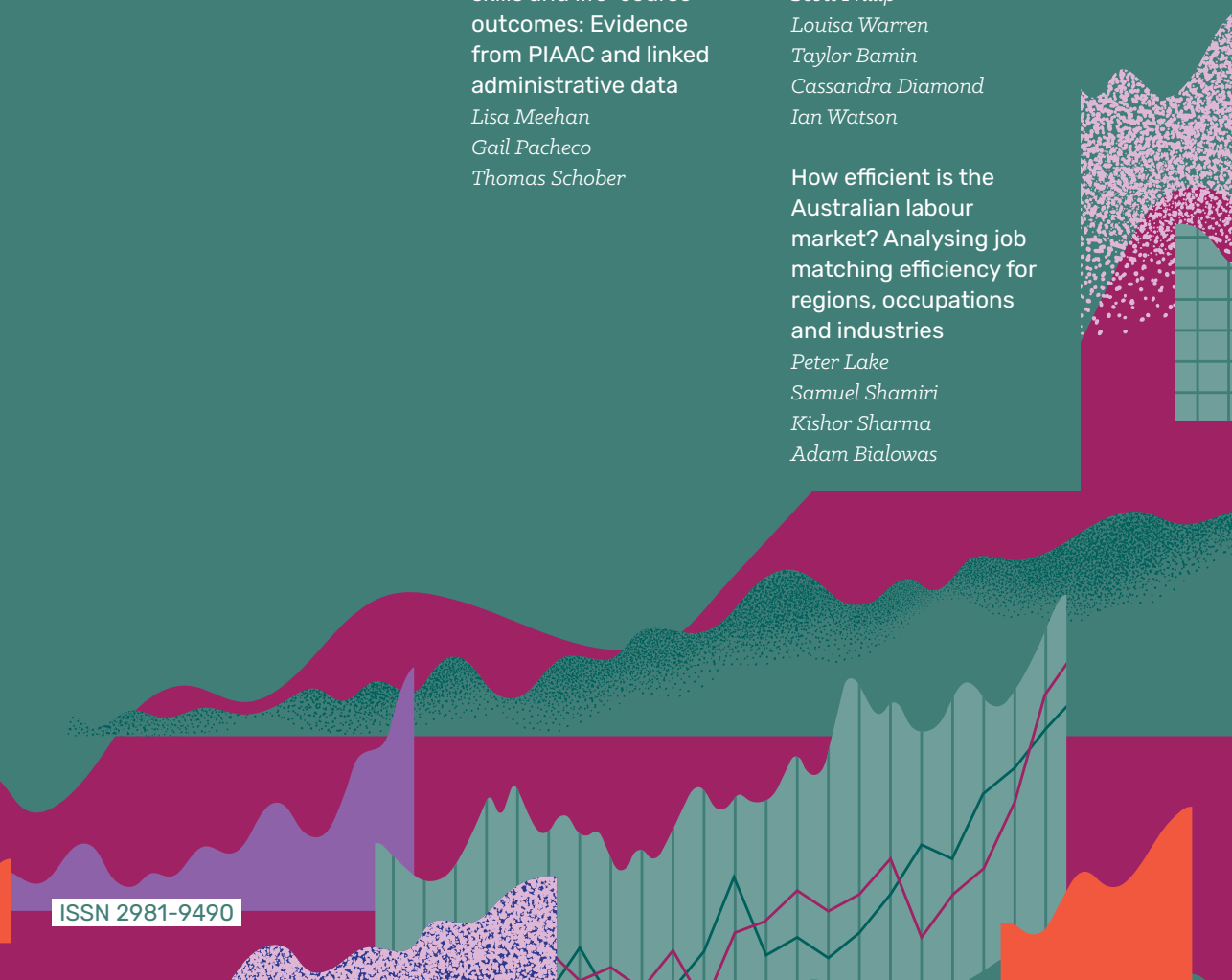
2024
Volume 27 | Number 1

AJLE

AUSTRALIAN JOURNAL OF LABOUR ECONOMICS

ajle.org

A journal of labour economics & labour relations



ISSN 2981-9490

AUSTRALIAN JOURNAL OF LABOUR ECONOMICS

A journal of labour economics & labour relations

ISSN 2981-9490
Official journal of the Australian Society
of Labour Economists

Graphic Design
Advance Press

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Contents

ISSN 2981-9490

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From the Managing Editor

Welcome to the first issue of the *Australian Journal of Labour Economics* (AJLE) for 2024. As usual we have articles of interest to our readers covering a range of labour market issues and using a variety of approaches to research. I am pleased to welcome New Zealand colleagues who have submitted papers for this issue.

The first paper, by Alexandra Ferguson of Stats NZ, discusses the use of longitudinal surveys to examine labour force stability using the New Zealand Household Labour Force Survey (HLFS) data as a case study. Stability relates to how long an individual remains in a certain labour market state, such as employment, unemployment, not in the labour force, over a period of time. Labour market instability can negatively impact people's wellbeing and incomes. It locks short-term employees out of employment protections like access to paid sick leave and can limit intermittently jobless people's access to social protection schemes. Alternatively, stability of unemployment would be expected to reduce wellbeing. The author demonstrates how to create and apply an alternative measure of the stability of individuals across longitudinal survey datasets, including a discussion of remaining limitations, in a way that complements pre-existing stability measures like duration of unemployment, job tenure, and Linked Employer-Employee Database (LEED) employment turnover. In the NZ data most people were completely stable, experiencing no changes to their labour market status during surveyed periods. A small minority of people, disproportionately Māori, Pacific, and female, experience high degrees of labour market instability. The paper does note some limitations of the analysis, but generally, the paper presents an interesting advance on current methods of measurement and scope for future research.

The paper by Lisa Meehan, Gail Pacheco and Thomas Schober from Auckland University of Technology, examines a number of outcomes over the lifetime of New Zealand (NZ) adults across different literacy and numeracy skill levels. The outcomes measured include rates of educational attainment, employment rates and average earnings, rates of hospitalisation, and rates of criminal offending and convictions. The study uses measures of literacy and numeracy proficiency of the working-age adult population using survey data for NZ from the Program for the International Assessment of Adult Competencies (PIAAC) which is an international study for measuring, analysing, and comparing adults' basic skills of literacy, numeracy, and digital problem solving. The outcome measures are then related, through very thorough and detailed analysis, to the literacy and numeracy measures. The results suggest low literacy and numeracy skills affect an individual's wellbeing, including via educational, labour market, health and justice outcomes. What's more, differences in outcomes between those with low literacy and numeracy skills and those with above-average skills may increase over time. This widening disparity gap is particularly evident for labour market outcomes, with earnings gaps between those with low and above-baseline skills increasing over the lifetime. The

paper obviously has significant implications for numeracy and literacy policy intervention, particularly among disadvantaged groups.

Claire M. Mason, Haohui Chen, Shanae M. Burns, Scott Philip, Louisa Warren, Taylor Bamin, Cassandra Diamond and Ian Watson, of the Commonwealth Scientific and Industrial Research Organisation (CSIRO), present an innovative approach to measuring changing demand for Indigenous workers in Australia. The authors apply artificial intelligence to identify Indigenous-focused job postings by subjecting an Australian national database of over 10 million job advertisements to a natural language processing algorithm. The algorithm classifies advertisements according to whether they encourage Indigenous applicants, require Indigenous cultural capability, prioritise Indigenous candidates or are not Indigenous-focused. Jobs advertisements are sub-classified according to a number of variables, such as industry, occupation and skill level. The results suggest policy programs to improve employability need to be better focused. The paper provides an interesting and innovative method of analysis which has many potential applications in labour market problems and policy.

The paper by Peter Lake, Samuel Shamiri, Kishor Sharma and Adam Bialowas, of Jobs and Skills Australia (JSA), seeks to estimate labour market matching (demand and supply) efficiency in Australia for occupations, regions and industries using disaggregated data from both the JSA and the Australian Bureau of Statistics (ABS). Labour market mismatch can result in many vacancies existing alongside high unemployment. If demand and supply imbalance due to frictions in the labour market, such as skills or regional mismatch, can be identified then this can provide the basis for labour market policy. The authors develop a model (MUVER) based initially on the traditional search and matching model to identify mismatch in different sectors of the labour market. The results in the paper are very promising with respect to using the model in policy analysis. Although the authors do note some limitations of the analysis these suggest fruitful areas for future research.

I would like to thank authors, the anonymous referees and co-editors for their contributions to the AJLE. Once again special thanks go to the AJLE's editorial assistant, Sandie Rawnsley, for doing an excellent job in making this issue possible.

Phil Lewis
Managing Editor

Using longitudinal surveys to discuss labour force stability: A New Zealand case study

ALEXANDRA FERGUSON *Stats NZ*

Abstract

Labour market stability is an underexamined characteristic in traditional labour market statistics, despite its importance. Labour market instability can negatively impact people's wellbeing and incomes by locking short-term employees out of tenure dependent employment protections and limiting intermittently jobless people's access to social protection schemes. Conversely, while not all stable circumstances are necessarily positive ones, stability is generally a desirable characteristic, bringing with it social and economic benefits.

Here, we present a supplementary measure to traditional labour market statistics that treats stability as a characteristic of individuals. We used a subsample of consistent respondents from New Zealand's Household Labour Force Survey (HLFS) to demonstrate how best to create and apply an alternative measure of the stability of individuals across longitudinal survey datasets, including a description of our approach and remaining limitations, in a way that complements pre-existing stability measures like duration of unemployment, job tenure, and LEED employment turnover.

The descriptive statistics we produce reveal that completely stable employment and lack of labour force participation over the surveyed period were common and highly correlated with age. Instability – here defined as experiencing 3 or more labour market changes over two years – was most common amongst younger adults, though a lingering minority of people continue to experience highly unstable labour market outcomes in each age group. Stable unemployment or underutilisation proved rare, but respondents experiencing high instability were also unemployed and/or underutilised much more frequently across the two-year surveyed period than more stable respondents.

JEL Codes: J62, J60, J01

Acknowledgement
Access to the Household Labour Force Survey (HLFS) data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Data and Statistics Act 2022. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

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Introduction

In labour market research, conventional statistical measures provide a nuanced picture of total labour market stocks for a given period, and aggregate changes across time. Some even provide a broad perspective on individual dynamics between two defined periods. However, none of these measures capture nuanced experiences as people navigate through various labour market statuses over longer time periods that may include any or all of employment, unemployment, and not in the labour force (NILF).

Here, we present an alternative approach that distinguishes itself from traditional stock measures and broad-flow statistics by defining labour market stability so it can be treated as a characteristic in subsequent analysis. We do so by taking a rotating panel survey – in this case, the New Zealand Household Labour Force Survey – and examining labour market outcomes for all the periods in which a respondent is surveyed. From there, we are able to produce some practical examples of basic descriptive statistics involving stability, reproduceable for any similar rotating panel sample from which longitudinal data can be extracted.

Stability is an important concept to measure as part of understanding labour market dynamics. Understanding whether flat levels quarter on quarter mean absolute stability or equal in- and out-flows is important for interpreting those numbers and understanding potential impacts. Beyond that, learning whether labour market churn is regularly and evenly spread or concentrated in particular groups can help researchers and decision-makers understand whether national labour markets are moving in a healthy way.

Job stability, in particular, matters when looking to move beyond measurements that indicate the presence of work to measurements that can be used to indicate the quality of that work. For people of prime working-age, for instance, we need to look for sustained employment over time as well as the number of people in work or gaining employment for a single quarter if we want to show successful job growth. Studies on job satisfaction frequently underline the importance of job security for respondents, such as the 2015 ISSP Survey on Work Orientations which showed that security was the most desired job characteristic, both on average across 37 countries and in New Zealand specifically (Clark, 2015; Volk and Hadler, 2018; MacCormick, 2019).

Short job tenures can also affect access to employment protections such as annual or sick leave, or access to social insurance schemes. In 2022, a New Zealand study discovered that 32.7 per cent of secondary caregivers were likely ineligible for a full two weeks' statutory leave from their waged job, as that requires a job tenure of 12 months or more. 17.5 per cent were ineligible for any statutory leave at all, as they had been employed in their role less than six months, a state which affected low-income fathers the most (Kulkarni and Mok, 2022).

Labour market transitions can have negative effects on individuals' incomes, which is also worth considering as part of stability analysis. This can be obvious if people move out of paid employment but can also be more subtle in cases when welfare receipt

depends on sustained periods of joblessness and people are intermittently employed. For some people, periods of employment may come with elevated income compared with benefit receipt, but then joblessness may come with zero income, leading to net negative effects over longer time periods.

Of course, labour market change can also be positive. Stability in unemployment is an entirely negative outcome. Labour market changes that indicate movement from a negative state to a positive one, like unemployment to employment, are obviously desirable. They can also be part of broader and desired life changes, like retiring or leaving the labour force to become a full-time parent. As such, one or two changes over an extended period are not necessarily a sign of instability or to be considered more negative than complete stability. In some cases, they can even act as examples of success, showing how individuals can transition successfully into a newly stable state.

This article aims to assist researchers and analysts in understanding how best to create and apply an alternative measure of the stability of individuals to diverse longitudinal survey datasets, including a description of our approach, data quality testing and subsequent recalibration impacts, and remaining limitations in the New Zealand context.

Standard uses of labour force surveys in measuring stability

Stocks measures

Labour force surveys are specifically designed for short-term snapshots of stock labour market outcomes as the best way to balance the need for timeliness and reliability through frequent collection of specific data from a representative sample. Any country that regularly produces labour market estimates through a household survey is likely producing stock measures of national labour market outcomes.

National labour market statistics produced from labour force surveys then rely on comparing aggregate measures, which tend to stay similar even as individuals experience change. This is because, in the absence of enormous economic shocks, people tend to shift between labour market outcomes in similar net quantities – roughly as many unemployed people finding work as formerly employed people entering unemployment, for instance.

Timely and reliable estimates of national labour statistics are crucial for informing policy, feeding into broader labour research, and acting as a basis for macro-economic monitoring.

Stocks measures can be used to discuss national labour market stability – whether headline rates of unemployment, employment and labour force participation

are steady – but provide no additional information about the underlying dynamism of labour market outcomes for individuals.

Direct questions about stability are asked each quarter, but they rely on the present state as a reference point and provide no way for people with highly unstable labour market outcomes to be identified. Duration of unemployment is one regularly used measure, which asks unemployed people how long they have remained unemployed. Another is job tenure, which quantifies how long employed people have remained in their current role. In both cases, this measures the length of time the respondent has been experiencing their present state up to the survey period.

Job tenure can also be produced using administrative sources, like taxation data, and tend to form the basis of analysis on job stability as defined as the continuing relationship between a single employee and single employer. This is an incredibly strong approach when measuring the length of that relationship, as a comprehensive source of all taxable wage and salary transactions over time. However, when using this approach to assess stability, this is limited to employment stability and excludes those who are unemployed or not in the labour force. It also resets with any job-to-job transitions, requiring additional work to examine individuals who have been stably employed for long periods but changed employers in that time.

While outside the scope of this work, similarly person-centric analysis could be done using LEED data to examine periods of employment and joblessness and incorporate some of the valuable information therein on job-to-job transitions and, potentially, forms of income other than employment.

Flows measures

Flow measures of labour market outcomes can be produced from longitudinal labour force surveys to analyse individuals' changing circumstances from one time period to another.

For example, a net increase in unemployment seen at the national level can be examined with flow data to determine whether that reflects more people entering unemployment or an increase in people staying unemployed over time. It can also determine where people who are exiting unemployment are going to, helping differentiate formerly unemployed people moving into employment from those moving out of the labour force.

Relatively few countries have official flows data publicly available, however. Flows are more complex than single period measures because, in addition to the requirement for surveying respondents for multiple quarters, the matched sample needs to be independently representative, so cannot rely on inflows and outflows in similar numbers from hard-to-reach groups creating a nationally representative picture for each individual quarter. Weights for responses should ideally also be produced across the periods examined when producing flows measures, allowing the matched sample to be weighted up to the full population across the total of the two periods being compared.

The United States is one of the few cases in which flows data is regularly published, as the Bureau of Labour Statistics produce a research series on labour force status flows from their Current Population Survey.

Research has also been done on the potential for extended flows series, such as Stats NZ's 2001 paper, *A longitudinal look at some data of the Household Labour Force Survey*. In that case, in addition to quarter-on-quarter flows, transitional probabilities were examined between the first interview quarter of a respondent and each of up to seven subsequent quarters. This still, however, focused on point-to-point measures as opposed to including all intermediary data collected.

Administrative measures, such as tax data, also regularly produce flows measures. In New Zealand, the Linked Employer-Employee Database (LEED) is the source of official statistics on worker accessions and separations data, from which a job turnover rate is produced. As with labour force surveys, this is limited to a single comparison between time x with time y. At the firm level, for example, a business expanding rapidly or laying off half their staff will have a high turnover rate if comparing a period before the change with one after the change occurs, but any subsequent measures comparing two periods after the change will not reflect the previous instability. In addition, administrative measures also tend to treat labour engagement as a binary – employed and not employed – due to the difficulty of reliably identifying availability and job seeking behaviour through administrative sources and thereby separating unemployment from those outside the labour force.

Flows data can provide some indication of labour market stability, specifically whether individual respondents were in the same labour market state in two surveyed periods. However, there are shortcomings in this use – looking at flows from two quarters a year apart will only compare those two snapshot points in time and not any of the interim periods.

This is particularly important to consider in countries where labour market outcomes are highly seasonal. As an example, the proportion of people in stable employment between one harvesting season and the next may look very different to the proportion in stable employment between fallow periods. In countries where agriculture is a major source of employment, a strong proportion of the country's workforce may habitually work two or three quarters, then remain outside the labour force the rest of the year.

Alternative approach

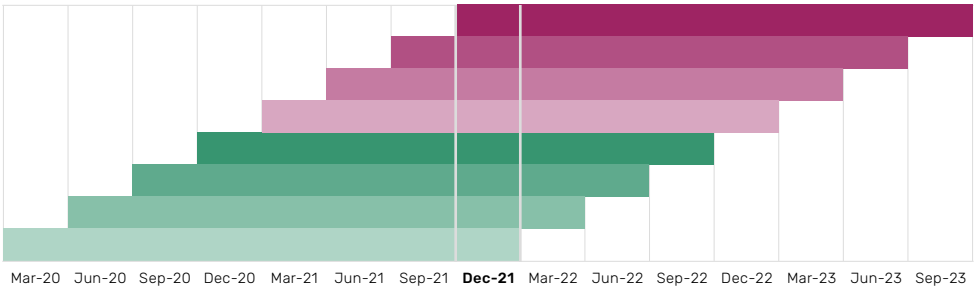
Stability as a measurable characteristic

Traditional approaches to labour market outcomes either ignore the regular labour market movements underpinning net stability or look at them as a trait of a given quarter – whether more or fewer people, in total, are moving between statuses than in previous quarters.

Another lens through which labour market movement can be understood, however, is as an individual characteristic. Which groups are more likely to experience labour market stability, or limited movement, and which groups experience extreme lack of stability?

In New Zealand, the Household Labour Force Survey (HLFS) is collected as a rotating panel survey of approximately 30,000 respondents each quarter. The staggered design means each quarter one eighth of the sample is rotated in and another eighth is rotated out, with each household is selected into the survey for two years. As a result, by selecting the HLFS sample from at least eight quarters back, each respondent can have eight quarters of historic or future labour market outcomes assigned to them for that period, as depicted in Figure 1.

Figure 1. Depiction of December 2021 representative sample by surveyed period for each wave of respondents



An example of how this could work would be someone who was interviewed from March 2020 to December 2021 quarters and was employed throughout. Their labour force characteristics over that time could be expressed as string 'EEEEEEEE', where the last 'E' represents the reference quarter of December 2021.

Alternatively, we could consider someone who was first selected in the December 2021 quarter. At the time of the December 2021 quarter, future labour market outcomes would be unknown. With the benefit of following quarters of data, however, we could represent their upcoming mixed unemployment/NILF outcomes from December 2021 to September 2023 quarters as string 'UNNUUNUN', where the first 'U' represents their unemployment in the December 2021 quarter.

This then allows us to derive a number of sub-variables, including how many movements any given respondent experienced; how long they experienced stability; how many quarters they were experiencing in any given labour market outcome, either continuously or across their full surveyed period; and what kinds of movements they experienced when shifting between outcomes.

Selecting a subsample

Using this characteristic approach, the HLFS sample can be looked at not just through the lens of their labour market outcomes in the December 2021 quarter, or their movement from September to December quarters, but what level of stability they had experienced or would go on to experience over their full two-year sample period.

To discuss stability, however, we need to limit our sample to those who have responded a minimum number of times in the period. This lets us avoid trying to draw conclusions about number of movements between labour market statuses experienced by respondents who may have only responded once or twice over the full two-year period.

This limited sample is likely to have quite different characteristics to those who responded more intermittently.

For our case study, we defined consistent respondents as those who responded at least six of a potential eight quarters. Choosing to include those who responded at least six quarters rather than the full eight was based on previous research into the use of longitudinal labour force survey data in New Zealand which indicated that samples of consistent respondents using this definition were larger and far more representative of the total population than a sample that was comprised only of those answering all eight quarters (Kuzmicich and Wigbout, 2001).

When selecting a subsample based on a specific characteristic, such as consistency of responding, it is important to measure the strength of association between selected characteristic and other variables. This allows us to estimate how biased our new subsample may be and determine whether it is appropriate to use to represent the entire population. Here, we chose to use a Rao-Scott chi square test to compare measured and expected results for our weighted survey sample.

In most cases, the p value alone can then be used to determine whether results produced using this subsample are significantly different from the group not selected or the entire population. If this value is 0.05 or less, this indicates at least 95 per cent confidence that differences are genuine or, alternatively, that there is a 5 per cent or less chance that differences are spurious. In some cases, the p value for determining significance will be lowered even further, to 0.01 for instance, to ensure 99 per cent confidence.

Using chi square p values can be challenging, however, when examining large samples, like those behind New Zealand's HLFS, where the sheer size of the groups being examined mean statistical significance does not always align with material effect size. An example of this could be proportion of urbanity in our valid/invalid samples in Table 1, which follow very similar trends but still have a p value of 0.1, indicating statistical significance at 90 per cent confidence.

In this case, we decided to also provide an interpretation of the magnitude of the difference between the proportion of our valid group and the national weighted sample to help represent effect size in addition to significance. For statistically significantly different groups, we decided that a mean absolute difference of up to 0.5 percentage points (pp) was negligible; up to 1.5pp small; up to 3.0pp medium, and over that large.

When examining our subsample through a demographic lens, Table 1 below shows that the limited weighted sample of consistent respondents was strongly older, more likely to be homeowners and more likely to be European than the original national sample. There were also moderately lower proportions who were of Māori ethnicity or of Māori descent, and minor changes to the proportion of the valid sample who were Pacific or Asian. Labour market outcomes, including labour force status, employment by full- and part-time, and underutilisation, also mildly differed in our limited sample compared with the national total.

Table 1. Data quality assessment of a limited sub-sample of consistent respondents to New Zealand's Household Labour Force Survey

December 2021 quarter (Total sample size = 30,293)	Consistent respondents (6+ quarters)	Excluded respondents (<6 quarters of data)	Rao-Scott chi square tests of independence between valid/invalid groups	Difference between proportions of total estimates and consistent respondents (percentage points [sample errors])	Effect size[1]
Characteristic					
Sex *n(%)*					
Male	1,399,200 (48.9)	621,900 (50.2)	*X² (1) = 6.8 p = 0.0104*	-0.4	-
Female	1,461,400 (51.1)	617,800 (49.8)		0.4	
Broad age *n(%)*					
15-29	490,000 (17.1)	512,700 (41.4)	*X² (2) = 1355 p = <.0001*	-7.3	Large
30-59	1,446,100 (50.6)	562,100 (45.3)		0.4	
60+	924,500 (32.3)	164,800 (13.3)		7.0	
Ethnicity *n(%)*[2]					
European	2,116,400 (74.0)	774,200 (62.5)	*X² (1) = 97 p = <.0001*	3.5	Large
Māori	365,600 (12.8)	243,500 (19.6)	*X² (1) = 92 p = <.0001*	-2.1	Medium
Pacific	150,400 (5.3)	100,100 (8.1)	*X² (1) = 35 p = <.0001*	-0.9	Small
Asian	400,000 (14.0)	223,200 (18.0)	*X² (1) = 19 p = <.0001*	-1.2	Small
MELAA	29,900 (1.0)	22,600 (1.8)	*X² (1) = 14 p = <.0003*	-0.2	-
Other	39,100 (1.4)	8,000 (0.6)	*X² (1) = 10 p = <.0021*	0.2	-
Māori descent *n(%)*[3]					
Maori descent	449,000 (15.7)	282,400 (22.8)	*X² (3) = 133 p = <.0001*	-2.1	Medium
No Maori descent	2,405,700 (84.1)	949,400 (76.6)		2.3	
Urbanity *n(%)*[4]					
Main urban areas	2,037,600 (71.2)	918,200 (74.1)	*X² (4) = 8 p = 0.1057*	-0.9	-
Secondary urban areas	163,000 (5.7)	54,900 (4.4)		0.4	
Minor urban areas	246,000 (8.6)	96,300 (7.8)		0.3	
Rural centres	50,700 (1.8)	22,300 (1.8)		0.0	
Rural areas	363,400 (12.7)	148,000 (11.9)		0.2	

Table 1. continued

December 2021 quarter (Total sample size = 30,293)	Consistent respondents (6+ quarters)	Excluded respondents (<6 quarters of data)	Rao-Scott chi square tests of independence between valid/invalid groups	Difference between proportions of total estimates and consistent respondents (percentage points [sample errors])	Effect size[1]
Household tenure *n(%)*[3]					
Dwelling owned or partly owned	1,652,000 (57.8)	467,100 (37.7)	*X² (3) = 661 p = <.0001*	6.1	Large
Dwelling rented (not owned and not held in a family trust)	685,600 (24.0)	623,400 (50.3)		-8.0	
Dwelling held in a family trust	505,500 (17.7)	134,500 (10.9)		2.1	
Labour force status *n(%)*					
Employed	1,959,300 (68.5)	875,000 (70.6)	*X² (2) = 85 p = <.0001*	-0.6	Small
Unemployed	48,600 (1.7)	43,800 (3.5)		-0.6	
Not in the labour force (NILF)	852,700 (29.8)	320,900 (25.9)		1.2	
Employment status *n(%)*					
Not employed	901,300 (31.5)	364,700 (29.4)	*X² (2) = 29 p = <.0001*	0.6	Small
Employed full-time	1,550,100 (54.2)	723,100 (58.3)		-1.3	
Employed part-time	409,200 (14.3)	151,900 (12.3)		0.6	
Underutilisation *n(%)*					
Not underutilised	2,694,000 (94.2)	1,118,000 (90.2)	*X² (4) = 150 p = <.0001*	1.2	-
Underemployed	69,100 (2.4)	37,600 (3.0)		-0.2	
Unemployed	48,600 (1.7)	43,800 (3.5)		-0.6	
NILF not actively seeking but available	37,900 (1.3)	23,000 (1.9)		-0.2	
NILF actively seeking, not currently available	11,000 (0.4)	17,300 (1.4)		-0.3	

1. Based on chi square and the mean absolute difference between the total population and consistent respondents in percentage points. A difference up to 0.5pp, or a p value over 0.05, is considered negligible; up to 1.5pp small; up to 3.0pp medium; and over 3.0pp large.
2. Each ethnicity tested against the counterfactual (e.g. European and non-European).
3. Residual values (e.g. unknown, refused to answer, blanks) included in chi square testing and totals, but excluded from further breakdowns and effect size calculations. As a result, proportions may not add to 100%.
4. Excludes outlying islands.

… Data not benchmarked
- Effect size negligible

Table 2. Data quality assessment of recalibrated sub-sample of consistent respondents to New Zealand's Household Labour Force Survey

December 2021 quarter (Reweighted sample size = 21,561)	Original total weighted population	Reweighted consistent respondents (6+ quarters)	Rao-Scott chi square tests of independence between original and reweighted groups	Difference between proportions of total estimates and reweighted consistent respondents (percentage points)	Effect size[1]
Characteristic					
Sex *n(%)*					
Male	2,021,100 (49.3)	2,021,100 (49.3)	*X^2 (1) = 0* *p = 1.00*	0.0	-
Female	2,079,300 (50.7)	2,079,300 (50.7)		0.0	
Broad age *n(%)*					
15-29	1,002,700 (24.5)	1,002,700 (24.5)	*X^2 (2) = 0* *p = 1.00*	0.0	-
30-59	2,008,300 (49.0)	2,008,300 (49.0)		0.0	
60+	1,089,400 (26.6)	1,089,400 (26.6)		0.0	
Ethnicity *n(%)*[2]					
European	2,890,600 (70.5)	2,952,700 (72.0)	*X^2 (1) = 15* *p = 0.0002*	1.5	Small
Māori	609,000 (14.9)	609,000 (14.9)	*X^2 (1) = 0* *p = 1.00*	0.0	-
Pacific	250,500 (6.1)	242,500 (5.9)	*X^2 (1) = 1* *p = 0.3163*	-0.2	-
Asian	623,200 (15.2)	602,300 (14.7)	*X^2 (1) = 2* *p = 0.1367*	-0.5	-
MELAA	52,400 (1.3)	46,000 (1.1)	*X^2 (1) = 14* *p = 0.1130*	-0.2	-
Other	47,100 (1.2)	47,800 (1.2)	*X^2 (1) = 0* *p = 0.7464*	0.0	-
Māori descent *n(%)*[3]					
Maori descent	731,500 (17.8)	728,400 (17.8)	*X^2 (3) = 14* *p = 0.0033*	-0.1	-
No Maori descent	3,355,100 (81.8)	3,355,100 (82.0)		0.2	
Urbanity *n(%)*[4]					
Main urban areas	2,955,800 (72.1)	2,961,400 (72.2)	*X^2 (4) = 7* *p = 0.1654*	0.1	-
Secondary urban areas	217,900 (5.3)	235,000 (5.7)		0.4	
Minor urban areas	342,300 (8.3)	338,200 (8.3)		-0.1	
Rural centres	73,000 (1.8)	70,400 (1.7)		-0.1	
Rural areas	511,300 (12.5)	495,300 (12.1)		-0.4	

Table 2. continued

December 2021 quarter (Reweighted sample size = 21,561)	Original total weighted population	Reweighted consistent respondents (6+ quarters)	Rao-Scott chi square tests of independence between original and reweighted groups	Difference between proportions of total estimates and reweighted consistent respondents (percentage points)	Effect size[1]
Household tenure *n(%)*[3]					
Dwelling owned or partly owned	2,119,100 (51.2)	2,293,600 (55.9)	*X² (3) = 180 p = <.0001*	4.3	Large
Dwelling rented (not owned and not held in a family trust)	1,309,000 (31.9)	1,102,400 (26.9)		-5.0	
Dwelling held in a family trust	640,000 (15.6)	676,20 (16.5)		0.9	
Labour force status *n(%)*					
Employed	2,834,300 (69.1)	2,882,900 (70.3)	*X² (2) = 20 p = <.0001*	1.2	Small
Unemployed	92,400 (2.3)	81,800 (2.0)		-0.3	
Not in the labour force (NILF)	1,173,600 (28.6)	1,135,600 (27.7)		-0.9	
Employment status *n(%)*					
Not employed	1,266,000 (30.9)	1,217,400 (29.7)	*X² (2) = 42 p = <.0001*	-1.2	Small
Employed full-time	2,273,190 (55.4)	2,283,400 (55.7)		0.3	
Employed part-time	561,105 (13.7)	599,400 (14.6)		0.9	
Underutilisation *n(%)*					
Not underutilised	3,812,100 (93.0)	3,826,200 (93.3)	*X² (4) = 21 p = 0.0004*	0.3	-
Underemployed	106,700 (2.6)	111,900 (2.7)		0.1	
Unemployed	92,400 (2.3)	81,800 (2.0)		-0.3	
NILF not actively seeking but available	60,800 (1.5)	60,300 (1.5)		0.0	
NILF actively seeking, not currently available	28,300 (0.6)	20,100 (0.5)		-0.2	

1. Based on chi square and the mean absolute difference between the total population and consistent respondents in percentage points. A difference up to 0.5pp, or a p value over 0.05, is considered negligible; up to 1.5pp small; up to 3.0pp medium; and over 3.0pp large.
2. Each ethnicity tested against the counterfactual (e.g. European and non-European).
3. Residual values (e.g. unknown, refused to answer, blanks) included in chi square testing and totals, but excluded from further breakdowns and effect size calculations. As a result, proportions may not add to 100%.
4. Excludes outlying islands.

… Data not benchmarked
- Effect size negligible

Recalibration to improve quality

Given the bias in our subsample, we therefore also needed to recalibrate our sample back to national benchmarks to mitigate the representation bias of our results.

In New Zealand, an integrated weighting approach based on the following benchmarks is used to ensure the Household Labour Force Survey is representative:

- Five-year age groups by sex
- The number of Māori (indigenous) adults by two age groups (15-29, 30+) and sex
- Region of household

These benchmarks refer to the target population of the non-institutionalised population 15 years and over who usually live in New Zealand. Recalibrating our limited sample to these benchmarks – based on the original total weighted population of the full survey – vastly improves the quality of our biased subsampled results, even for variables not directly calibrated like labour market outcomes and ethnicities other than Māori. Table 2 shows how the newly weighted subsample is significantly less biased than it was before recalibration, with the main lingering effect being a remaining increased likelihood of home ownership in the reweighted consistent respondent group.

Remaining limitations for analysis

Unmeasured residual bias

Creating this measure required us to assume that these consistent respondents could represent the stability patterns of our less consistent respondents.

We tested this assumption by examining stability by number of quarters responding, particularly those just below our cutoff of six. This testing showed that our eligible subsample had similar patterns of people experiencing no changes across their surveyed periods to those responding four or five quarters, and – as expected with more data points – a larger proportion of the eligible sample experiencing higher levels of instability and correspondingly smaller proportion experiencing one or two changes. This indicated to us that our subsample was appropriate to generally represent national stability.

However, it remains likely that there is a strong relationship between respondents who are unstable in their response patterns to the point of ineligibility and respondents who have highly unstable labour market outcomes. Visible in our data quality assessment of recalibrated data was strong lingering bias around homeownership, and minor biases

in favour of European and employed respondents, but there may also be latent biases around instability that are not visible in the examined variables. Our assumption is that this may lead to a minor underestimation of instability if people unable to respond regularly to the HLFS, such as those experience housing transience, are also more likely to be experiencing instability in their labour market outcomes.

From our testing, we believe that this approach is still appropriate to generally represent a national picture of stability, but this limitation should be noted for data users, particularly when using it to discuss those who are experiencing high levels of instability. It may also be possible to mitigate this latent bias further through use of non-response adjustment, using the more detailed information gathered from respondents who responded at least once, but less than six times.

Home ownership

As previously discussed, lingering bias remains around the proportion of our new limited sample who are homeowners compared with a national sample. This is to be expected – homeowners tend to live in the same location longer, and therefore systematically remain available for the same respondents to be interviewed over a full two-year period.

In New Zealand, unfortunately, there exists no regular official estimate of the national population by household tenure suitable as a quarterly benchmark. As such, the only way to reduce the lingering home ownership effect would be to assume the core HLFS levels were precisely correct and recalibrate to the estimates of the full sample. This is unlikely to be true, as it is not what the labour force survey was designed to measure.

Due to the lack of any official source, we simply choose to note this as a potential quality concern here but encourage countries with reliable and regular measures of homeownership to incorporate them in their recalibration should they wish to discuss labour market stability in this way.

Younger respondents

In New Zealand's HLFS, the target population are those aged 15 years and over. That means that if a household is selected while an existing resident is 13 or 14, they will not be interviewed until they turn 15.

When this is considered alongside Figure 1, the sample limitation is obvious – respondents aged 15 and 16 in the December 2021 quarter whose household had been selected previously would not have been eligible to respond for quarters in which they were <15. As a result, the sample of those who responded to the survey at least six of the previous eight quarters by single year age for these two groups is much smaller than all subsequent ages, leading to volatile and poor quality results.

In our analysis, we therefore choose to exclude people who were below the age of 17 in our reference quarter.

Older respondents

In New Zealand's HLFS, a special form of imputation is used for people aged 75 and over (75+).

If a household has only people aged 75+ when interviewed in its first quarter of participation, then we do not interview respondents quarterly. Instead, their current quarter responses are imputed by carrying over the data from their most recent interview. The only exception is in June quarters, when they are re-interviewed to confirm their current labour market outcomes and obtain income and disability data.

Since data for five or six quarters is carried forward from the other two or three quarters, households with only people aged 75+ are inappropriate for inclusion in this analysis and are therefore excluded.

Comparing time periods

One of the primary uses of labour market data is to put present economic conditions in the context of historical experiences. Our use of 15 quarters of data to create labour market stability as a characteristic for the full sample mean that this approach is not timely and requires an even longer time period to make comparisons.

As an example of this, consider trying to determine whether average labour market stability has increased or decreased between the September and December quarters of 2021.

Returning to Figure 1, you can see that seven of the waves included in the December 2021 quarter are also included in the September 2021 quarter, with only 1/8th of the sample moving out in the September quarter and a new 1/8th entering in the December quarter. Any changes observed will therefore only reflect the difference between those old and new waves, flattened significantly by the other seven waves' matching longitudinal labour market strings.

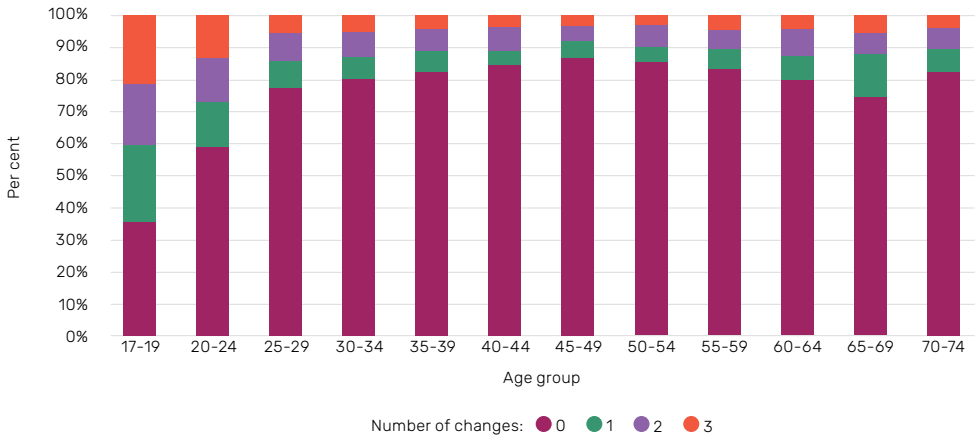
To consider change between groups, entirely independent samples would be optimal, and therefore a minimum of 15 quarters between them are required. The latest entirely independent grouping from our example December 2021 reference quarter would be the March 2018 quarter.

This method of analysing labour market stability can be used to understand which groups tend to be exposed to labour market instability or historical retrospectives to understand key economic periods of stability and instability. However, it will never be a timely measure of current experiences or short-term variability and should not be treated as such.

Examples of descriptive statistics produced with alternative stability measure

One of the simplest new measures that can be produced using this approach is the proportion of people experiencing change by age, which can be used to consider the relative labour market stability of each life stage, as shown in Figure 2.

Figure 2. Proportion of people experiencing changes in their labour market status, by age group, December 2021 representative sample



This simple graph can then be used as the foundation for subsequent analysis examining respondents in three broad groups – stable, moderately stable, and respondents experiencing instability.

Stable respondents

Stable respondents are those who experienced no changes to their labour market status at any surveyed point. Note that this does not necessarily mean no changes were experienced by the respondent, as brief shifts could occur between survey period, but it does mean that, each time they were interviewed, their labour force status was consistent. It also does not mean that the respondent felt secure in their labour market outcomes. For example, stable employment can exist for people on rolling fixed-term contracts or in businesses experiencing market challenges over long time periods.

Most people remained stable across their whole surveyed period, particularly when looking at age groups 25-64 and 70-74.

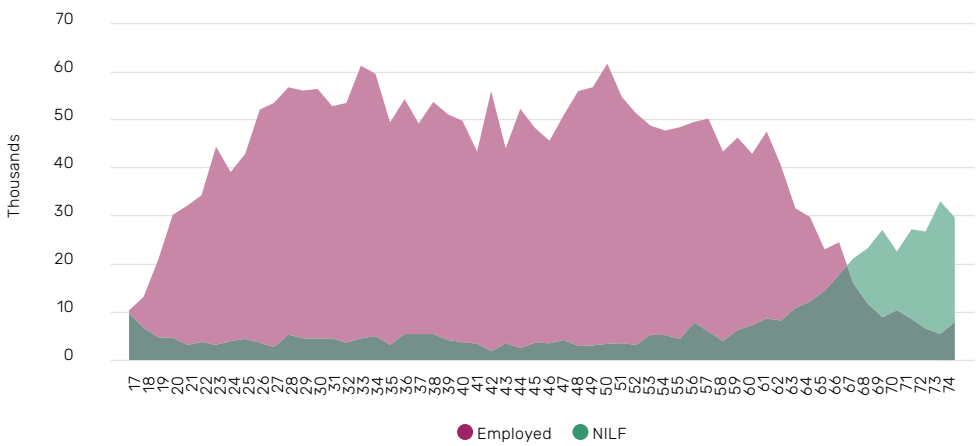
In theory, this stable group could include people who were consistently employed, unemployed, or NILF throughout their time in the HLFS. In practise, however, too small and variable a number of people in our sample were consistently unemployed to draw sensible conclusions from (1,100 ± 900, in our example December 2021 quarter).

Even when looking at the larger group of people who were stably underutilised, noting that this group overlaps with employment and NILF, only 8,800 ± 3,000 people were underutilised across their whole surveyed period. While a statistically significant group, it remains too small to dissect much further.

Stable unemployment and underutilisation will therefore not be discussed further, beyond noting that this fits with previously held assumptions that direct questions on the duration of unemployment are more likely to align with popular understanding of unemployment as joblessness or time since an appropriate job than with international statistical definitions of unemployment.

Overall, stable employment and NILF were both common and highly correlated with age, as the majority of people aged 21-64 were stably employed and the majority of people aged 69 to 74 were stably NILF. Ages 17-20 and 64-68 were the periods in which people were most likely to experience labour market changes, which will be discussed further in the 'moderately stable respondents' section.

Figure 3. Number of people consistently employed or NILF by age, December 2021 representative sample



Stable NILF

From 67 onward, more people were stably NILF than stably employed, and from 69 onward, they made up the majority of the population. Remaining consistently out of the labour force was also common amongst teenagers, and there was a steady group of people outside the labour force at even prime working ages.

When examined further, this group proves highly dependent on sex as well as age. Of the 475,400 stable NILF, approximately two-thirds (301,000) were women.

Table 3. Number and proportion of stable NILF engaged in broad main activity types by sex and age group, December 2021 representative sample

		Number and proportion of stable NILF engaged in broad main activity types by sex and age group				
		01.	02.	03.	04.	
Age band	Sex	Caregiving (children, other adults' and own)	Own-use or volunteer work (exc. caregiving)	Study or training	Free-time activities	Total stable NILF
17-25	Men	4,100 (21.6%)	§	8,400 (44.5%)	5,300 (28.1%)	18,800 (100%)
	Women	8,500 (36.2%)	2,500 (10.6%)	10,000 (42.8%)	2,400 (10.4%)	23,400 (100%)
26-59	Men	20,000 (52.3%)	6,800 (17.7%)	§	9,600 (25.1%)	38,100 (100%)
	Women	61,100 (58.5%)	28,300 (27.1%)	4,900 (4.7%)	9,000 (8.6%)	104,500 (100%)
60+	Men	15,400 (13.1%)	36,700 (31.3%)	§	62,200 (53.0%)	117,400 (100%)
	Women	28,200 (16.3%)	67,400 (38.9%)	§	73,300 (42.3%)	173,200 (100%)
All ages (17-74)	Men	39,400 (22.6%)	44,100 (25.3%)	9,500 (5.5%)	77,100 (44.2%)	174,400 (100%)
	Women	97,700 (32.5%)	98,100 (32.6%)	15,500 (5.2%)	84,700 (28.1%)	301,000 (100%)

§ indicates an estimate and rate suppressed because the estimate was < 1,000.
Stable NILF engaged in other and unknown activities excluded.

At younger ages (17-25), studying and training was the most common main activity for those who were consistently NILF, regardless of sex. Of the 42,100 young people who remained stably NILF, 18,300 were mainly engaged with study or training – 44.5 per cent of young men and 42.8 per cent of young women. For young women, caregiving responsibilities were the next most common, at 36.2 per cent, while young men were more likely to spend their time on free-time activities (28.1 per cent).

From 26 to 59, caregiving became the primary activity for both men and women who were consistently NILF. 58.5 per cent (61,100) of women and 52.3 per cent (20,000) of men who were consistently NILF at this age reported that their main activity was some form of caregiving. This included childcare, care for another adult, or own care due to sickness, illness, injury, or disability. Another 27.1 per cent (28,300) of women indicated that their main activity was some other form of work that was not paid employment or caregiving, such as volunteer work or own-use provision of services like household maintenance.

As previously noted, people remaining consistently NILF was most common amongst older age groups. Nearly 300,000 people aged 60 to 74 were consistently stably NILF – 173,200 women and 117,400 men. At this age, main activities were similar for men and women, primarily split between free-time activities and own-use or volunteer work. A small but significant subset were mainly engaged with caregiving responsibilities,

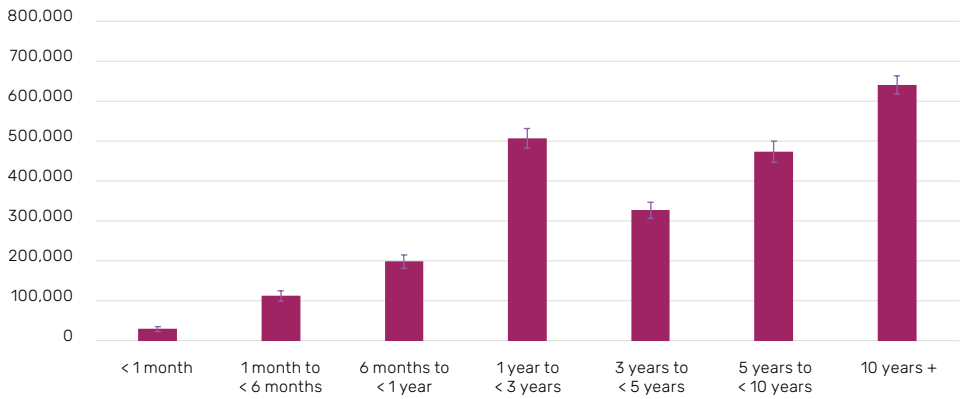
while the number of older stable NILF people who were primarily engaged with study and training was negligible.

Stable employment

Conversely, from 19 to 66 years old, more people were stably employed than stably NILF. From ages 21 to 64, the majority of people were consistently employed over their full surveyed periods.

This can be cross referenced against their reported job tenure, which showed 16.7 per cent of people who were consistently employed over their survey period had been at their current job for less than a year in the December 2021 quarter.

Figure 4. Number of people in stable employment over surveyed period, by job tenure, December 2021 representative sample



This job tenure variable is a December 2021 quarter snapshot, which may refer to the first or an early quarter in a respondent's surveyed period. Therefore, short job tenures for people who were stably employed can indicate one of two things:

1. Someone who was able to swiftly change jobs between survey periods without ever being recorded as NILF/unemployed in the HLFS, or
2. Someone who was first surveyed soon after starting a new job, that they have then gone on to have an extended tenure in as they remained stably employed for the following 21 months.

The first group is particularly interesting to consider when thinking about stable employment.

Research has shown that wage increases are "tightly and robustly associated with job-to-job transitions" in New Zealand (Ball et. al, 2019). As such, while remaining in a single long-tenure job may provide stability for workers, it comes with potential trade-offs in the form of subdued wages, with reduced income subsequently impacting long-term savings.

People who are able to move smoothly from job to job without any surveyed periods of joblessness manage to attain the potential benefits of job-to-job transitions while minimising the time spent in unstable circumstances. Additional research into this group of stable employed people could help provide further insights into the roles and industries in which employee-employer matching is efficient or which worker characteristics are in high demand.

Moderately stable respondents

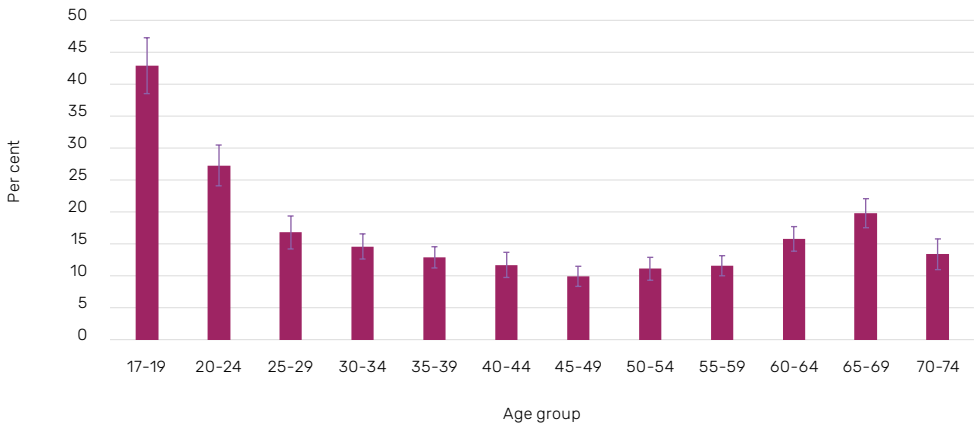
Moderately stable respondents are those who experienced one or two labour market changes across their surveyed period. It could include, for instance, someone moving from employment to NILF as they retire, or a student moving through NILF, unemployment, then employment as they graduate.

Life period changes like this are highly visible when analysing stability by age, with two 'bulges' in the proportion of people experiencing one or two changes over their surveyed period.

The first, and largest, is for people under 25, with 43.1 per cent of teenagers and 27.5 per cent of people in their early twenties experiencing one or two labour market changes over their two-year surveyed period. In terms of life stages, this makes sense, as the age in which people tend to transition from full-time education to employment. For many, it can also include periods of one-off employment during extended school or university holiday periods.

The second is between 65-69, when a growing proportion of the population make a single change in their labour market status. In New Zealand, this is the age at which eligible recipients for New Zealand Superannuation can begin receiving the government pension payments. Smaller swells can be seen in the age groups 60-64 and 69-74, but the majority of switching from employment to NILF comes in the 65-69 age group, once another source of income is available to most New Zealanders.

Figure 5. Proportion of the population who were moderately stable over surveyed period, December 2021 representative sample



The other shift into moderately stable labour market circumstances that can be inferred from labour force survey data requires a split by sex, which reveals that the majority of people aged 25-59 who were moderately stable were women, most of whom moved between employment and NILF.

In our sample, 296,600 people in this broad age band experienced one or two labour market changes, of whom:

- 40,700 were women moving from employment to NILF,
- 32,700 were women moving from NILF to employment, and
- 48,200 were women who began their time in the HLFS employed, moved to NILF, then returned to employment.

Many people in the 25-59 age group will be experiencing parenthood, and it is therefore our interpretation that this gendered difference shows the disproportionate instability introduced to women's careers from parenting. People on parental leave remain employed according to HLFS derivations, provided the respondent still remains connected to their job. For someone to be identified as NILF, they need to say that they do not have any form of employment, even one they were away from the previous week.

Moderate stability, while still stressful on the individuals experiencing one or two changes, can be considered generally choice based. The majority of labour market changes here are linked to broader lifestyle shifts that happen as people age and make different choices for themselves and their families. Not every period of moderate stability ends positively – employment to unemployment is only one labour market change, for instance, or someone may wind up unhappily retired and NILF – but the majority of shifts examined here fit with expected choice based lifestyle changes.

Respondents experiencing instability

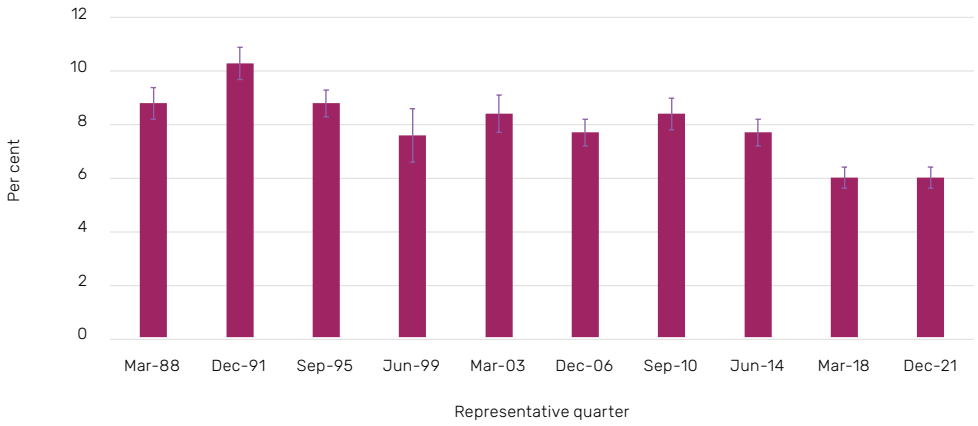
Instability here refers to experiencing 3 or more labour market changes over their surveyed period of up to two years. While most common amongst younger adults, a lingering minority of people experience highly unstable labour market outcomes in each age group.

In our December 2021 quarter sample, 220,500 people (6.0 per cent) experienced 3 or more labour market changes. Of this group:

- 115,400 experienced all three labour force statuses – NILF, employment and unemployment,
- 76,300 moved solely between NILF and employment,
- 18,900 moved solely between NILF and unemployment, and
- 9,900 moved solely between employment and unemployment.

Historically, 6.0 per cent experiencing instability is relatively low. Looking at the ten most recent representative quarters with independent surveyed periods, we can see that instability in the December 2021 quarter sample was unchanged from the March 2018 quarter sample, but lower than all other time periods examined. The highest rates of instability in this group were in the December 1991 quarter sample, which overlapped strongly with a national recession.

Figure 6. Proportion of people experiencing instability, independent representative quarters from March 1988 to December 2021



By age group, 21.4 per cent of teenagers, 13.3 per cent of people in their early twenties, and 3-5 per cent of each older five-year age band in the December 2021 quarter sample experienced 3 or more changes in labour market (see Fig. 2).

That there remains a group of respondents experiencing instability for each age band over 25 may be considered one of the most concerning from a policy perspective, given the noted negative impacts of instability and the relatively consistent size of the group experiencing instability.

As with many negative labour market outcomes, vulnerability to instability is also correlated with individual characteristics like gender and ethnicity. The rate of instability amongst women was 6.6 per cent, compared with 5.4 per cent of men. The Māori rate of instability was 8.2 per cent (compared with 5.6 per cent for non-Māori) and the Pacific rate was 8.9 per cent (compared with 5.9 per cent for non-Pacific), though this is likely correlated with age.

Instability can also be examined in conjunction with regular unemployment and underutilisation, which is used here to mean four or more quarters experiencing that state (whether irregular or steady). Stable unemployment or underutilisation is relatively rare, but respondents experiencing instability experienced regular unemployment and/or underutilisation at much higher rates than completely or moderately stable respondents did.

Of our 220,500 respondents experiencing instability, 7.2 per cent were unemployed for four or more of their surveyed quarters, compared with 0.3 per cent of more stable respondents. 25.8 per cent of respondents experiencing instability were underutilised for four or more quarters, compared with 2.6 per cent of more stable respondents.

Given the number of changes experienced by respondents experiencing instability, these four quarters are unlikely to qualify as long-term unemployment or underutilisation, as the traditional definition of long-term considers each period of unemployment independently. Instead, it highlights the limitations of that approach and the continuing stress of instability.

It should also be reiterated, at this point, that lingering biases in our sample may cause systematic underestimation of respondents experiencing instability, despite our quality improvements through recalibration. It seems fair to assume that non-homeowners, as they move houses more frequently, also find themselves in need of new employment more frequently, which can come with periods of unemployment and NILF as they shift. In addition, people who lose their jobs may also be losing the bulk of their income, even if eligible for social assistance, which can lead to loss of housing. Instability is rarely self-contained in a single aspect of a person's life, and it is likely that unstable labour market outcomes are closely connected with instability of responding to a labour force survey.

Conclusion

Labour market instability can negatively impact people's wellbeing and incomes. It locks short-term employees out of time bound employment protections like access to paid sick leave and can limit intermittently jobless people's access to social protection schemes.

To measure labour market stability, we are required to supplement traditional labour force survey stocks and flows measures. While valuable for other statistics, quarterly averages or movements between two isolated quarters are inappropriate when considering the prevalence of stability over an extended period.

This article presents a potential measure to appropriately create and assess labour market stability using longitudinal labour force surveys, like New Zealand's HLFS.

First, we treated stability as a measurable characteristic by looking at the number of changes experienced by respondents over their entire survey period. This required the individual respondents to have been surveyed for an extended period – in this case, at least 6 of a potential 8 quarters was considered to be the minimum required to reasonably assess stability.

This limitation does bring with it a number of potential biases. In New Zealand, respondents of this consistency are more likely to be of European ethnicity, less likely to be of Māori descent, and more likely to be fully utilised but not in the labour force. Above all, they're older homeowners – which makes sense, given the sample selection occurs at a household level, and single year tenancies are common for New Zealand renters.

As such, the second step required to measure stability was recalibration of our newly selected subsample. In our case, while this drastically lowered the measured biases, it could not fully eliminate the increased likelihood of our group to be homeowners nor means any unobserved biases were completely removed. This needs to be borne in mind for any subsequent analysis, particularly for respondents experiencing instability.

The final caveat is a more generic practical one. Stability takes time to measure well. It does not change quickly and is unlikely to change much quarter to quarter. This approach can form the foundation of deeper research pieces or be used for long-term historic comparisons but should not be considered a new regular measure for production and short-term comparison.

To demonstrate the potential value of this approach, a short set of descriptive statistics have been produced. While non-comprehensive, some interesting trends are immediately apparent.

Most people were completely stable, experiencing no changes to their labour market status during surveyed periods. For the bulk of the population, the prime working-age employment to retirement-age NILF shift works extremely well, and a single transition out of the labour force is seen at or near the age in which superannuation is available. Moderate stability can also be observed for many people under the age of 25, as they move from education to employment, and women shifting back and forth between employment and NILF through potential childbearing years.

A small minority of people experience high degrees of labour market instability at all ages. Over 90 per cent of them are employed for at least some of their surveyed period, but over a quarter are regularly underutilised. In addition to the strong youth affect, in New Zealand this group is disproportionately Māori, Pacific, and female.

While not all stable circumstances are necessarily positive ones, stability is generally a desirable characteristic for our working-age population, bringing with it a number of social and economic benefits. This paper provides researchers and analysts with a method to identify labour market stability at an individual level, as a potential first step toward prioritising programmes and policies aiming to improve labour market outcomes for those experiencing instability.

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Literacy and numeracy skills and life-course outcomes: Evidence from PIAAC and linked administrative data

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Abstract

This paper examines the life-course trajectories of NZ adults across different literacy and numeracy skill levels. This is done by using skill information for the working-age adult population (aged 16-65 years) collected in the Survey of Adult Skills (PIAAC). This sample is then linked with administrative data to track their life-course outcomes from 2008 to 2020. The outcomes of the one-fifth of NZ working-age adults who were assessed at below Level 2 in either literacy or numeracy (or both) are compared with those at or above this baseline.

It finds that adults with low measured skills have less favourable outcomes in a number of areas. They have lower rates of educational attainment, lower employment rates and average earnings, higher rates of hospitalisation, and higher rates of criminal offending and convictions. In addition, outcomes for Māori and Pacific peoples in both the low-skills and above-baseline groups are generally less favourable than those of their NZ European counterparts. For example, even among those with above-baseline skills, Māori and Pacific peoples have lower average earnings than NZ Europeans. These results provide a quantifiable evidence base regarding the role of literacy and numeracy skills with respect to a range of wellbeing outcomes over the course of an individual's life.

JEL Codes: I24, I26, J31, I14
Keywords: lifecourse trajectory; adult skills; literacy; numeracy; PIAAC

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Introduction

We examine the life-course outcomes of those living with low literacy and/or numeracy (L+N) skills in New Zealand (NZ) using data from the 2014 Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills. Following OECD (2019a) and Erwin, Meehan, Pacheco, and Turcu (2020), we define those with L+N skills below Level 2 proficiency in PIAAC as having low skills. This represents about one-fifth or over half a million NZ working-age adults with low L+N skills. These data are then linked to administrative data in Stats NZ's Integrated Data Infrastructure (IDI) to examine outcomes over time for those with low L+N skills compared with a group with above-baseline skill levels.

Low L+N skills may affect an individual's well-being in a number of inter-related ways. For example, international research finds that individuals with low L+N skills are more likely to leave school early (Parsons and Bynner, 2005), experience lower levels of labour market attachment (Baldini Rocha and Ponczek, 2011; Chiswick, Lee, and Miller, 2003), have worse health outcomes (Kakarmath *et al.*, 2018) and higher offending rates (Bynner, 2009). These factors also interact with each other. For example, poor educational outcomes are associated with poor labour market outcomes, which are in turn associated with greater risk of criminal behaviour (Bynner, 2009).

The available evidence on the relationship between adult skills and life-course outcomes has been, however, limited due to a lack of longitudinal data. There is also some evidence on the skills of cohorts of young people and their subsequent life-course outcomes. For example, Polidano and Ryan (2017) uses data from Australia's Programme for International Student Assessment (PISA) to measure reading and mathematics skills of a representative sample of 15-year-old students, linked to longitudinal survey data. It finds no relationship between full-time employment rates or earning capacity at age 25 and reading proficiency at age 15. However, it uses longitudinal survey data with a high attrition rate of 75 per cent, which results in a relatively small sample size, limits sub-population analysis and raises the possibility of attrition bias. Two NZ papers Meehan, Pacheco, and Schober (2023) and Meehan, Pacheco, and Schober (2022b) appear to be the only studies which use PISA linked to administrative data to examine the relationship between young people's skills and their subsequent outcomes, including educational, labour market, family formation, physical and mental health and justice outcomes.

In terms of the relationship between adult skills and life-course outcomes, the available data and, consequently, the evidence is even more limited. Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) use international PIAAC data to study labour market outcomes and find that the returns to skills are higher for prime-age compared to early-career workers. There is only limited information on other aspects of life within PIAAC, making it difficult to analyse the wider role of skills over the life cycle. Some countries have made advances in linking PIAAC to administrative data, including Canada, Germany and the Nordic countries (Denmark, Estonia, Finland, Norway and Sweden) (Maehler and Konradt, 2020). However, some of these linking projects are still in their early stages and

in cases where data are available, there has been limited use of it in research to date. For example, it appears that the analysis of the German linked data has been limited to methodological considerations of the linking approach (Daikeler, Gauly, and Rosenthal, 2020) and a comparison of earnings reported by PIAAC survey respondents and earnings from administrative data (Gauly, Daikeler, Gummer, and Rammstedt, 2020). Canada's linking of the Longitudinal and International Study of Adults (LISA) to PIAAC and administrative data, specifically tax, pension and immigration records, seems to be the most progressed, with the data being used in several papers (for example, see MacDonald, Arpin, and Quesnel-Vallée, 2022; Chatoor, MacKay, and Hudak, 2019; McLean, Bouaissa, Rainville, and Auger, 2019; Simard-Duplain and St-Denis, 2020; Zarifa, Seward, and Milian, 2019). However, it does not yet appear to have been used extensively, particularly in terms of examining lifecourse trajectories generally, and the relationship between skills and lifecourse trajectories specifically. This limited use may be due to data limitations – PIAAC 2012 was linked to the first wave of LISA, conducted in 2012, but only about 36 per cent of those in LISA 2012 also appearing in PIAAC 2012 (Simard-Duplain and St-Denis, 2020), which also raises questions of whether the overlapping sample was representative of the underlying population. For Norway, Barth *et al*. (2021) focuses on youth aged 16-24 who participated in PIAAC and examines the relationship between skills and NEET status two years after participating in PIAAC using PIAAC linked to administrative data. However, it does not examine adults in other age groups nor longer-term outcomes.

To the best of our knowledge, this is, therefore, the first study to use PIAAC linked to administrative data to examine the relationship between the skills of working-age adults (aged 16-65) and life-course outcomes. We follow individuals for two decades and examine a myriad of outcomes, including education, labour market, health and justice outcomes. We find that those with low L+N have less favourable education, labour market, health and justice outcomes than those with above-baseline skill levels.

Like Meehan, Pacheco, and Schober (2023), the relationships presented here are not causal in nature. For example, it may be that skills are causally linked to outcomes. However, there may be at least some element of reverse causation – for instance, employment in a role that has a high cognitive skill content may lead to an improvement in such skills. Alternatively, it may be that both skills and labour market, health and other outcomes are associated with unobservable attributes, such as the degree to which individuals discount the future. Or, some combination of all these factors may be at play.

In addition, while Meehan, Pacheco, and Schober (2023) follows a cohort of young people who are all aged 15 in 2009 for 11 years until 2020 with skills measured at the beginning of that period, this paper examines a nationally representative sample of adults who are aged between 16 and 65 in 2014 and examines their outcomes both before and after 2014. This, therefore, implicitly assumes that adults' skills do not change much over time. However, it should be kept in mind that it may also be the case that the time dimension of the influence of skills may run in both directions. For example, low L+N skills may be a precursor to leaving school early, but leaving school early may also have consequences for the developments of skills. Indeed, there is evidence that literacy and numeracy proficiency change over the lifespan as individuals age and over time (e.g.

Barrett and Riddell, 2016; Paccagnella, 2016; Desjardins and Warnke, 2012), and due to factors such as the characteristics of their jobs and workplaces (e.g. Billett, 2004; Skule, 2004), periods out of the workforce (e.g. Edin and Gustavsson, 2008) and their level of engagement with reading activities in everyday life (e.g. Reder, Gauly, and Lechner, 2020). Despite these limitations, the linking of PIAAC and administrative data provides an opportunity to gain insights into the life-course outcomes of adults living with low L+N.

The next section provides some background information on PIAAC and the linked administrative data used. Section 3 presents the main results. It first examines educational outcomes for those with low L+N skills versus those in the comparison group with above-baseline skill levels. It then examines labour market outcomes, followed by health and criminal activity outcomes. Section 4 concludes.

Background

This section provides background information on the PIAAC survey, the data used, and the characteristics of our population of interest.

PIAAC survey and skill levels

PIAAC Survey of Adult Skills, an Organisation for Economic Cooperation and Development (OECD) initiative, measures literacy and numeracy proficiency of the working-age adult population (aged 16 to 65 years). The survey design allows for comparisons across countries, languages, and cultures and it has been conducted in over 40 countries/economies.

PIAAC measures L+N proficiency on a 500-point scale that is converted into six proficiency levels, with below Level 1 being the lowest and Level 5 the highest. We define those with low L+N skills as being below Level 2 in either literacy or numeracy (or both). For literacy, those below Level 2 can perform tasks such as reading relatively short texts to locate a single piece of information, completing simple forms, understand basic vocabulary, determining the meaning of sentences and so forth. In contrast, those at Levels 4 and 5 can make complex inferences and appropriately apply background knowledge as well as interpret or evaluate subtle truth claims or arguments. Similarly, those below Level 2 in numeracy can complete tasks involving basic mathematical processes and perform simple processes involving counting, sorting and basic arithmetic. In contrast, those at Level 4 and 5 can understand a broad range of complex mathematical information (OECD, 2019a).

According to the 2014 cycle of NZ's PIAAC survey, just over one-fifth of NZ's working-age population were classified as having low L+N skills according to this definition. Comparing these shares internationally, NZ had relatively low shares of adults

with low literacy skills (about 12 per cent). Only five OECD countries had a lower share of adults below Level 2 literacy. While there is a high degree of correlation between literacy and numeracy scores (the correlation coefficient is 0.87), NZ does not compare as well to other countries in terms of numeracy. However, the share of adults below Level 2 was, at about 19 per cent, still less than the OECD average (OECD, 2019a). Despite this seemingly strong performance in international comparison, this still means that a sizeable share of NZ's working-age population has low L+N skills. Furthermore, as highlighted in Erwin, Meehan, Pacheco, and Turcu (2020), there are substantial differences in the share of those with low L+N skills across population groups. For example, the share is substantially higher among Māori and Pacific peoples.

Data and method

The Integrated Data Infrastructure (IDI) is a large research database managed by Stats NZ. It holds micro-data from various government agencies and surveys including PIAAC that can be linked at the individual level (Stats NZ, 2020). NZ participated in PIAAC in 2014 with 6,177 survey respondents.[1] Using the IDI, we can study life-course outcomes of respondents over time. We focus on their outcomes during their adulthood over the period 2008 to 2020, 7 years before to 7 years after participation in PIAAC.

We present the available data in three different ways. First, we follow individuals over time and compare skill groups in each calendar year. We do this for three age groups separately, to explore potential differences in life-course trajectories related to skills and age. This approach allows a clear distinction between whether an outcome is observed before or after the survey in 2014, when skills of participants are measured.

Second, we use the observable time period after the survey (2015 to 2020) to examine whether certain events ever occurred among all PIAAC participants. This allows us to analyse differences between skill groups even for outcomes that occur less frequently, such as mental health problems or court sentences.

Third, we pool all annual observations after the survey and regress outcomes on indicators for age, skill group, gender and year. The estimates are then used to calculate adjusted means (sometimes called predictive margins) for each age cohort. An advantage of this method is that it allows us to increase statistical power and paint a more precise picture of outcomes over the life cycle. The downside is that we observe skills only once per person and assign each person to a fixed skill group. This means we implicitly assume that skills do not change (much) as people age. Recall that PIAAC's population of interest are those aged 16-65 years. We restrict this pooled analysis to individuals aged 20 to 65, where this assumption that a person does not change skill groups may be more plausible compared to younger cohorts aged 16-19 years as many in this group will still be engaged

1 NZ also participated in the 2023/23 cycle. However, the data for that cycle were not yet available at the time of writing.

in secondary school education. However, it should be kept in mind that it may be the case that the relationship between skills and other outcomes is bi-directional. For example, low L+N skills may be a precursor to leaving school early, but leaving school early may also have consequences for the development of L+N skills. Likewise, L+N skill levels may influence which job a person has, but it is also the case that individuals who use L+N skills in their job are more likely to retain and develop these skills compared with those who do not use L+N skills at work, even if these individuals had similar L+N skill levels when entering the workforce. For example, Borgonovi, Choi, and Paccagnella (2018) finds that males' advantage in numeracy is relatively small in childhood but grows in adulthood, and suggests that a possible reason for this is that men are more likely to study and work in areas that make intensive use of numeracy skills given their over-representation in areas such as STEM.

We use multiple data sources to construct a range of outcome variables in addition to the information provided in PIAAC. The available observation period varies between data sets in the IDI. Most outcomes are available for our entire period of interest, 2008 to 2020, including income data from Inland Revenue (IR), injuries from Accident Compensation Corporation (ACC), hospitalisations, mental health problems and outpatient visits from the Ministry of Health (MoH) and criminal convictions from the Ministry of Justice (MoJ). Furthermore, we use data from the NZ Police on alleged offending (first full year 2010) and victimisation (2014). To analyse the participants' education, we use the complete history of educational enrolment, including tertiary education, industry training, and targeted training (starting in 2003) as well as compulsory education (starting in 2007) data from the Ministry of Education. Tables 9 and 10 in the Appendix provide a full list of the outcome variables of interest with their full descriptions.

PIAAC provides a set of 10 plausible values for literacy and 10 for numeracy. Similar to other international assessments such as PISA, PIAAC only collects a limited set of test answers from each respondent out of the full set of test items. To account for the resulting uncertainty of proficiency at the individual level, multiple imputation is used to construct plausible values based on information from the available test items and background questions (OECD, 2019b). All reported statistics are estimates generated using the Stata package Repest. Repest accounts for PIAAC's complex survey design by employing the Jackknife procedure with replicate weights for variance estimation and allows for the 10 plausible values for literacy and numeracy (Avvisati and Keslair, 2020).

There are some general limitations of PIAAC worth noting that are relevant to the present analysis. First, the survey is limited to measuring only specific aspects of literacy and numeracy. For example, literacy is based on understanding written texts and does not assess writing ability (PIAAC Literacy Expert Group, 2009). More generally, while this research focuses on L+N skills, it is important to keep in mind the potential for individuals with low L+N skills to possess other valuable skills such as communication skills, technical or job-specific skills, and so forth (Cochrane *et al.*, 2020; Erwin, Meehan, Pacheco, and Turcu, 2020). In addition, PIAAC was only administered in English in NZ.

Population characteristics

Our population of interest includes those who participated in PIAAC, could be identified in the IDI and live in NZ before or after the interview in 2014. To identify who resides in New Zealand, we build on Stats NZ's Administrative Population Census (APC). The APC determines usual residence based on activity in selected administrative data sources, mortality data, and international border movements (Stats NZ, 2021). Just over 91 per cent (5,628) of the 6,177 PIAAC 2014 participants are included in our analysis at some point (for information about the linkage methodology used by Stats NZ see Stats NZ, 2014). Those who are included in our analysis have very similar characteristics to the overall PIAAC sample - for example, the share of females, average age, the share born in NZ and other characteristics are almost identical between the two groups. Thus, bias due to the less than 100 per cent inclusion is unlikely to be much of an issue. This inclusion rate also compares favourably to, for example, the linking of German PIAAC data with administrative data from Germany's Integrated Employment Biographies (IEB). In the German case, 72 per cent of participants consented to the data linkage, and of these, 87 per cent could be identified in the IEB, resulting in a linkage rate of 63 per cent. Moreover, in the case of Germany, those who could be linked had different characteristics to those who could not be linked, such as higher average educational and skill levels (Daikeler, Gauly, and Rosenthal, 2020).

For the included individuals, we construct an annual panel of PIAAC participants covering the years 2008 to 2020 based on the APC resident population. Of the 5,628 participants who appear in our panel at any point in time, these restrictions result in between 5,061 and 5,535 individuals in our population of interest per year, representing between 2.2 and 2.6 million NZ residents aged 16-65 at the time of the interview in 2014.

About one-fifth (20.6 per cent) of the population are considered to have low skills according to PIAAC 2014, that is, their numeracy or literacy skills are less than Level 2. Table 1 compares the characteristics of this group to the residual group with skills above this baseline level. Females are overrepresented among those with low skills. About 56 per cent of the low-skills group are women, compared with 51 per cent of those with above-baseline skills. This contrasts with the cohort of 15-year-old students from PISA examined in Meehan, Pacheco, and Schober (2023), where boys were more likely to have low reading and/or mathematics skills due to similar proportions of boys and girls at the lowest levels of mathematics proficiency, but many more boys who did not reach Level 2 in reading. However, these PISA results combined with the current PIAAC findings are consistent with cross-country research on the evolution of skills over the life-course. In particular, this research finds that boys have higher numeracy skills than girls and that this gap increases with age, peaking at age 27, while girls have a small literacy advantage over boys but this gap closes over time and is negligible by age 27 (Borgonovi, Choi, and Paccagnella, 2018).

Those in the low-skilled group are also about 2 years older on average. This reduction in skills with age is as expected, and existing research suggests it is due to a combination of higher education levels among younger cohorts and because cognitive skills tend to peak at about age 25-30 before declining (see for example Calero, Murillo

Huertas, and Raymond Bara, 2019). This also highlights that the possibility of cohort effects should be kept in mind when interpreting the results in Section 3.

Those with low L+N skills are also four percentage points less likely to be born in NZ. This contrasts with Meehan, Pacheco, and Schober (2023), which finds 15-year-old students with low skills are more likely to have been born in NZ. This could be because the PIAAC test was administered in English only, and adults who were not born in NZ may, on average, have lower English language proficiency than those born in NZ, while this difference may be less apparent among the PISA cohort who are more likely to have migrated to NZ at a young age. Finally, those of Māori, Pacific peoples and Asian ethnicity are overrepresented among those with low skilled, while NZ Europeans are underrepresented.

Results

Education

Turning to our main results, we first look at educational outcomes. Since many PIAAC participants undertook education before the PIAAC survey, we look at educational attainment measures from the PIAAC survey in addition to outcomes measured in the IDI. PIAAC responses can include overseas education and qualifications attained prior to 2014 (when the survey was conducted). In contrast, the IDI administrative data on education includes NZ education and qualifications undertaken during the time period covered by administrative databases (2007 onwards for secondary school enrolments, 2003 onwards for enrolment in tertiary education, industry and targeted training,[2] July 1984 onwards for secondary school qualifications, October 1997 onwards for tertiary qualification completions).[3] As such, the coverage will be incomplete for many – for example, a PIAAC participant who was 50 at the time of the survey in 2014 would have completed school before 1984, when the secondary school data on obtained qualifications that is available in the IDI begins. Therefore, we focus more on educational enrolment information rather than educational attainment from the IDI.

Table 2 shows that, according to the PIAAC background questionnaire, those with low L+N skills have fewer years of education on average than those with above-baseline skills (12.2 years versus 14.3 years). They are also less likely to have a post-school qualification (46 per cent versus 68 per cent). In terms of IDI enrolment data, a lower share

2 Targeted training is industry training at sub-degree levels in targeted areas.
3 Within the IDI, information on highest qualification obtained, which includes foreign qualifications, are available from non-administrative sources, including the Census and some surveys, such as the Household Labour Force Survey.

of those in the low-skills group have been enrolled in any form of tertiary education at any point covered by IDI records (62 per cent compared with 71 per cent of the above-baseline group). Looking only at bachelor's degrees reveals even larger differences, with about three times as many of the above-baseline group having been enrolled in a bachelor's degree qualification compared with the low-skills group (23 per cent versus 8 per cent). The low-skills group are more likely to have enrolled in targeted training than the above-baseline group (16 per cent versus 6 per cent). There is no statistically significant difference between the low-skills and above-baseline groups in enrolment in industry training, with about a fifth of both groups having enrolled at some point.

Table 1. Characteristics by skill group

	(1) Low skills	(2) Above-baseline	(3) Difference	(4) p-value
Female	0.56	0.51	0.05	0.038
Age	41.54	39.68	1.86	0.002
Born in NZ	0.68	0.73	-0.06	0.008
Ethnicity				
NZ European	0.54	0.81	-0.27	0.000
Māori	0.23	0.11	0.12	0.000
Pacific Peoples	0.17	0.04	0.13	0.000
Asian	0.15	0.11	0.04	0.009
Middle Eastern/Latin American/African	0.01	0.01	0.00	0.662
Other Ethnicity	0.00	0.01	-0.00	0.044

Notes: This table compares average characteristics of those with low skills (Column 1) and those with above-baseline skills (2) for PIAAC participants who are ever in the population of interest. Column 3 shows the difference between skill groups, Column 4 shows the p-value testing the equality of the two means. The number of observations is 5,628. All observation counts are randomly rounded to base 3 in accordance with Stats NZ confidentiality rules.

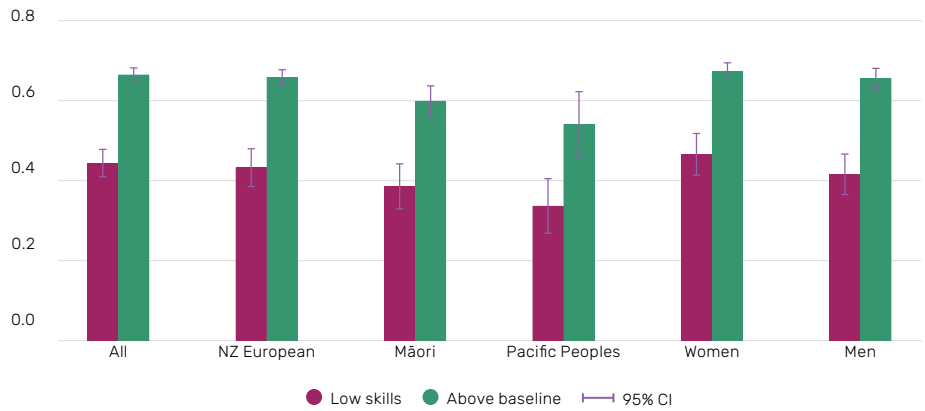
Table 2. Educational enrolment and attainment

	(1) Low skills	(2) Above-baseline	(3) Difference	(4) p-value
Educational attainment from PIAAC				
Years of education	12.17	14.34	-2.17	0.000
Any post-school qualification	0.46	0.68	-0.23	0.000
Enrolment information from IDI				
Tertiary education	0.62	0.71	-0.09	0.000
Bachelor	0.08	0.23	-0.15	0.000
Industry training	0.22	0.23	-0.01	0.568
Targeted training	0.16	0.06	0.09	0.000

Notes: This table compares average outcomes of those with low skills (column 1) and those with above-baseline skills (2). Column 3 shows the difference between skill groups, column 4 shows the p-value testing the equality of the two means. Enrolment information from IDI refers to ever being enrolled at any point in time covered by the available records.

Figure 1 further decomposes whether individuals have a post-school qualification based on PIAAC responses by gender and ethnicity reveals that Māori and Pacific peoples in both the low-skills and above-baseline groups are less likely to have a post-school qualification than their NZ European counterparts, although the differences for the low-skills groups are not statistically significant. There are no statistically significant differences between men and women for either the low-skills or above-baseline groups.

Figure 1. Any post-school qualification



Part of the reason for the difference in education levels between the low-skills and above-baseline group could be because the low-skills group are, on average, older, and education levels have increased over time resulting in younger people being more highly educated on average than older people. However, this is very unlikely to explain the entire difference in educational outcomes between the low-skills and above-baseline groups given the difference in average age between the two groups is only 1.5 years (see Table 1). In addition, other research where age is not a factor finds similar educational outcome differences. For example, following a cohort of young people who were all 15-years-old in 2009, Meehan, Pacheco, and Schober (2023) finds similar differences in educational outcomes by skill level, with 17 per cent of the young people with low skills having enrolled in a bachelor's degree by 2020 at age 26, compared with 55 per cent of those in the above-baseline group.

Labour market

This section analyses labour market outcomes. It examines employment, occupation, earnings and benefit receipt.

Employment

Figure 2 presents employment rates by age. We examine tax records back to 2008 and therefore focus on those aged 36 and over at the time of the PIAAC survey as those aged 36 would have been 30 in 2008 and therefore very likely to have completed formal education. For analysis that focuses on a cohort of young people over time, see Meehan, Pacheco, and Schober (2023).

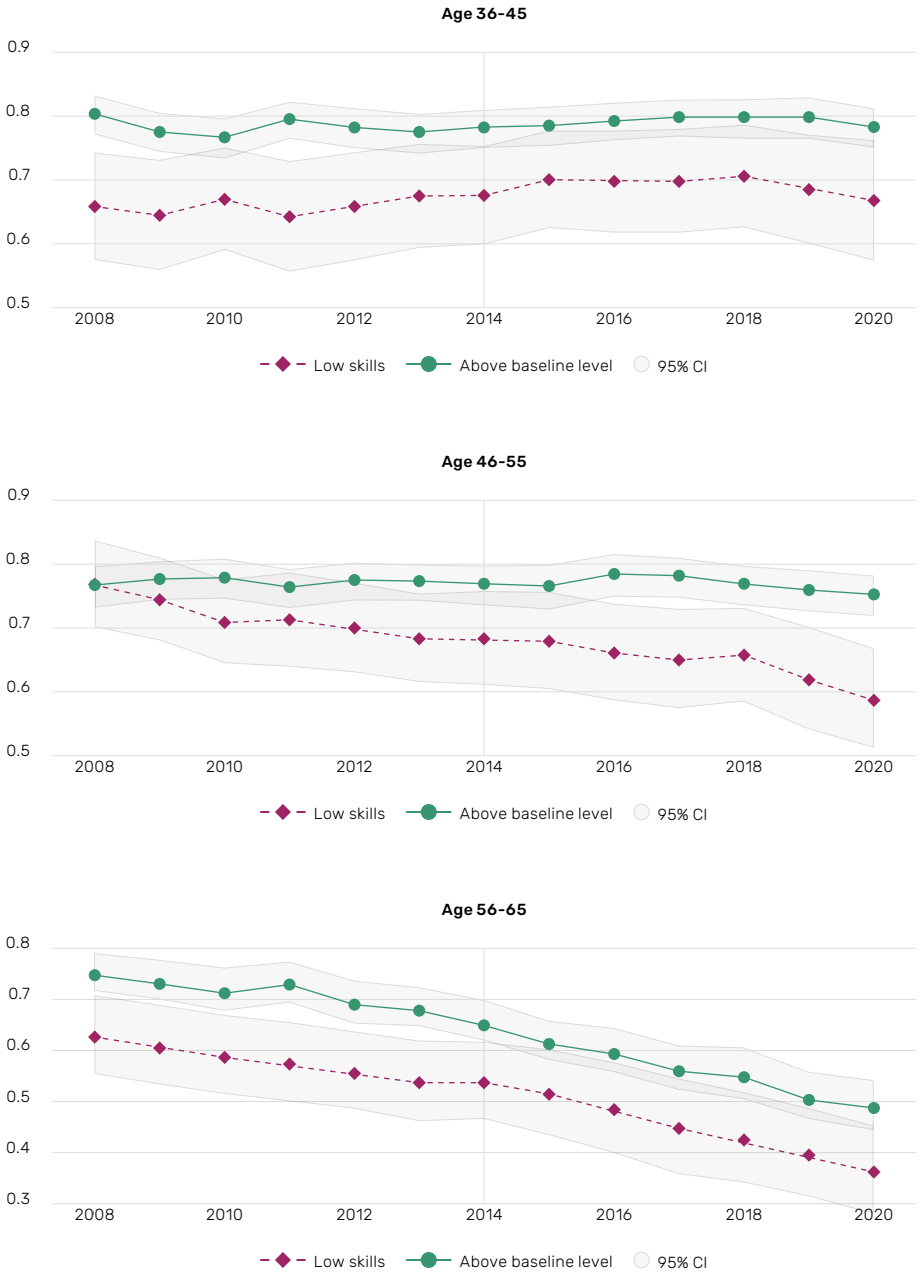
The left-hand panel of Figure 2 tracks those aged 36-45 at the time of PIAAC in 2014 back to 2008 and forward to 2020. It shows that those in the low-skills group have lower employment rates by about 10 to 15 percentage points than those in the above-baseline group, and the differences are statistically significant in most years.

Employment rates for those aged 46-55 in 2014 were similar among the low-skills and above-baseline groups in 2008, after which the employment rates among both groups fell, but they fell by more in the low-skills group. This may reflect that by 2020, the group were aged 52-64 years old, so some may have stopped working as they got older, with this more likely in the low-skills group who are also more likely to work in physical jobs (see 'Occupation' results below). However, the differences are only statistically significant from 2016 onwards. Moreover, skills and education are positively correlated and previous NZ research has found that higher educated older women (aged over 50) are more likely to participate in the labour market than less educated older women, although no statistically significant association was found between education and participation for men (Gorman, Scobie, and Towers, 2012).

For those aged 56-65 in 2014, the employment rates of both groups fell throughout the 2008 to 2020 period. While the low-skills group in this age category also have lower employment rates than the above-baseline group, the differences are generally not statistically significant.

Given we are examining people who have already spent some time in the labour force by the time they took the PIAAC assessment in 2014, reverse causation may also be part of the explanation for the positive association between employment and L+N skill levels. Previous research has shown that there is a negative relationship between time out of the workforce and skills (Edin and Gustavsson, 2008). In addition, skills increase with the use of those skills - for example, Reder, Gauly, and Lechner (2020) finds that literacy proficiency develops as a by-product of people's engagement in everyday reading and writing practices. Moreover, those in jobs where they use their literacy and numeracy skills may be more likely to retain their skill levels over time. For example, Borgonovi, Choi, and Paccagnella (2018) finds that the numeracy gap between young men and women increases as they age, and highlights that this is consistent with a greater specialisation of men in occupations that make more intensive use of numeracy skills. Therefore, reverse causation may also have a part to play: working more over one's lifetime, particularly in roles requiring L+N skills, may lead to greater measured skill level in PIAAC in 2014, and thus contribute to the observed positive association between employment and skill levels.

Figure 2. Employment indicators for different age groups

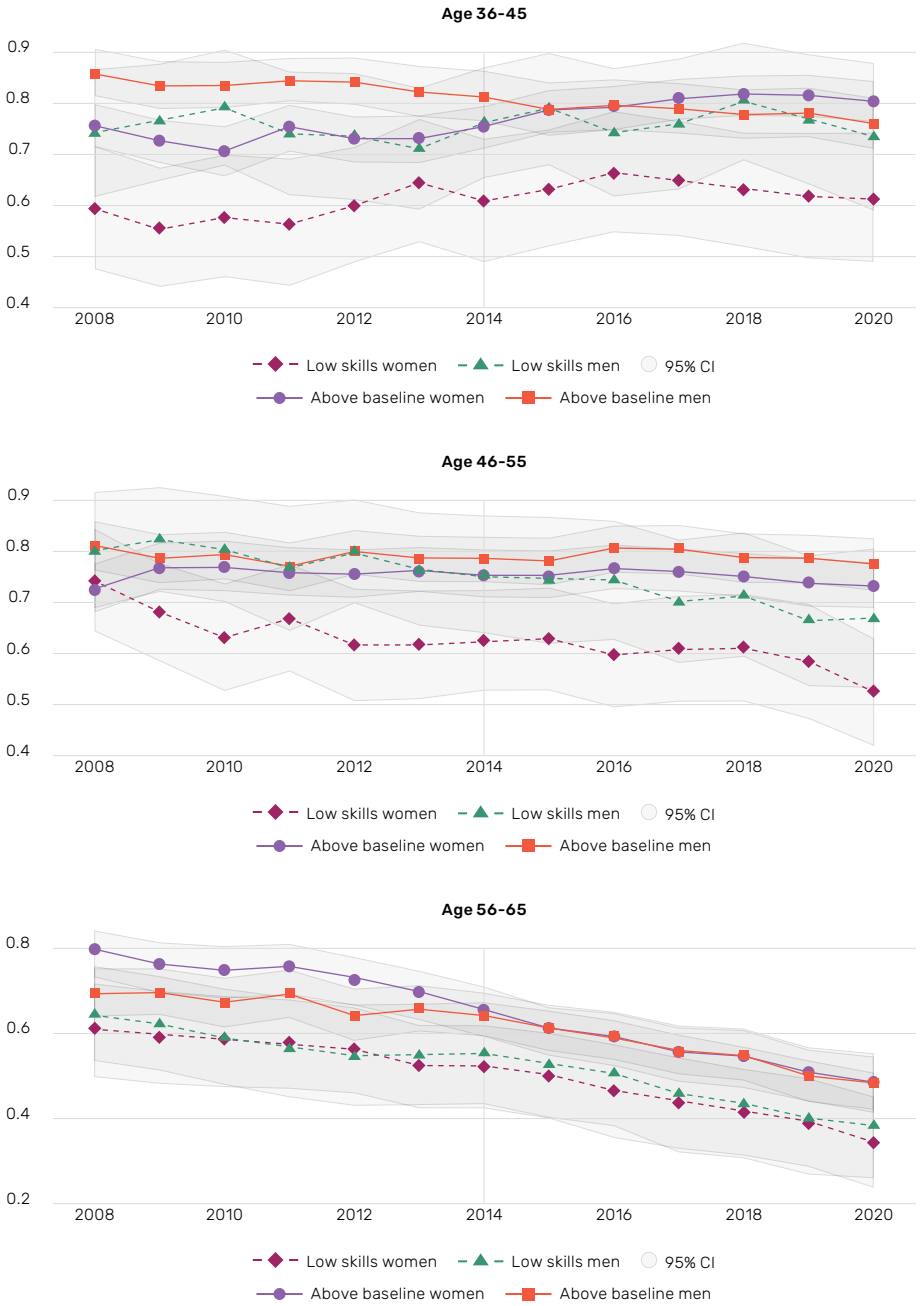


These employment patterns may differ by gender. As discussed in Meehan, Pacheco, and Schober (2023), differences in employment rates by skill level and gender could reflect differences in family formation patterns, for example. Consistent with Meehan, Pacheco, and Schober (2023), the group with the lowest employment rates tends to be women with low skills (see Figure 3). This difference is more pronounced among those aged 36-45 in 2014. When they are aged 30-39 years in 2008, their employment rates were lower than the other groups, including above-baseline women. This reinforces the idea that this may, at least in part, reflect parenthood patterns as their employment rates were particularly low when they were at an age when they were more likely to have young children, and these employment rates then increased over time. Consistent with this idea, Meehan, Pacheco, and Schober (2022a) show that women with low skills tend to have a higher average number of children than those in the above-baseline group.

In contrast to the results for women, the employment rate of men with low skills is more similar to men in the above-baseline group, with many of the differences not being statistically significant. For those aged 36-45 in 2014, men in the low-skills group have lower employment rates than men in the above-skills group in 2008, but their employment rates are relatively stable over time, while those of men in the above-skills group fall gradually so that the employment rates of the two groups converge over time.

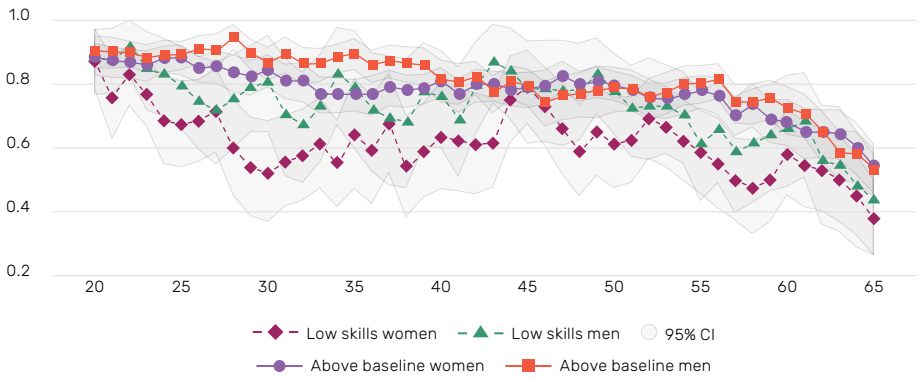
For those aged 46-55 years in 2014, the employment rates of both men and women with low skills fall over time while that of men and women with above-baseline skills do not. For those aged 56-65, the employment rates of all groups fall over time, which is expected as individuals begin to retire. Once again, many of the differences between the groups are not statistically significant.

Figure 3. Employment indicators for different age groups



To increase the statistical power of the group comparisons, as described in Section 2.2, Figure 4 pools all annual observations and regresses outcomes on indicators for age, skill group, gender and year. The adjusted means are then calculated to give employment rates across these dimensions. This shows that women in the low-skills group have the lowest employment rates, with the share employed decreasing as they age until about the age of 40, when their employment rate increases somewhat and only starts to decline again from about the age of 50. In contrast, the employment rates of women with above-baseline skills decrease slowly from the age of 20 before dropping more quickly after they are in their mid-50s. For men, those with above-baseline skills have higher employment rates than those with low skills when they are young, but this gap disappears in their late 30s as the employment rates of men with above-baseline skills decrease. However, as they enter their later working years, the employment rate of men with low skills starts to fall earlier and faster than that of men with above-baseline skills.

Figure 4. Any employment by age for different skill groups



Occupation

Table 3 presents occupation information from PIAAC 2014 data for those who are employed. Those in the low-skills group are more likely (relative to the above-baseline group) to be service workers and shop and market sales workers; plant and machine operators and assemblers; craft and related trades workers; elementary occupation workers, and less likely to be technicians and associated professionals; legislators, senior officials and managers; and professionals. For example, 8 per cent of workers in the low-skills group are professionals versus 24 per cent of those in the above-baseline group. There are some differences by gender. Women in the low-skills group are more likely to be service and shop and market sales workers, while men in the low-skills group are more likely to be craft and related trades workers.

Table 3. Occupations

	All		Women		Men	
	(1) Low skills	(2) Above-baseline	(3) Low skills	(4) Above-baseline	(5) Low skills	(6) Above-baseline
Service workers and shop and market sales workers	0.23*	0.13	0.38*	0.20	0.07	0.07
Plant and machine operators and assemblers	0.13*	0.04	0.06*	0.01	0.20*	0.07
Craft and related trades workers	0.13*	0.09	0.03	0.02	0.24*	0.16
Elementary occupations	0.11*	0.05	0.11*	0.04	0.12*	0.06
Technicians and associate professionals	0.11	0.15	0.07*	0.15	0.15	0.15
Legislators, senior officials and managers	0.08*	0.18	0.08*	0.14	0.09*	0.22
Professionals	0.08*	0.24	0.12*	0.28	0.05*	0.20
Clerks	0.08	0.10	0.13	0.16	0.04	0.04
Skilled agricultural and fishery workers	0.03	0.02	0.03	0.01	0.04	0.03

Notes: This table compares average outcomes of people with low skills and those with above baseline skills for different groups of the population. * indicates that the difference between skill groups is statistically significant at the 5% level. Occupational information for 2241 women and 1884 men comes from PIAAC.

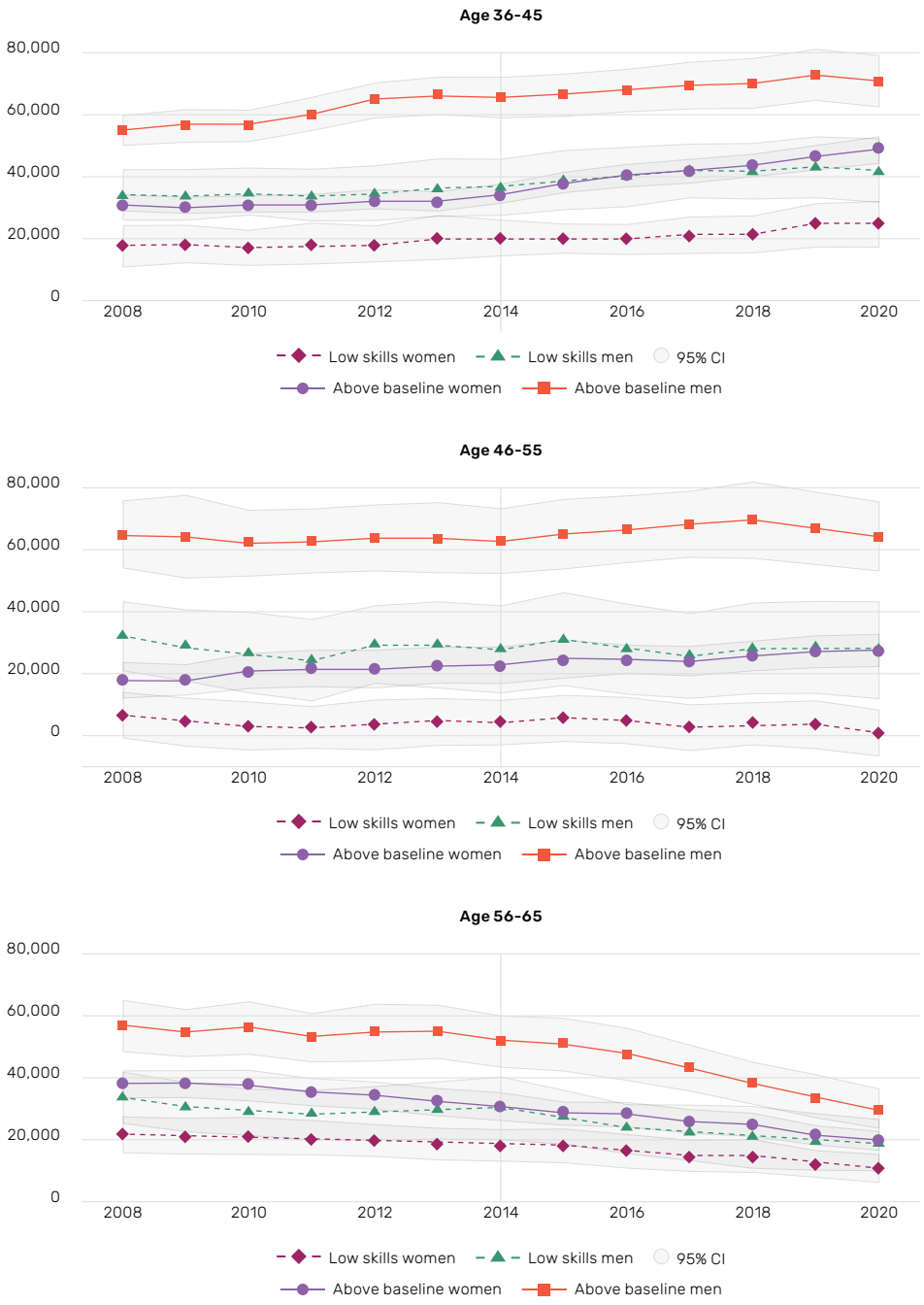
Earnings

We next look at earnings using tax data. All earnings are measured in 2020 prices using the consumer price index to adjust for inflation. Figure 5 presents earnings over time by age groups and gender. Those aged 36-45 in 2014 experience increases in earnings over time between 2008 (when they were 30-39 years old) and 2020 (when they were 42-51 years old), as expected as they gain work experience. Average earnings are highest among men with above-baseline skills, and their earnings growth is stronger than the other groups over time, leading to an increasing gap between this group and the other groups. Men with low skills have similar earnings over time to women with above-baseline skills. Above-baseline women have little growth in average earnings until about 2013. Women with low L+N skills have the lowest earnings and experience little earnings growth over time.

Those aged 46-55 in 2014 also experience some increases in earnings over time, although the rate of increase is slower than for the 36-45 year group, which is consistent with the expected pattern of larger earnings increases during the first years of entering the labour market. Once again, men with above-baseline skills have the highest average earnings, and women with low skills have the lowest.

For those aged 56-65, their average earnings are generally decreasing over time, with the rate of decrease increasing over time. This is as expected due to an increasing share of this group entering retirement over time.

Figure 5. Earnings for different age groups



These patterns of average earnings by age are even clearer in Figure 6 which pools the observations and shows adjusted means by skill groups, age and gender. The left-hand panel of Figure 6 shows that earnings generally increase steeply when individuals are young, followed by slower earnings growth, then a plateau followed by a decrease in earnings. This is as expected as individuals gain experience, enter their prime earning years, then begin to retire. This pattern is most pronounced for above-baseline men. The average earnings of men with low skills follows a similar pattern as those of above-baseline men, but at a much lower level. Women with above-baseline skills experience similar earnings growth as men with above-baseline skills for a few years when they are young before their earnings growth plateaus at a much younger age than for that of men. Women with low skills have low average earnings regardless of age and do not experience a strong increase in earnings when they are young as the other groups do, but instead have a slow increase in earnings by age up until they are in their late 40s.

To get a sense of the degree to which the patterns in the left-hand panel are due to employment rate differences by age, the right-hand panel restricts attention to those who are working. Across all groups, average earnings conditional on working are more positively correlated with age than the unconditional average earnings. For example, for above-baseline men, earnings do not start to decrease until about age 60. This also reveals that the average earnings of above-baseline women are still much lower than above-baseline men and are not, therefore, simply due to lower employment rates among women. Similarly, the average earnings of women with low skills is still much lower than that of men with low skills.

Figure 6. Earnings and earnings conditional on working by age for different skill groups

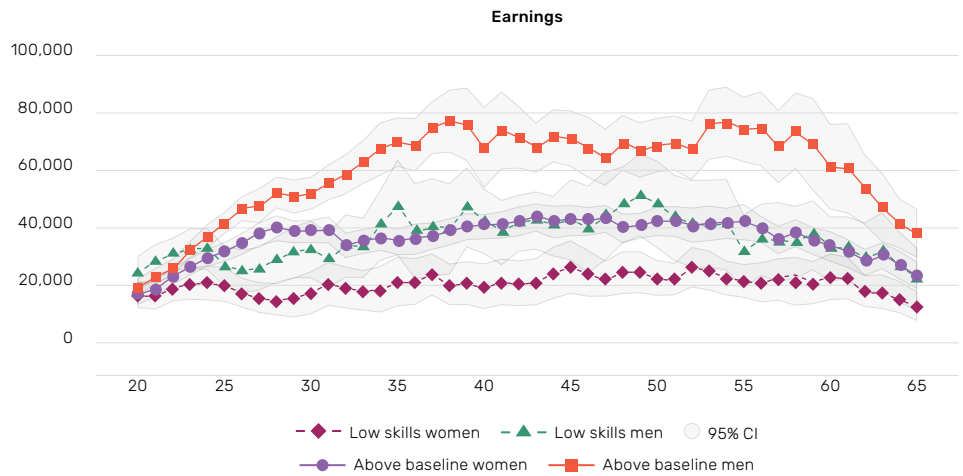


Figure 6. continued

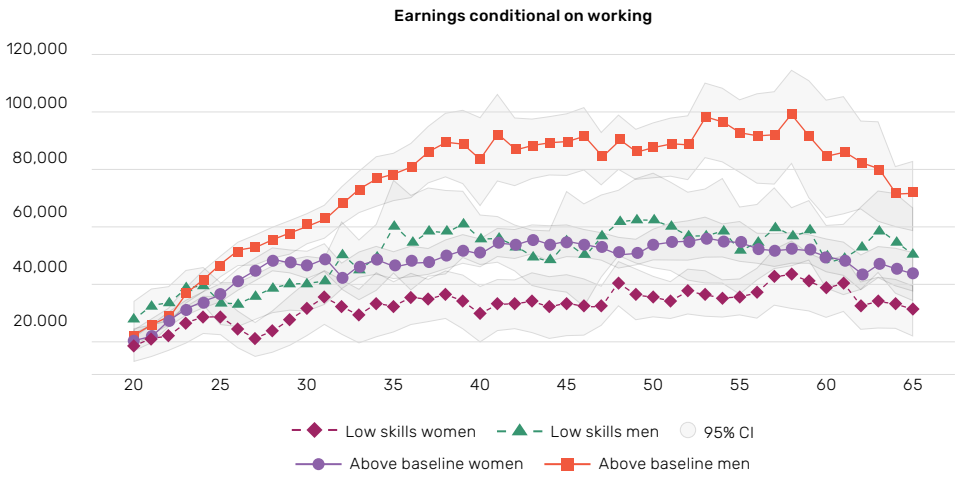
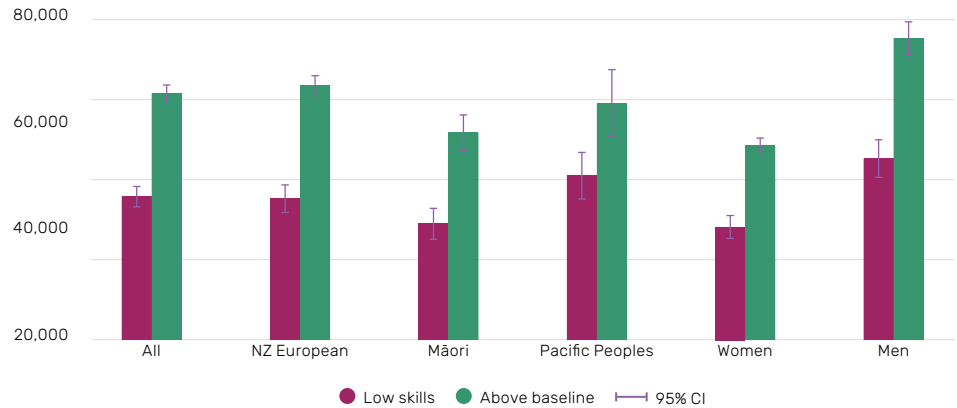


Figure 7 shows earnings by gender and ethnicity, where earnings is measured as the highest annual earnings we observe for an individual between 2015 and 2020. As discussed, men with above-baseline skills have higher earnings than women with above-baseline skills. The earnings of women with above-baseline skills are actually only slightly higher than that of men with low skills (and the difference is not statistically significant). Turning to ethnicity, NZ Europeans with above-baseline skills have the highest average earnings, followed by Pacific peoples with above-baseline skills, then Māori with above-baseline skills. For those with low skills, there is no statistically significant difference between NZ Europeans and Pacific peoples while Māori have lower average earnings.

Figure 7. Highest observed earnings



Benefit receipt

Figure 8 shows benefit receipt and average benefit payment amounts by age decomposed by skill level and gender, based on Ministry of Social Development (MSD) data on the receipt of a main benefit. This is based on the adjusted means for the pooled data. Women with low skills are more likely to receive a main benefit than men with low skills, while men with above-baseline skills are the least likely to receive a benefit. The share receiving a benefit tends to be highest when individuals are young. For example, the share receiving a benefit decreases over time for all four groups, although it increases after the age of about 50, with this increase being particularly strong among men with low skills. The average amount of benefit payments is also highest among women with low skills and lowest among men with above-baseline skills. This likely not only reflects the higher share receiving benefits among women with low skills, but also that those with dependent children generally receive higher benefit payments. For example, the vast majority of those receiving a sole parent benefit are women (91.3 per cent in the June 2022 quarter according to Ministry of Social Development, 2022). The amount received starts falling sharply at age 65 as people become eligible for NZ Superannuation and this replaces their receipt of a benefit.

Figure 8. Benefit receipt by age for different skill groups

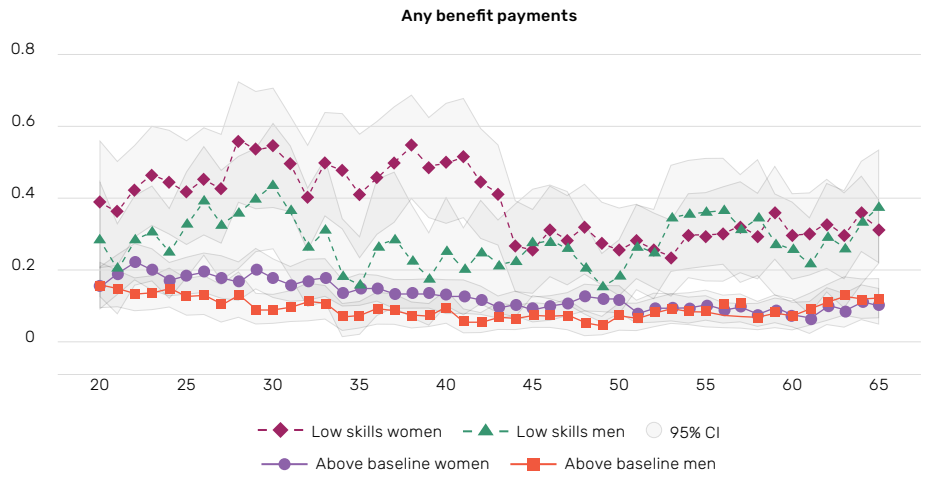


Figure 8. continued

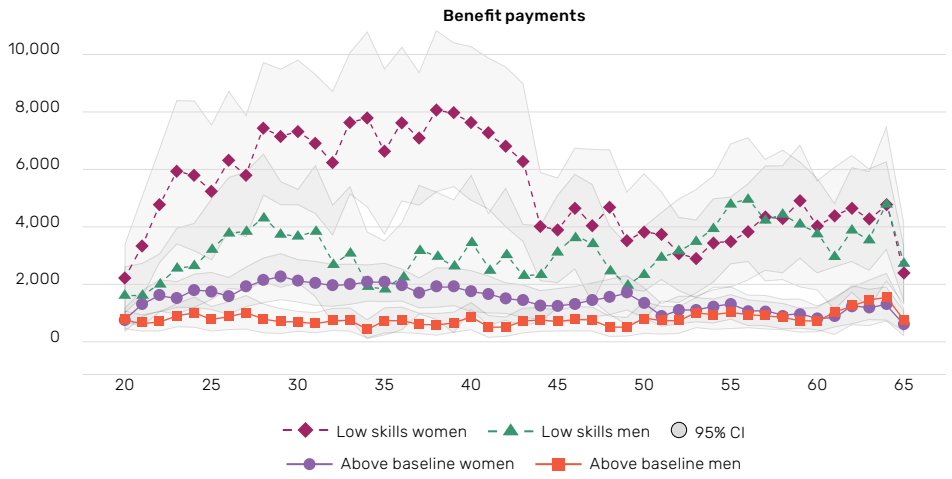
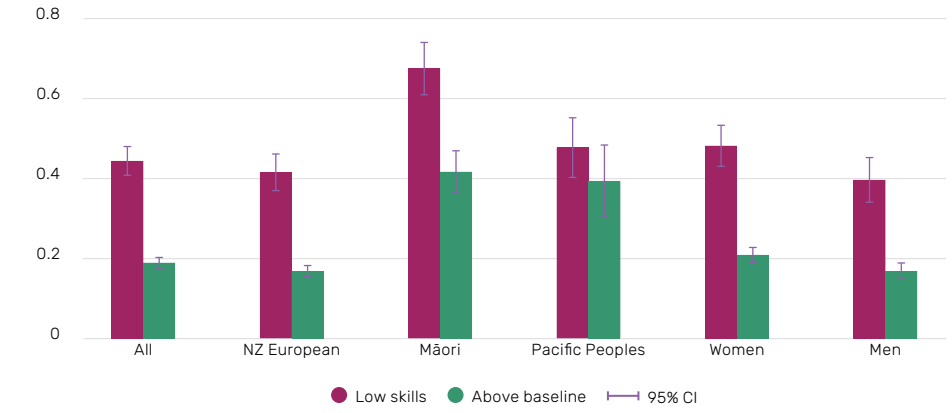


Figure 9 shows the share of individuals who have ever received a main benefit between 2015 and 2020 by gender and ethnicity. Consistent with Figure 8, women are more likely to have received a benefit than men within each of the skill groups. In terms of ethnicity, NZ Europeans with above-baseline skills are the least likely to ever have received a benefit. The rates of benefit receipt are higher for Māori and Pacific peoples. For example, Māori and Pacific peoples with above-baseline skill levels are more likely than NZ Europeans with low skills to have received a benefit (although the differences are not statistically significant).

Figure 9. Share of people who ever received benefits



Health

Another outcome that the existing literature highlights is associated with skill level is health. As such, this section examines hospitalisation, injury and mental health outcomes based on Ministry of Health data. Existing research highlights that higher literacy levels are associated with a range of health outcomes via a number of potential pathways. For example, people with low literacy tend to be less responsive to traditional health education messages, are less likely to use disease prevention services and are less able to successfully manage chronic disease (Berkman, Sheridan, and Donahue, 2011; Dewalt *et al*., 2004).

The measures of health care usage presented here are used as proxies for an individual's state of health. While health status and health care usage are likely highly correlated, health care usage is, in fact, a combination of actual health status and the propensity to access health care (as discussed in Meehan, Pacheco, and Schober, 2022b). For example, if those with above-baseline skills are more likely to access health services in the event of illness or injury than those in the low-skills group, and we find that those with low skills have higher health care usage, then the health care usage measures will be an underestimate of the true difference in health status between the two skill-level groups. However, the results presented below showing that health care usage is generally higher among those with low skills compared with the above-baseline group is in line with self-reported health status collected as part of PIAAC. For example, Scott (2018) finds a positive relationship between self-report health status and skill and education levels.

General health care use

Figure 10 shows the rate of hospitalisation by age groups. In general, those in the low-skills group have higher hospitalisation rates, although the differences are not statistically significant in general. The hospitalisation rates for the 36-45 years group are decreasing slightly over time, which is particularly evident among the above-baseline group. For those in the 46-55 year group, hospitalisation rates increase over time as the group ages, with this pattern being even more pronounced among the 56-65 year age group.

Figure 10. Share of people with hospitalisations for different age groups

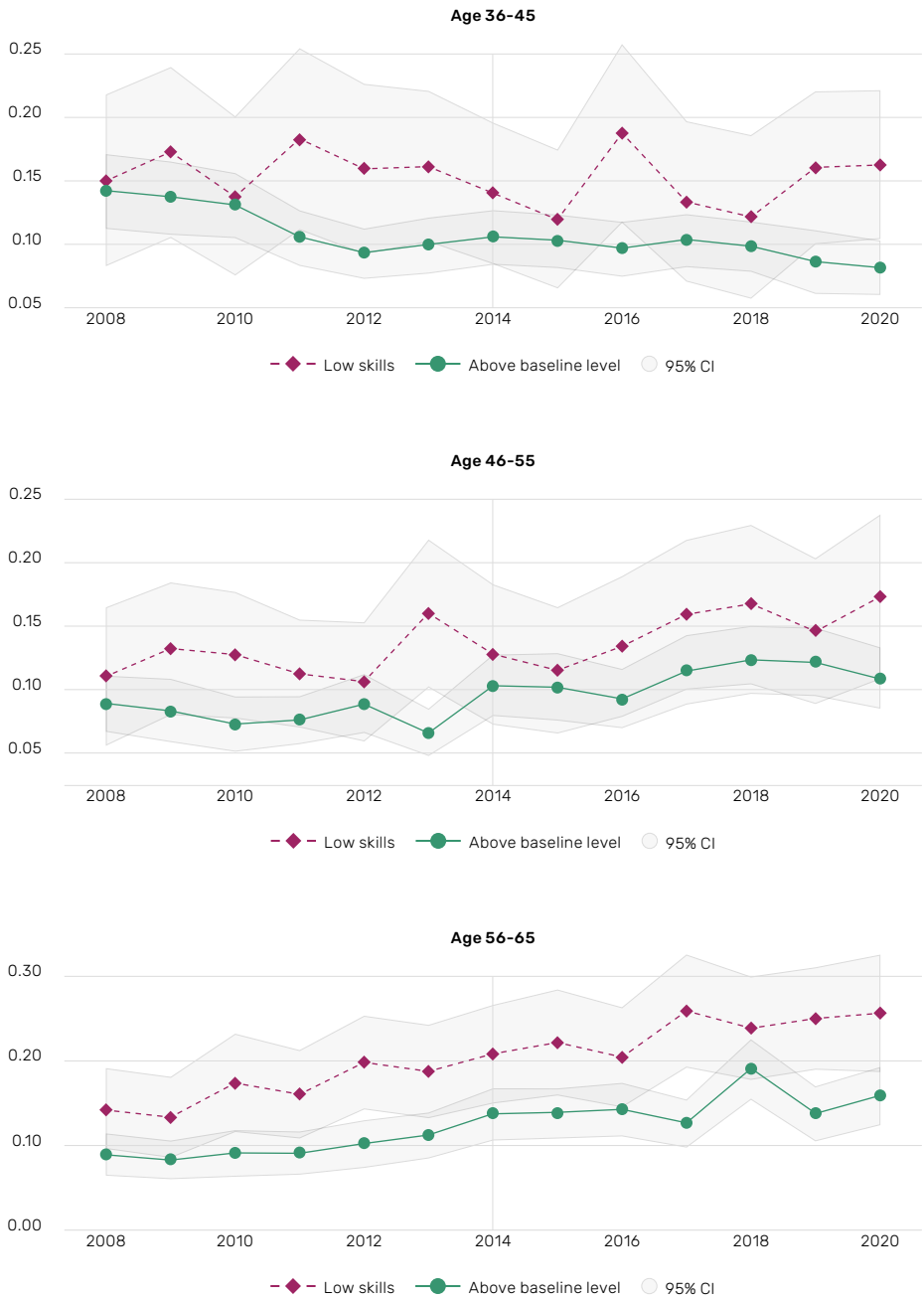


Table 4 shows health care utilisation over the 2015-2020 period and provides more details of the nature of the treatment. As in Figure 10, the rate of hospitalisation for any reason is higher among the those with low skills. Almost 53 per cent of the low-skills group have been hospitalised at least once during this time period, compared with 40 per cent of the above-baseline group. This could partly be because the birth rate among those with low skills is higher (Meehan, Pacheco, and Schober, 2022a). Therefore, the second row of Table 4 looks at hospitalisations excluding child birth, and finds that there is still a large and statistically significant gap between those with low and above-baseline skills (48 per cent versus 35 per cent). Looking at selected diagnosis groups, the hospitalisation rate for every diagnosis group is higher among the low-skills group, although the difference is only statistically significant at the 5 per cent level for musculoskeletal, digestive and nervous system and skin, tissue and breast issues. The share who have had at least one non-admitted secondary care event is also higher among those with low skills.

Once again, these differences in health care utilisation most likely reflect a combination of differences in health status and propensities to access health care. For example, the higher rate of emergency department visits among those with low skills could reflect poorer health status, but could also partly be because those with lower skills may have less access to primary health care for a variety of reasons.

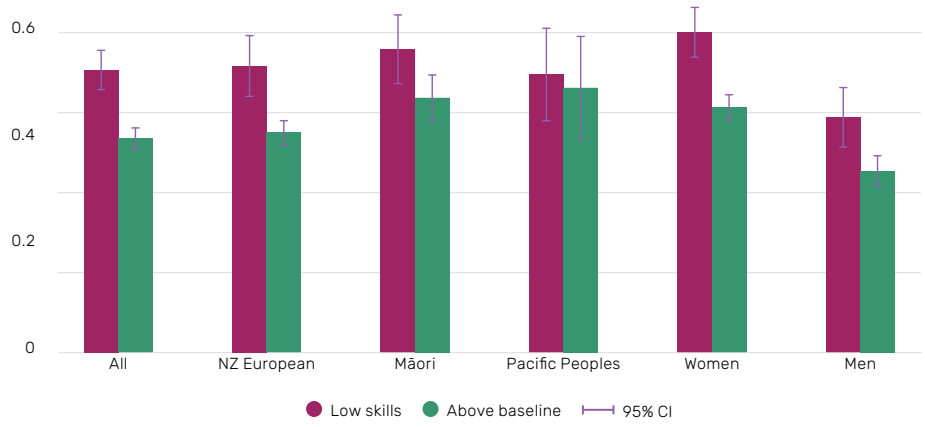
Table 4. Health care utilisation

	(1) Low skills	(2) Above-baseline	(3) Difference	(4) p-value
Hospitalisation	0.53	0.40	0.13	0.000
Hospitalisation (excl. childbirth)	0.48	0.35	0.13	0.000
Selected diagnosis groups				
Musculoskeletal system	0.08	0.04	0.04	0.000
Digestive system	0.12	0.09	0.03	0.037
Injuries	0.13	0.09	0.04	0.002
Ear, nose, mouth and throat	0.05	0.03	0.01	0.220
Nervous system	0.04	0.03	0.02	0.074
Skin, subcutaneous tissue and breast	0.07	0.04	0.03	0.000
Non-admitted secondary care events				
Any event	0.73	0.62	0.11	0.000
Emergency department visits	0.51	0.38	0.13	0.000
Other outpatient visits	0.63	0.51	0.12	0.000

Notes: This table compares health care utilisation for people with low skills (column 1) and those with above baseline skills (2). Column 3 shows the difference between skill groups, column 4 shows the p-value testing the equality of the two means.

Decomposing the share of those who have had any hospitalisation between 2015 and 2020 by gender and ethnicity shows that the hospitalisation rate is higher among women compared to men. Men (women) with low skills are more likely to have had at least one hospitalisation than men (women) with above-baseline skills. Looking at ethnicity, Māori have higher hospitalisation rates than NZ Europeans. While there is a statistically significant difference in hospitalisation rates between those with low skills and above-baseline skills for NZ Europeans and Māori, the difference is not significant for Pacific peoples.

Figure 11. Share of people with any hospitalisations



Injury

Examining injuries using ACC data, Figure 12 shows that there is no discernible differences in overall injury rates between those with low skills and those with above-baseline skills. Decomposing this by injury type (Table 5) and restricting attention to the post-PIAAC 2015-2020 period, those with low skills have higher rates of work injuries, which is as expected given they are more likely to be employed in physical roles (see 'Occupation' results in subsection 3.2). However, they are less likely to have sports injuries than their above-baseline counterparts. These results are consistent with Meehan, Pacheco, and Schober (2022b), which follows a cohort of 15-year-old students and finds there is no statistically significant difference in overall injury rates by skill level, but those with low skills have higher work injury rates and lower sports injury rates than those with above-baseline skills.

Figure 12. Share of people with any injuries for different age groups

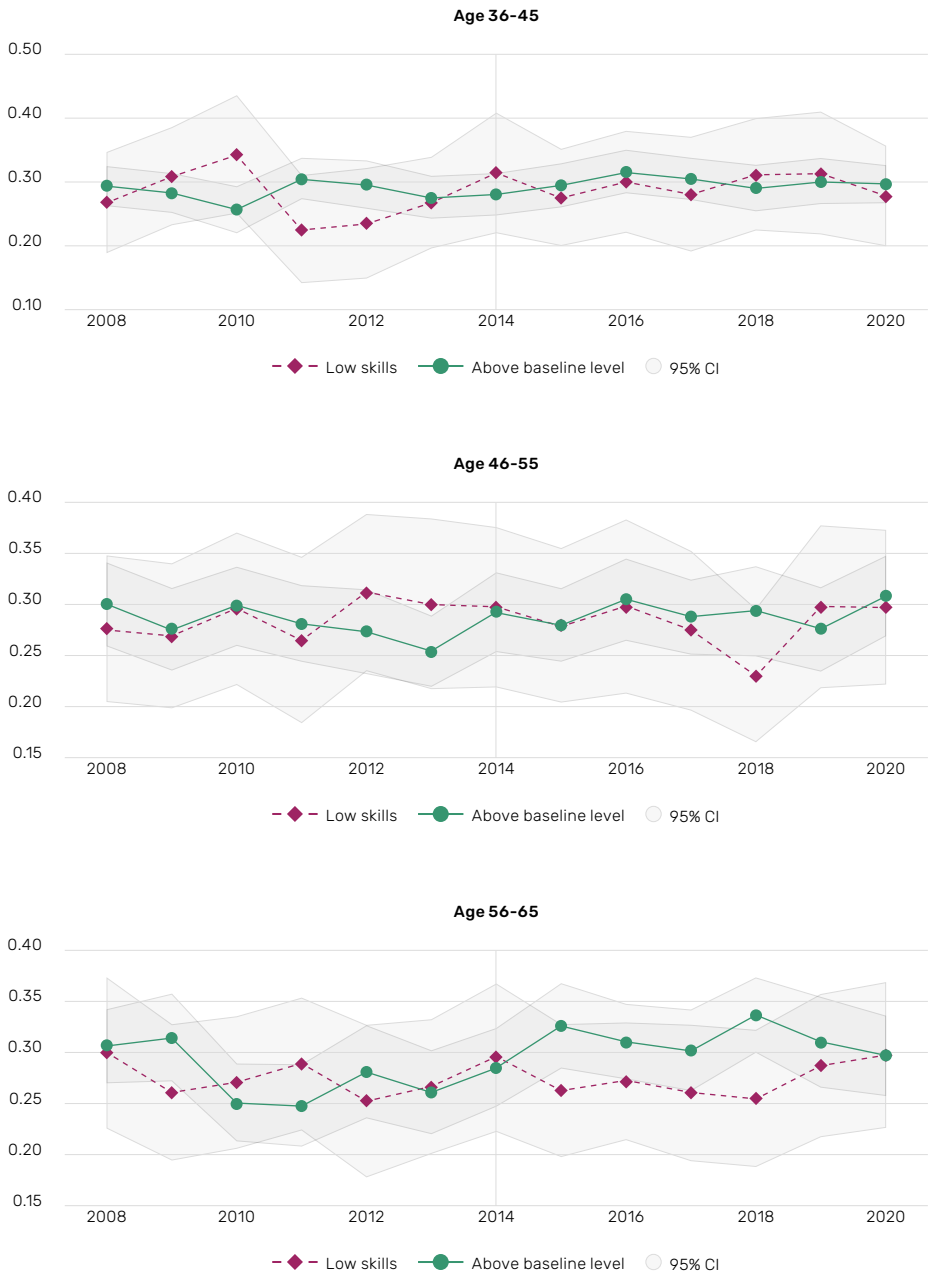


Table 5. Injuries

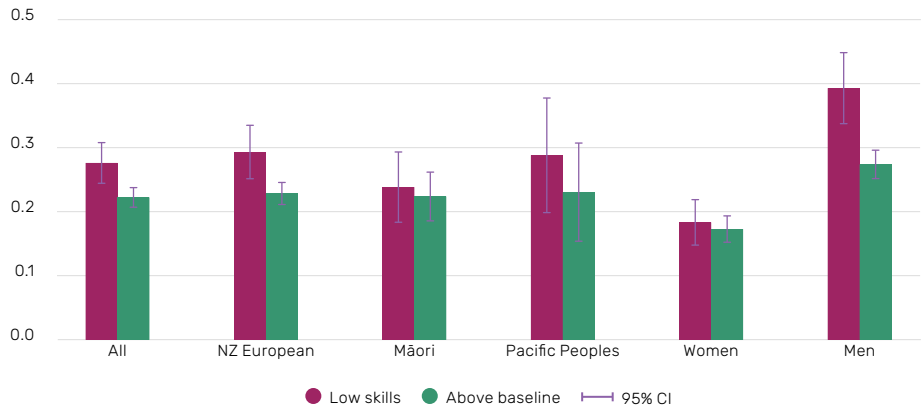
	(1) Low skills	(2) Above-baseline	(3) Difference	(4) p-value
Any injury	0.70	0.72	-0.02	0.224
Injuries at home	0.54	0.53	0.00	0.800
Road accidents	0.04	0.05	-0.00	0.757
Sport injuries	0.15	0.27	-0.13	0.000
Work injuries	0.28	0.22	0.05	0.005

Notes: This table compares the share of people with injuries for the group of people with low skills (column 1) and those with above baseline skills (2). Column 3 shows the difference between skill groups, column 4 shows the p-value testing the equality of the two means.

Figure 13 shows the share of people who have ever had a work injury by gender and ethnicity. As expected, men have higher rates of work injury than women, likely due to women working less hours on average (and therefore having lower exposure time to receive a work injury) and also being less likely to work in physical and dangerous roles. It may also reflect gender differences in risk preferences, particularly as women tend to have lower overall injury rates, not just work-related injury rates. Moreover, while those with low skills have higher work injury rates than those with above-baseline skills for both genders, the difference is much larger and statistically significant for men.

In terms of ethnicity, the work injury rates between 2015 and 2020 for Māori with both low skills and above-baseline skills is higher than their NZ European counterparts, although the differences are not statistically significant. This contrasts with Hennecke, Meehan, and Pacheco (2021), which finds that Māori and Pacific peoples have higher work-related injury rates than Europeans even after controlling for a range of individual and workplace characteristics. One explanation for the divergent results could be differences in the populations of interest. While Hennecke, Meehan, and Pacheco (2021) restrict the analysis to those who are employed in a given month, we consider work injuries for the entire population, including those who are not employed. Since Māori have a lower employment rate, this may also contribute to their lower work injury rate compared to Europeans.

Figure 13. Share of people with work injuries



Mental health

We now examine mental health outcomes. This is based on a combination of Ministry of Health information within the IDI following the method developed in Bowden *et al*. (2020). It combines information from pharmaceutical prescriptions, hospitalisations, mortality, and the Programme for the Integration of Mental Health Data (PRIMHD) data. We did not use data from disability support services (Socrates database) because of missing access, but this data source contributes less than 1 per cent of the identified mental health problems in Bowden *et al*. (2020).

In terms of caveats, as mentioned above, these data likely reflect a combination of the prevalence of mental health disorders and differences in the propensity to access health services across groups. With mental health, this is likely to be a larger issue than with physical health data, particularly among population groups where mental health disorders may be stigmatised, making it more difficult to seek medical treatment.

Figure 14 shows the share of people with mental health issues over time by age groups. There is no difference between the low-skills and above-baseline groups in the 36-45 year age group. For the 46-55 and 56-65 year age groups, a somewhat higher share of the low-skills group have had mental health issues, but these differences are not statistically significant. Across all three age groups, the share with mental health issues tend to increase over time as the groups age.

Figure 14. Share of people with mental health problems for different age groups

Figure 15 pools all observations and calculating adjusted means by skill level, gender and age. This more clearly shows that the share with mental health issues increases with age in general, although there is a dip in the share for men with low skills starting in about their mid-40s. Above-baseline men have the lowest rates of mental health issues, while women (both those in the above-baseline and low-skills groups) have the highest. However, the differences are generally not statistically significant.

Figure 15. Share of people with mental health problems by age for different skill groups

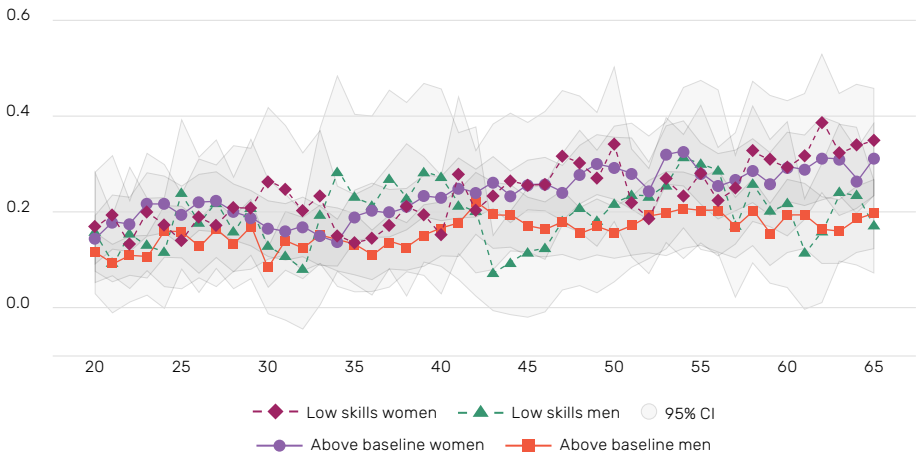


Table 6 examines whether an individual had any mental health issues over the 2015-2020 period. It further decomposes this into the type of issue experience. These results show no statistically difference in the overall rate of mental health problems between the low-skills and above-baseline groups. However, there are differences in the prevalence of the type of mental health issue. Consistent with Meehan, Pacheco, and Schober (2022b), those in the low-skills group are more likely to have substance abuse issues, while those in the above-baseline group are more likely to have sleep problems (significant at 10 per cent level).

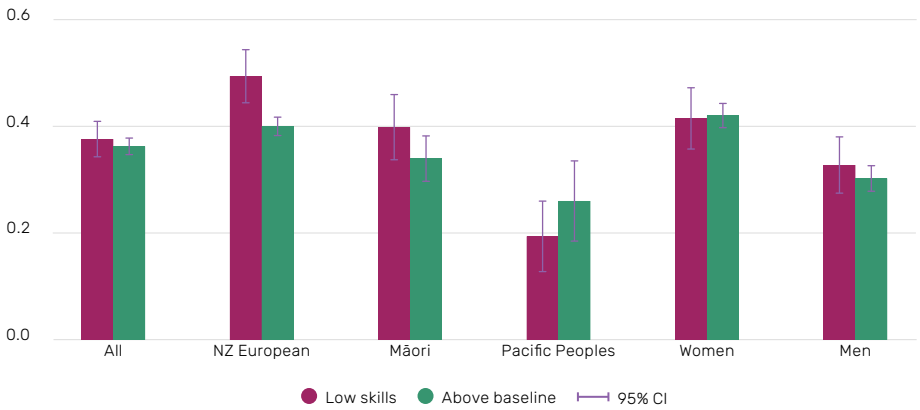
Table 6. Mental health disorders

	(1) Low skills	(2) Above-baseline	(3) Difference	(4) p-value
Any mental health problem	0.38	0.36	0.01	0.514
Emotional problems	0.17	0.16	0.01	0.413
Substance	0.08	0.03	0.05	0.000
Depression	0.12	0.11	0.01	0.454
Sleep problems	0.12	0.15	-0.03	0.058
Anxiety	0.08	0.08	0.00	0.807
Disruptive behaviours	0.01	0.00	0.00	0.756
Self-harm	0.01	0.01	0.00	0.305
Psychosis	0.02	0.01	0.01	0.018
Bipolar disorders	0.00	0.00	0.00	0.652
Eating problems	0.00	0.00	0.00	0.806
Personality disorders	0.00	0.00	-0.00	0.630

Notes: This table compares the share of people with mental health problems for the group of people with low skills (column 1) and those with above baseline skills (2). Column 3 shows the difference between skill groups, column 4 shows the p-value testing the equality of the two means.

Figure 16 shows the share of those who have ever had a mental health issue between 2015 and 2020 by gender and ethnicity. Women have higher rates of mental health issues than men. The difference is not statistically significant when comparing low skills men and women, but it is statistically significant when comparing above-baseline men and women. NZ Europeans have higher rates of mental health issues than Māori and Pacific peoples, although the differences between NZ Europeans and Māori are not statistically significant. Pacific peoples have the lowest rates of mental health issues. However, as speculated in Meehan, Pacheco, and Schober (2022b) this could be, at least in part, due to a lower propensity to seek medical treatment for mental health issues among Pacific peoples, particularly if it is generally more stigmatised among this population group. For example, Ministry of Health (2008) finds that Pacific peoples have a higher burden of mental disorder than New Zealanders in general, but that they are much less likely to access mental health services, and highlights that primary mental health care should include destigmatisation as a service component because of the way in which mental health issues are perceived by some Pacific communities.

Figure 16. Share of people ever having mental health problems



Crime

We next look at criminal activity outcomes. Figure 17 presents the share of individuals with alleged offences by age groups based on NZ Police offending records. As mentioned in Section 2.2 data are available for a shorter time period than some other outcomes investigated, such as employment and earnings. Across all three age groups examined, those with low skills have higher rates of alleged offending, although the differences are generally not statistically significant. Offending rates are higher among the younger group and lower among the older group, which is consistent with expectations as offending rates tend to be higher among younger people (Loeber and Farrington, 2014).

Figure 17. Share of people with offences for different age groups

Table 7 shows that the share of those with low skills who have ever been recorded as an alleged offender over the 2015-2020 period is 16 per cent compared with 6 per cent for those with above-baseline skills. These numbers appear quite high, particularly as they cover the shorter time period of 2015-2020, but this includes any type of offence, including low-level offences. In terms of the types of offences, the share of those in the low-skills group with offences against people, property and community are all higher than the share for the above-baseline group. Looking at the higher bar of convictions using Ministry of Justice data, about 9 per cent the low-skills group have been convicted of a crime, compared with 3 per cent of the above-baseline group. The shares are very similar to those of alleged offending, but the data for convictions also covers a longer time period. Those in the low-skills group are more likely to have received a fine, community work or supervision, home or community detention, and are more likely to have been imprisoned. Those with low skills are also more likely to have been victims of crime (18 per cent versus 13 per cent). This is consistent with a large literature that finds an overlap between those who are offenders and victims of crime (e.g. see Erwin, Hennecke, Meehan, and Pacheco, 2022, for NZ evidence).

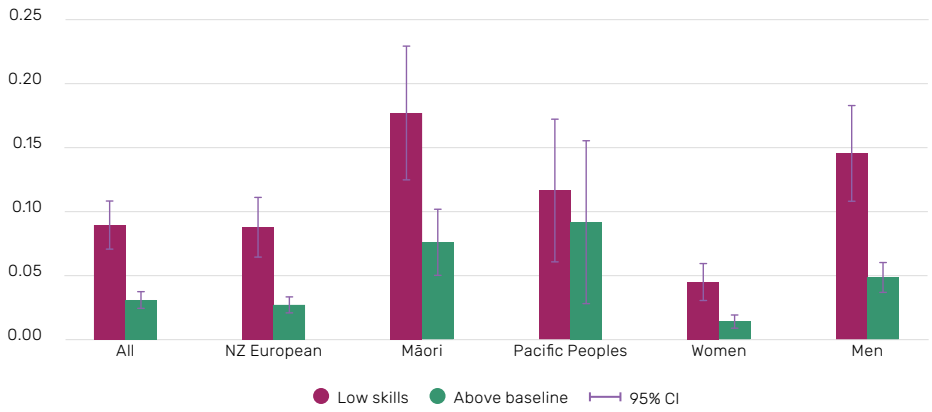
Table 7. Offending, court charges and victimisation

	(1) Low skills	(2) Above-baseline	(3) Difference	(4) p-value
Police recorded offence	0.16	0.06	0.10	0.000
Type of offences				
Offences against persons	0.09	0.03	0.06	0.000
Offences related to property	0.05	0.01	0.04	0.000
Offences against community	0.10	0.04	0.07	0.000
Conviction	0.09	0.03	0.06	0.000
Sentences				
Monetary	0.05	0.02	0.03	0.001
Community work / supervision	0.04	0.01	0.03	0.000
Home or community detention	0.02	0.00	0.02	0.001
Imprisonment	0.01	0.00	0.01	0.002
Victim of crime	0.18	0.13	0.05	0.003

Notes: This table compares average outcomes of students with low skills (column 1) and those with above baseline skills (2). Column 3 shows the difference between skill groups, column 4 shows the p-value testing the equality of the two means.

Figure 18 shows the share of people with convictions between 2015 and 2020 by gender and ethnicity. As expected, and consistent with aggregate crime statistics, men have much higher conviction rates than women. For both men and women, however, the conviction rate is higher among those with low skills. Looking across ethnic groups, a higher share of Māori have higher rates of convictions than NZ Europeans, which is consistent with NZ's population-level justice statistics (see, for example, Ministry of Justice, 2021). Within each ethnic group, the low-skills group has higher conviction rates, although the difference is not statistically significant for Pacific peoples. Interestingly, Māori with above-baseline skills have similar conviction rates as NZ Europeans with low skills.

Figure 18. Share of people with convictions



Different skill groups

In the analysis so far, we compare individuals with L+N skills below Level 2 in PIAAC to those with skills above this level, as the OECD uses this threshold to define populations with low proficiency (OECD, 2019a). Table 8 provides a sensitivity analysis by comparing our baseline results (which effectively compares the bottom fifth with the top four-fifths) to alternative definitions of low versus high performance for selected outcomes. Using proficiency scores in literacy and numeracy, we compare the top and bottom half, third, and quarter of respondents.

Looking at earnings, as expected, individuals in the bottom half of the L+N proficiency score distribution have higher average earnings than the low-skills group using the Level 2 definition (i.e. the bottom fifth). Likewise, the top half of the distribution have higher average earnings than the top four-fifth used in the Level 2 definition. Overall, this results in a slightly larger earnings gap between the low-skills and higher-skills group using the top and bottom half grouping than the Level 2 grouping (about $27,000 versus

$26,000). Comparing the top and bottom third and top and bottom quarter results in larger earnings gaps (approximately $37,000 and $44,000 respectively).

For the share receiving benefit payments, 44 per cent of those in the low-skills group based on the Level 2 definition received any benefit payment, compared with 19 per cent for the above-baseline group. In comparison, about a third of those in the bottom half of the skills distribution received any benefit payment, versus 14 per cent of those in the top half. This results in a smaller benefit-receipt gap overall (20 percentage points for the comparison of the top and bottom half versus 25 percentage points for the Level 2 definition). Comparing the top and bottom third and top and bottom quarter results in larger benefit-receipt gaps (28 and 32 percentage points respectively).

For the share with any hospitalisations, the comparison of the top and bottom half of the skills distribution yields the smallest gap (12 percentage points), followed by the Level 2 definition (13 percentage points), with the comparison of top and bottom quarter yielding the largest gap (20 percentage points). The gap in the workplace injury rate between the two groups is lowest among the Level 2 definition (5 percentage points) and largest among the top and bottom quarter comparison (13 percentage points).

Overall, while changing the definition of the comparison groups changes the relative magnitude of the differences in outcomes for the low-skills and higher-skills groups, the general patterns of differences remain.

Conclusion

This paper examines the life-course trajectories of NZ adults who participated PIAAC 2014 by using linked administrative data to track their outcomes from 2008 to 2020. PIAAC is a worldwide study administered by the OECD that assesses the literacy and numeracy proficiency of working-age adults (aged 16-65). This paper compared the outcomes of the approximately one-fifth of these adults who were assessed at below Level 2 in either literacy or numeracy (or both). We are able to follow these individuals over time, in the years both before and after PIAAC 2014, as PIAAC 2014 is linked to Stats NZ's IDI. This allows us to examine a range of outcomes using administrative data, such as education, labour market, health and criminal activity outcomes, using administrative data.

Table 8. Comparison of outcome for different skill groupings

	(1) Low performance	(2) High Low performance	(3) Difference	(4) p-value
Earnings				
Baseline results	35846.10	61753.94	-25907.83	0.000
Top and bottom half	42750.32	69798.45	-27048.12	0.000
Top and bottom third	39402.98	76651.67	-37248.69	0.000
Top and bottom quarter	37488.29	81144.41	-43656.12	0.000
Any benefit payments				
Baseline results	0.44	0.19	0.25	0.000
Top and bottom half	0.34	0.14	0.20	0.000
Top and bottom third	0.39	0.12	0.28	0.000
Top and bottom quarter	0.42	0.10	0.32	0.000
Any hospitalisation				
Baseline results	0.53	0.40	0.13	0.000
Top and bottom half	0.49	0.37	0.12	0.000
Top and bottom third	0.51	0.34	0.17	0.000
Top and bottom quarter	0.52	0.33	0.20	0.000
Work injury				
Baseline results	0.28	0.22	0.05	0.005
Top and bottom half	0.27	0.19	0.08	0.000
Top and bottom third	0.28	0.17	0.11	0.000
Top and bottom quarter	0.28	0.16	0.13	0.000

Notes: This table compares outcomes of those with low (Column 1) and high (2) performance for different skill groupings. Column 3 shows the difference between skill groups, Column 4 shows the p-value testing the equality of the two means. The number of observations is 5,559 for the baseline results and top versus bottom half, 3684 for top versus bottom third, and 2754 for top versus bottom quarter.

Adults with low L+N skills have lower average education levels. Based on PIAAC data, the average years of education for those with low skills is about two years lower than for those with above-baseline skills. Although IDI education data is incomplete for PIAAC adults since many would have completed their formal education before records begin, IDI enrolment data shows that those in the low-skills group are less likely to have enrolled in tertiary education at some point, with a particularly large difference in the share who have ever enrolled in a bachelor's degree (8 per cent versus 23 per cent).

The labour market outcomes of the low-skills group are also less favourable than those of the above-baseline group, with the results differing by gender. The employment rates of men in the low-skills and above-baseline groups are reasonably similar, while

those of women with low skills are lower than above-baseline women. Men with above-baseline skills have the highest average earnings of all the groups. Women with above-baseline skills do not experience the same earnings growth in their 30s as men, but their earnings do not decrease as quickly in their late working years. Women with low skills have the lowest average earnings. In terms of ethnicity, for the low-skills group, there is no statistically significant difference between the average observed earnings of NZ Europeans and Pacific peoples, while Māori have the lowest average earnings. For the above-baseline group, NZ Europeans have higher average earnings than Māori and Pacific peoples. Māori and Pacific peoples are also more likely to have received a main benefit for both the low-skills and above-baseline groups.

Those with low skills also have higher hospitalisation rates, with about 53 per cent having been hospitalised at some point over the period examined, versus 40 per cent of the above-baseline group. However, there is no statistically significant difference in injury rates, reflecting that work injury rates are higher among the low-skills group but sports injury rates are lower. There is also no statistically significant difference in mental health disorders overall, but those in the low-skills group are more likely to have substance abuse issues while those in the above-baseline group are more likely to have emotional, sleep problems.

In terms of criminal activity outcomes, those with low skills are more likely to have been an alleged offender and to have at least one conviction. As expected, a much higher share of men have convictions compared with women for both the low-skills and above-baseline groups. Also consistent with population-level justice statistics, a much higher share of Māori have convictions than NZ Europeans, with the share of Māori with above-baseline skills who have convictions being similar to the share of NZ Europeans with low skills.

Overall, the results are consistent with international research that highlights how low L+N skills may affect an individual's wellbeing, including via educational, labour market, health and justice outcomes. These results are also similar to those of Meehan, Pacheco, and Schober (2023) and Meehan, Pacheco, and Schober (2022b), which follows the outcomes of young people with low skills versus those with above-baseline skills from the age of 15 to 26. This suggests that these educational, earnings, health and justice outcomes that appear early in life do not dissipate. While it is difficult to make direct comparisons because some of the effects may be due to cohort differences, combining the results of this paper with these earlier papers suggests that differences between the low-skills and above-baseline groups may increase over time, at least on some dimensions. This widening disparity gap, for example, is particularly evident for labour market outcomes, with earnings gaps between those with low and above-baseline skills increasing as individuals enter their prime and late earning years.

Disclaimer

Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers. These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit https://www.stats.govt.nz/integrated-data/.

The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Competing interests

None to declare.

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A. Additional tables

Table 9. Definition of outcome variables (1)

Outcome	Description
Education enrolment	
Tertiary education	Enrolled in any tertiary education (Source: MoE tertiary qualification enrolment).
Bachelor	Enrolled in bachelor type tertiary education (MoE tertiary qualification enrolments).
Industry training	Indicator for workplace-based training (MoE industry training data).
Targeted training	Enrolled in targeted training programmes (Gateway, Skill Enhancement, Training Opportunities, Foundation Focused Training Opportunities Youth Training; MoE targeted training data).
Any schooling or training	Enrolled in compulsory education, tertiary education, industry training, or targeted training (MoE enrolment data).
Educational attainment	
Years of education	Years of formal education obtained (PIAAC).
Any post-school qualification	Whether post-school or tertiary qualification obtained (PIAAC).
Income and employment	
Earnings	Sum of wages, salaries and income from self-employment based on tax data in 2020 prices using the consumer price index (Inland Revenue (IR) derived income data).
Employed	Indicator for having any earnings (IR).
Occupations	Working in an occupation classified according to 1-digit ISCO 2008 level (PIAAC).
Benefit payments	Sum of benefit payments from the Ministry of Social Development (IR derived income data).

Table 10. Definition of outcome variables (2)

Outcome	Description
Health	
Any injuries	Indicator for injuries after accidents (Source: Accident compensation corporation (ACC) injury claims).
Injuries at home	Accidents that occurred at home (ACC).
Work injuries	Paid from ACC work account or claim occurred at place of work (ACC).
Road accidents	Paid from ACC motor vehicle account (ACC).
Sport injuries	Engaged in recreation/sporting activity at the time of the accident (ACC).
Mental health problems (emotional problems, substance, depression, sleep problems, anxiety, disruptive behaviours, self-harm, psychosis, bipolar disorders, eating problems, personality disorders)	Indicators for mental health problems using various data sources in the IDI following Bowden et al. (2020), including pharmaceutical prescriptions, hospitalisations, death causes, and the Programme for the Integration of Mental Health Data (PRIMHD).We did not use data from disability support services (Socrates database) because of missing access, but this data source contributes less than 1% of the identified mental health problems in Bowden *et al.* (2020).
Hospitalisation	Indicator for publicly funded hospital events (Source: Ministry of Health (MoH) national minimum dataset).
Hosp. excluding childbirth	Hospitalisation excluding Major Diagnostic Categories (MDC) 14 and 15.
Hospital Diagnoses	
Musculoskeletal system	Hospitalisation for MDC 8.
Ear, nose, mouth and throat	Hospitalisation for MDC 3.
Digestive system	Hospitalisation for MDC 6.
Injuries	Hospitalisation for MDC 21.
Nervous system	Hospitalisation for MDC 1.
Skin, subcutaneous tissue and breast	Hospitalisation for MDC 9.
Non-admitted secondary care events	Indicator for any non-admitted secondary care event (MoH National Non-Admitted Patient Collection (NNPAC)).
Emergency department visits	Emergency department event types (NNPAC)
Other outpatient visits	Outpatient and community referred events (NNPAC).
Crime	
Police recorded offence	Being proceeded against by the police. (Source: NZ Police recorded crime offenders data.)
Offences against persons	Divisions 1-6 of the Australian and New Zealand Standard Offence Classification (ANZSOC, Australian Bureau of Statistics, 2011), capturing acts that result in harm and affect a specific person (Police).
Offences related to property	Divisions 6-9 and 12 of ANZSOC such as robbery and theft (Police).
Offences against community	Divisions 10, 11, 13-16 of ANZSOC include offences against organisations, government and community (Police).
Conviction	Convicted by a court (Ministry of Justice (MoJ) criminal court charges).
Court sentences (monetary, community work or supervision, home or community detention, imprisonment)	Having the respective court sentence. Note that the data only records the five most serious sentences per charge (MoJ).
Victim of crime	Being recorded as crime victim. (Source: NZ Police victimisations).

Improving Indigenous employment or entrenching labour market segregation? Using Artificial Intelligence and online job ads to evaluate employers' Indigenous recruitment strategies

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Abstract

This study derives insight into changing demand for Indigenous workers by applying artificial intelligence to identify Indigenous-focused job postings. A natural language processing algorithm is used to classify a national database of online job ads according to whether they encourage Indigenous applicants, require Indigenous cultural capability, prioritize Indigenous candidates or are not Indigenous-focused. The analysis reveals significant growth in Indigenous-focused job postings but they are disproportionately concentrated in three sectors and one occupation group. In addition, although employers in sectors such as arts and recreation are advertising well-paid and high-skilled roles to Indigenous workers, there are other sectors where employers tend to advertise their more low-skill and low-wage roles to Indigenous workers. We also find that Indigenous-focused job postings are not well-aligned with Indigenous career pathways. Our research offers practical insights for Indigenous employment policy and our methodology can also be applied to evaluate employers' recruitment strategies for other target groups.

JEL Codes: J15, J21, J78
Keywords: Indigenous, labour market, social policy, labour economic

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Introduction

Government policy aimed at addressing inequities in Indigenous employment (Department of the Prime Minister and Cabinet, 2020; Hu *et al.*, 2019; Hunter, 1997; International Labour Organization, 2019) has been associated with improvements in labour market participation for Indigenous peoples[1] (Gray *et al.*, 2013; Steering Committee for the Review of Government Service Provision, 2020). There is also evidence that the employment of Indigenous peoples can deliver unique benefits for organisations (Ens *et al.*, 2016; Giblin, 1989; Scheyvens *et al.*, 2021). Nevertheless, Indigenous peoples still experience higher rates of unemployment, are more likely to be employed at the low-skilled end of the labour market and experience lower job retention than non-Indigenous people (Hunter and Gray, 2017; Lamb *et al.*, 2020).

Differences in employment outcomes for Indigenous peoples can be understood as a function of differences in opportunity structures resulting from labour market segmentation (Bosanquet and Doeringer, 1973; Harrison, 1972; Harrison and Sum, 1979; Leontaridi, 1998; Piore, 1972; Wachter, 1974). Segmentation theory recognises that the labour market is composed of non-competing segments. High-skilled, stable jobs that attract good wages and offer progression opportunities form the primary segment of the labour market. Low-skilled, unstable jobs, with substandard wages and limited training and development opportunities are found in the secondary labour market. Institutional barriers prevent vulnerable groups in the population from benefiting equally from education and training, with the result that their choices are mostly limited to the secondary labour market (Blakely, 1994; Harrison, 1972; Leontaridi, 1998). Their ability to move to the upper segment of the labour market is further constrained by the lack of training and development opportunities in the secondary segment of the labour market (Ashton, 1988; Felbo-Kolding *et al.*, 2019; Kenrick, 1981).

Labour market segmentation is influenced by factors such as social class, race and sex, which affect employment opportunities prior to entering the labour market through financial circumstances, attitudes, knowledge and access to schooling and formal training (Ryan, 1981; Valtonen, 2001). Within the labour market, segmentation is reinforced through biased recruitment, career development and promotion practices (Ryan, 1981). It is also influenced by employment services and government-funded training programs, which nudge the unemployed into low-skill training programs that essentially limit their options to the secondary sector (Ashton, 1988).

Indigenous employment is influenced by all these factors and more. The

1 For brevity, we use the terms "Indigenous peoples" and "Indigenous workers" throughout the manuscript to refer to Aboriginal peoples, Torres Strait Islander peoples and people who identify as both Aboriginal and Torres Strait Islander. The term "workers" is used in place of "peoples" when referring to people who are actively engaged in the labour market, as defined by the Australian Bureau of Statistics (2021c).

experience of colonisation has had traumatic effects on Indigenous Australians, who endured the loss of their lands, massacres and deliberate destruction of their culture and way of life. The ongoing effects of this trauma are visible in the disparities in their health and social outcomes (Griffiths *et al.*, 2016). Racism is still experienced by Indigenous peoples today (Paradies and Cunningham, 2009), perpetuated not only through prejudice and discrimination (Jones, 2000) but also through social norms, inherited disadvantage and internalised racism (Jones, 2000). Although Indigenous participation in higher education is improving, it remains below the rate of non-Indigenous Australians (Steering Committee for the Review of Government Service Provision, 2020). Under the Australian Government's Reconciliation Action Plan (RAP) program, employers are encouraged to commit to increasing the number of Indigenous Australians in their workforce. Reconciliation Action Plans have now been adopted by over two thousand Australian organisations (Reconciliation Australia, 2021). However, targets for Indigenous employment usually do not consider quality of employment, even though labour market segmentation represents another means through which disadvantage is perpetuated.

In this study, we used artificial intelligence (applied to online job postings) to investigate whether employers' Indigenous recruitment strategies are likely to entrench or address labour market segregation. A natural language processing (NLP) algorithm was trained to identify 'Indigenous focused' job postings. The algorithm classified job postings according to whether they specifically stated that Indigenous Australians (or Indigenous cultural capability) were required in the role, or that Indigenous Australians were encouraged to apply for the role. By differentiating Indigenous focused job postings from other job postings (which do not specifically encourage or require Indigenous Australians or Indigenous cultural capability) it is possible to investigate the quality and diversity of the roles for which employers seek Indigenous workers. In addition, the study investigated whether the location and qualification requirements of Indigenous focused job ads align with the locations and qualifications of Indigenous workers.

Our approach

Employers use job postings to describe the attributes they seek from job applicants. On the advice of Indigenous recruitment experts, we identified three ways that employers express demand for Indigenous workers in job postings. The strongest signals of demand for Indigenous workers are 'Identified' job postings. These positions require an exemption or intention against legislation because the position requires confirmation of Indigeneity and is only advertised to (or gives priority to) Indigenous peoples. The second type of job posting, which we call 'cultural capability' job postings, states that Indigenous cultural capability is a desirable or essential criteria to perform in the role. Finally, 'encouraging' job postings include a statement to the effect that Indigenous applicants are welcomed or encouraged. To understand the diversity and quality of the roles being advertised

to Indigenous workers, we compare the characteristics (industry of employment, occupation type, skill level and wage level) of these three types of 'Indigenous focused' job postings relative to other ('non Indigenous focused') postings. In addition, we compare the location and qualification requirements of Indigenous focused job postings with information about the location of and qualifications held by Indigenous workers. This analysis of the diversity, quality and alignment of Indigenous focused job postings reveals whether employers' recruitment strategies are likely to address or reinforce Indigenous labour market segmentation.

This research was Indigenous led. Leadership from Indigenous researchers and experts was provided through an internal Steering Committee (who defined the research objectives and supported interpretation of the data) and an external Advisory Group (who provided advice on maximising impact while respecting the complexity and sensitivity of research involving Indigenous data and career aspirations). Members of the project steering committee are also represented as authors of this research paper.

Materials and methods

Datasets

Online job postings

The national dataset of online job postings was provided by Adzuna Australia. Adzuna Australia aggregate online job postings from hundreds of sources, including job postings listed directly on the Adzuna Australia jobs board and other jobs boards, listings from some of Australia's major newspapers and job postings 'scraped' from employer websites sites. Job postings are classified according to the geographic location of the role being advertised, industry of employment (ANZSIC major division; Australian Bureau of Statistics, 2013), qualification level (Australian Standard Classification of Education; Australian Bureau of Statistics, 2001) and broad field of education (Australian Standard Classification of Education; Australian Bureau of Statistics, 2001). Duplicate postings are removed using an algorithm developed by Zhao *et al* (2021). The representativeness of the dataset has been evaluated in relation to Australian Bureau of Statistics labour force statistics and other commercially available job posting datasets and found to correspond well (Duenser and Mason, 2019; D. Evans *et al*., 2023).

The dataset of 10,561,471 job postings covered the period from January 2016 to December 2022. Skill levels were assigned to job postings using the skill level classification provided within the ANZSCO occupation taxonomy (Australian Bureau of Statistics, 2009), which is based on the level of qualification or years of experience required in the role. Skill levels range from 1 (requiring a Bachelor degree or higher or at least 5 years of experience) to 5 (requiring a Certificate I, secondary school education or a short period of on-the-job training). To improve interpretability, skill levels were reverse

coded for the analysis (so that a higher score represented a higher skill level) and treated as a continuous variable (rather than a categorical variable) in the analyses.
An NLP-based algorithm was used to identify three types of 'Indigenous focused job postings', using the following criteria, provided by the project Steering Committee:

> *Identified/priority job postings:* Only Aboriginal and/or Torres Strait Islander people can apply for the role, with evidence (Confirmation of Aboriginality (COA)) required. In some cases, the job posting may specify that non-Indigenous people may be considered for the role if no Indigenous people apply or just that Indigenous applicants will be given preference in the selection process. The posting states an exemption or intention against legislation (this includes Federal or State legislation) as an Equal Opportunity, Genuine Occupational requirement or Welfare measure.
>
> *Indigenous cultural capability required:* Evidence of being an Aboriginal and/or Torres Strait Islander person is not required. Non-Indigenous people can apply for the role but it is either essential or desirable to have cultural capability or experience working with Aboriginal and/or Torres Strait Islander peoples to perform in the role. Cultural capability is demonstrated understanding of Aboriginal and/or Torres Strait Islander cultural knowledge, skills and expertise, or the ability to work effectively with Aboriginal and/or Torres Strait Islander peoples.
>
> *Encouraging Indigenous applicants:* Aboriginal and/or Torres Strait Islander peoples are welcomed or encouraged to apply for the position. Non-Indigenous people can apply for the role and Aboriginal and/or Torres Strait Islander cultural capability is not an essential or desirable criterion for the role.

Job postings were classified as both Identified and cultural capability required if they met both definitions. The accepted measures for assessing the accuracy of a multi-class algorithm such as this one are precision, recall and F1 scores (Sokolova and Lapalme, 2009; Tsoumakas *et al.*, 2010). The measure of precision reflects how stringent the classifier is in detecting true positives (true positives as a proportion of true positives and false positives). The measure of recall reflects the classifier's ability to detect true positives when they occur (true positives as a proportion of true positives and false negatives). The F1 score takes into account the trade-off between precision and recall, providing a measure of overall performance. To provide a benchmark for the performance of the algorithm, precision, recall and F1 scores were calculated from ratings provided by multiple human raters. Table 1 shows the performance of the algorithm and Table 2 shows the same performance metrics for human experts. The algorithm out-performs the human raters in terms of precision but human raters achieve better recall statistics. The F1 scores suggest that the overall performance of the algorithm in classifying Indigenous focused job postings is just slightly lower than that of human experts.

Table 1. Precision, recall and F1 scores achieved by the algorithm (when compared with the human classified gold label dataset of Identified, cultural capability required, encouraging or not Indigenous focused job postings)

Type of job posting	Precision	Recall	F1 score
Identified	1.00	0.45	0.62
Cultural capability required	0.51	0.85	0.64
Encouraging	0.55	0.84	0.67
Not Indigenous focused	0.75	0.67	0.71

Table 2. Precision, recall and F1 scores achieved by comparing multiple human raters classifying job postings as Identified, cultural capability required, encouraging or not Indigenous focused

Type of job posting	Precision	Recall	F1 score
Identified	0.75	0.90	0.82
Cultural capability required	0.67	0.50	0.57
Encouraging	0.71	0.62	0.67
Not Indigenous focused	1.00	0.67	0.80

Wage level

Wage levels were assigned to job postings using weekly earnings data (specifically, the average weekly total cash earnings) for each ANZSCO four digit occupation. These weekly earnings data were obtained from the 21 May 2021 Survey of Employee Earnings and Hours (EEH) (Australian Bureau of Statistics, 2021a) which is based on a representative sample of approximately 52,000 Australian employees.

Location and qualifications of Indigenous workers

The 2021 Census of Population and Housing dataset (Australian Bureau of Statistics, 2021d) was used to generate counts of the number of Indigenous and non-Indigenous workers within each SA4 geographic region (based on their Place of Work)[2] and their highest formal qualifications (using the QALLP field and the QALFP fields from the Australian Standard Classification of Education to assess level and field of education).

2 Statistical Area 4 or SA4 geographic regions represent one of the standard spatial units used for publishing labour statistics (Australian Bureau of Statistics, 2018). The population of SA4 regions ranges from 100,000 to 500,000 persons and they are designed to represent the labour markets of the largest regional cities.

Census statistics for the working population reflect the number of respondents who were active in the labour force (working for an employer, working in own business or unemployed but looking for work) in the week before Census night (10 August 2021). Counts of workers broken down by field of education or level of education are lower than counts of workers broken down by SA4 location because some workers do not have a post-school formal qualification. The Australian Bureau of Statistics protects Census participants' privacy by introducing random (minor) perturbation of the data.

Results

Frequency and diversity of Indigenous focused job postings

Indigenous focused job postings represented approximately 13 per cent of all jobs posted between 2016 and 2022 (1 per cent represented Identified positions, 2 per cent required Indigenous cultural capability and 10 per cent encouraged Indigenous applicants). All three types of job postings showed a strong, increasing trend over time (see Figure 1). It is worth noting that this growth trend flattened somewhat between 2019 and 2020 which was when COVID-19 created a significant downturn in employment. This effect suggests that demand for Indigenous workers was disproportionately impacted by the pandemic, suggesting that Indigenous employment remains especially sensitive to labour market downturns (Hunter, 2010).

Figure 1. Timeline of Indigenous focused job postings

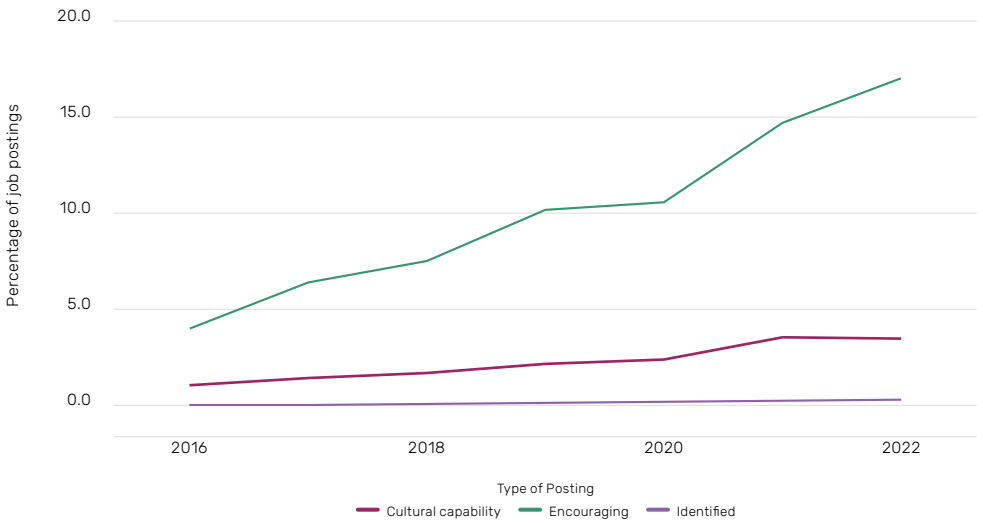


Figure 2 shows the same trends broken down by the industry division of the employer. It reveals that Indigenous focused job postings are concentrated in three sectors: public administration and safety, education and training, and health care and social assistance. Very few Indigenous focused job postings came from employers in other services, agriculture forestry and fishing, accommodation and food services, construction, transport postal and warehousing, financial and insurance services and manufacturing. Chi-square analyses (see Table 3) confirmed that the association between the industry division of the employer and the likelihood of a job posting being either Identified, requiring cultural capability or encouraging was statistically significant.

Figure 2. Industry divisions with a high and low percentage of Indigenous focused job postings

Table 3. Chi-square tests of independence for industry division and type of job posting

Type of job posting	df	X^2	p value
Identified vs. not Identified	18	24,940	0.000
Cultural capability required vs. not	18	214,862	0.000
Encouraging vs. not	18	587,225	0.000

In addition, certain occupational roles (in particular, community and personal service worker roles) were more likely to be Indigenous focused. Figure 3 visualises the proportion of Indigenous focused job postings over time, broken down by the type of occupation being advertised. Relatively few job postings for clerical and administrative workers, machinery operators and drivers, labourers and technicians and trades workers were Indigenous focused. Chi-square analyses (see Table 4) confirmed that the association between type of occupation and type of job posting was statistically significant.

Figure 3. Percentage of Indigenous focused job postings by year and major occupation group

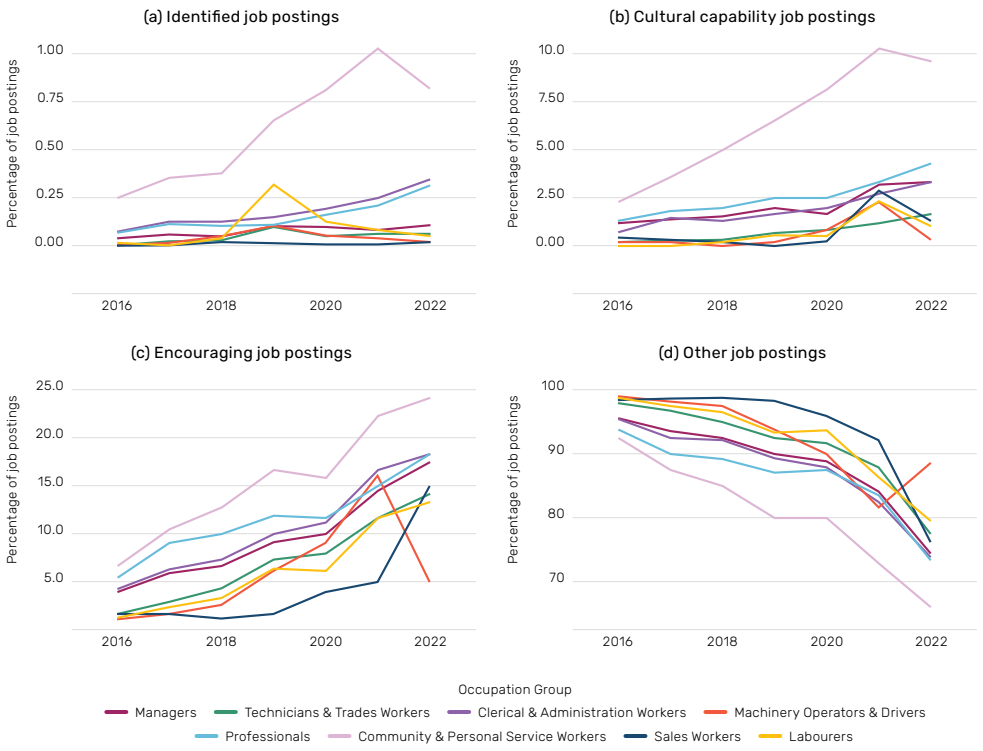


Table 4. Chi-square tests of independence for major occupation group and type of job posting

Type of job posting	df	X^2	p value
Identified vs. not Identified	7	16,009	0.000
Cultural capability required vs. not	7	111,129	0.000
Encouraging vs. not	7	127,074	0.000

Quality (skill and wage level) of Indigenous focused job postings

Having established that Indigenous focused job postings are not representative of job postings in general, the next step was to investigate the quality (skill level and salary level) of the roles being advertised to Indigenous job seekers. Since the likelihood of a job posting being Indigenous focused varies between industry divisions, a two-way Analysis of Variance was carried out, using both Industry division and type of job posting (Indigenous focused vs. not) as predictors of the skill and wage levels of the roles being advertised.

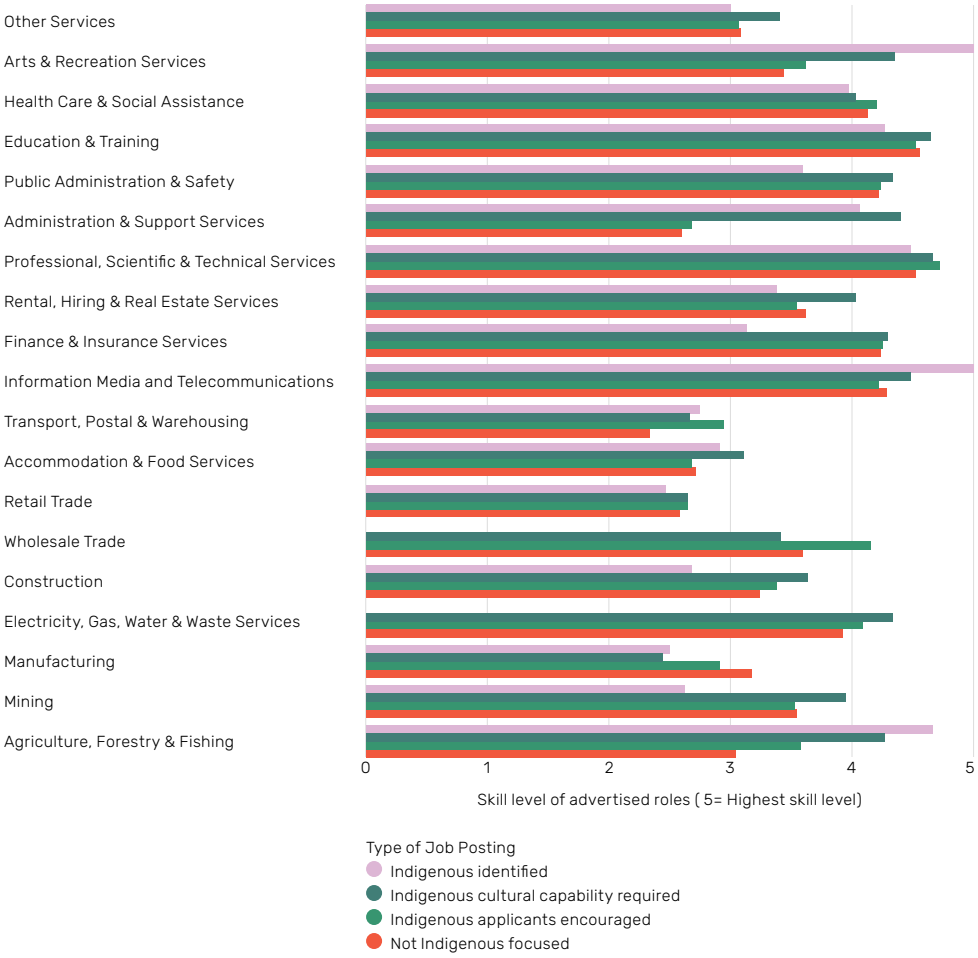
In the analysis predicting skill level, there was a significant two-way interaction, meaning that the relationship between type of job posting and skill level varied according to Industry division (see Table 5). Figure 4 visualises these effects. It shows variability in the average skill level of the roles being advertised in each industry division. For example, employers in the information, media and telecommunications divisions advertise more highly skilled roles (on average) than employers in retail trade. However, within each industry division there is additional variability in the skill level of Indigenous-focused job postings and non- Indigenous focused job postings. Identified job postings (represented by the lilac bar) tend to be for low-skill roles but in three industry divisions (information media and telecommunications, arts and recreation services and agriculture, forestry and fishing) this effect is reversed, with Identified positions being more high-skill on average than non-Indigenous focused job postings. Job postings requiring cultural capability (represented by the aqua bar) were more highly skilled than non-Indigenous focused (represented by the red bar) or encouraging job postings (represented by the green bar) except when posted by employers from the manufacturing industry division. Encouraging job postings are like non-Indigenous focused job postings in terms of their skill level, shown by the fact that the red and green bars tend to be similar in length within each Industry division.

Table 5. Comparing the skill level of Indigenous focused and other job postings across Industry Divisions

Source of variation	df	Sums of squares	F
Type of posting	3	143848	33763.29***
Industry division	18	5140412	201088.79***
Interaction	51	21114	291.52***
Error	10453701	14845937	

***p < .001

Figure 4. Skill level of Indigenous focused and other job postings



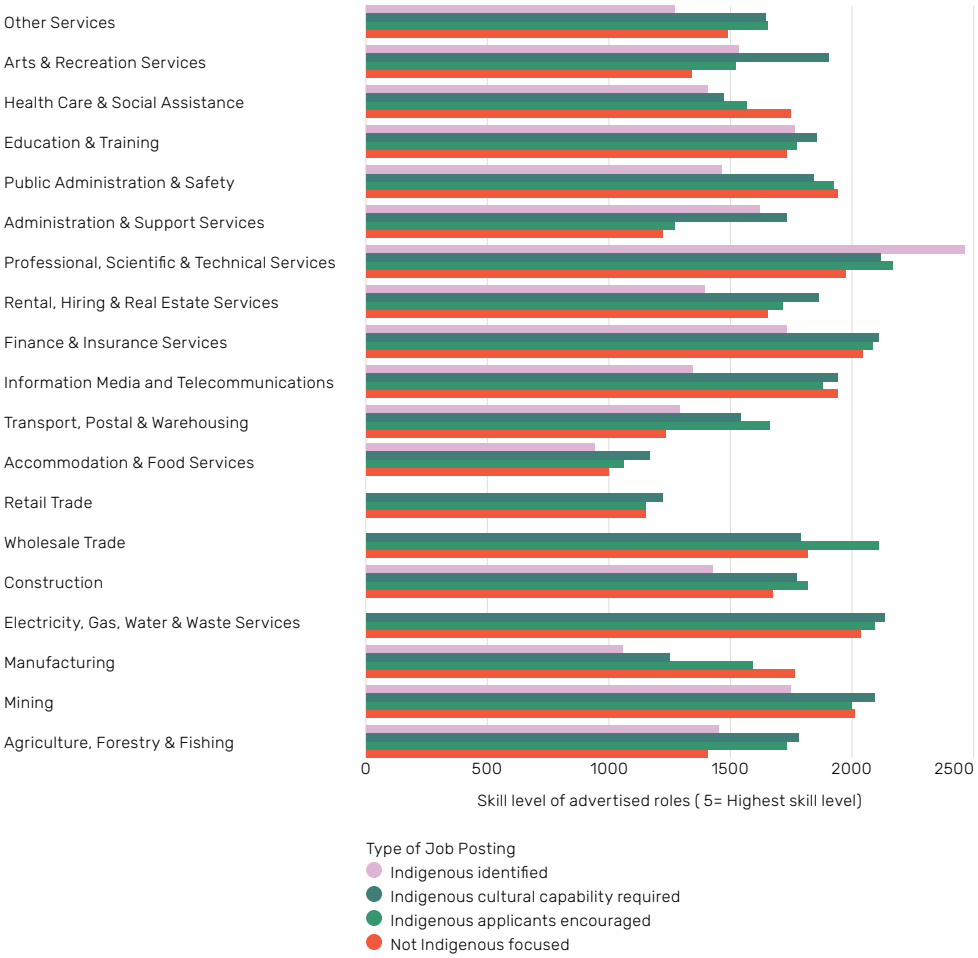
Since most job postings do not specify the salary offered in the role, the wage level associated with each job posting was calculated from weekly earnings data for occupations published by the Australian Bureau of Statistics (Australian Bureau of Statistics, 2021b). Again, there was a two-way interaction wherein both industry and type of job posting were associated with the average wage level of the roles being advertised (see Table 6). As shown in Figure 5, Identified job postings were usually for low wage occupations, except when they were posted by professional, scientific and technical services employers or administrative and support services employers. In other words, the Identified roles that employers create are for occupations that tend to attract low wages. The wages attached to roles that required cultural capability or encouraged Indigenous applications were mostly similar to the wages associated with non-Indigenous focused postings. However, the effect did vary according to industry division. For example, when employers in manufacturing and healthcare and social assistance advertise roles that require cultural capability, they tend to be in lower wage occupations than the other roles advertised by these employers.

Table 6. Comparing the average weekly earnings of Indigenous focused and other job postings across Industry Divisions

Source of variation	df	Sums of squares	F
Type of posting	3	3991100000	2585.67***
Industry division	18	1032300000000	111463.27***
Interaction	51	22810000000	869.27***
Error	10520669	5413100000000	

***p < .001

Figure 5. Wage level of Indigenous focused and other job postings

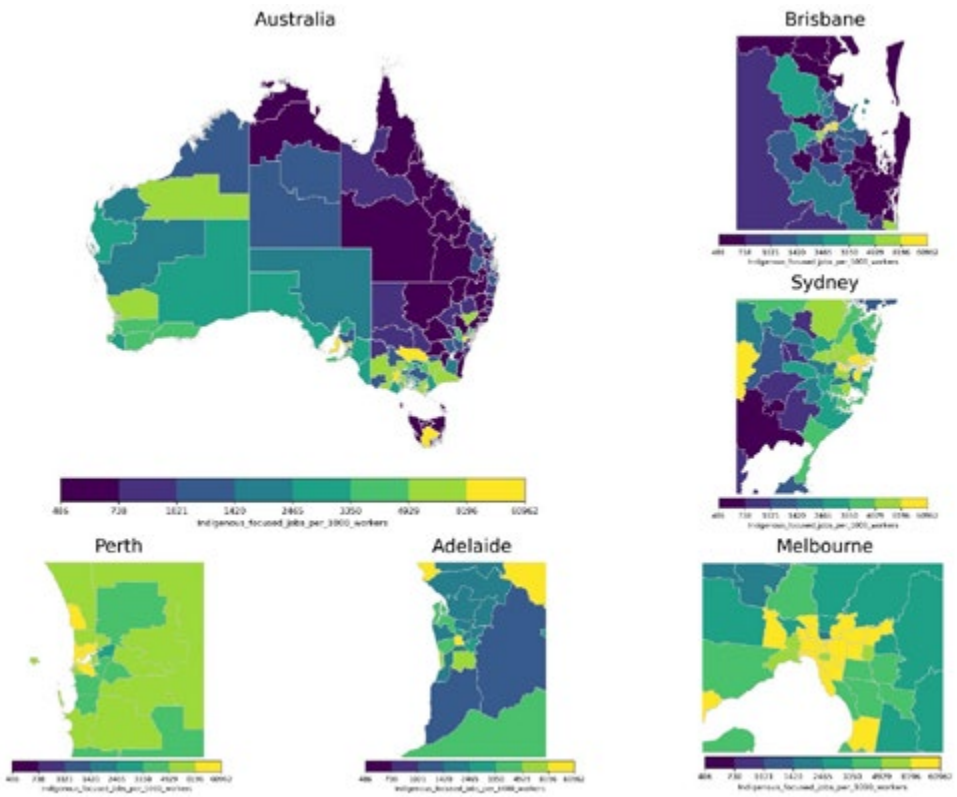


Alignment of Indigenous focused job postings

The analyses reveal some sectors where employers are using Indigenous-focused job postings to attract Indigenous workers to more high skill and salary roles. The impact of these efforts will depend on whether they are aligned with the career paths of Indigenous workers. Alignment is important given that Indigenous workers represent just over 2 per cent of the labour market and less than 1 per cent of workers with a Bachelor or higher degree (Australian Bureau of Statistics, 2021d).

In Figure 6, each region in Australia is colour coded based on the ratio of Indigenous focused job ads (between 2016 and 2022) per thousand Indigenous workers living in the region (at the time of the 2021 Census). The map shows that demand for Indigenous workers is concentrated in the capital cities (notably Sydney and Melbourne), but Indigenous workers live in regional and remote areas as well as the capital cities. In consequence, in one region of Australia there are only 39 Indigenous focused job postings per thousand Indigenous workers and at the other extreme, another region has 69,699 Indigenous focused job postings per thousand Indigenous workers.

Figure 6. Regional variability in the ratio of Indigenous focused job postings to Indigenous workers



To explore this issue in further detail, we calculated location and qualification quotients. Location quotients are a ratio of ratios that quantify how concentrated a particular industry, cluster, occupation, or demographic group is in a specific geographic region as compared to a reference area (e.g., the nation as a whole; Crawley *et al.*, 2013;

Miller *et al.*, 1991). Therefore, the location quotient for Indigenous focused job postings compares the proportion of job postings that are Indigenous focused in a particular region to the proportion of job postings that are Indigenous focused in the nation overall.

There are two, mathematically equivalent ways of calculating a location quotient:

$$\frac{(RIF/AIF)}{(R/A)} = \frac{(RIF/R)}{(AIF/A)}$$

RIF represents the number of Indigenous focused job postings in the region and AIF represents the number of Indigenous focused job postings in Australia. R is the total number of job postings in the region and A is the total number of job postings in Australia. The calculation is demonstrated with data from the Murray region of New South Wales. Out of the 22,384 job postings for the Murray region, 4,754 are Indigenous focused. This ratio is compared with the national ratio. Out of the 8,158,735 job postings in Australia, 865,863 are Indigenous focused. The two ratios are divided to produce the location quotient for Murray Region:

$$\frac{RIF/R}{AIF/A} = \frac{4{,}754/22{,}385}{865{,}863/8{,}158{,}735} = 2$$

A location quotient of less than one indicates that the region has 'less than its share' of Indigenous focused job postings relative to the rest of the nation. Conversely, a location quotient of more than one means that the region has 'more than its share' of Indigenous focused job postings. The location quotient of 2.00 for the Murray region indicates that the proportion of Indigenous focused job postings in this region is twice the proportion of Indigenous focused job postings for Australia as a whole.

To investigate whether the high demand for Indigenous workers in the Murray region is matched by a high proportion of Indigenous workers, a second location quotient is calculated, using employment data from the 2021 Census of Population and Housing. Out of the 53,408 workers in the Murray region of New South Wales, 1,372 identify as Indigenous. The total number of workers across all SA4 locations in Australia is 11,517,220, and of these, 246,988 identify as Indigenous. These figures can be used to calculate the Indigenous workers location quotient for the Murray region:

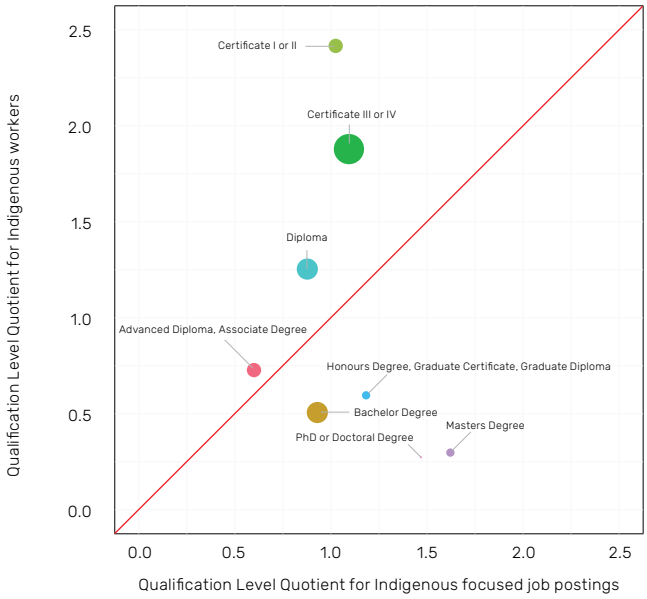
$$\frac{RIF/R}{AIF/A} = \frac{1{,}372/53{,}408}{246{,}988/11{,}517{,}220} = 1.2$$

The Indigenous workers location quotient of 1.2 means that the proportion of Indigenous workers in the Murray region is 1.2 times the proportion of Indigenous workers in Australia. Together, the two location quotients indicate that demand for Indigenous workers in the Murray region is twice as high than it is elsewhere in Australia but the proportion of Indigenous workers in the region is only 1.2 times higher than elsewhere in

Australia. Employers are therefore likely to find it challenging to recruit workers from the Murray region (relative to employers recruiting from other regions of Australia).

Comparing these demand- and supply-side location quotients (see Figure 7) reveals areas of misalignment in the Indigenous labour market. Each region of Australia is represented as a circle, with the size of the circle reflecting the size of the Indigenous workforce in the region. Regions that are far from the red diagonal line represent locations where demand for and supply of Indigenous workers is poorly aligned. For example, in the Queensland Outback there are two Indigenous workers for every Indigenous focused job posting; here, the supply of Indigenous workers is high relative to demand. Yet in the Western Australian Wheat Belt region there are more than four Indigenous job postings for each Indigenous worker. Employers seeking to recruit Indigenous workers for roles in the Western Australian Wheat Belt region will find it especially challenging.

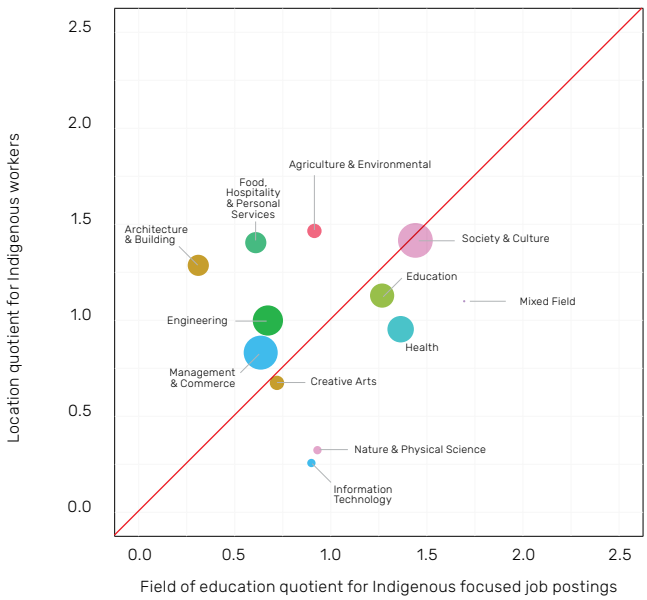
Figure 7. Alignment between demand for and supply of Indigenous workers based on location



This recruitment challenge will be magnified if the qualifications required in the roles are not aligned with the qualifications held by the Indigenous workers in the region. To investigate how qualification requirements contribute to labour market misalignment, the same formula is used to calculate field of education quotients. The Indigenous focused job postings quotients are based on job ads that specify a formal qualification in a specific field of education is required. A field of education will have a high Indigenous focused job postings quotient if the proportion of Indigenous focused job postings (relative to all job postings) is higher for job postings requiring qualifications in that field relative to job postings requiring qualifications in other fields. The corresponding Indigenous workers field of education quotient assesses whether the representation of Indigenous workers (within the pool of workers with qualifications in a specific field of education) is high or low relative to the representation of Indigenous workers across all fields of education. The figures for these analyses are captured from the 2021 Census of Population and housing.

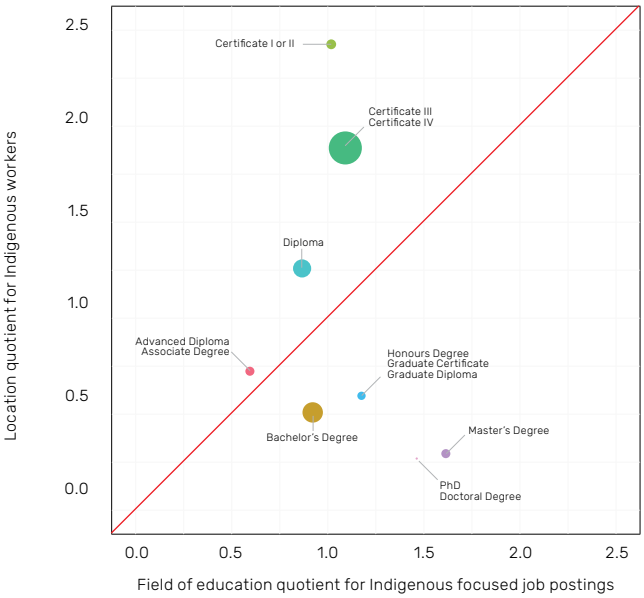
The two sets of field of education quotients are visualised in Figure 8. In this visualisation, the size of the circles reflects the number of Indigenous workers with qualifications in the relevant field. When the field of education is close to the red diagonal line, there is good alignment between demand for and supply of Indigenous workers in that field. The figure shows that demand for Indigenous workers in the fields of Information Technology and Natural and Physical Science is high relative to supply. Conversely, the supply of Indigenous workers with formal qualifications in Architecture and Building is high relative to demand.

Figure 8. Alignment between demand for and supply of Indigenous workers based on broad field of education



The same method can be used to compare the concentration of Indigenous workers and Indigenous focused job postings at different levels of formal education. The two sets of Qualification level Quotients are displayed in 9. In this figure, the size of the bubbles reflects the number of Indigenous workers with qualifications at that level. Figure 8 reveals that the challenge of attracting an Indigenous worker to fill an Indigenous-focused job posting is greatest when the role requires a Masters degree.

Figure 9. Alignment between demand for and supply of Indigenous workers based on level of qualification



Discussion

Using AI to analyse job postings reveals the lack of diversity in employment opportunities targeted towards Indigenous workers and opportunities to improve employers' Indigenous recruitment strategies. Despite a rapid increase in Indigenous focused job postings, demand is concentrated in three Industry divisions (public administration and safety, healthcare and social assistance and education and training) and one major occupation group (community and personal service workers). In some sectors (notably manufacturing, mining, construction), these employment opportunities

are concentrated in the secondary segment of the of the Australian labour market. However, there are a few sectors (arts and recreation, information, media and telecommunications, professional, scientific and technical services) where employers seek to attract Indigenous workers to high-skill and well-paid roles. The efforts of the latter employers are hindered by lack of alignment between the qualification and location requirements of Indigenous focused job postings and the actual locations and qualifications held by Indigenous workers.

This study was designed to provide insight into the extent to which employers' Indigenous recruitment efforts are likely to improve the quality of Indigenous employment. We find that efforts to recruit Indigenous workers (by posting Indigenous focused job ads) are strongest in the sectors with the highest proportion of public sector employment. We also observed a surge in advertised Identified positions in the South Australia (SA) health sector between the years 2021 and 2022 when there was an audit of institutional racism (Marrie and Bourke, 2020) and the release of the SA Rural Aboriginal Health Workforce Plan 2021-26 (South Australia Health, 2021). These patterns suggest that government targets aimed at improving the representation of Indigenous peoples in the workforce (e.g., Aboriginal Employment Unit, 2017; Australian Public Service Commission, 2019) are effective. However, it was employers in other sectors that were targeting Indigenous workers for their high-skill well paid roles. In addition, Identified job postings, which are designed to be filled by Indigenous peoples, tend to be for relatively low skill and low wage roles. Unless employers invest effort in upskilling Indigenous workers after they enter the organisation, these Identified positions will entrench existing differences in the skill level and earnings achieved by Indigenous workers.

The growth in other types of Indigenous-focused job postings (cultural capability and encouraging) is positive, in that it suggests employers have become more aware of the unique knowledge and capability offered by Indigenous peoples and the need to redress disadvantages experienced by Indigenous peoples. However, our findings suggest that they are not well aligned with the career pathways of Indigenous workers. Indigenous job seekers have the option to move to where a job is located and students can choose qualifications that align with demand in the labour market. Nevertheless, employment outcomes are poorer for Indigenous workers who live further away from labour markets (Biddle, 2010). If employers wish to improve the likelihood of attracting Indigenous workers to their organisation, they should consider how they might improve the alignment between the roles that they advertise to Indigenous workers and the career pathways chosen by Indigenous workers in the labour market.

Practical implications

The study suggests several strategies for addressing labour market segmentation. Geographic differences in the locations of Indigenous workers and employers seeking

to recruit these workers are a key source of misalignment in the labour market. Since nearly half of the Indigenous population live in predominantly rural regions, remote work arrangements represent a means through which employers in the cities could gain access to a larger pool of Indigenous workers. Remote work arrangements also have the potential to reduce the tension that can be experienced by Indigenous peoples who wish to progress their careers while maintaining their cultural identity and their connection to family, community and Country (Parkes *et al.*, 2015; Smith *et al.*, 2018). In addition, employers can improve their chances of attracting Indigenous workers by targeting Indigenous workers in fields such as architecture and building and agriculture and environment, where qualified Indigenous workers are well represented.

The research also reveals low engagement from Indigenous workers and employers in in STEM fields. The low number of Indigenous peoples with STEM qualifications is problematic because STEM qualified workers are in high demand (Leigh *et al.*, 2020; Qiyomiddin, 2024). Furthermore, there is likely to be increased demand for Indigenous workers in STEM organisations as the rights of Indigenous peoples to maintain, control, protect and develop their Indigenous Cultural and Intellectual Property becomes more widely recognised. To engage more Indigenous peoples with STEM careers, it is necessary to work with Indigenous communities at early stages of education since Indigenous students are under-represented in science subjects in high school (Cooper *et al.*, 2020). Students who have more contact with employers at school and University raise their career aspirations (Hughes *et al.*, 2016) achieve higher wages (Jackson and Bridgstock, 2020; Kashefpakdel and Percy, 2017; Percy and Mann, 2014), gain confidence and identify more ways of achieving their career goals (Mason *et al.*, 2022). STEM employers who are committed to improving the representation of Indigenous peoples in their field should be engaging with Indigenous students when they are still in school. STEM education could also be made more inclusive by giving coverage to Indigenous peoples' ways of building scientific knowledge and their deep understandings of weather, ecology, land management, medicine and astronomy (Christie, 1991; Green *et al.*, 2010; Norris and Hamacher, 2011; Oliver, 2013; Snively and Williams, 2008) in the science curriculum.

This research also provides valuable data to inform the education and employment decisions of Indigenous peoples (workers, students, carers, advisors). Educational outcomes are improved when Indigenous communities are empowered with information about the value of education (Dreise *et al.*, 2016). The data captured from job postings reveals the wide range of employers who seek Indigenous workers with high levels of formal education, providing evidence that educational investment will lead to employment (Dreise *et al.*, 2016).

Limitations

A limitation of this study is that it relies on job postings to identify where employers are seeking to attract Indigenous workers. It is possible that some employers who seek to attract Indigenous workers do not state this explicitly in their job postings. Moreover, the wording of job postings may not be a reliable indicator of cultural sensitivity and quality of employment. Establishing a business case, partnering with other organisations (e.g., specialist Indigenous employment services providers), investing in cultural competency training and supporting recruits with mentors are also recommended when seeking to attract and retain Indigenous workers (Generation One, 2013). Further research is needed to determine how many of the employers with Indigenous focused job postings provide a culturally safe environment, engage with Indigenous students in school and support the upskilling that is required to address the structural factors that lie behind continuing differences in opportunities for Indigenous Australians (Hunter, 1997; Karmel *et al.*, 2014; Stephens, 2010; Walter, 2015).

Directions for further research

Gaps in employment outcomes for Indigenous peoples relative to non-Indigenous peoples remain an issue around the world (Hu *et al.*, 2019; International Labour Organization, 2019). This study illustrates a novel method for investigating the extent to which employers' recruitment strategies are helping to increase the diversity and quality of employment opportunities for Indigenous peoples. The same method could be applied to monitor and evaluate employers' efforts to improve the representation of other diversity target groups and gain much needed insight into employers' engagement with these groups and the quality of the employment opportunities they provide. Moreover, big datasets of online job postings enable granular insights, making it possible to focus on opportunities in specific fields (e.g., public sector or private sector, STEM or non-STEM), geographic locations or occupations of interest.

A small but nevertheless important segment of the labour market that we did not focus on in this study is indigenous-owned businesses. Indigenous entrepreneurship represents an important means through which Indigenous peoples can create their own, culturally appropriate and high-quality career opportunities (Collins and Norman, 2018; Hunter, 2015b). The Australian government is supporting the growth of Indigenous businesses through preferential procurement policies, business grants and loan schemes (M. Evans and Polidano, 2022b). Indigenous-owned businesses achieve substantially higher rates of Indigenous employment than other Australian businesses across all of the industry divisions that they operate in (Eva *et al.*, 2024; Hunter, 2015a). The success of Indigenous-owned businesses in this regard has been attributed to both cultural and

geographic factors. Not only do Indigenous-owned businesses offer a culturally safe work environment, they are well-represented in the remote communities where Indigenous peoples live (Eva *et al.*, 2024). Further research exploring the relative importance of cultural and geographic factors for Indigenous workers' employment decisions would be desirable since it could inform non-Indigenous businesses' strategies for attracting and retaining Indigenous workers.

Finally, this study reveals the rapid growth in employers posting Indigenous focused job advertisements. There is currently no evidence as to whether Indigenous focused job postings are more likely to attract Indigenous applicants. In a focus group with Indigenous university students (carried out to inform our work in this space) we were told that jobs requiring Indigenous cultural capability are more desirable than Identified positions, since the latter can be associated with stigma. On the other hand, research carried out for the Australian Indigenous Employment Index (Minderoo Foundation, 2022) revealed that Indigenous employees had positive attitudes towards Identified roles. Systematic research is needed to determine whether the wording of job postings influences Indigenous job seekers, and if so, what information (e.g., statements encouraging Indigenous people to apply versus information about culturally sensitive workplace arrangements) is most useful for their decision-making.

Conclusion

The research reveals strong growth in employers seeking Indigenous workers through job postings. However, the diversity of these employment opportunities remains limited and the quality of the roles of being advertised varies according to the industry of employment. Importantly, the research reveals opportunities to strengthen the efforts of those employers who seek to engage Indigenous workers in high quality roles, by aligning their workforce strategies to reflect the geographic location and formal qualifications of Indigenous workers. Finally, the study illustrates a novel methodology that can be used to monitor progress in addressing labour market segmentation.

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How efficient is the Australian labour market? Analysing job matching efficiency for regions, occupations and industries

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Abstract

In an efficient labour market, employers fill vacancies in a timely manner, and those who are unemployed do not remain out of work for long. However, this is not always the case. During an economic downturn, workers who are laid off may possess different skills to those required in sectors that remain strong. As a result, the unemployed may remain unemployed for longer, because they are unable to find work. In addition, the remaining vacancies may go unfilled, as suitable workers cannot be obtained from the unemployment pool. In such circumstances, poor labour market efficiency is at play, and the economic and social costs can be substantial. Consequently, Jobs and Skills Australia (JSA) has been researching this topic by examining the question 'for a given level of vacancies (demand) and unemployment (supply), how many hires should be occurring in the labour market?'. Using data from both JSA and the Australian Bureau of Statistics (ABS), experimental insights into labour market efficiency for regions and occupations have been derived, paving the way for further research that may provide opportunities to inform economic and labour market policies. Our results tend to suggest that efficiency of the labour market in matching unemployed persons with jobs is currently relatively high and has broadly improved in recent years.

JEL Codes: J22; J23, J62, J38
Key words: Labour supply, labour demand; occupational market, public policy

This paper reflects the opinion of the authors and in no way represents the views of Jobs and Skills Australia or the Australian Commonwealth Government.

Acknowledgements
The authors would like to acknowledge and thank the following people/organisations for their engagement and feedback on the project to date: Jeff Borland (University of Melbourne), Matt Nolan (e61), Blair Chapman (ANZ), Commonwealth Treasury (Will Mackey), RBA research team and Lawrence Uren (University of Melbourne). We also acknowledge the feedback from the participants of 2023 UNSW Search and Matching Workshop, 2023 Australian Conference of Economists and 2023 Australian Labour Market Workshop, as well as JSA executive and colleagues.

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Introduction

This study provides an insight into the efficiency of Australian labour market at regional, occupational and industry level using disaggregated data. The understanding of the labour market efficiency is important because at any given point in time, there are typically hundreds of thousands of vacant jobs in the market[1] and yet also hundreds of thousands of unemployed persons. If there are so many jobs available, why do we still see unemployment? And conversely, if there are so many unemployed persons, why do vacancies still go unfilled? Clearly, the answer lies in understanding labour market efficiency, and in particular 'frictions' in the labour market. Such frictions hinder how quickly available workers can be matched to available jobs, and can arise from imperfect information, skills mismatch, geographic mismatch and policy-led distortions (among other things). Given this, analysing labour market efficiency may help inform policy responses – whether they be labour market policy, economic policy or education and skills policy levers.

Jobs and Skills Australia (JSA) has been researching this topic by examining the question *'for a given level of vacancies (demand) and unemployment (supply), how many hires should be occurring in the labour market?'*. In this context, the aim of this study is to understand how labour market efficiency varies across Australia. As such, we set out to estimate labour market matching efficiency in Australia for occupations, regions and industries. Using data from both JSA and the Australian Bureau of Statistics (ABS), experimental insights on labour market efficiency for regions, occupations and industry have been derived, which we termed the *MUVER model*.

The Model

Background to the Model

The roots of labour market efficiency analysis go back to the Search and Matching model.[2] It is essentially based on the production function concept with the numbers of unemployed (supply) and vacancies (demand) are taken as 'inputs' and the flow of

1 Warranted, there were periods following the onset of COVID-19 that the level of vacancies fell to very low levels. However, this is considered an atypical period.

2 The pioneer work in this area was done by Diamond-Mortensen-Pissarides (DMP) over the decades, resulting in the Nobel prize in economics for their 'fundamental contributions to search and matching theory' in 2010. Extensive discussion of this literate can be found in Petrongolo and Pissarides (2001). Also see, Blanchard and Diamond (1989) for the discussion on this topic.

newly matched worker-employer pairs as the 'output'. The resulting matching function describes the rate at which successful job matches 'output' are created from the stocks of 'inputs' and the relative weights of each input (labour demand and supply) in job matching process (see, Coles and Smith, 1996).

To help understand labour market efficiency in simpler terms, let us consider an example. Suppose there are two regions, both of which currently have one hundred vacancies and one hundred unemployed persons. Hypothetically, a perfectly efficient labour market would see the available workers (unemployed persons) quickly matched to the available jobs (vacancies), clearing the market leaving no structural or long-term unemployment or unfilled vacancies (shortages). However, suppose that in one region, we see eighty matches occur, and in another region, we see twenty matches occur. In this simplistic scenario, the difference in the number of matches can be thought of as a result of matching efficiency, or frictions.

Model Specification

In frontier analysis, the matching function represents the maximum achievable matches from the stocks of unemployed and vacancies as shown in figure 1 below. In the context of the Cobb-Douglass production function, we adopt the stochastic frontier analysis approach (SFA)[3], namely:

$$m_{it} = Au_{it}^{\alpha} v_{it}^{\beta} e^{\varepsilon_{it} - z_{it}} \tag{1}$$

With technical change, the matching function in equation (1) can be rewritten in a linear form as shown in Fahr and Sunde (2002;2004) and Ilmakunnas and Pesoal (2003) via logarithmic transformation as:

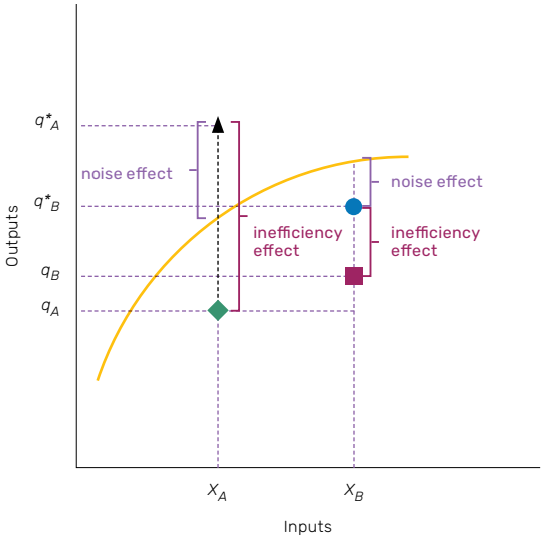
$$\log(m_{it}) = c + \beta \log(v_{it}) + \alpha \log(u_{it}) + wt + \varepsilon_{it} - z_{it} \tag{2}$$

Here, m_{it} refers to job matching, v_{it} refers to vacancies, u_{it} refers to unemployment, c is a constant term, t refers to a time trend, and α, β and w are parameters to be estimated. Subscripts it after the variables refer to occupation/region or industry and time. $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$ is an error term, while $z_{it} \sim N^{+}(0, \sigma_z^2)$ represents technical inefficiency in the job matching process. The stochastic frontier model is estimated by an econometric maximum likelihood estimation, which requires distributional assumptions of the error terms ε and -z. The technical efficiencies are defined as the ratio between the observed output and the stochastic frontier output i.e. $TE = e^{-z}$ (see, e.g. Coelli *et al.*, 2005, p. 244). The algorithm re-parameterizes the variance parameter of σ_{ε}^2 and the scale parameter of the inefficiency term σ_z^2 and estimates $\gamma = (\sigma_z^2 / \sigma_z^2 + \sigma_{\epsilon}^2)$.

3 See, Bauer (1990), Warren (1991), and Coelli *et al.*, (1998) for extensive surveys of the literature.

Using the model specified above, the new experimental model developed by Jobs and Skills Australia to estimate labour market efficiency for occupations, regions and industries is termed the *MUVER model*.

Figure 1. Visualisation of SPF analysis of efficiency



The Data

Analysis of labour market efficiency under the search and matching framework is predicated on obtaining appropriate data on matches, unemployment and vacancies. Given our interest in examining variations in efficiency at detailed levels, such data was required at disaggregated levels of occupation, region and industry. Developing this database was a major task and took considerable amount of time and resources. Recent developments in the availability of detailed labour market data makes this possible.

Table 1 below provides details of the relevant data underpinning the model, including the relevant coverage of the model and the relevant definitions utilised.

Table 1. Definition of data, coverage and sources

Focus	Occupational Model	Regional Model	Industry Model (validation)
Data availability			
Disaggregation	ANZSCO 2 digit	All capital cities & regional SA4s	ANZSIC 1 digit
Coverage[4]	41 of 46 series[5]	All series	18 of 19 series[6]
Frequency	Quarterly	Quarterly	Quarterly
Starting period	February 2006	May 2010	November 2009
Definitions			
Matches	Quarterly count of employed persons who report that they have worked for the current employer/business for less than three months		
Unemployment	Based on most recent occupation of employment	Based on place of usual residence	Based on most recent industry of employment
Vacancies	Estimated total number of new vacancies (flow) that arose during the quarter		Count (stock) of vacancies that exist at the survey reference date
Data sources			
Matches	ABS Labour Force Survey – Detailed (accessed via ABS Datalab)		
Unemployment	ABS Labour Force Survey – Detailed (accessed via ABS Datalab)		
Vacancies	JSA Internet vacancy Index adjusted using insights from JSA Recruitment Experience and Outlook Survey (see the snapshot summary below)		ABS Job Vacancy Series

Of note is the definition of matches used in our analysis. To utilise a consistent method across occupation, region and industry analysis, the definition of matches adopted for our analysis is *'the quarterly count of employed persons who report employment of less than three months'*. The logic of this definition is that since our data is quarterly, all persons who report employment of less than three months can thus be assumed to be a new hire (match) for that period.[7] Given the data available to us, this was considered the

4 Please note that where appropriate, missing values are imputed to support analysis and modelling using common imputation techniques. Where imputation was not possible (due to insufficient data), the series was excluded from the model coverage.

5 Some 2-digit occupations within the same 1-digit group were combined to enable modelling.

6 The ABS Job Vacancy Series does not include vacancy data for the Agriculture, Forestry and Fishing industry.

7 A review of the ABS Labour Force Survey methodology indicates that the respondents were asked how many months they have worked for the current employer/business (LFS questions 80 and 81). As such, employment data obtained from the ABS LFS may represent either the respondent's tenure

most appropriate approach for our analysis.

Regarding unemployment, the measures of unemployment by occupation and industry relate to the occupation and industry of employment *prior* to becoming unemployed. Similarly, regional unemployment is based on a person's current usual place of residence. By using these measures of unemployment, our model inherently assumes that the unemployed are seeking to return to their most recent occupation and industry, and in the case of our regional model, are looking for work within their current region. While we know transitions between occupations and regions occur in the labour market, this assumption is considered reasonable given the available data. Further research to expand the definition of supply in our model would be a worthy exploration.

Finally, for our vacancy measure, the JSA Internet Vacancy Index (IVI)[8] was adjusted using insights from the JSA Recruitment Experiences and Outlook Survey (REOS)[9] to take into account the fact that not all job vacancies are advertised online. By combining these two sources of labour market information, JSA has developed a new estimate of the total number of new vacancies each quarter. This measure was utilised in our modelling of labour market efficiency (matching efficiency) for occupations and regions. As the JSA IVI does not include industry data, data on industry vacancies was obtained from the ABS Job Vacancy Series, with the industry model predominantly acting as a point of validation for the regional and occupational results.

Results and discussion

The model specified above is estimated separately for occupations, regions and industries. Results are reported in Table 2 below.

in employment (if they were NILF or unemployed prior to commencing in the position) or tenure with an employer (if they were employed with another employer/business prior to commencing in their current position). In this way, the data effectively captures both movements into employment from unemployed/NILF and also between-firm movements in employment (for example, employer A in quarter 1 and then employed with employer B in quarter 2).

8 See https://www.jobsandskills.gov.au/data/internet-vacancy-index for further information about the JSA IVI.

9 See https://www.jobsandskills.gov.au/data/recruitment-experiences-and-outlook-survey for further information about the JSA REOS.

Table 2. Estimates of matching efficiency for occupations, regions and industries

JSA MUVER model Estimates of Job Matching Efficiency for Australia[10] Dependant variable: Log of matches			
Disaggregation	**Occupation**	**Region**	**Industry (validation)**
Focus	**3 digit ANZSCO**	**SA4 with GCCSAs for capital cities**	**1 digit ANZSIC**
Period	2006 to 2022	2010 to 2023	2009 to 2022
Constant	2.983 (0.124)***	2.331 (0.07)***	1.326 (0.117)***
Log Vacancies (V)	**0.223** (0.01)***	**0.304** (0.008)***	**0.231** (0.015)***
Log Unemployed (U)	**0.536** (0.016)***	**0.429** (0.009)***	**0.744** (0.017)***
Time (t)	-0.011 (0.003)***	-0.004 (0.001)***	0.06 (0.008)***
Efficiency	**0.829**	**0.744**	**0.807**
Sigma Squared (σ^2)	0.183 (0.019)***	0.23 (0.033)***	0.101 (0.009)***
Gamma (γ)	0.429 (0.061)***	0.604 (0.058)***	0.234 (0.069)***
Log likelihood	-751.338	-1,126.291	-185.237

As seen in Table 2, the estimated SFA function is monotonically increasing in v_{it} and u_{it}. The matching elasticity of vacancies is 0.22, 0.30 and 0.23, while the elasticity of unemployment is 0.54, 0.43 and 0.74 for occupation, region and industry models respectively (the elasticity of scale, obtained from the sum of the coefficients for v_{it} and u_{it}, is 0.76, 0.73 and 0.98 for occupation, region and industry models respectively). The estimates of efficiency are broadly consistent, ranging from 0.829 for the occupation model to 0.744 for the regional model and 0.807 for the industry model.

The Gamma parameter γ lies between zero and one, indicating the importance of the inefficiency term in the model.[11] As the estimate of γ is 0.429, 0.604 and 0.234

10 Differences in the model results are to be expected given the differing time periods, data sources and levels of disaggregation (for example, for the industry model, there are eighteen underlying industries whereas there are forty-one series in the occupation model).

11 If γ is zero, the inefficiency term z_{it} is irrelevant and the results should be equal to OLS results. In contrast, if γ is one, the noise term ε_{it} is irrelevant and all deviations from the production frontier are explained by technical inefficiency.

for occupation, region and industry models respectively we can conclude that the inefficiency term is important for explaining deviations from the production function. The time trend indicates very little technical change (negative) -1.1 per cent and -0.4 per cent for occupation and region models respectively, while it is positive 6 per cent for the industry model.

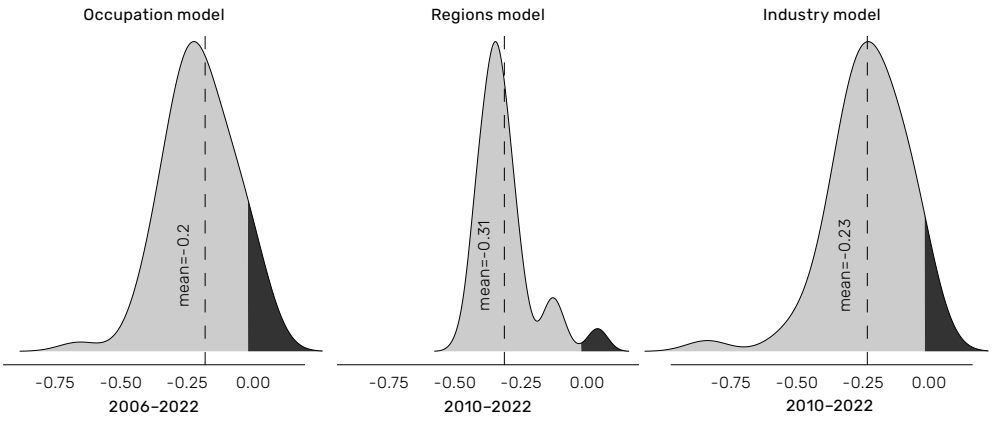
It is important that when examining the model outputs, we also analyse the results of the subsequent likelihood ratio test (Table 3). Under the null hypothesis (no inefficiency, only noise), the test statistic asymptotically follows a mixed χ^2-distribution (Coelli, 1995). The small P-value indicates that the data clearly reject the OLS model in favour of the stochastic frontier model, i.e. there is significant technical inefficiency.

Table 3. Results of Likelihood ratio test run on the JSA experimental MUVER model

Model 1: OLS (no inefficiency)	Occupation	Region	Industry (validation)
Model 2: Error components frontier	(2 digit)	(SA4)	(1 digit)
Likelihood ratio test result	167(0.0000)***	393(0.0000)***	167(0.0000)***

A well-known result due to Waldman (1982) also states that, in the standard normal/half-normal SFA model, estimated technical inefficiency will be zero if the OLS residuals are positively skewed. Such a result might cast doubt on the specification of the stochastic frontier model (Greene, 1990). By contrast, a negative skewness means that the residuals are left-skewed (negative), and in our case this would mean that it is likely that not all occupations/regions are fully technically efficient. In the case of our models, testing results show the residuals of the three models are indeed left-skewed (negative) as expected (see Figure 2).

Figure 2. Residuals of JSA experimental MUVER models

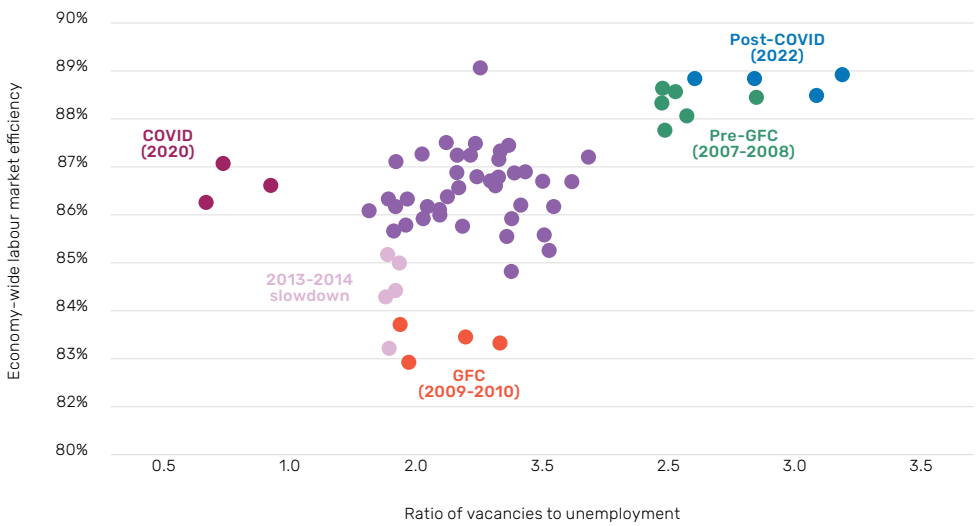


Sources: Based on JSA MUVER models.

Headline national results for Australia

Examining the average (mean) results from the modelling can provide an indication of trends in national matching efficiency across Australia. When we estimate the model by occupation, we can pool the results to obtain an average of matching efficiency for Australia over time (from 2006 to 2022). As demonstrated in Figure 3 (which compares the matching efficiency with the prevailing rate of vacancies to unemployment), matching efficiency for Australia has varied considerably over time. Following the height of COVID-19 in 2020, we found that matching efficiency remained relatively stable, despite a rapid decline in the vacancy rate (see maroon dots). This is in stark contrast to the GFC period (see red dots) and the slowdown in the labour market in 2013-14 (lilac dots), when economy wide matching efficiency appears to have declined. By contrast, in 2022, labour market efficiency reaches a similar point to that of the pre-GFC strength of 2007-08, with both the vacancy rate and matching efficiency very high. This suggests that during the very tight labour market conditions of these periods, the labour market became more efficient in matching unemployed persons to vacant jobs, potentially due to employers having to change their preferences or tastes to job suitability to fill positions (for example, by taking on workers who are only partially suitable for a job). This may suggest that in the short term, a tight labour market may actually support improved matching between unemployed workers and vacant positions.

Figure 3. Average matching efficiency for Australia compared with the vacancy rate, over time

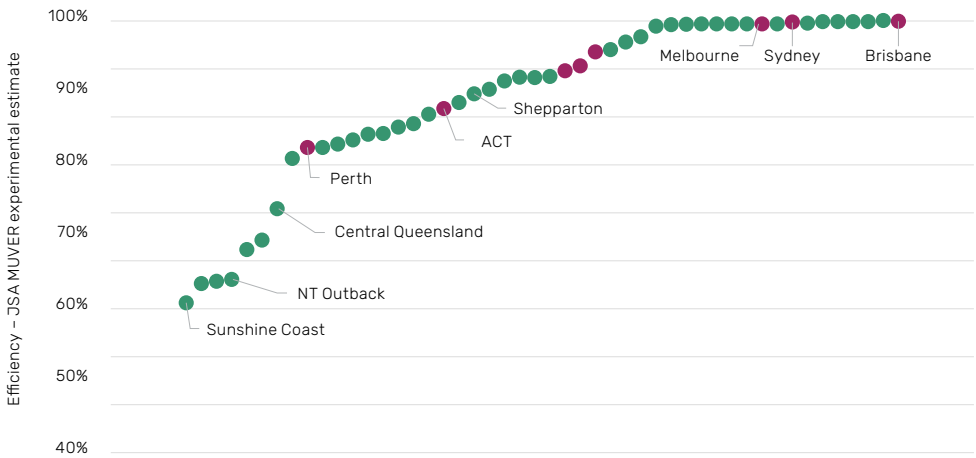


Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA experimental estimates of total vacancies and ABS Labour Force Survey unemployment estimates.

Detailed estimates of efficiency by region

When examining the estimates of matching efficiency by region (SA4 regions), we see the efficiency of the labour market in matching unemployed persons with job vacancies varies by region. As demonstrated in Figure 4, efficiency varies by region, with a number of regions effectively acting as "frontier" regions, where the labour market of the region is functioning efficiently. Metropolitan areas are identified by the maroon dots, with Melbourne, Sydney and Brisbane acting as aforementioned frontier regions. By contrast, Perth and ACT are less efficient.

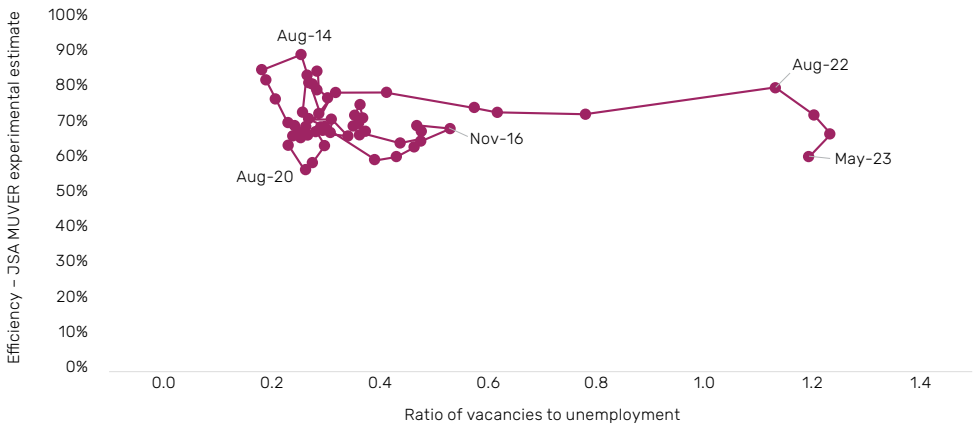
Figure 4. Estimates of matching efficiency by region – JSA experimental MUVER model, May 2023



Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency.

The model outputs of efficiency also enable the analysis of changes in efficiency over time. Examining the model's efficiency estimate relative to the ratio of vacancies to unemployment for the Sunshine Coast in Figure 5 shows that efficiency in the region particularly started to decline in late 2022. In addition, the level of efficiency in the Sunshine Coast also never reached the heights of August 2014, despite the very high vacancy ratio, perhaps indicating an emerging shortage of workers (or suitable workers) to fill available vacancies in the region, indicating efficiency may decline as labour market tightness persists.

Figure 5. Estimates of matching efficiency and ratio of vacancies to unemployment – Sunshine Coast



Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA experimental estimates of total vacancies and ABS Labour Force Survey unemployment estimates.

Combining estimates of regional labour market efficiency with JSA analysis of relative regional labour market strength (RLMI)[12] may also help categorise regional labour markets into types, helping to inform possible policy responses. Using this approach, and as detailed in Figure 5, we can classify each region into four distinct categories.

12 JSA's Regional Labour Market Indicator (RLMI) combines key indicators of spare labour market capacity, from both an employee and employer perspective, into a single, and easy to interpret, summary measure (with regions grouped into distinct categories of overall labour market performance, ranging from 'poor' to 'strong') which provides an accurate and reliable view of labour market performance. Factors included in the RLMI include the working age (15-64) employment rate, the unemployment rate, the JobSeeker income support rate, the underemployment rate and the vacancy fill rate. Further information about the JSA RLMI can be found at: https://www.jobsandskills.gov.au/data/regional-labour-market-indicator

Table 4. Approach to combining estimates of regional matching efficiency and regional relative labour market strength to categorise regions

Categorisation	Matching efficiency (JSA MUVER)	Relative labour market strength (JSA RLMI)	Description
'Frontier' regions	High	Strong	Experiencing good conditions and efficient rate of matching.
'Mismatched' regions	Low	Strong	Strong conditions, but lower matching efficiency. May reflect local unemployed persons being overlooked for candidates from other nearby regions (such as cities), either due to employer preferences or a mismatch in suitability.
'Job deficit' regions	High	Weak	A relatively high rate of matching is occurring. Vacancies are filled quickly, but there's insufficient vacancies to sufficiently reduce or clear unemployment.
'Challenging' regions	Low	Weak	Weak conditions, but also lower matching efficiency when a vacancy arises.

Helpfully, by identifying and classifying regions in such ways the associated possibilities for policy responses can be more directly targeted. This may include the targeting of wage subsides (for employers in 'mismatched' regions), training subsidies (for unemployed persons in 'mismatched' regions), job creation policies (for 'job deficit regions') and more comprehensive responses for 'challenging regions'. While experimental, this framework certainly provides a case for further interrogation and analysis of the methodology.

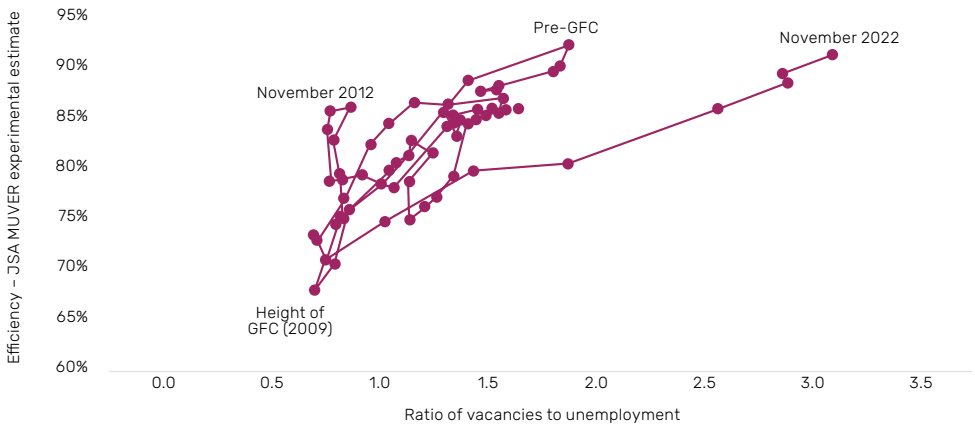
Figure 6. Comparison of regional efficiency estimates and relative labour market strength – JSA MUVER model and JSA RLMI

Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA RLMI estimates of Relative Labour Market Strength.

Detailed estimates of efficiency by occupation

Similar to the regional results highlighted in Figure 5, the model outputs of efficiency also enable the analysis of changes in efficiency over time for occupations. For instance, as per Figure 7, we can examine the model estimates of the matching efficiency for Construction Trades over time. This shows that efficiency of Construction Trades in matching unemployed persons (based on their most recent occupation) and job vacancies was particularly high in late 2022, on par with the results achieved prior to the onset of the GFC. By contrast, during the height of the construction downturn in the GFC of 2009, matching efficiency dropped rapidly. This was likely because the vacancy rate was very low, and those employers could be more selective when determining which available workers they wished to form a match with. This demonstrates the type of occupational analysis such model results may enable.

Figure 7. Estimates of matching efficiency and labour market tightness (ratio of vacancies to unemployment) over time – Construction Trades occupation



Sources: Prepared based on JSA MUVER experimental estimates of matching efficiency, JSA experimental estimates of total vacancies and ABS Labour Force Survey unemployment estimates.

Estimates of matching efficiency by occupation may also be informative in considering the prevalence of shortages across the labour market. It may be that persistent shortages arise from frictions that hinder the efficiency matching of unemployed workers to available jobs, such as due to a skills mismatch. However, in the short term, it may be that shortages – while costly for businesses – may prompt employers to change their preferences and tastes, such that they become more likely to take on unemployed persons who are partially suitable for a role and may otherwise be overlooked in more neutral labour market conditions. This, in turn, could lead to labour market efficiency increasing in the short term when shortages arise.

Conclusion, limitations and areas for further Research

Limitations and areas for further research

There are a number of limitations and gaps in the analysis that are worth noting. These provide opportunities for further examination in due course as the model is continuously improved by Jobs and Skills Australia. Particular limitations worth noting include:

- **Transitions in the labour market are difficult to measure.** While we selected the most appropriate measure of matches/hires we could identify (based on quarterly data of persons who are employed with a job tenure of less than three months), there are some hires and matches that are difficult to observe (such as internal within-in firm movements and promotions) and data quality can vary.
- **Unemployment is arguably a narrow definition of labour supply.** Given a large number of movements into employment also come from those not in the labour force, further research to consider expanded definitions of potential labour supply may be warranted, potentially including incorporating controls for different types of jobseekers.
- **The analysis does not attempt to evaluate the quality of a match.** Instead, the model focusses on the level (or rate) of matching occurring. As such, the quality of the match (including measuring labour productivity, job satisfaction, job tenure, wages, etc.) is not captured.
- **Understanding the drivers – or determinants – of matching efficiency has proven difficult.** Potential influencers of matching efficiency include wages, migration, unionisation rates, gender-based labour market segregation and other factors. While this is a strong area of interest, such analysis has proven challenging due to conceptual challenges in determining whether modelled associations are genuine causal relationships, as well as data limitations at disaggregated levels (among other factors). However, further work could be done to evaluate the incorporation of such drivers into our model as adjustment factors, as has been attempted in various literature.

Conclusion

JSA's experimental MUVER model uses a well-established labour market search and matching framework to provide a range of insights that improve our understanding of the functioning of the Australian labour market among geographic regions, industries and

occupations. Our results tend to suggest that efficiency of the labour market in matching unemployed persons with jobs is currently relatively high and has broadly improved in recent years. Given the labour market has recently been very tight, this likely reflects employers becoming more willing to take on unemployed persons to fill their vacancies. In fact, generally speaking, the labour market appears to be more efficient in matching unemployed persons to vacancies when there is an elevated level of shortages. This is because shortages – while costly for businesses – may prompt employers to take on unemployed persons who are 'partially suitable' for a job, and who may otherwise be overlooked in less tight labour market conditions. However, persistent shortages may nonetheless lead to an eventual decline of matching efficiency.

Combining estimates of regional labour market efficiency with analysis of relative labour market strength also helps identify several types of regional labour markets, while occupational analysis may also be useful for a range of policy applications. As JSA's new model of matching efficiency is experimental in nature, and subject to further review and development, further work is needed to validate and confirm these initial findings. JSA welcomes feedback and suggestions on how the analysis could be improved in the future.

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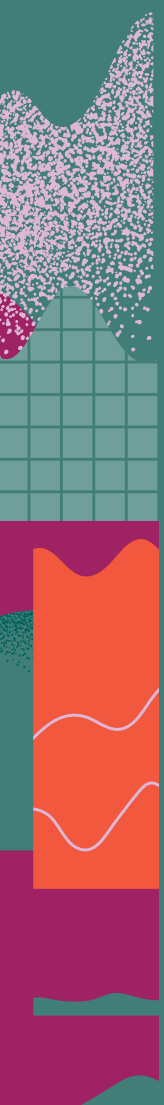

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