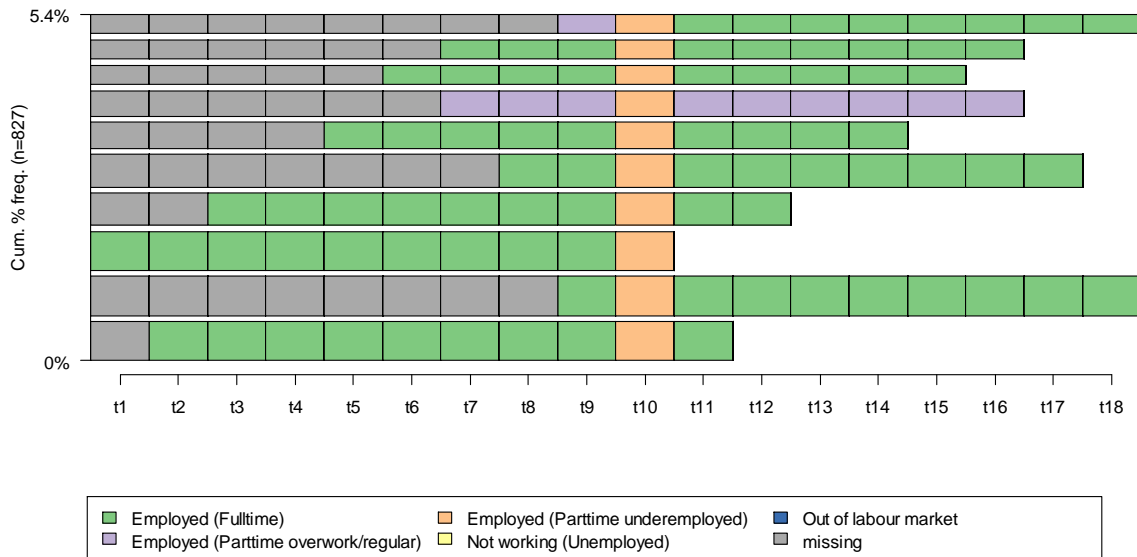
Figure 5 Comparison of the Most Common Patterns of Labour Force Status



Source: Authors' calculation from HILDA waves 1-10, unit record data

Figure 6 also shows the same common patterns as what found in Figure 5. Figure 6 displays that labour force sequences of people who have experienced episode of underemployment for their first time with observed transition (there are 729 people in the sample). Among the top 10 sequences clustered in the sample, the transition into and out from underemployment are more common to be found among those who work full time. Pathways from full time employment to underemployment and exit from underemployment to full time employment may indicate some short term shock that people have to adjust their labour status from working full time, underemployed and then to work full time again.

Figure 6 Most Common Patterns of Pathways related to Underemployment with Observed Transition



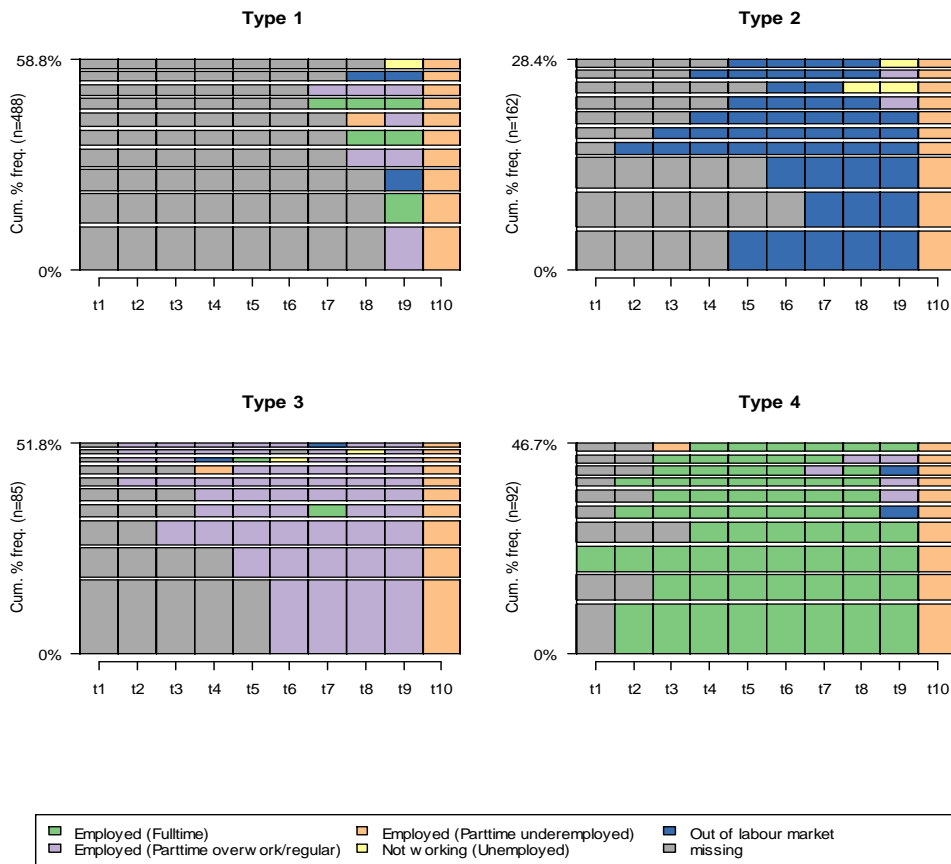
Source: Authors' calculation from HILDA waves 1-10, unit record data

To explore the heterogeneities in the pathway leading to underemployment, we further break down the trajectories into 4 type using clustering technique. The number of clusters was chosen to maximise the variations across types while maintaining a reasonable and interpretable variations within the same cluster. Figure 7 demonstrated the common labour trajectory leading to the underemployment event while Table 2 provides key descriptive statistics on the individuals in different cluster type.

The first entry cluster (Type 1) is characterised by mixed sequences of labour force status, as this cluster mostly capture the individuals who just entered HILDA survey.

The second cluster represents those who have been out of the labour force for some time and decide to come back to work but then underemployed. In terms of educational attainment, the second cluster contains only less than 30 per cent of people who have diploma degree or above, the lowest proportion compared to the other clusters. The other distinct characteristic of this cluster is that almost 36 per cent of observations in these clusters have chronic illness, and this proportion is the highest compared to the other clusters, which makes sense that when people suffer chronic illness then this may prohibit them to participate in the labour market. The sequences in the second cluster is also characterised mostly by women (83 per cent), on average only 66 per cent have partners or those who work only at only around 10.6 hours per week. The second cluster also consists some of unemployed people.

Figure 7 The Most Common Patterns into Underemployment



Source: Authors' calculation from HILDA waves 1-10, unit record data

People who are employed part time prior to the underemployed episode dominate the third cluster. Women again are concentrated in this cluster (95 per cent). This cluster is also associated with people who have partner, has the highest number of dependent children between 5 and 14 or the highest proportion of spouse illness compared to the other clusters. This cluster also consists of people who work on average around 22.5 hours per week.

The last cluster we have observed is Type 4 cluster dominated by the full time employment sequences. More than 50 per cent of this group are male and the majority has a partner, having the least number of children aged 5-14 or work on average 37.3 hours per week. Further, compared with the other clusters, this cluster has the highest proportion of people with educational attainment diploma degree or above.

Our next analysis will provide discussions about the most common patterns observed out of underemployment for each of entry type, so these are conditional exit clusters. Using similar method of analysis, we have three different exit sub-clusters for each type of entry. These have allowed us to examine different exit trajectory which depends on what type of entry prior to the underemployment.

Figure 8 shows that the most common patterns for exit sequence conditional on Type 1 entry who covers the recent entrants to underemployment, are either moving from underemployment to work part time (Subtype 2) or to work full time (Subtype 1). For the latter underemployment looks like as a pathway to full time employment and is characterised only by only around 55 per cent of them are women, consisting of a relatively more educated people than the other sub-types within this entry cluster with educational attainment of diploma degree and above (almost 40 per cent of them).

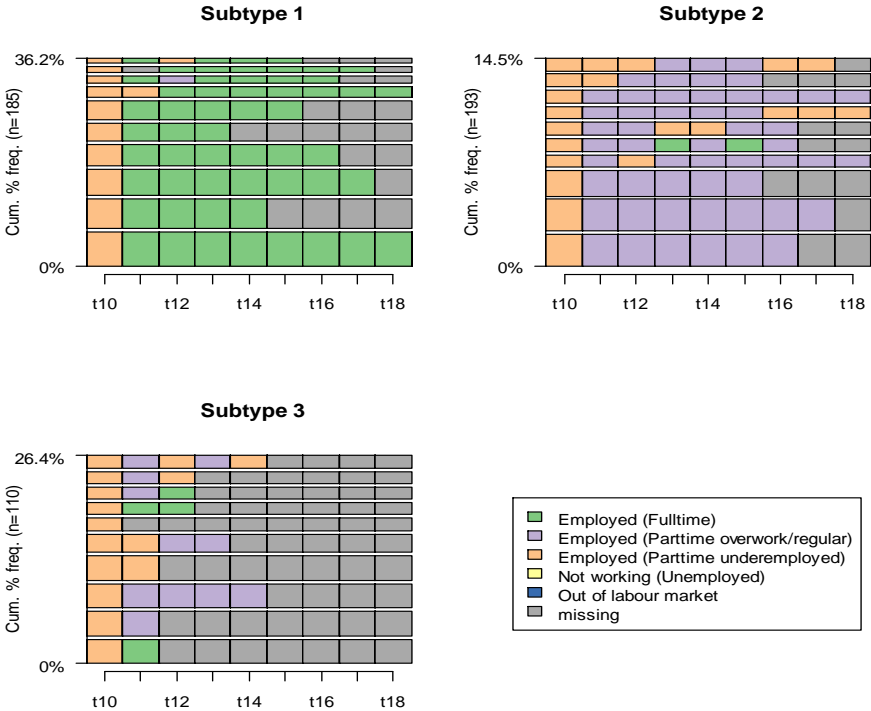
Table 2 Characteristics of people entering to and exiting from underemployment (Mean value across all waves)

	Female	Have a partner	Diploma Education or above	Hours of work	Chronic illness	Foreign Born (English Speaking Country)	Foreign Born (Non English Speaking Country)	Spouse Illness	Number of kids age between 0 to 4	Number of kids age between 5 to 14
Type 1 – mixed entry										
Subtype 1	0.546	0.751	0.395	35.124	0.209	0.097	0.178	0.123	0.098	0.628
Subtype 2	0.860	0.720	0.356	18.378	0.304	0.093	0.119	0.147	0.102	0.742
Subtype 3	0.764	0.738	0.372	24.197	0.250	0.136	0.118	0.127	0.095	0.517
Total	0.719	0.736	0.374	26.038	0.256	0.105	0.141	0.133	0.099	0.648
Type 2 – entry is dominated by out of labour market										
Subtype 1	0.797	0.656	0.313	10.430	0.375	0.094	0.141	0.221	0.129	0.736
Subtype 2	0.903	0.683	0.299	8.324	0.369	0.167	0.139	0.125	0.169	0.981
Subtype 3	0.731	0.583	0.231	17.565	0.290	0.115	0.231	0.211	0.070	0.713
Total	0.833	0.656	0.293	10.639	0.358	0.130	0.154	0.177	0.138	0.841
Type 3 – entry is dominated by working part time										
Subtype 1	1.000	0.810	0.722	27.910	0.192	0.167	0.056	0.156	0.214	1.188
Subtype 2	0.933	0.818	0.281	20.679	0.229	0.156	0.133	0.207	0.107	0.841
Subtype 3	0.955	0.823	0.394	21.856	0.300	0.045	0.045	0.159	0.086	1.085
Total	0.953	0.818	0.404	22.515	0.239	0.129	0.094	0.184	0.124	0.978
Type 4- entry is dominated by working full time										
Subtype 1	0.429	0.705	0.468	36.118	0.172	0.079	0.159	0.134	0.124	0.495
Subtype 2	0.375	0.817	0.300	43.072	0.144	0.188	0.000	0.100	0.140	0.501
Subtype 3	0.692	0.700	0.392	35.909	0.139	0.000	0.154	0.062	0.231	0.420
Total	0.457	0.724	0.428	37.298	0.163	0.087	0.130	0.118	0.142	0.485

Source: Authors' calculation from HILDA waves 1-10, unit record data

Another sub-cluster among this first entry is that some people who experience short entry trajectory can also experience quick exit (Subtype 3), while some have been exiting from underemployment by working part-time. Particularly in these two Subtypes 2 and 3, we have found some indication of extended period of underemployment.

Figure 8 Exit sequence conditional on Type 1 entry

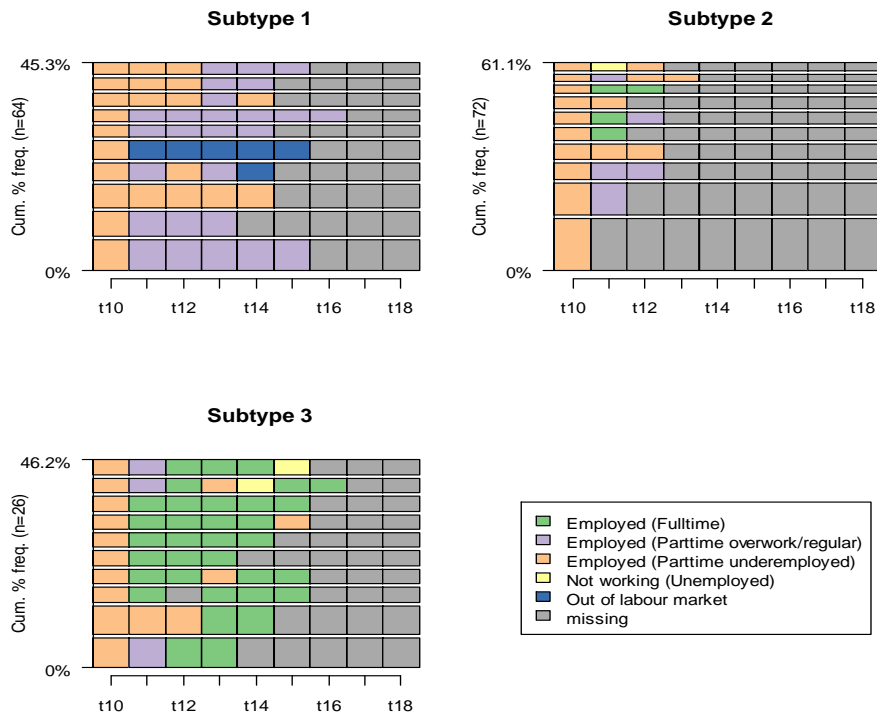


Source: Authors' calculation from HILDA waves 1-10, unit record data

Figure 9 shows the exit sequence conditional on Type 2 entry, the type of entry, which is characterised by people who have been predominantly out of the labour force prior to the underemployment. The more common sub-cluster within this entry, Subtype 2 is composed mainly by people who experience exit in a very short time with some evidence of extended period of underemployment. More than 90 per cent of these people are women and mostly still have a child between 5-14 years old.

Subtype 1 sub-cluster in this type of entry is characterised by people who work either part time or out of the labour market again following the episode of underemployment. People who have chronic illness or having spouse who suffer from illness are concentrated in this group. Finally, Subtype 3 is dominated by transition to full time employment, and characterised interestingly by 23 per cent of them are overseas born from the non-main English Speaking countries. This may indicate that for migrants who come from non-main English speaking countries, it will take a while for them to get a full time job, and it is likely they will experience some episodes of underemployment in their working life. In all three-exit types in this Type 2 entry, some persistence of underemployment, which lasts more than one period also exist.

Figure 9 Exit sequence conditional on Type 2 entry

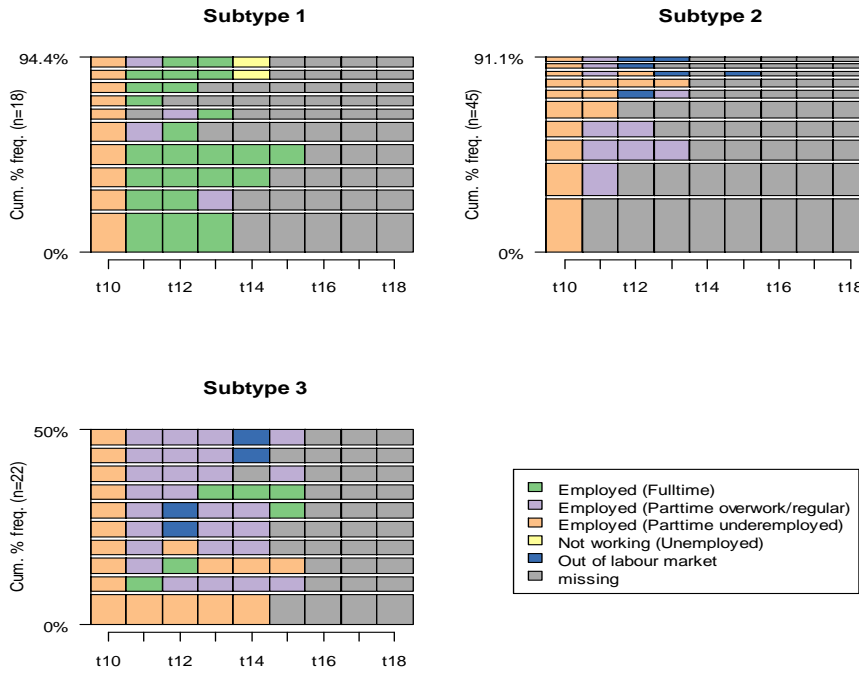


Source: Authors' calculation from HILDA waves 1-10, unit record data

Figure 10 further shows the exit sequence conditional on Type 3 entry, an entry which is dominated by people who work part time prior to the underemployment. Subtype 1 in this type of entry is dominated by those who have successfully move to full time employment and is characterised by all are women, 80 per cent of them have partner, the highest of all sub-clusters and have more than a child aged 5 to 14. Consistent with the fact that Type 3 consists of people with the relatively better human capital than the other clusters, women in this sub-cluster are highly educated with more than 72 per cent of them having qualification as diploma degree or above. This is contrasting with Subtype 2 sub-cluster, which covers a very short trajectory, that only 28 per cent of them having a tertiary degree qualification. In Subtype 2 sub-cluster, we also find episodes of extended underemployment. The same pattern is found in Subtype 3 sub-cluster which dominated by returning part time employment.

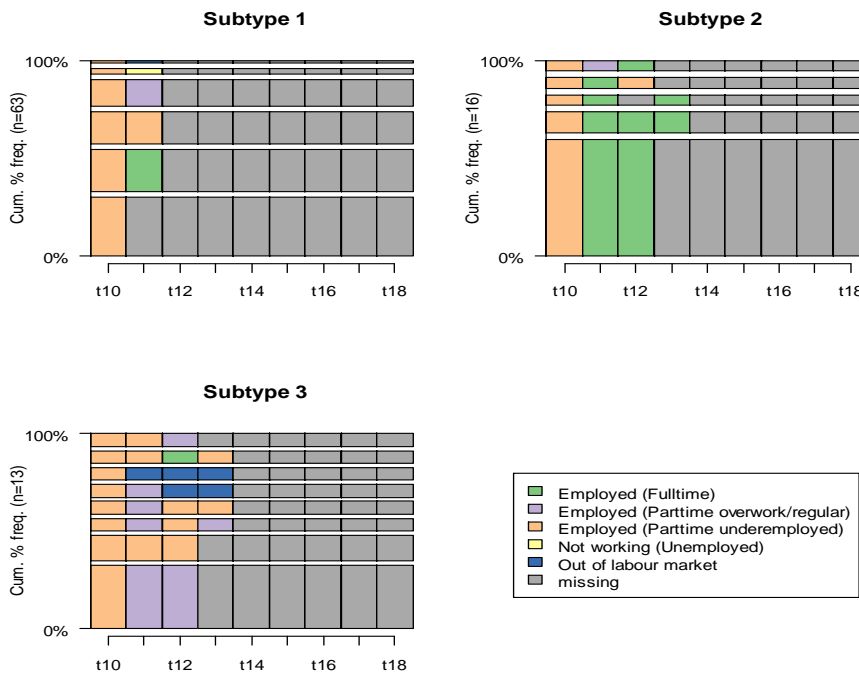
As discussed earlier, Type 4 entry is dominated by people who work for long period of full time employment prior to underemployment (Figure 11). People in this group are mostly men and having the least number of children. The exit sequences of this Type 4 cluster are relatively shorter knowing that our analysis is restricted into 10 waves of HILDA data and these people have been working full time for long periods of time. Subtype 1 sub-cluster is the most common exit cluster in this group with a shortest exit, followed by Subtype 2 sub-cluster, which covers those who work full time again after the underemployment. People in both clusters are mostly men, in contrast with Subtype 3, a sub-cluster dominated by people who work part time with extended period of underemployment and almost 70 per cent of people in this group are women. Subtype 2 sub-cluster is also characterised by people who work long hours, more than 43 hours on average per week or relatively higher proportion of foreign-born people particularly from English speaking countries (19 per cent).

Figure 10 Exit sequence conditional on Type 3 entry



Source: Authors' calculation from HILDA waves 1-10, unit record data

Figure 11 Exit sequence conditional on Type 4 entry



Source: Authors' calculation from HILDA waves 1-10, unit record data

We have discussed above the pathways of entry and exit conditional of entry are in fact heterogeneous. There is an indication that underemployment can serve as a pathway towards full time employment. We also observe longer period of underemployment in the data, which may indicate that the state dependent of underemployment exist. The cluster analysis shows that except for Type 4 cluster that is dominated by people who work full time, there is higher proportion of women experience underemployment than men in other clusters or exit sub-clusters. People with more human capital tend to be able to shift to other working labour force status either to work part time or full time. People born overseas from non-main English speaking countries are relatively associated more to underemployment than those who were born in main English speaking countries.

Reasons and Characteristics of Underemployed individuals

The findings above suggest various characteristics are associated with underemployment, and that the period of underemployment can extend longer and persist over time. This section discusses the reasons for individuals to be underemployed and their social and economic characteristics.

Having discussed sequences or pathways into and out from underemployment, Table 3 discusses reasons for working part time that have been answered by people who experience underemployment. Although these reasons do not provide direct answers of reasons for being underemployed, to some extent these reasons provide insights that can be teased out as being associated with underemployment. As discussed in the literature review, factors that affect underemployment may differ across gender, thus we analyse the characteristics in Table 3 according to gender.

Table 3 Reasons for Working Part Time for Underemployed Individuals

Reasons for working Part-time	Percentage		Difference compared with non-underemployed part-time worker	
	Male	Female	Male	Female
Own illness or disability	11.3%	6.2%	-3.1%	2.5%
Caring for children	7.8%	27.0%	-1.0%	-9.7%
Caring for disabled or elderly relatives [not children]	0.2%	1.5%	-1.0%	0.6%
Other personal or family responsibilities	1.6%	4.1%	-0.3%	-2.1%
Going to school, college, university etc.	6.2%	2.5%	1.0%	1.0%
Could not find full-time work	32.9%	20.6%	29.1%	18.4%
Prefer part-time work	10.1%	18.9%	-32.1%	-17.1%
Involved in voluntary work	0.0%	0.2%	-0.3%	-0.2%
Attracted to pay premium attached to part-time / casual work	0.4%	0.3%	0.0%	0.0%
Welfare payments or pension may be affected by working FT	0.2%	0.2%	-1.1%	-0.1%
Getting business established	5.3%	0.8%	3.4%	0.4%
Prefer job & part-time hours are a requirement of the job	15.0%	12.9%	2.4%	4.1%
Other or Refuse or Answer	9.0%	4.7%	3.1%	2.3%

Note: Number of underemployed part time observation: 2136, number of non-underemployed part time observation: 7397

Source: Authors' calculation from HILDA waves 1-10, unit record data

Looking at Table 3, for both gender, difficulty in finding full time work, preference to work part time or the type of the job that people prefer to do is only available part time are cited as common reasons of underemployment. Further, if we compare this with those who are not underemployed, “could not find a full time work“ stands out as the main reason that differentiate people who are underemployed and not underemployed and this is valid for both men and women, indicating that exploring this further may be useful for further research. Not finding a full time work may indicate for example skill mismatch between supply and demand or could simply mean that full time work are not available enough for oversupply of people who want to work full time. This to some extent explains the pattern we found earlier that there exists labour market transition towards underemployment for individuals who work full time mostly in other periods of their life.

A comparison between genders shows that more than 32 per cent of underemployed women cite family responsibilities (for children and relatives) as a reason of underemployment while in contrast, only a third of men (9.6 per cent) do so. On the other hand, more than 11 per cent of underemployed men reported that own illness and disability as reason of being underemployed compared to only 6 per cent of underemployed women.

IV. Empirical Modelling of Drivers of Underemployment

The earlier summary statistics provided suggests that transitions in and out of underemployment have some patterns (see Figures 7-11). However, the descriptive analysis cannot tell the likelihood of changing labour market status after underemployment. To further investigate the link between employment activities and underemployment, we would need to develop an empirical specification to model the transitions.

We focus our attention of the effect of previous underemployment experience on the likelihood of trapping in the state of underemployment. Assume we use y_{it} to denote underemployment of individual i at time t . Given a standard random effect probit model, we can specify the model with two-order lag as following:

$$y_{it}^* = y_{it-1}\beta_1 + y_{it-2}\beta_2 + X_{it}\beta_3 + a_i^y + \epsilon_i^y$$

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* > 0 \\ 0 & \text{if } y_{it}^* \leq 0 \end{cases} \text{ (if individual } i \text{ is working)}$$

y_{it}^* is the latent variable for underemployment, X_{it} is the characteristics of the individual, a_i^y is the individual effect for underemployment and ϵ_i^y is the error term. Since the individual experiencing causal underemployment might be different than the ones with persistent underemployment, we incorporate a double lag specification in the empirical model to allow some heterogeneities between these two groups.

There are, however, two potential problems associated with this particular model specification. Firstly, since underemployment is recorded only for those who are actually working, estimations based on the observed values only may incur biasness as the selection of staying out of the labour market or unemployment is not random. The model, therefore, may under or overestimate the impact of the variables of interests. Secondly, the dynamic nature the model implies an “initial condition problem” (Heckman, 1981), which needs to be corrected in order to obtain a more accurate estimate of lagged dependent variable.

Correction of Selection Bias

To correct for the two problems stated above, this paper adds in a selection bias control into the estimation. The method for selection control is effectively a panel data extension to the standard probit model with sample selection described by (Van de Ven and Van Pragg 1981). Initial condition problem is addressed using Wooldridge (2005)'s method.

For selection equation, we assume that observations are selected into the working population sample based a latent equation.

$$s_{it}^* = s_{it-1}\gamma_1 + s_{it-2}\gamma_2 + Z_{it}\gamma_3 + a_i^s + \epsilon_i^s$$

$$s_{it} = (s_{it}^* > 0)$$

s_{it}^* is the latent variable for underemployment, Z_{it} is the characteristics of the individual, a_i^s is the individual effect and ϵ_i^s is the error term in the selection equation. Since we have a panel dataset, we use a similar random effect specification for the latent variable. Therefore the actual probability of observing an underemployed worker at time t is

$$U = P(y_{it}^* > 0 | s_{it}^* > 0, X_{it}, Z_{it})$$

Using a bivariate standard normal distribution transformation with the assumption that the correlation between ϵ_i^y and ϵ_i^s is ρ , we can write the likelihood function of the joint estimation as

$$L_i = \prod_{s_i=0} \prod_{t=3}^T \left\{ 1 - \Phi \left(s_{it-1}\gamma_1 + s_{it-2}\gamma_2 + Z_{it}\gamma_3 + a_i^s \right) \right\}$$

$$\cdot \prod_{s_i=1, y_i=1} \prod_{t=3}^T \left\{ \Phi_2 \left(y_{it-1}\beta_1 + y_{it-2}\beta_2 + X_{it}\beta_3 + a_i^y, s_{it-1}\gamma_1 + s_{it-2}\gamma_2 + Z_{it}\gamma_3 + a_i^s, \rho \right) \right\}$$

$$\cdot \prod_{s_i=1, y_i=0} \prod_{t=3}^T \left\{ \Phi_2 \left(-y_{it-1}\beta_1 - y_{it-2}\beta_2 - X_{it}\beta_3 - a_i^y, s_{it-1}\gamma_1 + s_{it-2}\gamma_2 + Z_{it}\gamma_3 + a_i^s, -\rho \right) \right\}$$

Where Φ is the standard normal cumulative distribution, Φ_2 is the bivariate normal cumulative distribution. Additionally, we allow correlations between individual effects. Hence, the distribution of the unobserved individual effects can be described by a bivariate normal distribution as shown below. In the estimation, we allow the correlations between individual effects.

$$a \sim f \left(\begin{pmatrix} a_i^y \\ a_i^s \end{pmatrix}, \begin{pmatrix} \sigma_y^2 & \sigma_{sy} \\ \sigma_{sy} & \sigma_s^2 \end{pmatrix} \right)$$

Initial Conditions

Heckman (1981) suggests an approximation method for conditional distribution of the initial values using a reduced form equation based on the pre-sample information. Wooldridge (2005) proposes an alternative Conditional Maximum Likelihood (CML) estimators that considers the distribution conditional on the initial period value, and allows for the possible correlations between observed characteristics and the individual effect (Mundlak, 1978, Chamberlain, 1984, Wooldridge, 2005). In practice, this methods specifies the unobserved individual effectors conditionally on the initial values y_{it} and the within-means of time-variant explanatory variables \bar{x}_i . Therefore,

$$\alpha_i = \xi_0 + \xi_1 y_{i1} + \xi_2 \bar{x}_i + \eta_i$$

Where η_i is the new random effect that follows a normal distribution with mean zero. The method has the advantage of computationally efficient compared with other approaches while getting similar coefficients with Heckman's approach at lower computational cost (See Stewart, 2007; Akay, 2009). The method can be implemented by adding extra variables into the likelihood function.

Estimation

The model is estimated using simulated maximum likelihood methods with the simulated likelihood function as:

$$SL = \prod_{s_i=0} \frac{1}{R} \sum_{r=1}^R \prod_{t=3}^T \left\{ 1 - \Phi \left(Z'_{it} \gamma_2 + a_i^s \right) \right\} \\ \cdot \prod_{s_i=1, y_i=1} \frac{1}{R} \sum_{r=1}^R \prod_{t=3}^T \left\{ \Phi_2 \left(X'_{it} \beta_2 + a_i^y, Z'_{it} \gamma_2 + a_i^s, \rho \right) \right\} \\ \cdot \prod_{s_i=1, y_i=0} \frac{1}{R} \sum_{r=1}^R \prod_{t=3}^T \left\{ \Phi_2 \left(-X'_{it} \beta_2 + a_i^y, Z'_{it} \gamma_2 + a_i^s, -\rho \right) \right\}$$

Where Z'_{it} includes all variables used in the selection equation, X'_{it} includes all variables in the main equation. R is the total number of draws used in the estimation. In the estimation, X'_{it} and Z'_{it} would include a number of social economic variables extracted from the HILDA dataset. Besides, the model also includes variables that are likely to affect the reserve wage, such as non-labour income, wage rate interacting with number of kids, to allow for a higher degree of heterogeneities in the model.

V. Estimation Result

Table 4 reports key variables used in the estimation, their mean values, standard deviations and observation counts. Various income variables, household income, wage rate and other household income (non-earning income) are included to capture different dimensions of income, personal or households if there are more than a single person in a household. Chronic illness is included as an explanatory variable in the selection regression rather than in the main equation.

The total number of observations is lower than the one used for clustering analysis as only observations with non-missing information for all variables can be used in the estimation. Additionally, since the model uses lag specification, only observations from $t=2$ are counted. Given that the typical male and female career trajectories differ, we estimate male and female underemployment separately.

Table 4 Descriptive of key variables used in the estimation

	Male				Female			
	Main		Selection		Main		Selection	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Underemployment (t-1)	0.03	0.18			0.11	0.31		
Underemployment in both t-1 and t-2	0.01	0.11			0.05	0.21		
Working in t-1			0.89	0.31			0.75	0.43
Live outside of major urban cities	0.42	0.49	0.42	0.49	0.41	0.49	0.40	0.49
Total number of dependent children	1.15	1.24	1.15	1.25	0.98	1.12	1.04	1.17
Foreign born (English speaking	0.11	0.32	0.11	0.32	0.12	0.32	0.11	0.31

country)								
Foreign born (non-English speaking country)	0.12	0.32	0.12	0.33	0.12	0.32	0.14	0.34
Chronic Illness			0.25	0.43			0.25	0.43
Having a partner	0.80	0.40	0.78	0.41	0.74	0.44	0.73	0.44
Education (Diploma or above)	0.37	0.48	0.35	0.48	0.41	0.49	0.38	0.48
Age	48.06	4.73	47.60	4.87	48.11	4.74	47.56	4.94
Other Household Income (Ln)*	9.65	2.87			10.14	2.64		
Hourly Wage Rate (Ln)	2.74	1.27			2.82	1.01		
Lagged Other Household Income (Ln)			9.61	2.74			10.17	2.43
Binary dummy - no kids	0.17	0.37	0.17	0.38	0.15	0.36	0.14	0.35
Binary dummy - have dependent children 0-4	0.10	0.29	0.10	0.31	0.04	0.20	0.06	0.23
Binary dummy - have dependent children 5-14	0.16	0.37	0.15	0.36	0.17	0.38	0.17	0.38
Binary dummy - have dependent children 15-24	0.12	0.32	0.11	0.32	0.14	0.35	0.13	0.34
Total number of observations		10,926		13,419		11,409		15,273

Note: Other household income is defined as total household income subtracted by the labour earnings of the individual

The estimation is based on the Simulated Maximum Likelihood method described in Train (2003), and uses 30 draws from Halton sequences. Halton sequence is preferred over pseudo random numbers given its lowered computational cost for given accuracy requirement (Train, 2003; Cappellari, 2006). The estimation results are reported in Table 5 and Table 6, where the main equation coefficients are presented in the first two columns and the selection coefficients are presented in the last two columns.

The coefficients for the selection equation are as expected. Across two tables (Tables 5 and 6), we find that there is a significant increase in propensity of working if the individual was previously employed. Chronic disease, as expected, reduces one's likelihood of employed. Naturally, there are also some differences between male and female's estimates. We find that age and education are not significant for employment for this particular male cohort but significant for females. It is possible that working experience plays a more important role in later stage of the career for male workers. Additionally, previous non-labour earnings and kids are also a factor for female while the same variables do not seem to change the likelihood of male employment significantly.

The main equation estimates focuses on the propensity of being underemployed. Since the estimation includes both full time and part time workers, we capture the overall effect on engaging in the part-time underemployed work. The result shows that, workers who experienced underemployment in previous periods are more likely to experience underemployment again, a finding that is significant and consistent for both male, and female. The significant coefficient for "both underemployment in t-1 and t-2" further confirms the path dependency in terms of underemployment.

The estimation also suggests that individuals who are married or in a de facto relationship is significantly less likely to experience underemployment. Partnering is likely a protective factor from being underemployed for both gender. This can be potential explained by the different expectation of work between singles and married couples. We also find that the monetary compensation from work, as indicated by wage rate, has no impact on the feeling of underemployment for both male and female. This suggests that underemployment links more to other factors, such as the job satisfactions, rather than the pay check. Other household income, which is used as a control for exogenous earnings, also has limited impact although we do observe that other household income reduces the chance of underemployment for male with dependent children aged 15-24 and increases the propensity of underemployment for females without child.

There are not many variables that are consistently significant across male and female estimations besides lagged employment status and being in a committed relationship. This implies that the men and women are exposed to very different labour market environments, which result in structural differences in the labour market behaviours.

Being born in a non-English speaking country seems to contribute significantly to the underemployment tendency for male but not so much for females. This implies the language-specific skills or having overseas qualifications that are not recognised could be examples of the barriers that prevent the foreign-born workers to realise their job preferences in male dominated fields. Education does not seem to play a major role in underemployment but does contribute to the likelihood of employed in female cases. The presence of children does not seem to affect the likelihood of male employment significantly although the total number of children positively correlates with the propensity of underemployed. Living in major urban cities is likely to contribute to underemployment among men only. As for women, the presence of children in the household would affect one's labour supply but not the propensity of underemployment. This pattern could be attributed to the typical gender role in domestic affairs. Age, once again, is only a significant factor for women but not men. It is likely that the difference in the job types and employment trajectories contributes to the patterns.

Table 5 Estimation Result for Men

	Main		Selection	
	Coeff.	S.E.	Coeff.	S.E.
Underemployment (t-1)	0.708*	(0.122)		
Underemployment in both t-1 and t-2	0.465*	(0.160)		
Underemployment (Initial value)	1.006*	(0.169)		
Working in t-1			1.165*	(0.086)
Working (Initial value)			0.677*	(0.139)
Live outside of major urban cities	0.509*	(0.232)	-0.775*	(0.188)
Total number of dependent children	0.177*	(0.073)	0.061	(0.060)
Foreign born (English speaking country)	-0.128	(0.142)	-0.125	(0.110)
Foreign born (non-English speaking country)	0.289*	(0.122)	-0.066	(0.113)
Chronic Illness			-0.237*	(0.085)
Having a partner	-0.406*	(0.122)	0.327*	(0.095)
Education (Diploma or above)	0.005	(0.479)	0.998	(0.549)
Age * 0.1	0.633	(1.353)	2.162	(1.139)
Age squared * 0.01	-0.041	(0.138)	-0.223	(0.116)
Other Household Income (ref group: no dependent kids)	0.037	(0.022)		
Other Household Income interacts with "no kids"	0.020	(0.033)		
Other Household Income interacts with "have dependent children age 0-4"	-0.009	(0.086)		
Other Household Income interacts with "have dependent children age 5-14"	0.057	(0.091)		
Other Household Income interacts with "have dependent children age 15-24"	-0.128*	(0.057)		
Hourly Wage Rate (ref group: no dependent kids)	-0.077	(0.045)		
Hourly Wage Rate interacts with no kids	-0.064	(0.078)		
Hourly Wage Rate interacts with have dependent children 0-4	0.021	(0.077)		
Hourly Wage Rate interacts with have dependent children 5-14	0.087	(0.080)		
Hourly Wage Rate interacts with have dependent children 15-24	0.064	(0.076)		
Lagged Other Household Income (Baseline, no dependent kids)			0.001	(0.016)
Lagged Other Household Income interacts with "no kids"			0.003	(0.024)
Lagged Other Household Income interacts with "have			0.018	(0.072)

dependent children age 0-4”				
Lagged Other Household Income interacts with “have dependent children age 5-14”			0.062	(0.041)
Lagged Other Household Income interacts with “have dependent children age 15-24”			-0.071	(0.073)
Binary dummy - no kids	-0.339	(0.543)	0.728	(0.398)
Binary dummy - have dependent children age 0-4	-0.059	(0.951)	-0.425	(0.745)
Binary dummy - have dependent children age 5-14	-0.920	(1.018)	-0.655	(0.430)
Binary dummy - have dependent children age 15-24	1.271	(0.651)	0.698	(0.789)
Constant	-4.273	(3.296)	-4.152	(2.796)
Sigma in the main equation (σ_y)	0.881	(0.100)		
Sigma in the selection equation (σ_s)			0.758*	(0.071)
Covariance (σ_{sy})	-0.244*	(0.068)		
Selection (ρ)	0.975	(0.085)		
Year Dummies		Yes		Yes
Mean Values of time variant variables		Yes		Yes

Note:

1. The model also includes year dummies which are not reported in this table
2. Likelihood ratio test of $\rho = \sigma_{sy} = 0$ is rejected at 0.05 level
3. * means statistically significant at 0.05 level

Table 6 Estimation Result for Women

	Main		Selection	
	Coeff.	S.E.	Coeff.	S.E.
Underemployment (t-1)	0.666*	(0.065)		
Underemployment in both t-1 and t-2	0.242*	(0.083)		
Underemployment (Initial value)	0.620*	(0.076)		
Working in t-1			1.171*	(0.060)
Working (Initial value)			0.392*	(0.079)
Live outside of major urban cities	-0.054	(0.151)	-0.172	(0.138)
Total number of dependent children	0.027	(0.049)	-0.109*	(0.051)
Foreign born (English speaking country)	-0.071	(0.082)	0.060	(0.098)
Foreign born (non-English speaking country)	0.096	(0.080)	-0.177	(0.098)
Chronic Illness			-0.373*	(0.067)
Having a partner	-0.358*	(0.068)	0.174*	(0.075)
Education (Diploma or above)	-0.107	(0.293)	1.379*	(0.291)
Age * 0.1	1.811*	(0.904)	2.903*	(0.934)
Age squared * 0.01	-0.197*	(0.094)	-0.320*	(0.096)
Other Household Income (ref group: no dependent kids)	0.018	(0.014)		
Other Household Income interacts with “no kids”	0.078*	(0.030)		
Other Household Income interacts with “have dependent children age 0-4”	0.071	(0.121)		
Other Household Income interacts with “have dependent children age 5-14”	-0.027	(0.035)		
Other Household Income interacts with “have dependent children age 15-24”	-0.002	(0.041)		
Hourly Wage Rate (ref group: no dependent kids)	0.021	(0.037)		
Hourly Wage Rate interacts with no kids	-0.100	(0.069)		
Hourly Wage Rate interacts with have dependent children 0-4	0.002	(0.084)		
Hourly Wage Rate interacts with have dependent children 5-14	0.065	(0.057)		
Hourly Wage Rate interacts with have dependent children 15-24	0.016	(0.062)		
Lagged Other Household Income (Baseline, no dependent kids)			-0.002	(0.016)

Lagged Other Household Income interacts with “no kids”			-0.029	(0.027)
Lagged Other Household Income interacts with “have dependent children age 0-4”			0.187*	(0.061)
Lagged Other Household Income interacts with “have dependent children age 5-14”			0.055	(0.035)
Lagged Other Household Income interacts with “have dependent children age 15-24”			-0.052	(0.052)
Binary dummy - no kids	-1.040	(0.613)	0.560	(0.490)
Binary dummy - have dependent children age 0-4	-0.852	(1.363)	-2.425*	(0.679)
Binary dummy - have dependent children age 5-14	0.043	(0.408)	-0.719	(0.382)
Binary dummy - have dependent children age 15-24	-0.054	(0.491)	0.438	(0.572)
Constant	-5.601*	(2.178)	-5.112*	(2.275)
Sigma in the main equation (σ_y)	0.606*	(0.049)		
Sigma in the selection equation (σ_s)			0.815*	(0.053)
Covariance (σ_{sy})	-0.095*	(0.041)		
Selection (ρ)	0.745*	(0.084)		
Year Dummies		Yes		Yes
Mean Values of time variant variables		Yes		Yes

Note and source: See Table 5

As the coefficients in the model are not directly comparable as they are part of the more complicated non-linear transformation, It is sometimes easier to compare the marginal effects of the independent variables. Table 7 calculates the overall marginal effect of having a job and being underemployed with respect to the key variables. As shown, past employment trajectory variables are among the largest coefficients in the table. The numerical comparison between male and female also suggests that the impact of previous underemployment is higher for females and males. Besides previous employment status, age is also a major factor for females. The propensity of underemployment increases by 2.25% per year as the female worker ages. Monetary related variables, as discussed earlier, show little impact for both male and females.

Table 7 Marginal Effects

	Male		Female	
	Mfx	S.E.	Mfx	S.E.
Underemployment (t-1)	0.016*	(0.005)	0.082*	(0.010)
Underemployment in both t-1 and t-2	0.011*	(0.004)	0.030*	(0.010)
Underemployment (Initial value)	0.023*	(0.005)	0.076*	(0.009)
Working in t-1	0.000	(0.000)	0.001	(0.001)
Working (Initial value)	0.000	(0.000)	0.000	(0.000)
Live outside of major urban cities	0.012*	(0.006)	-0.007	(0.019)
Total number of dependent children	0.004*	(0.002)	0.003	(0.006)
Foreign born (English speaking country)	-0.003	(0.003)	-0.009	(0.010)
Foreign born (non-English speaking country)	0.007*	(0.003)	0.012	(0.010)
Chronic Illness	-0.000	(0.000)	-0.000	(0.000)
Having a partner	-0.009*	(0.003)	-0.044*	(0.008)
Education (Diploma or above)	0.000	(0.011)	-0.012	(0.036)
Age * 0.1	0.015	(0.031)	0.225*	(0.111)
Age squared * 0.01	-0.001	(0.003)	-0.024*	(0.012)
Other Household Income (ref group: no dependent kids)	0.001	(0.001)	0.002	(0.002)

Other Household Income interacts with “no kids”	0.000	(0.001)	0.010*	(0.004)
Other Household Income interacts with “have dependent children age 0-4”	-0.000	(0.002)	0.009	(0.015)
Other Household Income interacts with “have dependent children age 5-14”	0.001	(0.002)	-0.003	(0.004)
Other Household Income interacts with “have dependent children age 15-24”	-0.003*	(0.001)	-0.000	(0.005)
Hourly Wage Rate (ref group: no dependent kids)	-0.002	(0.001)	0.003	(0.004)
Hourly Wage Rate interacts with no kids	-0.001	(0.002)	-0.012	(0.008)
Hourly Wage Rate interacts with have dependent children 0-4	0.000	(0.002)	0.000	(0.010)
Hourly Wage Rate interacts with have dependent children 5-14	0.002	(0.002)	0.008	(0.007)
Hourly Wage Rate interacts with have dependent children 15-24	0.001	(0.002)	0.002	(0.008)
Lagged Other Household Income (Baseline, no dependent kids)	0.000	(0.000)	-0.000	(0.000)
Lagged Other Household Income interacts with “no kids”	0.000	(0.000)	-0.000	(0.000)
Lagged Other Household Income interacts with “have dependent children age 0-4”	0.000	(0.000)	0.000	(0.000)
Lagged Other Household Income interacts with “have dependent children age 5-14”	0.000	(0.000)	0.000	(0.000)
Lagged Other Household Income interacts with “have dependent children age 15-24”	-0.000	(0.000)	-0.000	(0.000)
Binary dummy - no kids	-0.008	(0.013)	-0.127	(0.075)
Binary dummy - have dependent children age 0-4	-0.001	(0.022)	-0.107	(0.168)
Binary dummy - have dependent children age 5-14	-0.021	(0.024)	0.005	(0.050)
Binary dummy - have dependent children age 15-24	0.029	(0.016)	-0.006	(0.060)

VI. *Discussions and Concluding Remarks*

Underemployment is generally accepted as a significant weakness for an economy, hindering economic growth and giving rise to labour market inefficiencies and the waste of potentially experienced workers. From the workers’ perspective, underemployment leads to lower job satisfaction, higher job turnover, poorer mental and physical health and persistently lower earnings. Recent policy debates have identified underemployment among mature aged workers as a significant economic and social issue for Australia, and highlighted the role of improved labour market attachment in promoting the well-being and economic contributions of older-aged workers.

This paper is the first in Australia to examine underemployment in the context of labour market histories for mature aged workers, and the first to employ hierarchical cluster analysis to identify particular typologies of labour market transitions in this context. Combining the results from hierarchical clustering analysis with econometric models of labour market transition, we find there to be significant variations in the propensities for different social groups to experience underemployment.

Work trajectories are found to be correlated with social economic variables, and as expected, we find that individuals with strong labour market characteristics experience less underemployment overall. Our research finds that women and migrants particularly men who were born in non-English speaking countries face a heightened risk of underemployment. Age is also significant determinant of underemployment for women.

Importantly, our analyses further suggest that previous labour market history is a significant factor in determining current underemployment, even after taking full account of workers' human capital, current earnings potential, demographic and local labour market characteristics. This is a significant finding both in relation to an understanding of current patterns of underemployment in Australia, and in the potential responses and interventions that might protect vulnerable Australians from extended periods in underemployment. State dependence in underemployment suggesting that previous underemployment, in and of itself, begets further periods of underemployment. This highlights the importance (and indeed efficiency) of policy designs that identify points of intervention at different points in the life course to promote and reinforce improved labour market trajectories.

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