

Skills mismatch in the labour market

Concepts, data sources, and measures





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Purpose and summary

Purpose

Skills mismatch: Concepts, data sources, and measures aims to improve understanding about skills mismatch in the labour market and provide guidance to enable people to choose the appropriate measures to answer their specific policy questions. In this sense, the paper is directed at researchers and analysts and at policy makers.

The paper also intends to raise awareness and understanding about skills mismatch among the general public.

We're also asking for feedback on the direction for future research.

[See Skills mismatch feedback form.](#)

A skills mismatch can broadly be defined as a situation in which the skills of a person do not match the skill requirements of a job. A person can be either well matched, over-skilled, or under-skilled for a certain job. The concept is typically used in a labour market context. Skills mismatches matter because they are important drivers of economic and social developments – on an individual and aggregate level.

Data sources and measures

In New Zealand we have several data sources; some information is collected by Stats NZ, other information is **collected and provided by the OECD's** Programme for the International Assessment of Adult Competencies (PIAAC).

The data source **shouldn't** be confused with the measure applied to the data. The International Labour Organisation (ILO) proposes the normative and statistical measures of skills mismatch, which we apply to the New Zealand Household Labour Force Survey (HLFS) data. We also explain the OECD measure of skills mismatch, which is applied to the New Zealand PIAAC data. All measures have specific advantages and disadvantages and make certain assumptions (see the appendix for a summary).

Structure of this paper

This paper starts with a brief introduction to the topic of skills mismatch. It includes a working definition and the objectives we want to achieve by sharing this paper.

We then discuss different types of skill mismatch, such as vertical and horizontal skills mismatch. We explain different data sources and measures that can be used to analyse skills mismatch. Firstly, we concentrate on the ILO guidance – proposing to use the normative or statistical measure for analysis. We show how we can apply it to the HLFS data we hold at Stats NZ.

Secondly, we introduce the OECD measure and how data from the PIAAC can be used to analyse skills mismatch. We finish by looking at the future of measuring skills mismatch.

Summary of key points

- Skills mismatches in the labour market matter as they affect economic, social, and individual growth and well-being.
- There are a variety of skills mismatches.
- Different data sources and measures can be used to identify and assess skills mismatches.
- The ILO suggests using the normative measure or the statistical measure, which can be applied to Stats NZ HLFS data or census data.
- The OECD collected information in New Zealand as part of the PIAAC.
- **Based on the OECD's survey** data information, we adopted a measure that combined qualitative information with quantitative verification.
- The complexity of measuring skills mismatch will remain a challenge – we want your feedback to direct future research.

Introduction to skills mismatch

This section defines skills mismatches in the labour market and explains why they matter. It also outlines the objectives of this paper.

Working definitions

We define skills as the qualifications, experiences, soft skills, and other talents a person brings to the job. Skills mismatch is broadly defined as a situation in which **a person's** skills do not match the skills requirements of a job. Generally a mismatch is assessed on two components:

- what a person brings to the job – measured through skills, qualifications, years of education, or the field of study
- what a job requires – measured through a person's **occupation** or the tasks their job involves.

Bringing both components together, a person can be characterised as well matched, over-skilled, or under-skilled for a certain job. We can also talk about qualification mismatch or field of study mismatch. A person can have a qualification that is too high or too low for the **job's** requirements. Or they might have studied a field that is not relevant to the job the person is working in.

'Skills mismatch' is typically used in a labour market context. It usually describes **an employee's** situation in relation to his or her skills and the job they are doing, but can also apply to self-employed people, the unemployed, and those not in the labour force (in relation to their previous or future job).

Skills mismatches matter to the economy and society because they are important drivers of economic and social developments – on an aggregate and individual level.

In the economy a high level of skills mismatch is negatively related to labour productivity. One explanation is a lack of allocative efficiency. That is, if workers are employed by a low-productivity company, higher-productivity companies have a more limited pool of workers to draw from. As a result, more-productive companies have difficulty attracting skilled labour and gaining market shares at the expense of less productive companies (McGowan and Andrews, 2015).

From a worker's perspective, a good match between their skills and **a job's** requirements contributes to greater job satisfaction and motivation (Rihova 2016). If people do not have the opportunity to work in their desired field and utilise their skills it can demotivating and detrimental to both their personal well-being and their productivity.

Objectives

This paper provides guidance to enable people to choose the appropriate measures to answer their specific policy questions. Researchers, analysts, and policy-makers need to be aware of the limitations, assumptions, advantages, and disadvantages of the evidence presented to use the information most effectively.

The type and level of skills people have **are becoming more important, both for individuals'** employment prospects and for the success of New Zealand businesses. While the country has an increasingly educated and skilled labour force, mismatches exist for the supply of and demand for particular types of skills. One result of this is that people who have difficulty finding employment appropriate to their skills take jobs where those skills are underutilised.

We include analytical briefs on skills mismatches to illustrate the situation for different demographic groups, and in different industries or occupations.

We have several possible research questions for these briefs.

- What proportions of people are working in occupations for which they are over-qualified, or in occupations not related to their qualifications?
- In which occupations and industries are over-qualified workers most commonly employed?
- Which demographic groups are most likely to be under-utilising their qualifications (ie sex, age, ethnicity, birthplace, and region).

Feedback

Although these questions might interest people, your feedback will drive our future work. Please provide us with feedback on your need and preference for further work.

[See Skills mismatch feedback form.](#)

Types of skills mismatch

This section explains different types of skills mismatch. While these can be defined for the overall economy and for individuals, **this paper's focus is on** skills mismatch for individual workers.

For individuals, we often talk of being over- or under-skilled, meaning someone has more or less skills than are required for the job. Depending on what data is available, being over- or under-skilled can be indicated by years of education or level of qualification. Someone with more (or fewer) years of education than is required for a job can be classified as over- (or under-)educated. Similarly a person with a higher (or lower) qualification than is required by the job can be classified as over- (or under-)qualified. This is referred to as vertical mismatch.

Being under-skilled can also mean that skills previously used in a job are no longer required. This is skills obsolescence, a concept often used where new technology becomes available and the workforce needs to move from paper-based, manual work, to IT and computer-based work.

If someone has studied in a field that is not relevant to their job, they are not well matched. This is referred to as horizontal mismatch.

Within the economy as a whole, skills mismatch can occur when the demand or supply for a particular type of skill exceeds the supply or demand of people with that skill. We refer to this as a skill shortage or skill surplus. For instance, countries draw up skill-shortage lists to help fill vacancies with migrants who have the skills on that list.

Note: this paper does not focus on skill shortages or surpluses in the New Zealand economy.

An over-qualified person **isn't** necessarily over-skilled

Although the definitions sound straightforward, reality can be more complex. Imagine a former university professor now working as a receptionist of a small family hotel. Technically they would be classified as over-qualified as **you don't** need a PhD to do a receptionist's **job**. Yet a receptionist needs to have strong communication and organisational skills, **which the professor doesn't have**. Therefore the professor is both over-qualified but under-skilled (ILO, 2014).

This example helps illustrate the difference between formal level of qualification, or time spent in education, and **'soft'** skills unrelated to **a person's technical capabilities** or educational attainment. Such skills include personal attributes someone needs to succeed in the workplace, such as communication skills, the ability to cooperate, or the ability to think critically. Capturing soft skills is very challenging.

Being over-qualified is not necessarily a bad thing. A receptionist with a PhD may be perfectly happy being a receptionist and may derive many other benefits from having a high level of education. At a societal level, having a well-educated population can have benefits, even if many people are over-qualified for their jobs. It is important to understand which skills mismatches matter to the economy, society, and the individual, and which mismatches need research and policy attention.

Different data sources and measures for mismatch analysis

Skills mismatch can be analysed using different data sources and measures, depending on the analytical focus and intended outcome. The choice of data source might also depend on the availability of data rather than on choosing the best possible data source to answer a research question. Chosen measures for analysis are often proxies, such as years of education (as a proxy for supply of skills) and occupation (as a proxy for demand for skills).

Commonly used measures are:

- self-reported (or self-assessed) skills mismatch
- measures derived from comparing skill proficiency and skill use, or level of education and occupation.

There is no agreement internationally on a single ‘correct’ measure for skills. The concept (skill) and the associated measures are complex and it is difficult to collect meaningful information on skills. For example, measuring behaviour, social, or soft skills is very challenging but is a vital part of how and how well a person is doing their job.

In New Zealand we have several data sources providing information on skills. Stats NZ collects some, while other information is collected and provided by the OECD. Stats NZ data allows us to assess skills mismatch by using proxies to compare the level of qualification, years of education, or field of study with occupational requirements. Currently Stats NZ has no self-reported skills mismatch information. The OECD measure is based on a combination of self-reported skills mismatch and proxy-based information.

Stats NZ data sources: HLFS and census

The Household Labour Force Survey (HLFS) and census are data sources that provide information about highest level of qualification, occupation, and (from the census) field of study.

The strength of the HLFS is its comparatively large sample size (30,000 individuals) and regular quarterly reporting. Being a survey about the labour market, it is a natural fit when assessing skills mismatch in the workplace. Data users can contextualise skills mismatch information with broader labour market indicators. However, field of study is not asked of respondents. Also, occupational information might be less robust when compared with other data sources due to HLFS being a sample survey.

In contrast, the strength of census is that it includes the entire resident population living in New Zealand. Field of study is collected, which constitutes an asset of this dataset. Occupational information is more robust, especially at lower levels of the classification. However, a census is only conducted every five years and has a limited suite of supporting labour market statistics.

These two data sources can be used when applying the ILO measures to map skills mismatch. We concentrate on applying the ILO measures to the HLFS data.

ILO measure of skills mismatch based on HLFS data

The international authority on labour statistics is the International Conference of Labour Statisticians (ICLS). The ICLS makes recommendations on selected topics of labour statistics in its resolutions and guidelines, which are then approved by the **tripartite (governments, workers’ and employers’ organisations)** Governing Body of the International Labour Organisation (ILO) before becoming part of the set of international standards on labour statistics.

Since 2008, the ICLS has discussed skills mismatch as part of underutilisation measures, which refer to wider mismatches between labour supply and demand.

Joint information on underutilisation, based on time-related underemployment, unemployment, and the potential labour force, has been part of New Zealand’s quarterly labour statistics releases since 2016.

For a more comprehensive assessment of the labour market, the ICLS recommends that ‘skill-related inadequate employment’ is an important component to consider (19th ICLS, Resolution concerning statistics of work, employment and labour underutilization). The reason for this is that **if someone’s skills are well matched to the occupational requirements**, it is “a major factor

shaping labour market outcomes, economic growth, productivity and competitiveness” (ILO 2014). Stats NZ is not directly measuring skill-related underemployment at present.

In *Skills mismatch in Europe* (2014) the ILO provides guidance on skills mismatch for the first time. Two approaches are suggested, both with inherent advantages and disadvantages: the normative and statistical measure. The normative measure is qualifications-based and uses a high level of occupation, while the statistical measure is based on years in education and a lower level of occupation.

The normative measure

The normative measure is based on the International Standard Classification of Occupations (ISCO). This measure divides the major occupational groups (at first-digit level, or the highest level of the classification) into three main groups and assigns a level of education to each group – in line with the International Standard Classification of Education (ISCED).

Table 1
The high-level concordance of the normative measure

Category	ISCO	ISCED
Highly skilled	Managers (1), Professionals (2), Technicians and associate professionals (3)	First stage of tertiary education (5), Second stage of tertiary education (6)
Medium skilled	Clerical support workers (4), Services and sales workers (5), Skilled agriculture, forestry and fishery workers (6), Craft and related trades workers (7), Plant and machine operators and assemblers (8)	Upper secondary education (3), Post-secondary non-tertiary education (4)
Low skilled	Elementary occupations (9)	Lower secondary education or second stage of basic education (2), Primary education or first stage of basic education (1)
Source: Stats NZ		

Every worker in a particular occupation with the assigned level of education is considered well matched. Those who have higher level of education are considered over-qualified, and those with less education than assigned are considered under-qualified. This means the normative measure assumes that a certain level of qualification reflects the requirements of a job in a certain occupation. Skills mismatch occurs if the level of education does not match the occupational requirements.

Technically we are assessing education-occupation mismatch. When applied to the HLFS data we are using the measure for highest qualification to assess the level of education. Consequently we should talk about qualification-occupation mismatch. However, for ease we will continue to use the term skills mismatch.

The advantage of the normative measure is that, over time, we consistently classify workers in a given occupation and with a given level of education as under-qualified, over-qualified, or well matched. However, concordance is established on a high level, and we group a broad range of occupations – especially in the medium-skilled category (see table 1). This obscures a wide range of skill differences in each category, which can be considered a disadvantage.

An additional disadvantage of the normative measure is that it does not take into account the actual distribution of educational attainment. In New Zealand, where the level of education is generally high, workers in most jobs may be better educated than required by the job – the proportion of over-educated is therefore likely to be higher as well.

Applying the normative measure to the HLFS

ANZSCO, which is the occupation classification used in the HLFS, and ISCO do not concord perfectly, even at the lowest level of both classifications. However, ANZSCO categories can be concorded broadly to the ISCO groupings.

Table 2 shows the differences in concordance.

- ANZSCO major groups 1, 2, and 3 are **‘highly skilled’**, including managers, professionals, technical and trades workers.
- ANZSCO major groups 4, 5, and 6 are **‘medium skilled’**, including community and personal service workers, clerical and administrative workers, and sales workers.
- ANZSCO major groups 7 and 8 are **assigned as ‘low skilled’**, including machinery operators and drivers, and labourers.

Table 2
Concordance of ISCO and ANZSCO

Category	ISCO (used in ILO normative measure)	ANZSCO (used in HLFS)
Highly skilled	Managers (1), Professionals (2), Technicians and associate professionals (3)	Managers (1), Professionals (2), Technical and trades workers (3)
Medium skilled	Clerical support workers (4), Services and sales workers (5), Skilled agriculture, forestry, and fishery workers (6), Craft and related trades workers (7), Plant and machine operators and assemblers (8)	Community and personal service workers (4), Clerical and administrative workers (5) and sales workers (6)
Low skilled	Elementary occupations (9)	Machine operators and drivers (7), Labourers (8)
Source: Stats NZ		

The classification for highest qualification used in the HLFS, and ISCED, also do not concord perfectly. However, the HLFS highest qualification categories can be concorded broadly to the intention of the ISCED groupings. Table 3 shows the differences in concordance.

Table 3
Concordance of ISCED and HLFS highest qualification

Category	ISCED	HLFS highest qualification
Highly qualified	First stage of tertiary education (5), Second stage of tertiary education (6)	PhD or other doctorate degree (1), Master's degree (2), Bachelor's degree with honours, Postgraduate certificate, diploma (3), Bachelor's degree, graduate certificate, diploma level 7 (4), Certificate, diploma level 6 (5), Advanced trade certificate (6)
Medium qualification level	Upper secondary education (3), Post-secondary non-tertiary education (4)	Certificate, diploma level 5 (7), Trade certificate (8), Certificate, diploma level 4 (9), Other NZ post-school qualification (10), Post-school certificate, diploma, level unknown (11), Other overseas post-school qualification (12), Overseas secondary school qualification (13), Other NZ school qualification (14), Post-school level 3 (15), NZ higher school certificate, NZ A or B bursary scholarship, NCEA level 3, NZ university entrance from 1986 (16), Post-school level 2 (17), NZ sixth form certificate, NCEA level 2, NZ university entrance before 1986 (18), Post-school level 1 (19), NZ school certificate, NCEA level 1 (20)
Low qualification level	Lower secondary education or second stage of basic education (2)	Secondary school qualification not specified (21), No qualification (22)
Source: Stats NZ		

Using the concordances above, the ILO normative measure translates into the table 4 summary.

Table 4
Applying the normative measure to the HLFS

Category	ANZSCO	HLFS highest qualification
Highly skilled	Managers (1), Professionals (2), Technical and trades workers (3)	PhD or other doctorate degree (1), Master's degree (2), Bachelor's degree with honours, Postgraduate certificate, diploma (3), Bachelor's degree, graduate certificate, diploma level 7 (4), Certificate, diploma level 6 (5), Advanced trade certificate (6)
Medium skilled	Community and personal service workers (4), Clerical and administrative workers (5) and Sales workers (6)	Certificate, diploma level 5 (7), Trade certificate (8), Certificate, diploma level 4 (9), Other NZ post-school qualification (10), Post-school certificate, diploma, level unknown (11), Other overseas post-school qualification (12), Overseas secondary school qualification (13), Other NZ school qualification (14), Post-school level 3 (15), NZ higher school

Category	ANZSCO	HLFS highest qualification
		certificate, NZ A or B bursary scholarship, NCEA level 3, NZ university entrance from 1986 (16), Post-school level 2 (17), NZ sixth form certificate, NCEA level 2, NZ university entrance before 1986 (18), Post-school level 1 (19), NZ school certificate, NCEA level 1 (20)
Low skilled	Machine operators and drivers (7), Labourers (8)	Secondary school qualification not specified (21), No qualification (22)
Source: Stats NZ		

The statistical measure

The second measure the ILO recommends is the statistical measure. This measure is based on a **worker's occupation** (two-digit level – a more-detailed level) and their years of full-time education.

For each occupation group, the mean number of years of education the workers have and its standard deviation are measured. Well-matched workers are people whose years of education fall within one standard deviation of the mean required in their occupation group. These workers commonly make up 68 percent of their occupation group, assuming the years are normally distributed. Workers who are over- or under-skilled have more (or fewer) years of education than the mean required, by more than one standard deviation. This indicates the statistical measure assumes the mean number of years of education for an occupation reflects the requirements necessary to do the job.

An advantage of the statistical measure is that instead of looking at three occupation groups (derived from eight) this measure uses 43 groups. A possible disadvantage might be that it is sensitive to the **country's** general educational attainment level, because higher education levels over time result in higher mean levels for all workers. With greater educational participation, the mean years of education in most occupations increases, but this may not reflect actual increases in **the job's** skills requirements.

Applying the statistical measure to the HLFS

In line with ILO guidance, the highest level of qualification in the HLFS has to be converted into years spent in education. We did this using the same conversion as the New Zealand socio-economic index 2013, for consistency. Table 5 shows how many years of education each level of qualification assumes.

Table 5
Educational classifications converted to years of education
2013 Census and Ministry of Education

HLFS highest qualification	Years of education
PhD or other doctorate degree (1)	20

HLFS highest qualification	Years of education
Master's degree (2)	18
Bachelor's degree with honours , Postgraduate certificate, diploma (3)	17
Bachelor's degree, Graduate certificate, diploma level 7 (4)	16
Certificate, diploma level 6 (5)	14.5
Advanced trade certificate (6)	13.5
Certificate, diploma level 5 (7)	13.5
Trade certificate (8)	12.5
Certificate, diploma level 4 (9)	12.5
Other NZ post-school qualification (10)	11.5
Diploma level unknown (11)	11.5
Overseas post-school qualification (12)	11.5
Post-school certificate, Other overseas secondary school qualification (13)	12
Other NZ school qualification (14)	11
Post-school level 3 (15)	11.5
NZ higher school certificate, NZ A or B bursary scholarship, NCEA level 3, NZ university entrance from 1986 (16)	13
Post-school level 2 (17)	11.5
NZ sixth form certificate, NCEA level 2, NZ university entrance before 1986 (18)	12
Post-school level 1 (19),	11.5
NZ school certificate, NCEA level 1 (20)	11
Secondary school qualification not specified (21)	11
No qualification (22)	10
Source: Stats NZ and Ministry of Education	

OECD data source: PIAAC

The Organisation of Economic Cooperation and Development (OECD)'s Programme for the International Assessment of Adult Competencies (PIAAC) developed and conducts the Survey of **Adult Skills**. The survey measures adults' proficiency in three skill domains: literacy, numeracy, and problem solving in technology-rich environments. It also gathers information on how adults use their skills at home, at work, and in the wider community.

The OECD discusses skills mismatch as part of its mission to promote policies that will improve the economic and social well-being of people around the world. The OECD works **with workers' and employers' organisations** through the Business and Industry Advisory Committee to the OECD and through the Trade Union Advisory Committee.

Data for New Zealand was collected from 6,177 adults between April 2014 and February 2015. The target population for the survey was the 16–65 years, non-institutionalised, population residing in the country at the time of data collection, irrespective of nationality, citizenship, or language status.

Proficiency is described on a scale of 500 points, divided into levels. Each level summarises what a person with a particular score can do. Six proficiency levels are defined for literacy and numeracy (levels 1 to 5, plus below level 1) and four are defined for problem solving in technology-rich environments (levels 1 to 3, plus below level 1).

In addition to skill proficiency, PIAAC also gathers information on skills use and self-reported skills mismatch. All three pieces of information are used to measure skills mismatch.

OECD measure of skills mismatch from PIAAC data

Workers are asked if they feel they 'have the skills to cope with more demanding duties than those they are required to perform in their current job' and whether they feel they 'need further training in order to cope well with their present duties'. Well-matched workers are those who neither feel they have the skills to perform a more demanding job, nor feel the need for further training to be able to perform their current job satisfactorily.

Workers are classified as well-matched in a skill domain if their proficiency score is between the minimum and maximum score for **workers who answered 'no'** to both questions (in the same occupation and country). The 5th and 95th percentiles are used instead of the actual minimum and maximum – to limit the impact of outliers. Workers are over-skilled in a domain if their score is higher than the maximum of the self-reported, well-matched worker; they are under-skilled in a domain if their score is lower than the minimum score for these workers.

Based on this procedure the proportions of workers who are over-skilled, under-skilled, and well matched, can be calculated in each occupation and for each skill level.

Comparing the ILO (normative and statistical) and OECD measures

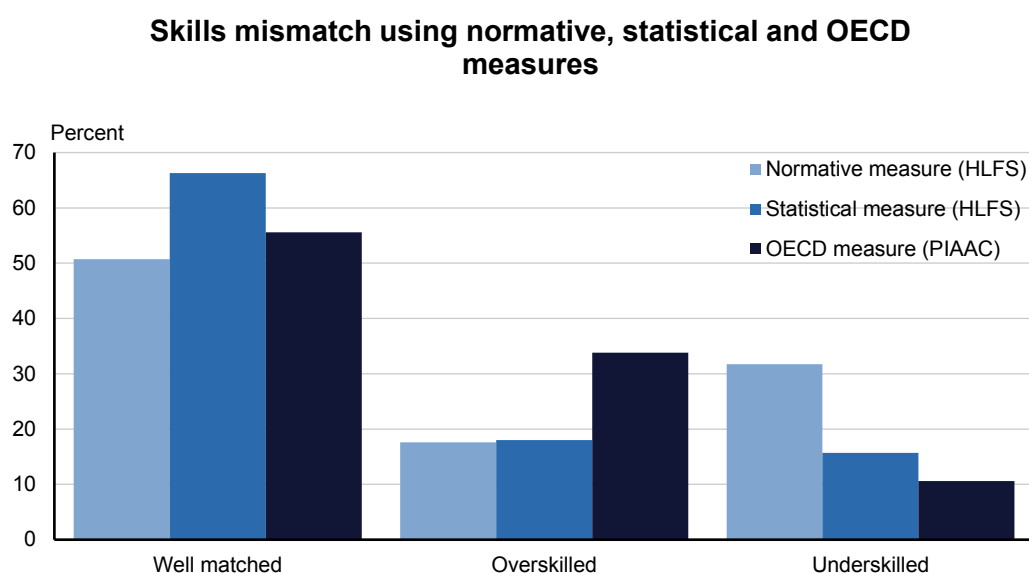
Figure 1 provides a high-level overview of the proportions of well matched, over-skilled, and under-skilled workers, by each measure introduced in this paper. The proportions that are well matched using the normative, statistical, and OECD measures range from around 50 percent to 66 percent. The proportion of over-skilled workers ranges from 17–33 percent and the proportion of under-skilled from 10–31 percent.

The greatest variability for the three measures is in the proportion of under-skilled people. This could be attributed to the inherent assumptions of each measure.

For example, for the normative measure we assume a manager needs a high level of education to be well matched. Yet a manager might have their job due to experience rather than educational achievement. If so, this manager would be considered under-skilled because the measure assumes that experience is irrelevant.

The comparatively low proportion of under-skilled for the OECD measure might be partly due to assuming that people can judge accurately if their skills match the occupational requirements. Yet subjective assessments by respondents are vulnerable to measurement errors, which can result in lower levels of under-skilled people (Flisi et al, 2016).

Figure 1



Note: HLFS data is for June quarter 2017 and PIAAC data is for April 2014 to February 2015 (latest available).
Source: Stats NZ

New Zealand ranks higher than OECD average

The Ministry of Education and the Ministry of Business, Innovation and Employment have released a number of summary reports based on PIAAC data. These are available on the [Education Counts](#) website.

- [Skills in NZ and around the World: Survey of Adult Skills](#) (June 2016)
- [Skills and Education: Survey of Adult Skills](#) (June 2016)
- [Skills at Work: Survey of Adult Skills](#) (June 2016)
- [Youth Skills: Survey of Adult Skills \(PIAAC\)](#) (July 2017)
- [Survey of Adult Skills: Adults' Financial Literacy Activities](#) (August 2017).

According to these summary reports, New Zealand has a highly skilled population. We rank fourth among OECD countries in literacy, 13th in numeracy, and 5th in problem solving in a technology-rich environment.

New Zealand also ranks first in the OECD for the use of reading skills at work, and has above-average use at work of writing, numeracy, IT, and problem-solving skills. Skill use at work has a significant, positive relationship with labour productivity – across countries and industries, even when adjusting for skill proficiency (OECD, 2016; Quintini, 2014). New Zealand appears as an outlier country in this relationship; our population is highly skilled (on average) and our workforce uses these skills frequently at work, yet our labour productivity is low by OECD standards (Conway, 2016).

Wages are a (imperfect) proxy for individual productivity. Recent international research has shown that skill proficiency and skill use at work (two proxies for human capital) are significantly related to wages and other labour market outcomes, such as labour force participation and employment status (OECD, 2016; Lane & Conlon, 2016; Hanushek et al, 2013). Skills influence labour market outcomes even after controlling for years of education or highest qualification. Lane & Conlon (2016) found that returns vary by level of education. Yet there is a significant wage gap between well-matched and mismatched workers (Montt, 2017).

Outlook for the future

This section looks into the future of measuring skills mismatch, which remains a challenge.

The world of work is changing, often due to the increasing availability and use of new technologies, which means that skill requirements change. Workers have to be able to develop, use, or monitor new technologies, and/or develop new skills that cannot be performed by new technologies. These developments might make it more challenging to accurately account for skills that are well matched and used in a job.

It will be increasingly important:

- to assess what drives and causes skills mismatch
- to provide a measure which allows policy-makers to identify which skills mismatches require policy intervention
- to clarify how skills can be allocated more meaningfully and efficiently.

The following complex tasks need innovative solutions in all areas discussed in this paper:

- clarifying the concept of skills mismatch
- using and/or developing existing or new data sources
- using and/or developing existing or new measures.

The measures discussed in this paper are useful to provide context and insight about skills mismatch in New Zealand. For example, using HLFS data we can provide information on skills mismatch by:

- sex and age
- urban and rural divide
- region
- job tenure – how long a person worked in a specific job
- employment status – whether a person is an employee, employer, self-employed, or unpaid family worker

- temporary or permanent employee
- permanent, casual, temporary agency, fixed term, or seasonal employee
- being born in or outside New Zealand and how long they have been here.

Feedback requested

We strongly encourage you to provide feedback on your needs and preferences for skills mismatches information. We are particularly interested in your feedback to the following questions.

- Did you find this paper useful? If yes, how did you or might you use the measures discussed?
- If no, why do the measures not seem useful, or what stops you from using them?
- Would you find it useful if we published data and analysis using the normative and/or statistical measure?
- If yes, which measure would be more useful and informative to you?
- Would you find it useful if we analysed specific topics of interest? For example, should we focus first on a specific occupation group (eg managers) or group of people (eg women)?
- If yes, which are your topics of interest?

[See Skills mismatch feedback form.](#)

References and further reading

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Appendix: Overview of measures

	Normative measure	Statistical measure	OECD measure
Data source	Household surveys and census	Household surveys and census	PIAAC (OECD Survey on Adult Skills)
Indicators	Proxies: highest level of qualification (supply) and occupations (demand)	Proxies: years of education (supply) and occupations (demand)	Proxies: Based on literacy proficiency scores for people who report themselves as well matched (ie those who neither feel they have the skills to perform a more demanding job, nor feel the need for further training to be able to perform their current job satisfactorily)
Occupation	First level ISCO-88/ANZCO is divided into three groups	Two-digit level ANZCO	Not applicable
Education/skill	Above is assigned to ISCED-97	Mean (or mode) number of years of education and its standard deviation (+/-1), based on New Zealand socio-economic index 2013	<p>1. Literacy proficiency scores – people reporting themselves as well matched (ie those who neither feel they have the skills to perform a more demanding job, nor feel the need for further training to be able to perform their current job satisfactorily)</p> <p>2. Literacy proficiency scores are used to create a quantitative scale of the skills required to perform the job for each occupation (based on 1-digit ISCO codes)</p>

	Normative measure	Statistical measure	OECD measure
			3. Identify a minimum and maximum threshold value (eg 5th and 95th percentile) to identify who is well matched, under-, and over-skilled
Match, overeducated, undereducated	If you are in an occupational group and you have the assigned level of qualification you are well matched. If you have more/less qualification than required, you are over-/under-qualified	If you are in an occupational group and you have the assigned years of education, +/- one standard deviation, you are well matched. If you have more/less years of education than required you are over-/under-qualified	If you are within the threshold of your occupation you are well matched. Over- and under-skilled workers are those with higher/lower scores than the maximum/minimum threshold in their occupation
Advantages	Relatively easy to measure Workers are categorised consistently over time	Less heterogeneity within groups of jobs when compared with the normative measure Less sensitive to the average level of educational attainment (increases in educational attainment result in higher mean education levels)	Respondents whose proficiency scores reside within the bounds are not counted as mismatched, regardless of whether they self-report as being well-matched or mismatched. More precise than qualification mismatch as it takes into account skill gain or loss
Disadvantages	Doesn't take the the actual distribution of the measure into account Broad range of occupations in major group 4-8	Mean (mode) levels of education might or might not be driven by job requirements Sensitive to cohort effects	Definition is narrower than for qualification mismatch as it concentrates on one aspect of skills (partial assessment), such as literacy or numeracy Does not identify specific skills deficits or excesses

	Normative measure	Statistical measure	OECD measure
			<p>Difficult to measure skill deficit by self identification</p> <p>Uses 1-digit occupation code (all jobs with the same occupation code have the same skill requirements)</p>
Assumptions	Uses a pre-determined mapping between the job and the required education level	Calculated mean (mode) numbers of years for groups of occupations reflect job requirements	Based on qualitative information (ie a self-assessment of mismatch) which is verified by quantitative information on skill proficiency.