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Herwig Immervoll
OECD and IZA

Daniele Pacifico
OECD

Marieke Vandeweyer
OECD

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Faces of Joblessness in Australia: An Anatomy of Employment Barriers Using Household Data*

Australia's economy and labour market have escaped a dramatic downturn following the global financial economic crisis. Yet, a substantial share of working-age Australians either were not working or worked only to a limited extent as the global recovery gathered pace between 2013 and 2014. 18% were without employment during an entire year; a further 6% had weak labour-market attachment, e.g. working only a fraction of the year. This paper extends a method proposed by Fernandez et al. (2016) to measure and visualise employment barriers of individuals with weak labour-market attachment using household micro-data. It first develops indicators to quantify employment obstacles under three headings: (i) work-related capabilities, (ii) incentives, and (iii) employment opportunities. A novelty in this paper is a statistical procedure for calibrating the definition of barriers in a way that maximises their explanatory power in predicting employment outcomes. A statistical clustering algorithm then identify groups with similar combinations of barriers. The resulting typology provides insights on the most pressing policy priorities in supporting different groups into employment in Australia. We identify seven distinct groups, each calling for a specific flavour of activation and employment-support policies. The most common employment obstacles are limited work experience, low skills and poor health. Financial disincentives, care responsibilities and scarce job opportunities are less widespread overall but were important barriers for some groups. Almost one third of jobless or low-intensity workers face three or more simultaneous barriers, highlighting the limits of policy approaches that focus on subsets of these employment obstacles in isolation.

JEL Classification: C38, H31, J2, J6, J8

Keywords: employment barriers, profiling, activation, policy coordination

Corresponding author:
Herwig Immervoll
OECD
2, rue André Pascal
75016 Paris
France

E-mail: Herwig.Immervoll@oecd.org

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Faces of Joblessness in Australia: An anatomy of employment barriers using household data

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1. Introduction

Across OECD countries, between 16 and 50% of working-age individuals are without employment, and a significant share of workers are in unstable jobs, or work intermittently or fewer hours than they would like (OECD, 2017). The factors contributing to joblessness or underemployment are varied and can relate to individual circumstances and characteristics, to specific policy choices, or to the broader economic context, such as a cyclical economic downturn. Good-quality information on the employment barriers that people are facing is crucial for formulating strategies to overcome them, and for assessing the effectiveness of existing policy measures aiming to strengthen labour-market outcomes.

This paper provides background material for the report *Connecting People with Jobs: Key Issues for Raising Labour Market Participation in Australia* (OECD, 2017). It maps employment barriers in Australia and uses the information to identify distinct and policy-relevant groups of people with no, or with limited, labour-market attachment. A key motivation behind deriving policy-relevant clusters of jobless individuals is the finding from the literature on activation and employment-support policies (AESPs) that careful targeting and tailoring to individual circumstances are crucial factors for policy success.[1] The paper builds on and extends a method proposed by Fernandez et al. (2016), who used European household microdata for measuring employment barriers and for dividing the heterogeneous population of people with potential labour-market difficulties into smaller sub-groups, each characterized by a unique profile of employment obstacles that calls for a different mix of activation and employment support policies.[2]

Although employment obstacles can rarely be observed directly, it is possible to construct proxy indicators using the information provided in surveys. Fernandez et al. (2016) derived a series of quantitative measures of a broad range of labour-market obstacles, including "capability barriers" (e.g., skills, work experience, health, family responsibilities), "incentive barriers" (e.g., financial work incentives), and "opportunity barriers" (e.g., limited demand for workers in different regions or labour-market segments).

[1] See for example OECD (2015), OECD (2013) and European Commission (2015).

[2] The methodology has been developed as part of the "Faces of Joblessness" project (www.oecd.org/social/faces-of-joblessness.htm), undertaken jointly by the OECD, the European Commission and the World Bank, and focusing on 12 European countries.

To make scores in each of these domains directly usable as input into clustering analysis, they are typically converted into binary indicators as this simplifies the statistical model and facilitates the interpretation of the results.[3] However, the calculation of binary indicators involves the determination of cut-off points if the underlying variable is defined over a range of numerical values. As the choice of thresholds is essentially arbitrary, Fernandez et al. (2016) discretize the underlying variables using considerations rooted in the European policy dialogue, e.g. taking fixed proportions of the median in the overall population - an approach that is functionally equivalent to commonly used measures of "low" wage levels and of relative poverty. Using data for Australia, we instead propose a simple method for endogenously determining critical values for employment obstacles in a way that maximises the information content of the resulting indicators. The underlying idea is to find the values that, in a statistical sense, provide the best separation of groups with no or "weak" labour market attachment and those with stable and full-time employment.

An empirical application using the survey on Household, Income and Labour Dynamics in Australia (HILDA) shows that 18% of the working-age individuals in Australia have no labour market attachment whereas a further 5.5% has a "weak" labour market attachment. The employment barriers that are most common among these 24% of the working-age population are limited work experience, low skills and health limitations. Although financial disincentives, care responsibilities and scarce job opportunities are less widespread overall, they represented important barriers for some groups. A striking finding is that large shares of those with no or weak labour-market attachment face multiple simultaneous employment barriers: 29% face three or more significant barriers, highlighting the limits of policy approaches that focus on subsets of these barriers in isolation.

The rest of this paper is structured as follows. Section 2 describes how to adapt the methodology developed in Fernandez et al. (2016) to the HILDA data, and outlines a novel data-driven method for identifying *(i)* groups with "weak" labour market attachment, and *(ii)* those facing different types of employment obstacles of statistically meaningful magnitudes. Section 3 presents the resulting incidence of employment barriers and derives clusters of individuals with similar combinations barriers. Section 4 discusses implications of the empirical results in the context of recent policy initiatives and developments.

[3] See for example Collins and Lanza (2009).

2. Extent and incidence of labour-market difficulties

This section determines potential target groups for activation and employment-support policies (Section 2.1), and then derives concrete measures of work-related capabilities, work incentives and job opportunities that can present employment obstacles at the individual level (Section 2.2). The empirical implementation employs the Household, Income and Labour Dynamics in Australia (HILDA) survey, drawing on the analysis by Fernandez et al. (2016), who used data from the EU Survey of Income and Living Conditions (EU-SILC).[4] It utilises the rich information on individuals' labour-market situation during different points of the year, together with rich data on individuals' family and other socio-economic circumstances.

2.1. Potential target group for activation and employment-support policies

Individuals with labour market difficulties frequently move between non-employment and different states of precarious employment. As a result, limiting attention to snapshots of non-employed (or underemployed) individuals at a specific point in time, such as those based on labour force surveys, may not capture the true size of the population with labour market difficulties and a need for policy intervention. It is therefore useful to consider a longer reference period, and to determine "weak" labour market attachment in relation to the activity patterns during this period. The reference period employed in this paper is the period starting in July 2013 and ending in June 2014.[5]

To cover the potential scope of activation and employment-support policies (AESPs), one may focus on working-age individuals who are persistently out of work throughout the reference period (i.e. those who have been either unemployed or economically inactive), plus individuals whose labour market attachment is "weak", in the sense that their work intensity is significantly below somebody with full-year full-time employment. We define low work intensity to include individuals with *unstable jobs*, who either work only sporadically during the year (i.e., less than a fraction y of full-year employment), and those who have *restricted working hours* (i.e., working less than a fraction h of full-time hours per week). Combining these two dimensions of partial employment, one can define a criterion of low work intensity, where total annual working hours during the year are below a certain fraction $x = y \cdot h$ of potential full-time, full-year working hours. The empirical problem is then to solve for a threshold x that results in a meaningful overall target group given the employment patterns and labour-market context in Australia.[6]

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[4] See Wilkins (2016) and (Eurostat, 2017) for details on the HILDA and EU-SILC surveys.

[5] HILDA provides information on the main economic activity during each month of the past fiscal year, which in Australia starts on the 1st of July and ends on the 30th of June. Although, in principle, the survey longitudinal structure allows covering a longer reference period, the use of a 12-month period makes results comparable with other international income surveys, where the information on past activities do not typically go beyond the past fiscal year (e.g. the SILC for EU countries).

[6] Following Fernandez et al. (2016), we also include in the group of low-intensity workers individuals with *near-zero earnings*. These are people reporting significant work activity during the income reference period but zero or near-zero monthly earnings of less than the first percentile of the earnings distribution. In addition to possible classification error, the very low reported earnings could signal potential labour market difficulties, such as underpayment and/or informal activities.

The rationale for including people with low work intensity as a potential target group for activation and employment-support policies is a conjecture that their barriers for full employment, and therefore their need for policy support, show meaningful similarities with the population of jobless individuals.[7] Consistent with this conjecture, we empirically identify a threshold x that maximizes similarities between low-work-intensity individuals (Group B) and those who are persistently out of work (Group A). In practice, the degree of similarity between these two groups is assessed in terms of a vector $\boldsymbol{v} = [v_1, v_2, v_3]$ of variables collecting information on own work-related capabilities v_1 (e.g. skills, care responsibilities, health status), work incentives v_2 and job opportunities v_3. These variables are the same as those used later for measuring employment barriers (Section 2.2).[8]

We employ a simple three-step procedure to derive a metric that summarises differences in these multiple employment-barrier domains into a single index of statistical distance. First, we define a space of J broadly reasonable criteria x_i of low work intensity to search over. We select $J = 4$ discrete full-time equivalent (FTE) thresholds of 6 months per year (i.e., $x_1 = \frac{1}{2}$), 4 months ($x_2 = \frac{1}{3}$), 3 months ($x_3 = \frac{1}{4}$), and 2 months ($x_4 = \frac{1}{6}$). Each threshold results in an associated group B_i, whose size and composition is of course determined by the threshold, with lower thresholds resulting in smaller groups that can also be expected to be successively more similar to the persistently jobless who do not work during the entire year.

For each group, we then estimate an average probability of persistent joblessness (i.e., of membership in Group A), conditioning on vector $\boldsymbol{v}$. In line with the above consideration, this probability is expected to be greater for lower thresholds x. Finally, and since a choice based only on the resulting probabilities would result in a trivial solution of the smallest threshold, we formulate a choice function that accounts for the trade-off between two conflicting objectives: *(i)* maximizing the similarities of the two groups, and *(ii)*

According to HILDA data, and in contrast to findings for some European countries reported in Fernandez et al. (2016), the group with near-zero earnings is, however, small in Australia (see Figure 3).

[7] This paper does not attempt to distinguish between voluntary and involuntary joblessness or reduced work intensity. Our approach is descriptive in this respect and takes no position on whether policy intervention is justified for specific groups. The aim is to describe an empirical strategy to identify the most common combinations of employment barriers of a broad group with *potential* labour market difficulties. The distinctions between voluntary and involuntary aspects may not be ideal also from a policy perspective. For instance, those saying they do not want employment, or prefer to work part-time, may do so as a result of employment barriers they face, such as care obligations or weak financial incentives, which policy might seek to address. Moreover, if extended voluntary labour-market inactivity or underemployment creates or exacerbate certain types of employment barriers, it may subsequently give rise to involuntary labour-market detachment or partial employment in later periods.

[8] This method allow selecting those with 'some' labour market attachment who have similar employment obstacles to those without *any* labour market attachment. Without this step, potentially any person without full-time employment could be part of Group B. This is not ideal from a policy perspective and can also create problems when trying to identify population groups with homogenous employment obstacles. In general, one can expect that the higher the intensity of employment obstacles, as measured by vector $\boldsymbol{v}$, the lower the probability of labour market attachment. If so, it is possible to identify a certain level of employment obstacles beyond which individuals with 'little' labour market attachment become *statistically* similar to those without any labour market attachment.

maintaining a statistically meaningful sample size of Group B. Formally, the choice function (CF) is:

$$CF = \log\left(\frac{\sum_{i=1}^{N_j} \Pr_i(\text{Group A }|\text{Group B}_j = 1,\ \mathbf{v}_i)\,/N_j}{\sum_{i=1}^{N_j} 1(\text{i} = \text{Group A})\,/N_j}\right)$$

Where $\Pr_i(\text{Group A }|\text{Group B}_j = 1,\ \mathbf{v}_i)$ is the estimated score of a logistic regression for the probability of persistent joblessness, conditioning on vector $\mathbf{v}_i$ and membership to group B_i.[9] N_j is the number of individuals in group Bj, and $1(\text{i} = \text{Group A})$ is the indicator function that takes value 1 if individual i is in Group A (no labour market attachment), and zero otherwise. The numerator is the average estimated probability of Group A membership for individuals in group B_j, while the denominator is the share of individuals in the total target population who are persistently out-of-work.[10]

Figure 2.1 displays densities of estimated probabilities of Group A membership of individuals of the different Groups B_j. Inspection of the distribution modes (0.2, 0.35, 0.5 and 0.55, respectively) confirms the intuition that lower work-intensity thresholds maximise probabilities and, hence, minimise differences between Groups B and A. However, Table 2.1 shows that the choice function is maximised for threshold $x_3 = 0.25$.

Accordingly, in the analysis that follows, the target group is composed of working-age Australians (ages 18-64) with potential labour-market difficulties as follows:[11, 12] those who do not work at all during the year, as well as those who are gainfully employed for less than 25% of full-time full-year hours, based on the employment calendar information in HILDA and the working hours reported at the time of the interview.

[9] Vector $\mathbf{v}_i$ includes the same variables used later for measuring employment barriers (Section 2.2). Table B.1 in Annex B provides information on the estimated coefficients for the four selected thresholds (6 months of work per year, 4 months, 3 months, and 2 months).

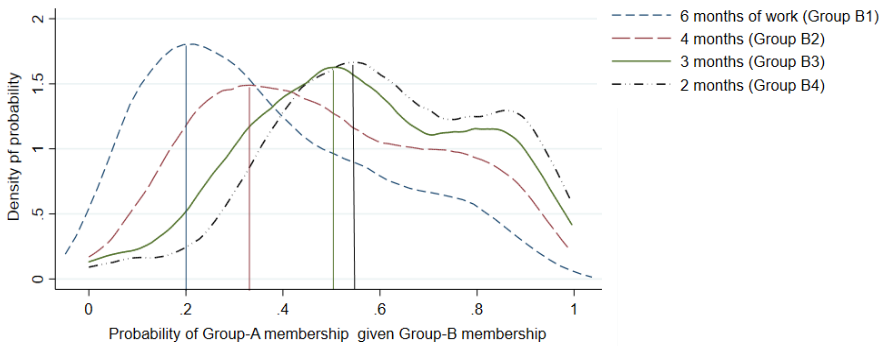
[10] As the denominator is inversely proportional to the share of the group with weak labour-market attachment, the different growth rates of these two objects ensure that the function CF has at least one global maximum in the *J* space: The groups with no and weak labour market attachment are likely to remain dissimilar also for small *j* thresholds, and one can expect the numerator to increase at a decreasing rate with *j* whereas the denominator would increase at a more stable rate.

[11] See footnote 7.

[12] It is worth noting that, with a definition of working-age as 18-64, some individuals whom policy makers may wish to include in the scope of AESPs are nevertheless not included in the target group in this note. Although the 18-64 age cut-offs are common in empirical work, they are becoming less suitable as populations age, especially in countries that are actively seeking to increase retirement ages beyond 65.

Figure 2.1. Probability of persistent joblessness during the entire year (Group A).

Low-work intensity individuals, using different "low intensity" thresholds.



Note: Predicted probabilities from a discrete choice model with logistic distribution. The dependent variable is equal to one for individuals who are persistently out of work during the entire year (Group A), and zero for individuals with low-work intensity, using alternative full-time equivalent thresholds of 6 months per year (Group B1), 4 months (Group B2), 3 months (Group B3), and 2 months (Group B4). Annex B provides information on the estimated coefficients for the four groups (Table B.1.)

Source: Author calculations based on HILDA 2014.

Table 2.1. Determining statistically meaningful thresholds for "low work intensity"

Low-work intensity threshold [fraction of full-time, full-year employment]		1/2	1/3	1/4	1/6
Percentiles of the probability of being "persistently" out of work	10%	9	17	27	36
	25%	18	29	40	46
	45%	26	38	51	56
	50%	32	46	55	61
	75%	53	68	75	80
	90%	73	83	89	91
Average probability [P]		37	48	56	60
Standard deviation		24	24	23	22
Share of low-work intensity individuals [L] (% of target population)		44	30	23	16
Choice function: ln(P/(1-L))		-0.42	-0.38	**-0.32**	-0.33

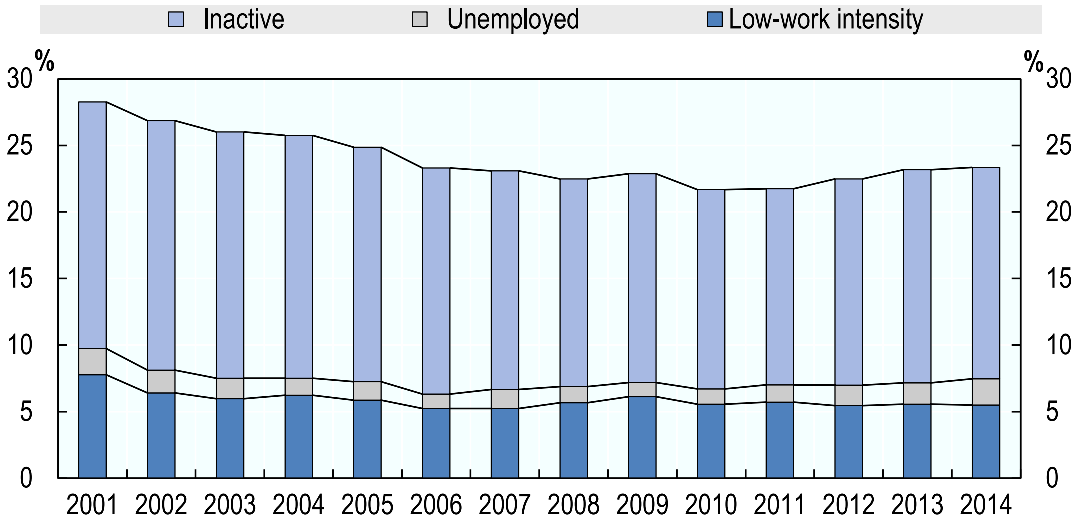
Note: see notes text and Figure 2.1 for details on the estimated models. The choice function is the logarithm of the average estimated probability divided by the share of out-of-work individuals in the target population.
Source: Authors' calculations based on HILDA, 2014.

Figure 2.2 shows trends in the size and composition of the target population between HILDA survey years 2001 and 2014 (referring to fiscal years 2000/2001 to 2013/2014). Individuals who are persistently out of work due to unemployment or inactivity account for over three-quarters of the target population. The size of the target population declined from 28.3% in 2001 to 22.5% in 2008. Following the global financial crisis, the target population saw a very slight and short-lasting increase in 2009, before declining again in 2010 and 2011. In 2014, after the commodity price crisis, the share of people without a job or with low work intensity stood at 23.4%.

The long-term decline in the target population was driven by a combination of falling labour-market inactivity and a reduction in the number of workers employed for less than 3 months during the year, or less than 10 hours a week. The more recent increase in the share of the target population can be attributed to the growth of the share of the persistently out-of-work group (consistent with the known decline in the employment rate and the increase in the unemployment rate following the GFC and the commodity price crisis, see also (OECD, 2017).

Figure 2.2. Population with potential labour market difficulties: Trends

% of the working-age population (18-64), 2001-2014.

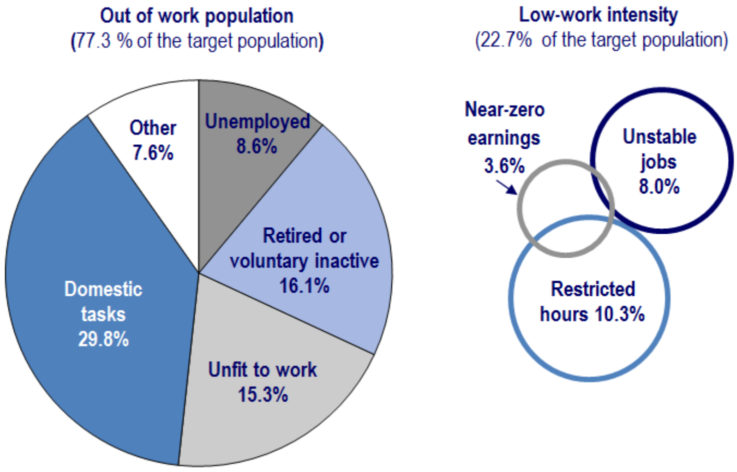


Note: A top-up sample was incorporated into the data in 2012, a small break might be observed between 2011 and 2012.
Source: Author's calculations based on HILDA.

Figure 2.3 provides a more detailed breakdown of the population with potential labour market difficulties in 2014. Almost a quarter of them (23%) are in the low-work intensity group. The most common status among the out-of-work population was inactivity because of domestic tasks (30% of the target population), followed by 16% who reported that they were retired and another 15% who declared being unfit to work. Only a comparatively small minority (8.6% of the target population) was unemployed (i.e., out of work, available for work, and actively looking for a job). The majority of individuals with low work intensity worked part-time throughout the year (10.3% of the target population), reflecting also the comparatively high and increasing share of part-time workers in the Australian workforce. 8% spent part of the year out of employment (unstable jobs, 9%) and 3.6% reported working throughout the year but with no or near-zero earnings.

Figure 2.3. Population with potential labour-market difficulties: Size and composition

% of the total target population, 2014



Note: The breakdown of the out-of-work population is based on the information on the main activity status provided at the moment of the HILDA interview.
Source: Authors' calculations based on HILDA 2014.

2.2. Employment barriers

Individuals with no or weak labour-market attachment often face a number of employment barriers that prevent them from fully engaging in the labour market. Although these barriers cannot be measured directly, proxy indicators can be developed using the information provided in surveys like HILDA. Following Immervoll and Scarpetta (2012), employment obstacles can be categorised into three broad groups: *(i)* insufficient work-related capabilities, *(ii)* lack of incentives, and *(iii)* scarce job opportunities. HILDA allows calculating measures of work-related capabilities (e.g. skills levels, childcare needs, health status), financial work incentives (e.g. proxies of the "substitution" and "income" effects described in economics textbooks), and job opportunities using information on labour-market slack in different regions and labour-market segments. Table 2.2 describes how to calculate these measures in the HILDA survey as well as the steps for deriving the resulting employment-barrier indicators.

Equivalent to the earlier problem of finding a suitable threshold for classifying employment as "low-intensity", calculating a binary employment barrier indicator from the underlying measure requires setting a cut-off point.[13] The remainder of this section proposes an approach to identify these cut-offs in the Australian context, utilising the rich information on individual characteristics contained in the microdata.

[13] The use of binary indicators for clustering analysis has several advantages. Binary indicators facilitates the interpretation of the results, simplifies the statistical model and avoid the use of distributional assumptions for the employment barrier indicators. See Collins and Lanza (2009) for a discussion on this point.

Table 2.2. Identifying work capabilities, work incentives and job opportunities in HILDA

Measures and related employment barriers indicators

Qualifiers that require setting a threshold are underlined.

	Measure	Barrier
Work-related capabilities		
Education and skills	(i) the highest educational attainment (7 categories), and (ii) the professional skill level based on the current or last occupation (8 broad groups, ANZSCO-06 classification system).	If an individual reports low education *or* low professional skills. Individuals with a tertiary degree are assumed not to face this employment barrier even if their most recent job was low-skilled.
Health	(i) degree of limitation in work-related activities as a result of physical and mental health conditions (from "no limitations" to "full incapacity" in 10 discrete categories), and (ii) mental health status (based on the SF-36 Health Survey, from "poor" to "good" on a scale between 0 and 10).	If an individual reports limitations in their work-related activities as a result of significant health problems or if they have a poor mental health score.
Care responsibilities	(i) the hours of care per week, and (ii) the number of "potential" caregivers in the household. Potential caregivers are family members aged 18-75 with no severe health-related limitations who are either unemployed, economically inactive or part-time workers working less than 30 hours per week.	If an individual has a family member who requires care, and if they are either the only potential care giver in the household, or the only person who is inactive or working part time because of care responsibilities. Family members requiring care are: children under the age of 12 who do not receive enough hours of non-parental childcare a week; adults above 65 reporting severe health limitations; working-age adults who are persistently out-of-work due to a permanent disability and report severe health limitations in their activities.
Work experience	Years spent in paid work relative to potential work experience. Potential experience is defined as the total time an individual could have spent in employment, based on age and the average time needed to achieve the highest educational achievement they report in the survey	The indicator takes one of two values: 1 for those who have no past work experience *at all*, 2 for those who have *some* work experience but this is low compared to potential experience.
Financial work incentives		
Earnings-replacements	Amount of means-tested, out-of-work benefits defined as a percentage of potential earnings. Potential earnings are estimated with a regression model corrected for endogenous sample selection. The explanatory variables are: age, age squared, education, gender and area of residence.	If the amount of means-tested, out-of-work benefits are high with respect to the individual's estimated potential earnings. For underemployed individuals actual earnings are netted out from the potential earnings.
Non-labour income	The part of household income that is unrelated to own work effort. This is calculated as the household financial year regular income minus labour income and means-tested benefits. The resulting non-labour income is divided by the "modified OECD" equivalence scale	If the household's income excluding that relating to the work efforts of the individual in question, adjusted for household size, is high compared to the median value in the working-age population. Individual incomes that are subtracted from the household income are own earnings and earnings-replacement benefits.
Job opportunities		
Job opportunities	The risk of being unemployed for more than 7 months in the own labour-market segment, despite active job search and willingness to take up employment immediately. This risk is calculated with a regression model controlling for age, education, gender, nationality and region of residence.	If an individual has a high risk of not finding a job despite active job-search and willingness to take up employment.

Note: Based on Fernandez et al. (2016), see there for a detailed presentation of the methodology for deriving each measure. The mean-tested benefits considered as earnings replacements in Australia are: *service pension, wife pension and widow allowance, carer allowance, youth allowance, parenting payment, pensions/benefits from overseas governments, seniors supplement, disability support pension, war widows pension, sickness allowance or special benefit, other government pensions/allowances, Newstart allowance, disability pension, partner allowance, Austudy / Abstudy, paid parental leave, double orphan pension, community development employment project, age pension* (for individuals on early retirement), *family tax benefits, other non-income support payments, other allowances*. According to the ANZSCO-06 classification system, low-skill

occupations are "cleaners and laundry workers", "construction and mining labourers", "farm, forestry and garden workers", "food preparation assistants" and "other labourers".
According to the HILDA documentation, mental health conditions that can affect work-related activities are essentially two: *i)* "A nervous or emotional condition which requires treatment" and *ii)* "Any mental illness requiring help or supervision". The SP-36 mental health score covers instead a broader range of mental health conditions, e.g. tiredness, nervousness, exhaustion and depression, which could also affect work-related capabilities as well as the chance to find a job.

Several of the measures in Table 2.2 are categorical (e.g. health limitations) while others are defined over continuous values (e.g. earnings-replacement benefits). In their application using data for EU countries, Fernandez et al. (2016) apply thresholds that are either common in European policy work (e.g. less than an upper-secondary degree for individuals with "low" education), or are based on specific empirical considerations (e.g. studying the distribution of the underlying measure in the working-age population and considering fixed proportions from the median). By contrast, this paper explores the possibility of using a data-driven approach to determine critical values for employment obstacles. Starting from the conjecture that the employment-barrier indicators are indeed relevant for people's employment outcomes, the approach consists in choosing values that maximise the explanatory power of the resulting indicators for identifying working-age individuals with labour market difficulties.

The method we use for determining barrier thresholds is related and consistent with the ones used to identify the group with "low work intensity" (see Section 2.1), identifying optimal threshold values by exploiting the information content of vector $\boldsymbol{v}$ and searching for "optimal" values that maximise the differences between two population groups.[14]

Figure 2.4 shows a range of possible critical values for each measure described in Table 2.2, along with the corresponding goodness-of-fit index in the vertical axis and the "optimal" threshold (the horizontal dotted line) identified using the procedure outlined

[14] In practice, the method is based on the following steps: *i)* identify a group with "good" employment (i.e., those outside the "target" group of jobless and low-work intensity workers used in this paper); *ii)* specify a space of *N* potential critical values for each measure v_i included in vector $\boldsymbol{v}$, as defined in Table 2.2, and calculate the *N* related binary employment barrier indicators, e.g. $x_{i|j} = 1(v_i > t_j)$ where t_j is one of the *N* potential critical values for indicator x_i and $1(\ )$ is a function that is equal to one when the argument is true and zero otherwise. *iii)* Estimate *N* probability models of becoming part of the target population (as defined above) for those with a "good" quality employment, while conditioning on $\boldsymbol{v} = [\boldsymbol{v}_{s\neq i}|\ x_{i|j}]$ with $j = 1,..,N$. This means estimating the same model *N* times using as explanatory variables all the measures included in vector $\boldsymbol{v}$ (Table B.2 shows the baseline regression) except for the measure of interest, e.g. v_i, which enters each model run as a (different) binary indicator depending on the selected critical value. *iv)* Select as the "optimal" threshold the value that maximises the model's explanatory power, which is summarised in an index based on standard goodness-of-fit measures. The selected measures are the *Adjusted* R^2, the *McKelvey & Zavoina's* R^2, the Akaike and the Bayesian information criteria. As these measures can lead to different "optimal" choices, we first standardise these measures and then use their average to identify the optimal threshold.

above.[15, 16] Results show that Australians with insufficient work related capabilities have often one (or more) of the following barriers:[17]

- less than an upper-secondary degree;
- a mental health score below 4.8 in a scale between 0 (“poor”) and 10 (“good”);
- a degree of health-related limitations in work-related activities of at least 5, in a scale from 0 (no limitations) to 10 (full incapacity); [18]
- childcare responsibilities during more than 30 hours per week;
- actual total work experience amounting to less than 60% of potential work experience given the person’s age and schooling;
- “low” financial work incentives, with earnings replacement benefits amounting to at least 50% of their potential gross earnings and / or with access to substantial income that does not depend in their own work effort (equivalent household income

[15] For some indicators, the method outlined above requires to restrict the estimation sample to meaningful sub-groups. Consider the earnings replacements indicator (Table 2.2). As the majority of benefit recipients are actually part of the target population, a binary indicator based on a very low threshold, which would identify nearly all benefit recipients, would have a strong predictive power. Similarly, higher thresholds would identify smaller groups of benefit recipients in the target population and the resulting indicator would lose explanatory power. As a result, the algorithm will select eventually an indicator with a very low threshold, as this maximises the model’s predictive power. This effect disappears if the estimation sample includes only individuals with *strictly positive* entitlements. In this case, those with low entitlements will be more likely to be out of the target population and the model’s predictive power will therefore increase with the threshold values, at least up to the point where the group with “high” earnings replacement benefits becomes too small and loses statistical significance. The notes to Figure 4 specify the reference estimation sample for each indicator. Annex B provides more information on the regression models.

[16] The range of potential critical values shown in Figure 2.4 depends on the type of indicator. For the two categorical measures, i.e. the educational attainment and the degree of health limitation in work-related activities, the range covers all categories except the first one: the last stage of tertiary education (PhD degree and professional Doctorate) and the ‘no health limitations’ category for the health variable. As for the continuous measures, Figure 2.4 includes any meaningful potential thresholds such that the number of units that are above or below the selected threshold is higher than 50 individuals in both groups identified by the dependent variable. The group size of are above and below the selected threshold has an impact on procedure described in the text. When one of the groups becomes too small the standard error of the estimated coefficient of the related employment barrier indicator becomes large, and the coefficient insignificant. As a result, the variable loses predictive power (if any) and thereby contributes less and less to the goodness-of-fit index, which implies that the lines shown in Figure 2.4 first decrease and then become flat.

[17] Table B.4 provides more information on the employment barrier indicators, including the standard errors of the related coefficients. The table provides information also on the distribution of the underlying measures used to derive the final indicators.

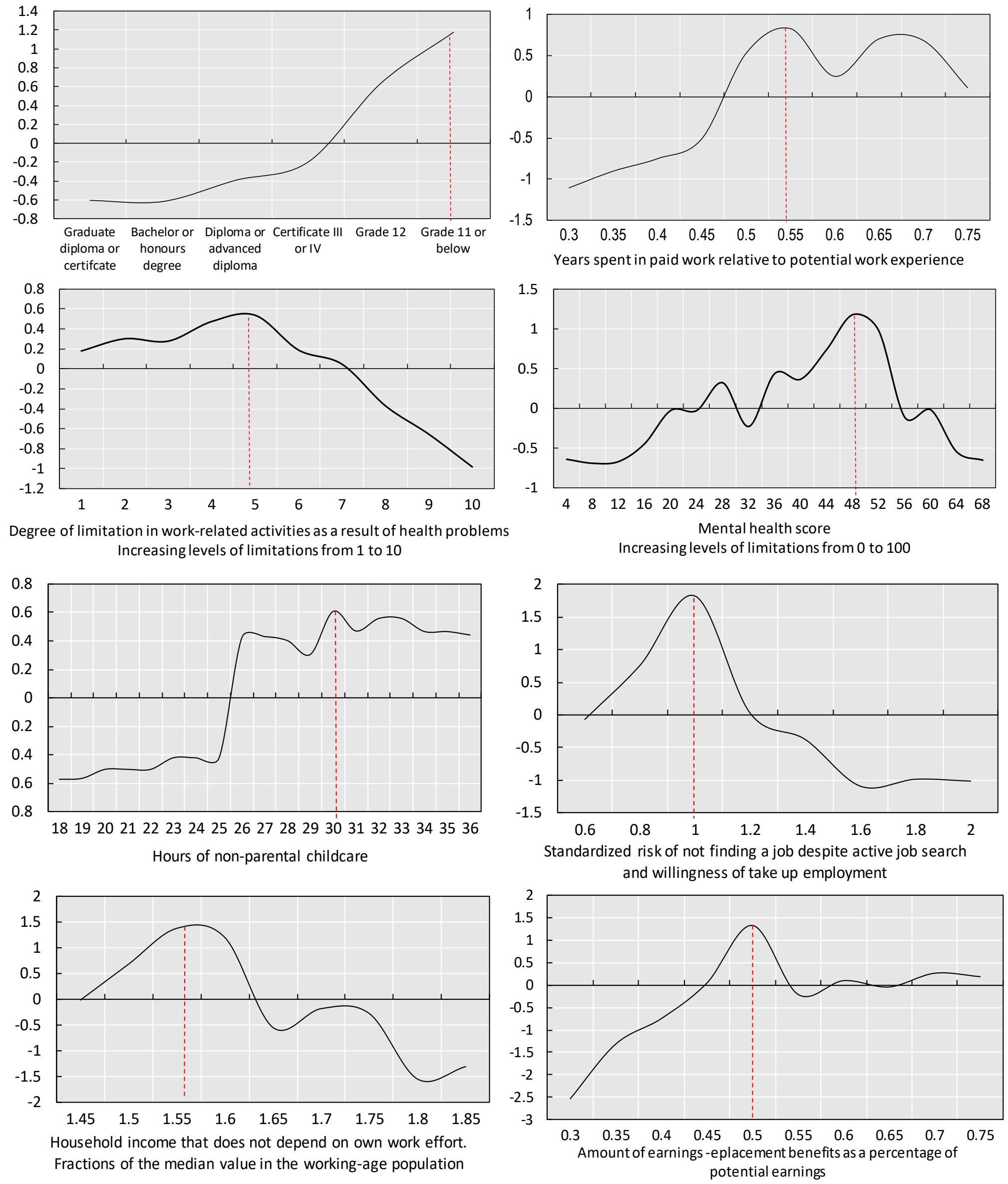
[18] The barrier for health-related limitations in work-related activities includes both physical and mental health limitation, and therefore partially overlaps with the “poor” mental health barrier. However, the SP-36 mental health score covers a broader range of mental-health indicators, which can also affect work-related capabilities (see notes to Table 2.2 for details). A confirmation of this is the limited overlap between the two health-related employment barrier indicators: only 28% of the working age population with “poor” mental health declare health limitations in work-related activities. Also, among the group with health-related obstacles (as defined in Table 2.2), about 48% have both physical limitations in work-related activities and a “poor” mental health score but do not report any work-related limitation due to mental conditions.

of at least AUD 45 586, 1.55 times the median value in the working-age population);

- "scarce" job opportunities with a standardised risk of not finding a job in the own labour market segment higher than 1.[19]

Figure 2.4. Identifying statistically optimal cut-off values for employment-barrier indicators

Goodness-of-fit index for alternative threshold values.



[19] The risk of scarce job opportunities is calculated using a probability model ("*probit*") that estimate the probability of not finding a job controlling for a series of observable characteristics (see Table 2.2). The risk of scarce job opportunities is the standardised value of the predicted probabilities in the working-age population. This risk has zero mean and unit variance in the working age population; it ranges between -.1.4 and 1.4 with a median of -0.18 (see also Table B.3).

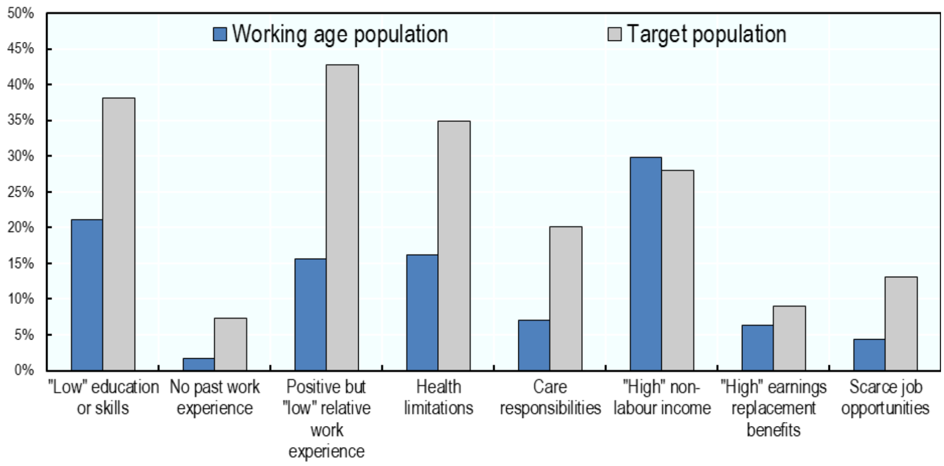
Note: see Table 2.2 for details on the underling employment barrier indicators. The estimation sample has been restricted for the following indicators: "high" care responsibilities (sample: mothers with children under 12), "high" earnings replacements (sample: individuals with positive earnings replacements), "high" non-labour income (sample: individuals with positive amounts of non-labour income); "limited" work experience (individuals with positive work experience but with less years of work experience than the years of potential experience). Education level "Grade 11 or below" corresponds to lower secondary or below, "Grade 12" to general upper secondary, "Certificate III or IV" to vocational upper secondary or vocational post-secondary non-tertiary, "Diploma or advanced diploma" to short-cycle tertiary, "Bachelor or honours degree" and "Graduate diploma or certificate" to bachelor's or equivalent.
Source: Authors' calculations based on HILDA 2014.

3. Faces of Joblessness in Australia

This section uses the indicators defined above to examine the incidence of employment barriers. Employment barriers are significantly more common among the jobless and low-intensity workers (the "target population") than in the working-age population as a whole (Figure 3.1), indicating that they have explanatory power and are indeed reasonably well associated with employment outcomes. "Low recent work experience", "lack of skills" and "health limitations" are the most frequent barriers (43%, 38% and 35% of the target population, respectively) whereas "scarce job opportunities" and "high earnings-replacement benefits" are much less common (13% and 9%). "High levels of non-labour income" is the only employment barrier whose incidence is higher in the working-age population, e.g., because those with strong labour-market attachment may be more likely to have a high-earning spouse as a result of selection effects in the family formation process ("assortative mating").

Figure 3.1. Prevalence of employment barriers

As a percentage of the target and working-age population, 2014

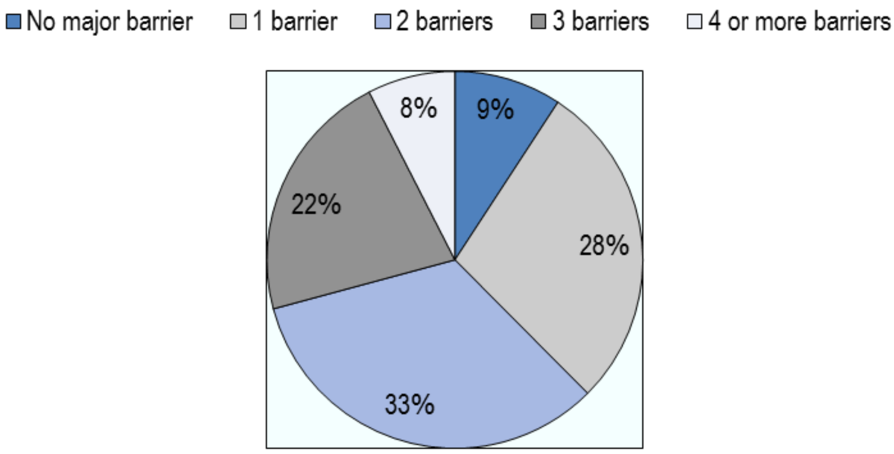


Note: See Section 2.2 for the definitions of the barriers.
Source: Authors' calculations based on HILDA 2014.

A notable finding is that only 28% of individuals in the target population face just a single employment barrier whereas about one third face two simultaneous barriers, and another third face three barriers or more (Figure 3.2). Less than 10% do not face any of the employment barriers assessed here. For this group, the employment-barrier indicators are either below the respective thresholds used in this report, or their limited labour-market attachment is indeed unrelated to the barriers discussed here: they may have a strong preference for leisure, or they experience other barriers that reduce the likelihood of employment but cannot be captured in the present analysis.

Figure 3.2. Number of simultaneous employment barriers

As a percentage of the target population, 2014



Source: Authors' calculations based on HILDA 2014.

3.1. Target groups for activation and employment-support policies

The employment-barrier indicators can be used in conjunction with a statistical segmentation method (Latent Class Analysis, LCA) to reveal (unobserved, "latent") groups in the target population of jobless and underemployed individuals that are meaningful for designing, tailoring and targeting activation and employment support policies.[20] The objective is to obtain groups (or "classes") of individuals with combinations of employment barriers that are as similar as possible within groups, and as different as possible between groups.[21]

[20] LCA exploits the interrelations of an array of indicators through a fully-specified (i.e. parametric) statistical model that organizes a sample of individuals into homogeneous and separated groups. See e.g. (Goodman, 1974) and (Henry, 2006). This paper adapts to Australian data the LCA model described in Fernandez et al. (2016).

[21] The analysis of employment obstacles based on LCA is different from a traditional regression analysis. Regression models would, e.g., show how each barrier in isolation affects the risk of facing potential labour market difficulties while holding all other barriers constant. By contrast, the LCA-based segmentation approach uncovers interrelations between employment barriers and how they jointly determine observed labour-market outcomes. The focus on joint patterns of employment barriers is relevant as the success of activation policies typically depends on their ability to address real-world combinations of different labour-market obstacles.

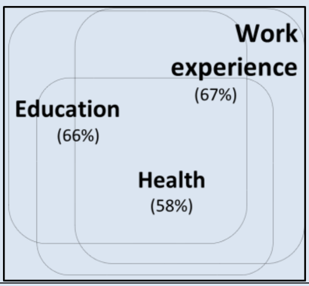
The segmentation method suggests that the population of individuals with no or weak labour market attachment can be separated into seven distinct groups (see Annex B and Figure 3.3). Below, we report results for each group using Venn diagrams illustrating the incidence and the three most common employment barriers, and the degree of overlap between them. A short summary reports other selected individual and household characteristics to describe group members in more detail. This information can help attach labels ("faces") to group members, although labels are necessarily arbitrary to some extent and cannot substitute for careful examination of the comprehensive list of employment barriers and socio-economic characteristics. Results on the full set of characteristics are in Table A.2.

Group 1: "Older women with low education levels, limited work experience or health limitations"

Group 1 represents 25% of the target population and consists largely of prime-age women (68% of members are female, average age 49 years) who are labour-market inactive (94%). The majority have low education or skills (66%) and limited work experience compared to their potential (67%). About 58% suffer from some long-standing physical or mental health limitations, with 29% reporting poor mental health and 20% a severe physical or mental impediment for work. 44% receive sickness and disability benefits and 10% receive unemployment benefits. Individuals in this group face an average of 2.2 employment barriers, the third-highest level of all groups (Figure 3.3). The average equivalised household income is relatively low (AUD 37 040 per year on average in comparison to an average of AUD 60 664 in the working age population), with more than half of this group living in households in the bottom quintile of the income distribution, and the risk of poverty is the second highest (55%) of all groups.

Box 3.1. "Women with low education levels, limited work experience or health limitations"

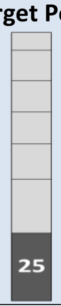
Main employment barriers[1]



Selected characteristics[2]

49 years old (average)
Majority women (68%)
Labour-market inactive (94%)
15 years in paid work (average)
11.5 years of schooling (average)
Equivalised disposable income: AUD 37 040
2.2 simultaneous employment obstacles (average)

% of the Target Po



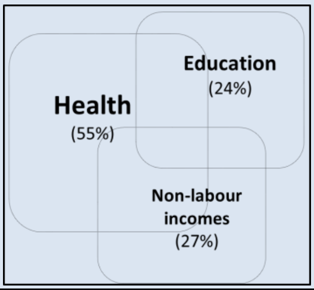
Note: 1. Surface areas in the diagram are proportional to the number of members facing the related barrier ("Proportional Venn Diagrams"). The outer square represents the group size (100%). The diagram shows the three most prevalent barriers in the group and is based on the indicators discussed in Table 2.1.
2. Characteristics that distinguish this group from other groups, i.e., categories that have a high probability of occurring in the group.
Source: Calculations based on HILDA 2014, see Table A.1and Table A.2 for full results.

Group 2: "Early retirees with significant work experience but poor health"

The second group accounts for 20% of the target population, and generally consists of older men (the average age is 56, 75% are aged 55-64 years) with considerable paid work experience (31 years on average, the highest of the seven groups). More than half suffer from a long-standing physical or mental health limitation, and 27% receive sickness and disability benefits and 10% receive unemployment benefits. The majority are labour market inactive (83% during the reference period) with 39% reporting their activity status as "retired" and 21% as "unable to work" because of sickness or disability at the time of the interview. Compared to other groups, individuals in this group are less likely to face multiple simultaneous employment barriers (see Figure 3.3).

Box 3.2. "Early retirees with significant work experience but poor health"

Main employment barriers



Selected characteristics

56 years old (average)
Majority men (67%)
Labour-market inactive (83%)
31 years of paid work (average)
12.8 years of schooling (average)
Average equivalised disposable household income: AUD 46 618 per year
1.1 simultaneous employment obstacles (average)

% of the Target Pop.

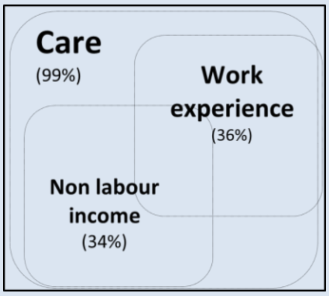
Note: See notes to Box 3.1.

Group 3: "Mothers with care responsibilities"

The third group, which accounts for 13% of the target population, almost entirely consists of prime age (the average age is 34, 95% are aged 25-54) women (96%) with young children who have a partner. These families have on average two children and the average age of the youngest child is two. In the vast majority of cases the partner works (86%), meaning that care responsibilities fall on members of this group as they receive only little non-parental childcare (the average is 12 hours per week, the lowest of all groups with children). 84% of individuals in this group were labour market inactive throughout the reference period and 75% were still inactive at the moment of the HILDA interview (while 10% were unemployed). Long periods of inactivity also help to explain why over a third (36%) of individuals in this group has low overall work experience relative to their potential. This happens despite the high education level characterising this group, with an average of 14.5 years of schooling (the highest of all groups) and 68% of members having completed an advanced diploma or a graduate degree. The other common employment barrier characterising this group is weak work incentives resulting from high levels of household income that are not related to their own work effort (34% of members).

Box 3.3. “Mothers with care responsibilities”

Main employment barriers



Selected characteristics

34 years old (average)
Women with children living with their partner
Average age of the youngest child: two
Labour-market inactive
10 years of paid work (average)
14.5 years of schooling (average)
Average equivalised disposable household income:
AUD 40 906 per year
2.0 simultaneous employment obstacles (average)

% of the Target Pop.

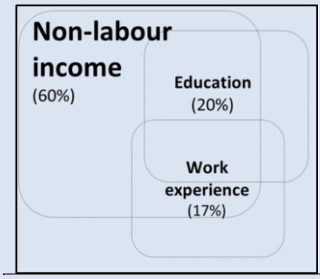
Note: See notes to Box 3.1.

Group 4: “Underemployed workers with weak financial work incentives”

Group 4 represents 12% of the target population and it is the only group, where the majority of individuals are “underemployment” (83%), as opposed to inactive or unemployed (17%). Individuals in this group are also mostly prime age (average age 40) women (66%). About half of the members worked throughout the reference period for 10 hours per week or less and another 23% worked for no more than three months during the same period. Another 20% reported work activity throughout the reference period but declared zero or *near zero* earnings; of this 35% were self-employed who mainly declared *zero* earnings throughout the year, while 64% were part-time employees who reported some positive, but low earnings. Only 20% of the part-time employees in this group reported being “involuntary part time”. Of the others, 53% wanted to work part time (27% because they prefer working part-time, 11% because they like their job, and 15% due to education) while 17% had care responsibilities and 7% a long-standing illness or disability. Many individuals in this group face weak financial incentives to work: 74% live in households where at least one other person has employment earnings (the second-highest percentage of all groups) and for 60% of members the level of household income that is not related to own work effort is particularly high (i.e. more than AUD 45 586 per year; Table A.2).

Box 3.4. “Underemployed workers with weak financial work incentives”

Main employment barriers



Selected characteristics

40 years old (average)
Mostly women
Some work activity during the reference period
20 years of paid work (average)
13.4 years of schooling (average)
Average equivalised disposable household income:
AUD 54,729 per year
1.1 simultaneous employment obstacles (average)

% of the Target Pop.

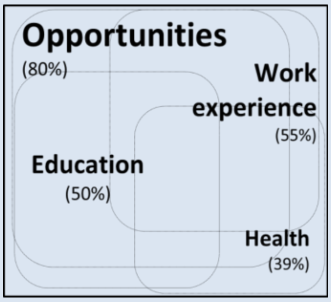
Note: See notes to Box 3.1.

Group 5: "Long-term unemployed with limited work experience and low education"

Representing 12% of the target population, group 5 consists largely of younger individuals (average age 31) facing scarce job opportunities (80%): many have been actively seeking employment for more than a year, with an average unemployment spell of 16 months. The majority (57%) were unemployed at the moment of the interview while 40% were labour market inactive. 46% received unemployment benefits during the income reference period. As a result of this long period out of work, the majority (55%) have limited work experience relative to their potential. Half also have low education or skills whereas a significant number (39%) reported a long-standing physical or mental health limitation (the average mental health score is the second-lowest of all groups, with 26% having a score which is lower than 6). Compared to other groups, individuals in this group are more likely to face multiple simultaneous employment barriers (Figure 3.3). The average equivalised household income is the second lowest of the seven groups and the risk of poverty is high (53%).

Box 3.5. "Long-term unemployed with limited work experience and low education"

Main employment barriers



Selected characteristics

31 years old (average)
Mostly men (63%) who are unemployed (57%)
10% belong to an indigenous population group
16 months of unemployment (average)
9 years of paid work experience (average)
12.7 years of schooling (average)
Average equivalised disposable household income: AUD 34 547 per year
High risk of poverty (53%)
2.7 simultaneous employment barriers (average)

% of the Target Pop.

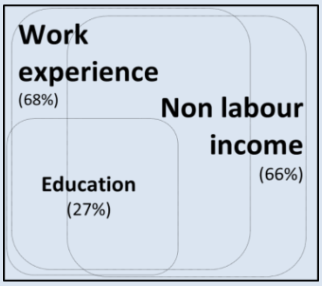
Note: See notes to Box 3.1.

Group 6: "Older women in higher-income households with limited work experience"

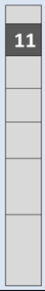
Accounting for 11% of the target population, Group 6 mainly consisting of older women (average age 50) who are largely labour market inactive (87%). Although all members have worked in the past with an average of 16 years of paid work experience, for 68% of them this is short relative to their potential experience. 72% share the household with an employed adult (the partner in most cases) and most of them (66%) have relatively weak work incentives due to high levels of household income (mostly the partner's earnings) that is not related to their own work effort. The (equivalised) household income is the highest among all seven groups, at AUD 66 680 per year on average. 46% report their activity status as "house work", 21% as "retired" and 16% as inactive due to "other reasons". About one third has low education or skills. The number of average simultaneous employment barriers is 1.8 on average (Figure 3.3).

Box 3.6. "Older women in higher-income households with limited work experience"

Main employment barriers | **Selected characteristics** | **% of the Target Pop.**



50 years old (average)
Women
Labour market inactive
16 years of paid work experience (average)
13.2 years of schooling (average)
Average equivalised disposable household income: AUD 66 680 per year
1.8 simultaneous employment obstacles (average)



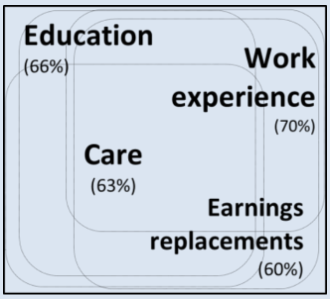
Note: See notes to Box 3.1.

Group 7: "Younger mothers with multiple employment obstacles"

Group 7 represents 7% of the target population and consists of younger (33 years on average) women (97%) with children (98%, two children on average). 17% of group members belong to an Indigenous population. The majority were labour-market inactive throughout the reference period (89%), with 71% reporting "house work" as their main activity. Family circumstances are not uniform within the group, however, with 44% in a partnership and one third reporting being lone parents (and the remaining 20 percent consisting mainly of multifamily households). Their children are of pre-school age (the youngest is 3 years old on average) and 63% of the women in this group face significant care responsibilities without access to other potential care givers in the household. Although almost all members receive income support in the form of family benefits (95%), 56% are at risk of poverty, the highest proportion of all groups. Benefits tend to be means-tested and can weaken the incentives to look for employment or take up work: for 60% of individuals the earnings-replacement benefits are high relative to potential earnings in work. The average years of schooling (11.9 years) are the lowest of all seven groups, and 66% have low education. One in three suffer from long-standing physical or mental health issues and the mental-health score is particularly low (less than 6 out of 10) for more than one fourth of them. The average number of simultaneous employment barriers is 3.4.

Box 3.7. "Younger mothers with multiple employment obstacles"

Main employment barriers | **Selected characteristics** | **% of the Target Pop.**



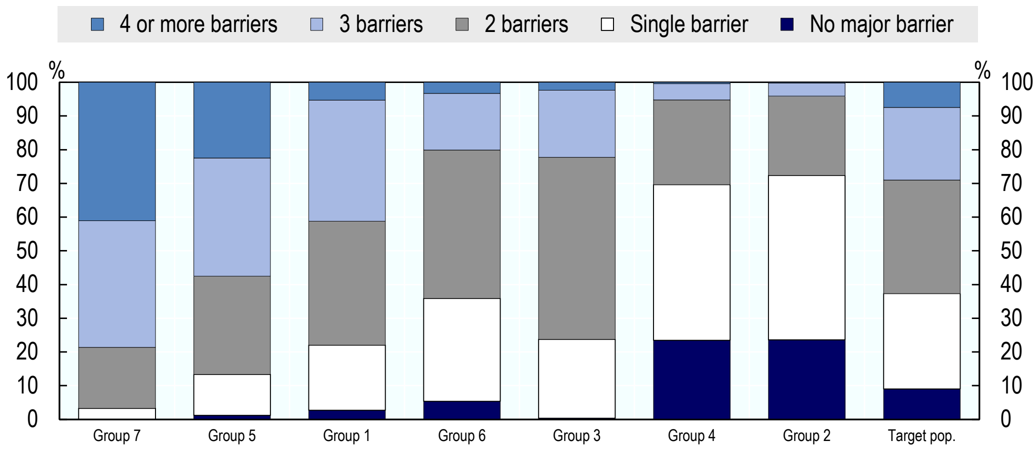
33 years old (average)
Women with young children
17% belong to an Indigenous population group
Labour market inactive
11.9 years of schooling (average)
6 years of paid work experience (average)
Average equivalised disposable household income: AUD 29 920 per year
At risk of poverty
3.4 simultaneous employment obstacles (average)

Note: See notes to Box 3.1.

In most groups a majority face multiple simultaneous employment barriers (Figure 3.3). This result means that addressing only one of those obstacles might not be enough to boost employment levels significantly. For instance, Group 7 (“Younger mothers with multiple employment obstacles”) shows the highest number of simultaneous barriers, with over three quarters of group members facing three or more barriers. The majority of Group 5 (“Long-term unemployed with limited work experience and low education”) also face three or more simultaneous obstacles. Only two of the groups mostly face only a single employment barrier: Group 1 (“Women with low education levels, limited work experience or health limitations”), and Group 4 (“Underemployed workers with weak financial work incentives”).

Figure 3.3. Incidence of multiple simultaneous employment barriers

Percentage of group size



Note: Horizontal axis reports group sizes. Groups are as follows: 1. “Women with low education levels, limited work experience or health limitations”, 2. “Early retirees with significant work experience but poor health”, 3. “Mothers with care responsibilities”, 4. “Underemployed workers with weak financial work incentives”, 5. “Long-term unemployed with limited work experience and low education”, 6. “Older women in higher-income households with limited work experience”, 7. “Younger mothers with multiple employment obstacles”.
Source: Calculations based on HILDA 2014.

4. Discussion and implications for the policy debate

The literature on activation and social protection systems more generally, commonly emphasises targeting and tailoring of policy interventions to individual circumstances as crucial factors for policy success. Yet, relatively little is known about what these individual circumstances look like or how they may translate into employment barriers that policies aim to address. Policy discussions do not necessarily reflect this. They commonly refer to proxy grouping, such as “young people”, “older workers”, “benefit recipients” or “mothers”. An implicit assumption is that these groupings are useful for describing different sets of employment barriers that may inform policy design and implementation. But if members of the same proxy groups face in fact quite different sets of employment barriers, then policy interventions targeted on the basis of age, benefit receipt or family situation alone may be ill-adapted to the needs of jobless individuals. In some cases, proxy labels may even distract attention from the specific employment obstacles that policies seek to address, and suitable policy responses and priorities may require more granular descriptions of labour-market groups.

One notable inference from the results reported in this paper is that proxy groupings, which are commonly referred to in the policy debate, such as "mothers" are indeed far from homogeneous. For instance, the results point to **two separate groups of mothers with children** (Groups 3 and 7) with very different patterns of both employment obstacles, and individual / household circumstances. While childcare support is important for both groups, the "*younger mothers with multiple employment obstacles"* (Group 7) will also require additional and coordinated measures to address skills deficits and strengthen work incentives.

Results also point to **two groups of older women** (Groups 1 and 6). "*Women with low education levels, limited work experience or health limitations"* (Group 1) face a number of problems that may be additive. In particular, they have much lower education and work-related skills than the group of "*Older women in higher-income households with limited work experience"* (Group 6). Unlike Group 1, Group 6 can typically draw on financial resources that do not depend on their own work effort. Many women in Group 1 have severe health limitations, signalling the need for policy measures support the active participation of people with disabilities.

Groups 1 and 6 are older than the group of younger mothers (Groups 3 and 7) discussed above and their employment barriers are different too. For instance, fewer care responsibilities for the older women in Groups 1 and 6 are not surprising. In principle, the groups of younger and older mothers could nevertheless be linked to the extent that they represent different life-cycle stages for women experiencing labour-market difficulties around the time of family formation. For instance, care responsibilities and other barrier at younger ages may drive the outcomes observed around 15 years later if employment difficulties around the time of family formation have scarring effects. Further work would be needed to empirically verify this conjecture. If confirmed, such a pattern would underline the important role of effective employment-support policies during the earlier stages of adulthood.

Two **groups of people reporting poor health**, including Group 1 discussed above, as well as the "*experienced early retirees with health limitations"* (Group 2) may both benefit from flexible working arrangements or activation measures tailored to individuals with health problems. The majority of Group 6 are older individuals with some work experience, who are, however, generally subject to less demanding activation requirements than younger Australians (OECD, 2012).

A substantial share of jobless **youth** are "*long-term unemployed with limited work experience and low education*" (Group 5). Scarce job opportunities and low education are key barriers in this group and the two are likely linked given generally lower demand for low-skilled workers. In view of the young age of this group, targeted policies aiming to improve employment-relevant skills of disadvantaged youth appear especially important. For instance, for many disengaged youth an exclusive focus on education may not necessarily be the best way forward, as the multiple barriers in this group suggest that improve work readiness must be part of a reintegration strategy.

The “*underemployed workers with weak financial work incentives”* (Group 4) had some work activity during the year and 70% report holding a “casual job” (Table A.2), an employment contract offering less protection against dismissal than regular open-ended or fixed-term contracts. Their profile is, however, relatively heterogeneous otherwise. For instance, one quarter of them is under 25 while another is over 55. As for the “*Older women in higher-income households with limited work experience*” (Group 6), factors that may discourage fuller labour-market participation of Group 4 include the availability of substantial other income sources in their households. This is also in line with a large share (40%) reporting “preferences” as the main reason for not working full-time. In these cases, the availability of “casual jobs” strengthens labour-market attachment but it may not necessarily act as a stepping stone towards “standard” employment and reduced dependence on support from other family members.

Annex A. Additional tables

Table A.1. Prevalence of employment barriers in each group (latent class estimates)

Percentage of individuals with selected characteristics, by group, 2014.

	Abbreviated cluster name	Older low-educated	Experienced early retirees	Mothers with care responsibilities	Under- employed workers	Long-term unemployed	Women living in higher-income HH	Mothers with multiple obstacles	Target population	Working age population[a]
	Cluster number	*1*	*2*	*3*	*4*	*5*	*6*	*7*		
	Cluster Size (% of target population)	**25**	**20**	**13**	**12**	**12**	**11**	**7**	**100**	
Core indicators	"Low" education or skills	66	24	9	20	50	27	66	38	21
	No past work experience	6	0	8	17	15	0	18	7	2
	Positive but "low" relative work experience	67	8	36	8	55	68	70	43	16
	Health limitations	58	55	5	10	39	9	34	35	16
	Care responsabilities	8	0	99	0	3	3	63	20	7
	"High" non-labour income	9	27	34	60	12	66	5	28	30
	"High" earnings replacements benefits	6	2	9	2	13	0	60	9	6
	Scarce job opportunities	0	8	2	2	80	0	22	13	4

Note: Boxes 3.2 and 3.3 describe the indicators and applicable thresholds. Group sizes refer to the target population as defined in Box 3.1. Colour shadings identify categories with high (dark blue) and medium (lighter blues) frequencies. Complementary categories (e.g. "high" education) are omitted. Additional information on model selection and model specification is provided in Annex B. a) Persons aged 18-64 excluding full-time students.
Source: Authors' calculations based on HILDA, 2014.

Table A.2. Detailed characteristics of group members

Percentage of individuals with selected characteristics (†, †† denote averages), by group, 2014.

	Abbreviated cluster name	Older low-educated	Experienced early retirees	Mothers with care responsibilities	Under- employed workers	Long-term unemployed	Women living in higher-income HH	Mothers with multiple obstacles	Target population	Working age population[a]
	Cluster number	*1*	*2*	*3*	*4*	*5*	*6*	*7*		
Cluster Size (% of target population)		**25**	**20**	**13**	**12**	**12**	**11**	**7**	**100**	
Number of individuals (frequency, in thousands)		**697**	**556**	**380**	**336**	**328**	**316**	**192**	**2 805**	13 339
Number of simultaneous barriers††		2.2	1.1	2.0	1.1	2.7	1.8	3.4	1.9	1.0
Women*		68	33	96	66	37	100	97	66	50
Age groups*	Youth (18-24)	0	0	4	24	42	2	24	10	10
	Prime age (25-54)	60	25	95	54	56	56	74	57	70
	Old-age (55-64)	40	75	1	22	2	42	2	33	20
Age††		49	56	34	40	31	50	33	44	42
Education	Lower secondary or less	63	23	8	16	45	25	61	36	20
	Upper secondary	12	12	24	31	26	18	16	18	16
	Cert III / Cert IV / Adv diploma	18	43	33	26	23	32	18	28	34
	Bachelor / Grad diploma / Postgrad / Master	7	21	35	26	6	25	5	18	30
	Years of education (average)	11.5	12.8	14.5	13.4	12.7	13.2	11.9	12.8	13.6
Health	Limitations in work activities (score: 10=max, 0=min)††	4	3	0	1	2	1	1	2	1
	Have "severe" health limitations in work activities	20	15	0	4	7	4	6	11	3
	Good mental health (score: 10=max, 0=min)††	6.1	7.0	7.6	7.4	6.3	7.4	6.4	6.8	7.3
	Have "poor" mental health	29	17	6	10	26	9	27	18	11
Migrant		29	32	43	27	23	39	21	31	31
Indigenous		6	2	3	2	10	2	17	5	3
Household type (members with 15+ years are considered "adults")	Single	27	23	0	14	28	10	0	18	16
	Couple without children	45	55	0	50	36	45	0	38	39
	Couple with children	9	7	83	25	15	31	44	26	29
	Lone parents	2	1	6	2	4	1	33	4	3
	2+ adults with/without children	8	8	3	6	7	6	4	6	6
	Multifamily households	8	7	7	4	11	7	18	8	6
Have children* (less than 15 years)		18	13	100	27	28	38	98	38	37
Number of children† (less than 15 years)		1.8	..	2.1	2	2	2	2.1	2.0	2
Age of the youngest child†		7	..	2	8	6	8	3	4	5
Hours of non-parental childcare†		22	..	12	38	31	32	22	19	32
Household with other working household members		43	44	86	74	53	72	48	57	67
Had any work activity	During the reference period	6	13	27	83	25	15	7	23	82
	During the last two years	22	36	42	87	56	33	25	41	86
	During the last three years	34	51	55	89	69	44	38	52	89
Type of labour market attachment during the reference period	Unstable jobs (≤ 3 months)	..	..	14	23	..	..	..	9	2
	Restricted working hours (≤ 10 hours a week)	..	..	13	48	..	..	..	11	3
	Employees with zero or near-zero earnings	..	..	2	20	..	..	..	4	1
Main reason for restricted working hours	Illness or disability	..	..	..	7	..	..	..	8	5
	Care or family responsabilities	..	..	..	17	..	..	..	30	30
	Education	..	..	..	15	..	..	..	10	8
	involuntary (cannot find FT work)	..	..	..	20	..	..	..	16	14
	Prefer working part time	..	..	..	27	..	..	..	23	25
	Prefer current job	..	..	..	11	..	..	..	10	17
	Other reasons	..	..	..	2	..	..	..	3	2
Main activity during the reference period	Working	3	9	12	61	2	10	2	13	67
	Unemployed	3	8	4	7	47	3	9	10	8
	Inactive	94	83	84	32	51	87	89	77	25
Main activity at the time of the HILDA interview	FT worker	0	2	0	13	0	0	0	2	55
	PT worker	3	8	15	55	3	10	3	13	21
	Unemployed	2	9	10	6	57	2	9	12	4
	Retired	22	39	0	1	2	21	1	16	4
	Unfit to work/disable	32	21	1	4	13	6	4	15	4
	House work	31	12	60	9	6	45	71	30	7
	Other inactive	9	9	15	12	18	16	12	12	5

Table A.2. Detailed characteristics of group members (cont.)

Percentage of individuals with selected characteristics (†, †† denote averages), by group

	Abbreviated cluster name	Older low-educated	Experienced early retirees	Mothers with care responsibilities	Under- employed workers	Long-term unemployed	Women living in higher-income HH	Mothers with multiple obstacles	Target population	Working age population[a]
	Cluster number	1	2	3	4	5	6	7		
Cluster Size (% of target population)		**25**	**20**	**13**	**12**	**12**	**11**	**7**	**100**	
Type of employment	Employee	..	..	..	64	..	..	..	64	85
	Self-employed	..	..	..	35	..	..	..	33	14
	Family business	..	..	..	2	..	..	..	3	0
Share of emloyees with "casual" job		..	..	..	68	..	..	..	68	17
Length of unemployment spell (months)†		..	..	..	..	16	..	..	16	12
Years of paid work experience† (average)		15	31	10	20	9	16	6	17	19
Equivalised disposable household income (AUD/year - average)		37 040	46 618	40 946	54 729	34 547	66 680	29 920	44 182	60 664
Position in the income distribution	Bottom quintile	55	29	41	25	53	15	56	40	15
	Second quintile	31	22	33	20	26	20	32	26	19
	Third quintile	5	26	15	18	16	19	9	15	21
	Fourth quintile	5	12	7	17	2	26	3	10	22
	Top quintile	4	10	4	20	3	20	1	9	22
AROPE (eurostat methodology)		55	29	40	25	53	16	56	40	15
Material deprivation (eurostat methodology)		8	2	0	1	8	1	7	4	1
Benefits, recipiens and average amounts (AUD/year)	Sickness and disability recipients (%),	44	27	2	10	18	10	11	12	6
	they receive, on average†	17 521	16 885	..	..	..	..	..	9 170	16 030
	Unemployment benefits recipients (%),	10	10	2	10	46	4	9	15	6
	they receive, on average†	..	..	..	..	10 588	..	..	4 854	7 833
	Social Assistance recipients (%),	5	3	1	3	1	4	1	1	1
	they receive, on average†	..	..	..	..	..	..	..	..	11 502
	Family-related benefits recipients (%),	29	21	83	25	18	30	95	33	26
	they receive, on average†	13 868	10 319	10 856	..	..	9 330	22 128	1 364	8 697
Live in rural area*		13	13	10	11	10	10	10	11	10
Area of residence	Major cities	65	67	74	73	70	75	61	69	74
	Inner regional AUS	22	22	15	17	19	17	23	20	17
	Outer regional AUS	12	10	10	9	10	6	14	10	8
	Remote AUS	1	1	1	1	1	2	1	1	1

Note: ".." means "unavailable because of limited number of observations"; "†" means "average across observations with strictly positive values"; †† means "average across all observations"; * means that the variable enters as an additional indicator in the latent class model, see Annex B for details. (a) The working age population is calculated for persons aged 18-64 excluding full-time students.

Colour shadings identify categories with high (darker) and medium (lighter blues) frequencies. The average number of simultaneous barriers per individual is computed for the core indicators in Table A.1. Income quintiles refer to the entire population. The at risk-of-poverty rate is the share of people with an equivalised disposable income (after social transfer) below 60 % of the national median. Material deprivation is defined as not being able to afford at least three of the following items: washing machine, telephone, TV, decent and secure home, substantial meal at least once a day, a week's holiday away from home each year, motor vehicle, AUD 500 in savings for an emergency, when it's cold keep at least one room warm. Sickness and disability benefits include Sickness Allowance or Special Benefits, Disability Support Pension, Disability Pension, and Mobility Allowance. Unemployment benefits include NewStart Allowance, Youth Allowance, and CDEP. Social assistance benefits include Service Pension, Wife Pension or Widow Allowance, Partner Allowance, War widow's pension, Abstudy/Austudy, Seniors Supplement, and Bereavement Allowance. Family-related benefits include Carer payment, Parenting payment, Carer allowance, paid parental leave, Double Orphan pension, Maternity Payment, School Kids Bonus, and Family Tax Benefit.

Source: Authors' calculations based on HILDA 2014.

Annex B. Methodological details

Regression estimates

Table B.1. Identifying individuals with "weak'' labour market attachment.

Logistic regression estimates for the probability of being persistently out of work for those with different levels of labour market attachment.

	Group B1 (6 months of work)		Group B2 (4 months of work)		Group B3 (3 months of work)		Group B4 (2 months of work)	
Measure	Coef.	P value	Coef.	P value	Coef.	P value	Coef.	P value
Earnings replacements	2.630	0.000	2.269	0.001	1.721	0.001	1.724	0.019
Earnings replacements ^2	-2.875	0.000	-2.521	0.005	-1.663	0.009	-1.731	0.060
Non Labour income	0.073	0.006	0.110	0.002	0.088	0.001	0.128	0.036
Non labour income ^2	-0.004	0.387	-0.007	0.255	-0.005	0.471	-0.008	0.268
Work experience	-2.620	0.000	-2.734	0.000	-2.755	0.000	-2.966	0.000
Professional skill level								
Managers	baseline							
Professionals	-0.383	0.741	-0.226	0.473	-0.138	0.432	-0.140	0.354
Technicians and Trades	-0.329	0.378	-0.059	0.806	-0.012	0.164	-0.047	0.867
Community and Personal Services	-0.273	0.370	-0.142	0.193	-0.105	0.132	-0.132	0.213
Clerical and Administrative	-0.328	0.693	-0.258	0.091	-0.451	0.053	-0.243	0.084
Sales	0.431	0.000	0.354	0.001	0.517	0.005	0.317	0.024
Machinery Operators and Drivers	0.582	0.016	0.397	0.005	0.596	0.000	0.754	0.017
Labourers	0.607	0.002	0.627	0.006	0.737	0.001	0.973	0.002
Highest educational attainment								
PhD	baseline							
Graduate degree	-0.072	0.806	-0.428	0.214	-0.334	0.395	-0.282	0.515
Bachelor degree	-0.329	0.209	-0.671	0.126	-0.659	0.250	-0.622	0.596
Diploma or advanced diploma	0.105	0.707	0.157	0.625	0.218	0.545	0.039	0.925
Certificate III or IV	0.247	0.344	0.203	0.496	0.142	0.242	0.124	0.739
Grade 12	0.561	0.008	0.423	0.003	0.332	0.002	0.319	0.003
Grade 11 or below	0.405	0.008	0.350	0.001	0.236	0.007	0.197	0.002
Degree of limitation in work-related activities								
0 (no limitations)	baseline							
1	-.142	0.801	-0.062	0.928	-0.087	0.916	-0.119	0.626
2	-0.001	0.996	-0.090	0.807	-0.096	0.824	0.135	0.801
3	-0.045	0.869	0.240	0.504	0.322	0.415	0.163	0.721
4	0.448	0.161	0.916	0.032	1.010	0.060	0.836	0.158
5	0.340	0.044	0.196	0.286	0.172	0.414	0.040	0.867
6	0.119	0.092	0.421	0.032	0.685	0.043	0.771	0.066
7	1.188	0.000	0.999	0.000	0.958	0.002	1.093	0.006
8	0.765	0.004	0.606	0.047	0.392	0.028	0.074	0.008
9	1.400	0.001	1.301	0.008	0.909	0.003	0.789	0.005
10 (can't work)	1.599	0.000	1.859	0.001	1.744	0.005	1.815	0.004
Mental health index	-0.045	0.001	-0.046	0.005	-0.057	0.001	-0.061	0.001
Mental health index^2	0.002	0.002	0.003	0.006	0.001	0.002	0.002	0.005
Hours of non-parental childcare	-0.060	0.000	-0.041	0.004	-0.026	0.009	-0.023	0.002
Hours of non-parental childcare^2	0.001	0.001	0.003	0.017	0.008	0.054	0.007	0.060
Job opportunities index	-0.233	0.006	-0.144	0.023	-0.327	0.014	-0.278	0.044
Job opportunities index^2	-0.018	0.300	-0.027	0.204	-0.003	0.901	-0.013	0.616
Constant	2.899	0.000	3.564	0.000	4.141	0.000	4.653	0.000
Pseudo R2	0.345		0.331		0.329		0.316	
Number of observations	4098		3398		2814		2754	

Note: Members of groups B1 to B4 are those with weak labour market attachment, where "weak" is measured in terms of months of work during the reference period. The dependent variable is equal to one for those who are persistently out of work during the reference period and zero for those who have some positive labour market attachment. Higher values of the mental health index denote a better mental health. Higher values of the job opportunity index denote less job opportunities. Earnings replacements are measured in terms of potential earnings. Non-labour income is defined as a percentage of the median income in the reference population. See Table 2.2 for further details on the independent variables.
Source: Authors' calculations based on HILDA 2014.

Table B.2. Risk of facing labour market difficulties for those with 'good' employment

Logistic regression estimates for the probability of being part of the target population when using measures of work-related capability, work incentives and job opportunities.

	Coef.	P-value
Earnings replacements	1.020	0.000
Earnings replacements ^2	-0.099	0.052
Non Labour income	-0.365	0.000
Non labour income ^2	0.041	0.000
Work experience	-4.969	0.000
Professional skill level		
Managers	baseline	
Professionals	-0.603	0.001
Technicians and Trades	-0.002	0.993
Community and Personal Services	0.085	0.690
Clerical and Administrative	-0.475	0.008
Sales	0.762	0.003
Machinery Operators and Drivers	0.629	0.000
Labourers	1.187	0.000
Highest educational attainment		
PhD	baseline	
Graduate degree	-0.065	0.825
Bachelor degree	-0.222	0.368
Diploma or advanced diploma	0.010	0.166
Certificate III or IV	0.037	0.090
Grade 12	0.328	0.005
Grade 11 or below	0.853	0.000
Degree of limitation in work-related activities		
1 (no limitations)	baseline	
1	-0.896	0.321
2	0.736	0.039
3	0.637	0.253
4	0.944	0.004
5	2.070	0.000
6	2.544	0.000
7	3.777	0.000
8	4.276	0.000
9	5.329	0.000
10 **(Can't work)**	7.943	0.000
Mental health index	-0.062	0.000
Mental health index ^2	0.001	0.003
Hours of non-parental childcare	-0.016	0.000
Hours of non-parental childcare ^2	0.001	0.379
Job opportunities index	0.323	0.000
Job opportunities index ^2	0.253	0.021
Constant	5.028	0.001
Pseudo R2	0.44	
Number of observations	5360	

Note: Individuals with 'good' quality employment are those who worked full-time throughout the reference period with annual earnings above the 25th percentile of the full-time earnings distribution. The dependent variable is equal to one for those who have no or weak labour market attachment, and zero otherwise. "Weak" means less than one fourth of the potential full-time, full-year working hours (Group B3 in Table B.1). Higher values of the mental health index denote a better mental health. Higher values of the job opportunity index denote less job opportunities. Earnings replacements are measured in terms of potential earnings. Non-labour income is defined as a percentage of the median income in the reference population. See Table 2.2 for further details on the independent variables.
Source: Authors' calculations based on HILDA 2014.

Table B.3. Average marginal probability of facing labour market difficulties for those with 'good' employment

Calculations based on a logistic regression for the probability of being part of the target population conditional on the 'optimal' employment barrier indicators.

	Average marginal probability		logistic regression estimates	
	Effects	Standard error	Coefficient	P value
High earnings replacements	0.563	30.57	0.09	1.87
High non-labour income	0.483	52.67	-0.06	2.35
Low work experience	0.846	44.88	2.78	15.35
Low education	0.921	23.79	0.89	3.98
Low skills	0.594	42.28	0.75	4.64
Poor health	0.899	46.53	3.35	18.96
High care responsibilities	0.952	68.87	4.31	19.47
Scare job opportunities	0.824	19.63	2.48	6.68
Constant	-	-	-2.07	-9.55
Pseudo R2			0.55	

Note: Standard Errors for the average marginal effects calculated with the 'delta' method. The employment barrier indicators are calculated using the 'optimal' selected thresholds. The sample includes individuals with 'good' quality employment, i.e. those who worked full-time throughout the reference period with annual earnings above the 25^{th} percentile of the full-time earnings distribution, and those who have no or weak labour market attachment, where 'weak' means less than one fourth of the potential full-time, full-year working hours (Group B3 in Table B.1).
Source: Authors' calculations based on HILDA 2014.

Table B.4. Descriptive statistics for the employment barrier measures and the related indicators

	Limitations in work-related activities	Mental health	Work experience	Non-labour income	Earnings replacements	Hours of care	Education	Job opportunities
Measure								
Mean value	0.77	7.32	0.69	1.46	0.89	11.05	5.00	0.00
Standard deviation	2.10	1.75	0.28	1.53	5.44	21.88	2.60	1.00
10th percentile	0.00	3.80	0.23	0.34	0.28	0.00	2.00	-0.68
25th percentile	0.00	6.40	0.53	0.64	0.33	0.00	3.00	-0.49
Median value	0.00	7.60	0.78	1.16	0.42	5.00	5.00	-0.18
75th percentile	1.00	8.80	0.91	1.86	0.60	36.00	6.00	0.28
90th percentile	4.00	9.20	0.96	2.77	1.11	64.00	7.00	0.82
Barrier								
Selected threshold	5.00	4.80	0.60	1.55	0.50	30.00	7.00	1.00
Estimated coefficient of the employment barrier indicator calculated at the optimal threshold value	2.45	0.57	2.13	0.58	0.02	5.51	0.38	2.07
z statistic of the coefficient estimated at the optimal threshold value	14.00	6.93	11.2	5.83	5.24	10.11	4.21	5.16
Pseudo R squared of the regression model estimated at the optimal threshold value	0.44	0.44	0.38	0.42	0.61	0.55	0.43	0.44

Note: Standard Errors for the average marginal effects calculated with the 'delta' method. The employment barrier indicators are calculated using the 'optimal' selected thresholds. The reference sample is the working age population for all indicators except: the hours of care (sample: mothers with children under 12), earnings replacements (sample: individuals with positive earnings replacements), non-labour income (sample: individuals with positive amounts of non-labour income); work experience (sample: individuals with positive work experience but with less years of work experience than the potential experience). See footnote 15 for details.
Source: Authors' calculations based on HILDA 2014.

Latent class analysis

Latent Class Analysis does not automatically provide an estimate of the *optimal* number of latent classes. Models with different number of classes are estimated sequentially and the optimal model is chosen based on a series of statistical criteria. The model selection process starts with the definition of a *standard* latent-class model that is repeatedly estimated for an *increasing number of latent classes* (Step 1).[22] The choice of the *optimal* number of classes is primarily based on goodness-of-fit and error-classification statistics (Step 2, see also Figure B.1), and then on the analysis of potential misspecification issues (Step 3). Fernandez et al. (2016) describes these steps in detail and provides guidelines for practitioners interested in adapting the approach to specific analytical needs or data.

Figure 3.2 summarises graphically the Step 2 outlined above for using HILDA 2014; The blue bars show the percentage change of the *Bayesian Information Criterion* (BIC, (Schwarz, 1978))[23] for increasing numbers of latent groups, whereas the black line shows, for the same groups, the *classification error statistics* (Vermunt & Magidson, 2016).[24] In general, a smaller value of the BIC indicates a more optimal balance between model fit and parsimony, whereas a smaller value of the classification error statistics means that individuals are well-classified into one (and only one) group. In Figure 6 the BIC is minimised for a model with 10 classes and the classification error of 15% indicates that the model provides a good representation of the heterogeneity in the underlying data.

Post-estimation tests based on the *Bivariate Residuals* (Vermunt & Magidson, 2016) show for the 10-class model some residual *within-group* correlation between 4 pairs of indicators. This indicates that the model violates to some extent the Local Independence Assumption (LIA).[25] Increasing the number of latent classes always reduces the residual dependencies between indicators. For instance, the 15-class model shows no signs of local dependencies, but this comes at the cost of a higher classification error (22%).

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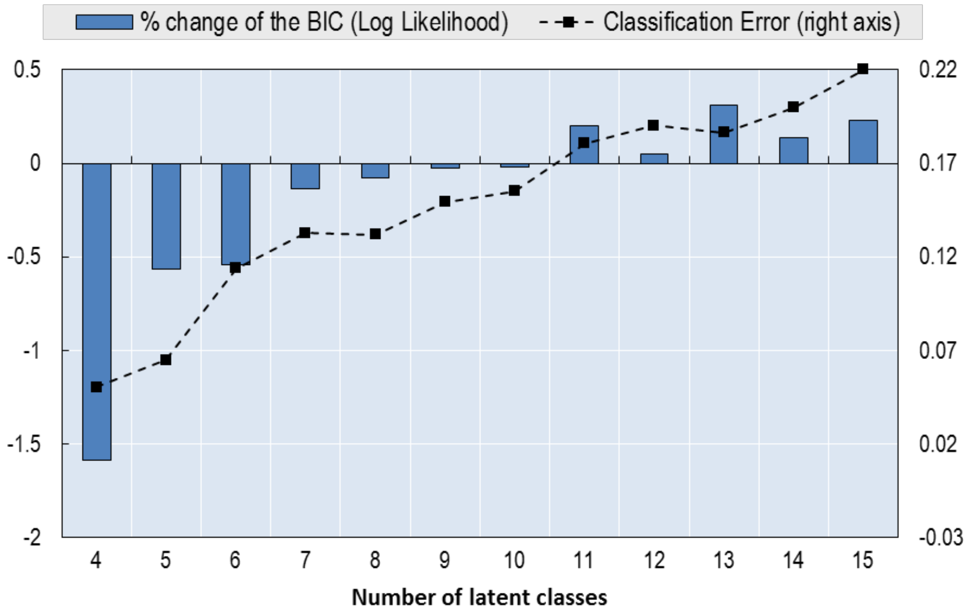
22 . A *standard* latent class model means that the likelihood function is derived under the so-called Local Independence Assumption (LIA). See Fernandez et al. (2016) for details.

23 . The BIC summarises into a single index the *trade-off* between the model's ability to fit the data and the model's parametrisation: a model with a higher number of latent classes always provide a better fitting of the underlying data but at the cost of complicating the model's structure.

24 . The classification error shows how-well the model is able to *classify* individuals into specific groups. To understand the meaning of the classification error index it is important to keep in mind that LCA does not assign individuals to specific classes but, instead, estimates probabilities of class membership. One has therefore two options to analyses the results: allocate individuals into a given group based on the highest probability of class-membership (*modal* assignment) or *weighting* each person with the related class-membership probability in the analysis of each class (*proportional* assignment). The classification error statistics is based on the share of individuals that are miss-classified according to the modal assignment.

25 . The LIA shapes the algebraic specification of the model and, in practice, requires the indicators to be *pairwise* independent *within* latent groups. Bivariate residuals are Pearson chi-squared tests comparing the *observed* associations between pairs of indicators with the *expected* association under the assumption of *local independence*; large differences between estimated and observed associations signal violations of the LIA.

Figure B.1. Selection of the optimal number of latent classes



Source: Authors' calculations based on HILDA 2014.

Following Fernandez et al. (2016) and Vermunt and Magidson (2016), the residual dependencies between indicators is addressed with the so-called *direct effects*; these are ad-hoc terms that enter the specification of the likelihood function to model explicitly the *joint* probabilities of pairs of indicators conditional on group membership. The inclusion of direct effects eliminates any residual correlation between the relevant pair of indicators but it also requires repeating the model selection process, as the new baseline model with local dependencies may lead to a different optimal number of classes. For the new baseline model with direct effects the BIC points to a 7-class model with a classification error of 12%. This specification represents therefore the favourite solution used in this report.[26]

26 . Age and gender define labour market segments that are worth including in the latent class model to account for differences between and within latent groups. Fernandez et al. (2016) discuss three possibilities for including additional variables in the model's specification. In HILDA 2014 the favoured specification in terms of lower classification error, interpretation of the clustering results and specification tests includes age and gender as "active" covariates (Vermunt J. , 2010). Figure 6 is based on a model that already includes information on age (3 categories: 18-29, 30-54, 55-64) and gender.

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