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Skills, Economic Crises and the Labour Market*

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Do higher skills help mitigate the negative impact of economic crises? We study the effect of two major economic setbacks—the Global Financial Crisis (GFC) in 2007–09 and the COVID-19 period from early 2020—on wage progression for New Zealanders with different skill levels. For our analysis, we link the PIAAC survey data on literacy and numeracy skills with the Inland Revenue's tax records that document the entire workforce's monthly labour market information. During the GFC, the adverse impact of the economic shock on wage progression appears to be significantly lower for the higher-skilled population. Moreover, those in the low-skilled group who changed employers during the GFC experienced the largest wage drop. However, during the more recent period of COVID-19 restrictions, we find little evidence of skill-based differences in wage progression. In some years, low-skilled workers even experienced slightly faster wage growth than high-skilled workers.

I Introduction

The positive effect of skills on wages and employment has been well documented in the economic literature (McIntosh & Vignoles, 2001; Murnane *et al*., 2000; Carneiro & Heckman, 2003; Hanushek *et al*., 2015). Moreover, empirical evidence shows that skills contribute to a country's economic growth (Hanushek & Woessmann, 2008). However, in most countries, a significant portion of the workforce acquires only basic skills, making *upskilling* a critical policy issue. But skills might not only have a positive long-term labour market impact but also provide resilience against economic shocks (Hanushek *et al*., 2017).

This paper examines two distinct economic crises—the Global Financial Crisis of 2008/09 and the COVID-19 period of 2020/21—to explore how skill levels influenced the impact of these shocks on wage progression in New Zealand.

To that end, this paper contributes to the literature on the heterogeneous impact of

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economic crises. Previous research shows that economically vulnerable workers, including racial minorities, younger workers and those with less education, are disproportionately affected by economic downturns (Hoynes *et al*., 2012a; Adams-Prassl *et al*., 2020; Couch *et al*., 2020b). These findings hold across examinations of different crisis periods, including the Global Financial Crisis (GFC) and the more recent COVID-19 pandemic (e.g. Adams-Prassl *et al*., 2020; Daly *et al*., 2020; Liang, 2022).

To date, there is little empirical evidence on how economic crises differentially affect workers with low- versus higher-skill levels. This gap likely exists because datasets that link skill measures to longitudinal earnings, allowing researchers to track individuals' labour market outcomes over time, are seldom available. As a result, many studies use educational attainment as a proxy for skill level in the absence of direct measures of skills, such as literacy and numeracy proficiency.

However, while education and skills are positively correlated, education is an imperfect proxy for skills. For example, Hanushek *et al*. (2015) found that skills command a wage premium over and above the education wage premium, likely reflecting the higher productivity of skilled workers. In economic crises, workers with higher skills may fare better not only because they are more productive but also for specific reasons, such as superior job search capabilities and the ability to demonstrate how their skills are transferable across roles.

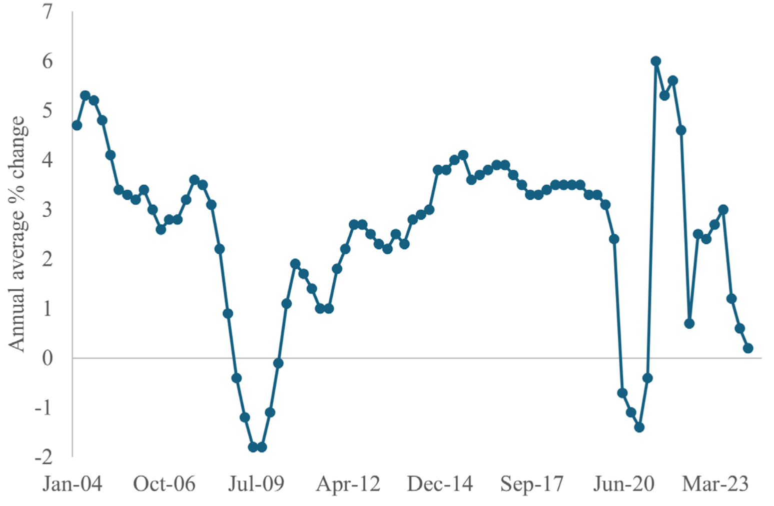
This study appears to be the first to examine how economic crises affect labour market outcomes for workers with different skill levels. We use a novel dataset that links measures of individual skills to longitudinal tax data on earnings. Specifically, our analysis draws on the Organisation for Economic Co-operation and Development's (OECD) Programme for the International Assessment of Adult Competencies (PIAAC), which provides literacy and numeracy scores for a representative sample of New Zealand adults in 2014. While most surveys measuring skills provide only cross-sectional labour market data, we address this limitation by linking the PIAAC survey to New Zealand administrative datasets, including monthly Inland Revenue income data. This linkage allows us to track participants' earnings from wages and salaries over two decades.

Using these data, we examine the effects of two distinct crises—the GFC and the COVID-19 pandemic—on earnings growth for workers with different skill levels. Both crises are evident in New Zealand's GDP growth data, which shows two recessions in the last two decades: one in 2009 during the GFC and another in 2020 during the pandemic (see Fig. 1).

However, these two crises were markedly different. The GFC was primarily a financial crisis that triggered demand-side shocks. In contrast, the pandemic caused a sharp economic slowdown driven by New Zealand's policy response and supply-side constraints including global supply chain disruptions, even though underlying demand remained strong. Furthermore, the government's COVID-19 response package was significantly larger than the fiscal stimulus deployed during the GFC (Maani *et al*., 2021; Dunn *et al*., 2023). This was also accompanied by substantial monetary policy easing, including lowering the Official Cash Rate to its effective lower bound and the deployment of additional tools such as large-scale asset purchases (Reserve Bank of New Zealand, 2022). As evident in Figure 1, the GDP recovery from the recession during the COVID-19 period was considerably stronger than the recovery following the GFC, although it was more volatile. Therefore, we aim to understand how the distinct nature of these crises may have resulted in differences in outcomes based on skill levels.

We hypothesise that the impact of skills on wage progression differs between the two crises due to their distinct natures. Specifically, during the GFC, which was primarily a demand-driven crisis, we expect lower-skilled workers to have been more adversely affected, particularly when changing employers. In contrast, during the COVID-19 pandemic, the supply-side nature of the disruption, combined with the government's extensive wage subsidy scheme and strong demand for services deemed 'essential' by the New Zealand government, may have mitigated these skill-based

FIGURE 1
Real Gross Domestic Product.



Source: Reserve Bank of New Zealand https://www.rbnz.govt.nz/statistics/key-statistics/economic-indicators on 26 September 2024. Shown is the Growth in Real Gross Domestic Product (GDP) for New Zealand.

differences, resulting in more similar wage trajectories for lower- and higher-skilled workers.

We use PIAAC's literacy and numeracy scores, measured on a 500-point proficiency scale, to classify skill levels. Individuals are defined as low-skilled if both scores are below 200, while those scoring higher are classified as higher-skilled. Based on this definition, between 4 and 5 per cent of individuals are identified as low-skilled.

Our primary outcome variable is the annual progression of monthly wages. To examine the effect of skills, we include (among other variables) a binary indicator for higher skill levels, a year identifier and their interaction term. This allows us to assess skill-specific differences in wage progression. Given low-skilled workers are often low paid, we conduct additional analysis focusing on individuals whose earnings from wages and salaries belonged to the two lowest deciles in the previous year.

During the GFC period, we find that wage growth slowed across all skill levels. In 2007/08 and 2008/09, wage growth was notably lower than the reference year of 2005/06 for both low-skilled and higher-skilled workers. However, the decline was more pronounced for low-skilled workers. On average, low-skilled, low-earning workers experienced 11.2 per cent lower wage growth in 2008/09 compared with 2005/06, while higher-skilled, low-earning workers saw a much smaller reduction of 2.1 per cent.

To explore why low-skilled workers face greater wage growth reductions during economic downturns, we analysed workers based on whether they stayed with their current employer or changed jobs. Among workers who remained with the same employer, we find no significant skill-based differences in wage progression. However, low-skilled workers who changed employers experienced a sharp wage decline. For example, in 2008/09, the wage progression of low-skilled, low-earning workers who changed employers was, on average, 28.8 per cent lower than in 2005/06. In contrast, higher-skilled, low-earning workers who changed employers experienced a small increase of only 0.2 per cent.

Although our data cannot distinguish between voluntary versus involuntary job separations, the significant wage decline for low-skilled workers who switched employers suggests that job loss resulting in involuntary job change had a larger impact on their wages than on those of higher-skilled workers. This may reflect the fact that low-skilled workers are more likely to be employed in sectors that are sensitive to demand shocks, such as hospitality and retail, where job opportunities are more limited during downturns. Additionally, low-skilled workers may have less bargaining power or fewer transferable skills, making it harder for them to secure new roles at similar or higher wages following job loss.

For the COVID-19 period, we do not observe differences in wage progression between skill groups. One possible explanation is the introduction of the wage subsidy scheme, a government policy designed to protect jobs during the pandemic. We find that the scheme had a more positive impact on the wage progression of low-skilled workers compared with higher-skilled workers.

The remainder of the paper is structured in the following way: Section II reviews the literature on the relationship between skills and labour market performance, and provides an overview of the GFC and the COVID-19 periods in New Zealand. Section III introduces the datasets used in the analysis. Section IV outlines the empirical identification strategy. Section V presents and discusses the findings. Finally, Section VI concludes.

II Background

(i) Human Capital, Skills and Labour Market Outcome

According to OECD (1998, p. 9), human capital is defined as "the knowledge, skills, competencies and other attributes embodied in individuals that are relevant to economic activity." Human capital comprises various interrelated traits, including cognitive skills and non-cognitive attributes such as personality characteristics, motivation, behavioural dispositions and even physical appearance (OECD, 2013). However, many of these individual-level attributes that contribute to human capital are unobservable.

As a result, empirical research often uses educational attainment as a proxy for human capital. Numerous studies have explored the relationship between years of schooling and labour market performance to highlight the economic and wellbeing implications of human capital or skill (Bowen & Finegan, 1966; Leigh, 2008; Forbes *et al*., 2010). However, education does not perfectly capture an individual's true level of human capital. People may also develop their basic skills through alternative means, such as on-the-job training and life experiences, rather than formal education.

In their seminal paper, Blackburn and Neumark (1993) use data on white males from the US National Longitudinal Survey of Youth to show that not all high school students benefit equally from attending college, as labour market returns depend on cognitive skills.[1]

Over the past two decades, numerous studies have examined the effect of individuals' literacy and numeracy skills on labour market outcomes. Murnane *et al*. (2000) use the US-based National Longitudinal Survey of the High School Class of 1972 (NLS72) and High School and Beyond (HS&B) datasets to "demonstrate that cognitive skills are important determinants of subsequent earnings" [p. 562]. Similarly, McIntosh and Vignoles (2001) provide UK-based evidence showing that higher literacy and numeracy skills increase wages and the likelihood of employment.

Cognitive ability, as measured by the Armed Forces Qualifying Test scores, is also positively associated with hourly wages (Carneiro & Heckman, 2003). In Australia, Chiswick *et al*. (2003) find that participants of the 1996 Australian Aspects of Literacy Survey who perceive themselves as having excellent numeracy skills are more likely to

[1] OECD (2013, p. 103) identifies three limitations of using education level as a proxy for human capital: (i) educational qualifications provide information about only a subset of skills, (ii) the time elapsed since the qualification was awarded may affect its market value, and (iii) cross-country differences in the quality of education and training.

participate in the labour force compared with those with only good numeracy skills. Using data from the Australian Adult Literacy and Lifeskills Survey, Shomos (2010) shows that improving literacy and numeracy skills increases both labour force participation and hourly wages for men and women. These findings are corroborated by Shomos and Forbes (2014), who use PIAAC data to observe similar effects for Australian men and women.

Further supporting international evidence, Antoni and Heineck (2012) find a positive relationship between literacy skills and labour market outcomes using the German Working and Learning in a Changing World Survey. Extending the focus beyond literacy and numeracy, Lane and Conlon (2016) demonstrate that improving Information and Communication Technology (ICT) skills also enhances employment prospects and wages. Their estimates show that individuals with low ICT skills and formal education achieve smaller returns than those with high ICT skills but no formal education. These findings underscore the broad importance of skills in determining labour market success.

In a seminal study, Hanushek *et al*. (2015) analyse the effect of skills on wages in 23 OECD countries. Consistent with the above findings, the study shows that higher cognitive skills—measured using PIAAC measures of literacy, numeracy and problem-solving skills—are associated with higher wages in all examined countries. This result holds even when controlling for years of schooling, although the estimated returns to skills are somewhat reduced when years of schooling is included as a factor.

Cross-country comparisons by Iversen and Strøm (2020) further highlight the positive impact of improving literacy and numeracy on employment outcomes. When controlling for age and country-specific fixed effects, the analysis finds that the effect of skills on employment is more pronounced in countries with centralised wage bargaining systems and strict employment protection laws compared to countries without these institutional characteristics. This underscores the role of labour market institutions in shaping the returns to skills.

At the macro level, the cognitive skill level of a labour force is positively correlated with GDP per capita levels, indicating that countries with a more skilled workforce tend to achieve higher levels of economic development (Hanushek & Woessmann, 2008; Vignoles, 2016). Similarly, Eckstein *et al*. (2016) find a positive association between cognitive skills and GDP, further emphasising the importance of workforce skills for national economic performance.

Research on the labour market returns to skills in New Zealand remains limited. Maré and Chapple (2000) use the International Adult Literacy Survey (IALS), the first international skills survey and a precursor to PIAAC, to show that improving literacy results increases both the likelihood of employment and earnings. Using the subsequent Adult Literacy and Lifeskills Survey (ALLS), Earle (2009) finds that a one-standard-deviation increase in literacy and numeracy skills corresponds to a 20 per cent difference in hourly earnings on average.

These findings are supported by Dixon and Tuya (2010), who demonstrate that higher skill levels are associated with higher average hourly earnings and longer job tenure. In addition, Erwin *et al*. (2020) provide an empirical portrait of adults with low literacy and numeracy skills and find that less skilled individuals are less likely to work full time and more likely to be unemployed. These studies collectively highlight the significant role of skills in shaping labour market outcomes in New Zealand.

(ii) The GFC and its Impact on New Zealand

The GFC of 2007–09 had a substantial negative impact on the New Zealand economy. Employment in New Zealand declined sharply, particularly between 2008-Q4 and 2009-Q4, exceeding even what most other OECD economies experienced (OECD, 2012). Not surprisingly, New Zealand also witnessed a 3.1 per cent decline in its total output, which, however, was below the OECD average decline of 5.3 per cent.

As in most previous recessions, economically vulnerable groups were disproportionately affected during the GFC. For example, the unemployment rate among young workers (aged 15–24) increased by 5.7 percentage points from 11.9 per cent in 2008-Q4 to 17.6 per cent in 2009-Q4. In contrast, the unemployment rate for prime-age workers (aged 25–54) increased by only 1.6 percentage points, from 3.2 per cent in 2008-Q4 to 4.8 per cent in 2009-Q4.[2]

Additionally, workers with no or only school qualifications and those on temporary contracts faced a high risk of redundancy (OECD, 2012). Job losses were also unevenly distributed across industries. According to Maré and Fabling (2013), the construction, manufacturing, and finance and insurance industries were the three most affected industries.

To mitigate the adverse impact of the GFC, the New Zealand government implemented several temporary response measures. To maintain public confidence in the banking system, the government implemented the *Crown Retail Deposit Scheme* in 2008, which guaranteed the repayment of deposits in failed financial institutions. Additionally, a Wholesale Guarantee Facility was established to help banks access funding during the liquidity crisis.

For individuals who lost their jobs, several different labour welfare programmes were introduced. These included the *ReStart Transitional Relief Programme*, which provided limited transitional assistance for people who had lost their jobs and were seeking suitable work; *Redundancy Support*, which aimed to help staff transition into alternative employment or training; and *Job Support Scheme*, which offered an allowance to workers who agreed to work reduced hours. According to a Ministry of Social Development (2009) report, 4,500 people received ReStart assistance and the Job Support Scheme saved over 400 jobs. However, this was in the context of the unemployment rate rising from 4.4 per cent in 2008Q4 to 6.6 per cent in 2009Q4, representing an increase in the number of unemployed of nearly 50,000.[3]

(iii) The COVID-19 Period in New Zealand

To contain the spread of COVID-19, most OECD countries implemented lockdowns in early 2020. On 28 February 2020, the first COVID case was reported in New Zealand. In response, the government adopted a zero-COVID elimination strategy. Initial measures included restrictions on indoor gatherings of more than 100 people. Additionally, on 19 March 2020, international borders were closed to all but New Zealand citizens and permanent residents, and on 9 April 2020, an order requiring all individuals entering the country to undergo managed isolation and quarantine was issued.[4]

On 25 March 2020, New Zealand entered a strict lockdown (officially known as Level 4). The lockdown included working-from-home orders for workers in sectors deemed ‘non-essential’ by the New Zealand government, border closures and restricted mobility (see Prickett *et al.*, 2020). The initial lockdown ended on 8 June 2020, but subsequent shorter-term lockdowns were imposed whenever cases of COVID-19 in the community were detected. The specifics of what was permitted during lockdowns depended on the extent of community transmission. During the strictest Level 4 lockdowns, New Zealand had the most stringent COVID-19 policy response in the world (Hale *et al.*, 2021; Gibson, 2022a,b). Figure 2 also illustrates that New Zealand maintained high levels of restrictions even as other countries began to ease theirs. This prolonged stringency reflects New Zealand’s commitment to a zero-COVID elimination strategy, which relied heavily on repeated lockdowns and strict border controls.

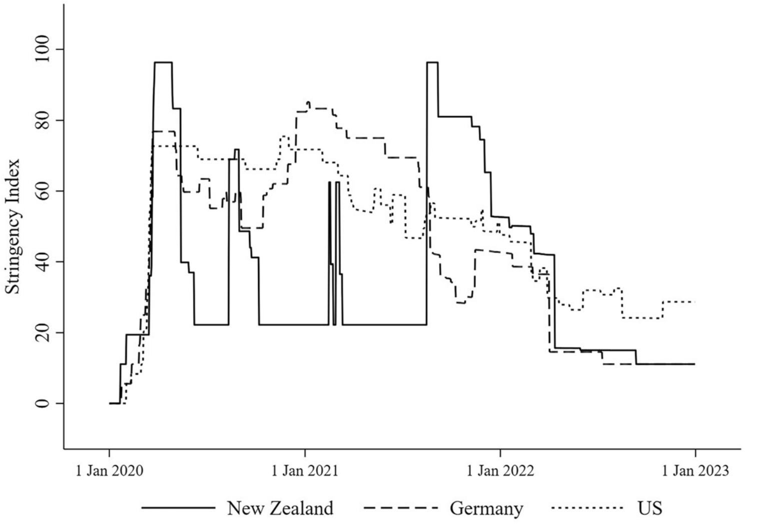
In October 2021, the government began transitioning from an elimination strategy to a management-focused approach. This shift centred on vaccinations, including the introduction of vaccine passes for individuals aged 12 and over, and workforce vaccine mandates for sectors like healthcare. By December 2021, the government formally abandoned the elimination strategy and implemented a new protection framework

[2] Numbers retrieved on 21 October 2021 from the *OECD Short-Term Labour Market Statistics*, available at https://stats.oecd.org/.

[3] Numbers retrieved on 20 November 2021 from the Household Labour Force Survey series available from https://infoshare.stats.govt.nz/.

[4] Retrieved from https://covid19.govt.nz/alert-levels-and-updates/history-of-the-COVID-19-alert-system/ on 10 August 2021; and https://www.mbie.govt.nz/immigration-and-tourism/isolation-and-quarantine/managed-isolation-and-quarantine/about-miq/miq-timeline on 20 November 2023.

FIGURE 2
Stringency Index of COVID-19 Response for Selected Countries.



Source: Hale *et al*. (2021). Data Accessed From https://github.com/OxCGRT/covid-policy-tracker on 4 September 2024.

for managing COVID-19 (Meehan *et al*., 2024a).

New Zealand's borders fully reopened in July 2022,[5] and the last workforce vaccine mandates were removed in September 2022 (Meehan *et al*., 2024a). Finally, in August 2023, all remaining restrictions, including the mandatory seven-day isolation period for positive cases and the requirement to wear masks in healthcare facilities, were lifted.[6]

Given that lockdowns led to the temporary closure of numerous businesses classified as 'non-essential' by the government, the strategy posed a significant risk of substantial job losses. This risk was particularly acute for workers in sectors where remote work was not feasible, such as retail and hospitality. To mitigate these risks and protect employment, the New Zealand government introduced the large-scale, nationwide *COVID-19 Wage Subsidy Scheme*.[7]

The scheme was designed to help employers retain staff, support self-employed individuals in maintaining their businesses, and, most importantly, prevent widespread job losses. The subsidy was capped, which meant it covered a higher proportion of wages for low-income earners, offering greater support to the most financially vulnerable workers.

The pandemic had a significant impact on the New Zealand labour market. In 2020, almost 1.5 million—62 per cent of all jobs—were supported by the wage subsidy scheme (Ministry of Social Development, 2022). Notably, the government's COVID-19 policy response was far larger in scale and reach compared to the measures taken to restore economic stability during the GFC (Maani *et al*., 2021).

[5] Retrieved from www.beehive.govt.nz/release/new-zealand's-border-fully-open-visitors-and-students on 20 November 2024.

[6] Retrieved from www.beehive.govt.nz/release/all-covid-19-requirements-removed on 20 November 2024.

[7] Retrieved on 10 August 2021 from www.workandincome.govt.nz/COVID-19/wage-subsidy/index.html.

An outcome evaluation of the wage subsidy scheme finds that it had a positive effect on firm survival rates and job retention (Hyslop *et al*., 2023). However, despite this scheme, there were still instances of permanent layoffs and increases in unemployment benefit recipients (Fletcher, 2020; Fletcher *et al*., 2021). Although the unemployment rate remained at around 4 per cent in the March and June quarters of 2020, it dramatically increased to 5.3 per cent in the September quarter of that year—the highest since 2016 (Stats NZ, 2020b). In New Zealand's largest city, Auckland, which faced the greatest impact of COVID-19 and the associated policy measures (including more frequent and prolonged lockdowns), the number of unemployed rose by 16,000 from the first to the third quarter of 2020. Nationally, employment fell by 22,000, the third-largest drop in employment since records began (Stats NZ, 2020b).

However, the labour market recovered reasonably quickly, with weekly hours, employment and the underutilisation rate, which had all been affected by the COVID-19 pandemic, returning to pre-COVID-19 levels. For example, the unemployment rate had returned to 4 per cent by June 2021.

The COVID-19 response has induced significant structural changes globally in the nature and composition of current business operations. For instance, large segments of the population began working from home as a routine practice (e.g., Brynjolfsson *et al*., 2020). Additionally, the pandemic's effects on employment and wages have been highly heterogeneous, varying by job type and worker characteristics.

For example, Graeber *et al*. (2021) found that in Germany, self-employed women were significantly more likely to experience wage losses than their male counterparts. Similarly, Foster (2020) reports that young workers in Australia were disproportionately more likely to drop out of the labour force, whereas mid-life workers were far less affected. In Austria, Gulyas and Pytka (2020) observe that females, low-paid workers and employees at younger, smaller and lower-paying firms were most adversely affected by lockdown restrictions.

In the United States, Hershbein and Holzer (2021) find that low-wage and minority workers bore the brunt of the pandemic's economic impact. Swedish data analysed by Campa *et al*. (2021) show that COVID-19 restrictions primarily affected young and foreign-born individuals. Similarly, Casarico and Lattanzio (2022) highlight that young, temporary and less-educated workers faced a much higher likelihood of job loss during the pandemic.

III *Conceptual Framework*

This paper builds on the idea that skills may provide resilience against economic shocks through multiple mechanisms. First, workers with higher literacy and numeracy skills may be more productive, enabling them to retain jobs or command higher wages during downturns. Second, higher skills may improve job search capabilities, enabling faster re-employment or better-quality matches after displacement. Third, higher-skilled workers may be better able to signal transferable skills to new employers, reducing the wage penalties associated with job changes.

In contrast, lower-skilled workers may be disproportionately vulnerable during crises. They may face higher risks of displacement, weaker bargaining power and larger wage penalties when changing employers. These channels are consistent with findings in other contexts (Hoynes *et al*., 2012b; Hanushek, 2015; Couch *et al*., 2020a).

However, the nature of the economic crisis matters. The GFC primarily disrupted demand and financial conditions, leading to widespread layoffs and wage stagnation. In contrast, the COVID-19 period involved supply restrictions, government-mandated shutdowns and substantial policy responses such as the Wage Subsidy Scheme. This may have reduced the relative disadvantage of lower-skilled workers compared to the GFC.

IV *Data and Descriptive Statistics*

PIAAC is a widely used survey that provides measures of skill. Administered by the OECD, PIAAC assesses and analyses the skills of the working-age adult population (aged 16–65 years). Conducted in over 40 countries, the survey evaluates adults' proficiency in literacy, numeracy and problem-solving in technology-rich environments. Its primary purpose is to facilitate cross-country comparisons of overall cognitive skill levels (Hanushek *et al*., 2015).

PIAAC focuses on measuring three cognitive skills that are "broadly transferable (generic) in nature" (OECD, 2013, p. 102). However, the survey is not meant to capture inter- and intra-personal skills or personal attitudes.

New Zealand participated in PIAAC in 2014. To ensure that the survey is representative across multiple dimensions, specific groups like ethnic minorities, were oversampled. Our primary variables of interest are the individuals' literacy and numeracy skills, separately measured on a 500-point proficiency scale. We define an individual as 'low-skilled' if their numeracy and literacy scores are both below 200; otherwise, they are classified as higher-skilled. This approach aligns with the OECD's categorisation of scores into different skill levels. Specifically, the OECD classifies individuals with scores below 176 as 'Below Level 1' and those with scores between 176 and 226 as 'Skill Level 1'. Our chosen cut-off point for the low-skilled population lies within the two ceiling scores of the OECD's lowest skill level classifications. However, we additionally check whether our empirical findings are affected by the chosen threshold.

It is worth noting that this definition results in a relatively small share of the population (around 5 per cent) being classified as 'low-skilled'. This is a direct consequence of following the OECD's categorisation of skill levels, where scores below 200 in both literacy and numeracy are indicative of severe skill limitations. We experimented with higher thresholds to capture a larger proportion of the workforce (see Section V 'Robustness tests' and Table S1). However, increasing the threshold risks classifying individuals with moderate or even adequate skill levels as low-skilled, which would weaken the interpretation of our findings. Despite the small size of the group, we consistently observe meaningful and statistically significant effects, underlining the importance of this subgroup for understanding vulnerability to economic shocks.

It is also important to note the empirical implications of the underlying assumption of constant skill levels. Since the PIAAC survey data in our analysis were collected in 2014, the time-invariant nature of these skill measures necessitates the assumption that individual skills remain unchanged during economic crises. Consequently, our findings do not support causal conclusions.[8]

Although the PIAAC dataset provides a comprehensive set of individual-level information, we additionally draw demographic and other time-invariant characteristics from a range of administrative data sources incorporated within the Integrated Data Infrastructure (IDI). The IDI is a large research database hosted by Statistics New Zealand (Stats NZ). It contains population-wide longitudinal microdata about individuals, households and organisations, sourced from government and non-government agencies, as well as Stats NZ surveys. The data are confidentialised by assigning a unique identifier to each individual, enabling linkage across datasets.

To examine how the impact of economic shocks on wages differs across skill levels, we link the PIAAC (2014) dataset with labour market information from the IDI's Inland Revenue data. For this analysis, we focus on two periods: 2005–2010 for the GFC and 2018–2023 for the COVID-19 pandemic, as noted in Section IV. That is, we analyse labour market information in the 2 years prior to the GFC and COVID-19 periods, as well as in the aftermath of both

[8] New Zealand also participated in the 2023 cycle of PIAAC; however, the data were unavailable at the time of writing. Once these data become accessible, it may be possible to assess the plausibility of the assumption that skill levels, as measured by PIAAC, remain relatively stable within individuals over time. This could be done by matching respondents from the 2014 and 2023 surveys based on characteristics such as age, ethnicity, migration status, and formal education level to evaluate the consistency of measured skill levels over time. We also considered the possibility of using the 2006 Adult Literacy and Life Skills Survey (ALL) data for New Zealand to test this assumption. However, significant design differences between PIAAC and ALL would make it challenging to determine whether observed differences reflect genuine changes in individuals' skill levels or arise from differences in survey design.

events. As noted in Section II, the last of New Zealand's COVID-19 restrictions were lifted in August 2023.

We focus our primary analysis on working-age men aged between 25 and 60 to ensure a consistent and relatively stable sample for analysis. This age range is less likely than younger or older age ranges to include individuals who are transitioning into or out of the labour market, such as students or retirees. Focusing on men also minimises potential complexities from gender-specific labour market patterns, such as maternity leave or higher rates of part-time work among women. However, we also provide supplementary results for working-age women at the end of Section V to offer a broader perspective on the gender dimension of the findings.

One limitation of the tax data we use is the absence of information on hours worked or hours paid. Since men in this age group are traditionally more likely to be in full-time employment, our primary analysis centres on this demographic. Nonetheless, we also present some findings for women to provide a broader perspective on labour market outcomes.

The Inland Revenue employer monthly schedule (IR-EMS) data provides monthly earnings and employment-related information, enabling the construction of a longitudinal monthly panel. This dataset, available from April 1999 onward, covers the entire New Zealand workforce and includes monthly data on all income sources. Among the seven potential income categories, our analysis focuses specifically on earnings from wages and salaries. We use the monthly gross earnings aggregated across all employers for each individual.

Each job in the dataset is linked to a unique employer identifier, which includes all employers with at least one employee receiving wages or salaries. To account for industry-specific effects on wage progression, we use the Australian and New Zealand Standard Industrial Classification 2006 (ANZSIC06), which is associated with each employer identifier. Furthermore, we track each employer back to their first recorded entry in the IR tax data. Given that economic literature indicates that businesses are most likely to exit the market during their early years, we categorise employers into three groups: (1) less than 2 years old, (2) 2–-4 years old and (3) more than 4 years old.

The comprehensive nature of the IR-EMS data also allows us to calculate the average wage for each employer-month pair and rank firms by their average wage levels. This enables the identification of low- and higher-paying firms, which may exhibit different survival probabilities during economic shocks. Additionally, we capture the number of unique employees receiving wages and salaries each month, which helps classify firms into size categories: very small (<10 employees), medium (10–25 employees) and large (>25 employees).

The dataset also accounts for individuals holding multiple jobs within a month. By using tax codes, we can distinguish between an individual's primary employment and secondary jobs.

For our analysis, we exclude self-employed individuals to focus solely on wage-and-salary earning employees. Since the IR-EMS data do not explicitly identify self-employment, we first remove all individuals employed at businesses with three or fewer employees. This accounts for the possibility that family members may occasionally support a self-employed business owner. We also drop all individuals whose wages and salaries are recorded in the IR-EMS data but who also file an IR3 tax return (which must be completed by self-employed individuals subject to specific criteria[9]).

In addition to the IR-EMS data, we link our PIAAC spine with other IDI datasets. First, we use the information provided by the Department of Internal Affairs (DIA) on the date (at the monthly level) of marriage/civil union registration and, where applicable, its

[9] IR3 tax returns need to be completed if the individual received more than $200 (before tax) in income from one of the following sources: self-employment, overseas, rental property including Airbnb and Bookabach, research and development tax incentives, 'under the December table' cash jobs, an estate, trust or partnership. See here for details (retrieved on 7 December 2021: https://www.ird.govt.nz/income-tax/income-tax-for-individuals/what-happens-at-the-end-of-the-tax-year/individual-income-tax-return—ir3).

legal dissolution. We use birth record data to count the number of biological children below 18. We have access to border movement data, which provide precise information on when individuals travel in and out of New Zealand. We remove the respective months if travel endured for more than 30 days. We also use information from the Ministry of Education to identify periods of tertiary education enrolment, excluding these spells from the analysis.

We also make use of two datasets that Stats NZ generates. The first one is the 'personal details file', which provides ethnicity information. The data includes demographic information and lists all ethnicities an individual has recorded across all data sets within the IDI. To assign a single ethnicity to each individual, we follow Stats NZ's approach of prioritising ethnicity. The ordering of prioritisation is the following: (i) Māori; (ii) Pacific Peoples; (iii) Asian; (iv) Middle East, Latin America or African (MELAA); (v) Other; (vii) European. The highest-ranked ethnic identity is assigned based on the aforementioned ordering in the case of multiple recorded ethnicity. The second source of information is the 'address notification data', which prioritises the address history to provide a best-guess list of residential addresses. We use this information to assign a regional indicator on the monthly level.

For each individual, we calculate the log difference in the year-on-year difference in total monthly wages and salaries (e.g., comparing March 2006–March 2007). We trim our dataset by removing the top and bottom 5 per cent of the wage changes. Our final sample consists of 1,119 individuals and 40,710 individual-month pairs for the GFC period and 1,305 individuals and 38,736 individual-month pairs for the COVID-19 period. The fraction of low-skilled workers is 5.4 per cent (60 individuals) for the GFC period and 4.4 per cent (57 individuals) for the COVID-19 period. We further calculate the individual's rank in the earnings distribution for each month and label those that belong to the bottom two deciles as low earners. Among this low-earnings group, the fraction of low-skilled individuals is substantially higher: 8.8 per cent during the GFC period and 7.0 per cent during the COVID-19 period.

Table 1 presents the mean wage progression for low- and higher-skilled individuals for both periods. In the top panel (Panel A), the data indicate that during the GFC period, low-skilled individuals experienced faster wage growth compared to higher-skilled individuals prior to the crisis (2005/06 and 2006/07). However, during the GFC years, wage growth for the low-skilled group slowed relative to their higher-skilled counterparts. This decline in wage growth for the low-skilled is even more pronounced among those in the bottom two deciles of the earnings distribution, as shown in Panel B.

For the COVID-19 period, differences in wage growth between low- and higher-skilled individuals are less pronounced, both before and after the economic shock. Interestingly, low-skilled workers experienced slightly faster wage growth than higher-skilled workers during the COVID-19 restrictions. While this difference is statistically significant only for the full sample (Panel A) in the 2021/22 period, it is consistent with the possibility that pandemic-related policy interventions, such as the wage subsidy scheme and increases to the minimum wage, may have disproportionately supported lower-paid and therefore lower-skilled workers during this period. We explore this potential explanation further in Section V.

V *Empirical Identification Strategy*

We are primarily interested in empirically documenting the variation in labour market implications of an economic crisis by different skill levels. Specifically, our focus is on how wage progression was affected by the GFC and COVID-19 restrictions. For our analysis, we estimate the following models for the GFC and COVID-19 periods, respectively:

$$\Delta y_{i,t} = \beta \mathrm{HS}_i + \delta_{\mathrm{GFC}} \mathrm{GFC}_{i,t} + \theta_{\mathrm{GFC}} \mathrm{GFC}_{i,t} \times \mathrm{HS}_i + \eta X_{i(t-12)} + u_{it}, \quad (1)$$

$$\Delta y_{i,t} = \beta \mathrm{HS}_i + \delta_{\mathrm{COVID}} \mathrm{COVID}_{i,t} + \theta_{\mathrm{COVID}} \mathrm{COVID}_{i,t} \times \mathrm{HS}_i + \eta X_{i(t-12)} + u_{it}, \quad (2)$$

TABLE 1
Mean Annual Wage Progression by Skill Level and Year

	GFC period				COVID-19 period		
Δ_{year}	Low-skilled	Higher-skilled	Difference	Δ_{year}	Low-skilled	Higher-skilled	Difference
Panel A: *Full sample*							
2005/06	0.046	0.032	0.014	2018/19	0.042	0.037	0.005
	(0.013)	(0.003)	(0.012)		(0.013)	(0.002)	(0.012)
2006/07	0.056	0.037	0.019*	2019/20	0.019	0.021	−0.002
	(0.013)	(0.003)	(0.011)		(0.015)	(0.003)	(0.013)
2007/08	−0.003	0.030	−0.034***	2020/21	0.044	0.036	0.008
	(0.011)	(0.003)	(0.011)		(0.014)	(0.003)	(0.013)
2008/09	−0.003	0.009	−0.012	2021/22	0.055	0.022	0.033***
	(0.011)	(0.002)	(0.010)		(0.014)	(0.002)	(0.012)
2009/10	0.03	0.022	0.008	2022/23	0.018	0.014	0.004
	(0.011)	(0.002)	(0.011)		(0.013)	(0.002)	(0.012)
Observations	2,181	38,529			1,692	37,044	
Panel B: *Low earnings*							
2005/06	0.165	0.155	0.010	2018/19	0.128	0.130	−0.002
	(0.020)	(0.009)	(0.023)		(0.019)	(0.007)	(0.021)
2006/07	0.152	0.143	0.009	2019/20	0.119	0.120	−0.002
	(0.020)	(0.008)	(0.021)		(0.023)	(0.007)	(0.024)
2007/08	0.072	0.125	−0.052**	2020/21	0.108	0.138	−0.030
	(0.016)	(0.008)	(0.020)		(0.021)	(0.008)	(0.024)
2008/09	0.050	0.113	−0.063***	2021/22	0.129	0.113	0.015
	(0.014)	(0.008)	(0.018)		(0.023)	(0.007)	(0.024)
2009/10	0.070	0.126	−0.056***	2022/23	0.127	0.100	0.026
	(0.016)	(0.007)	(0.019)		(0.022)	(0.007)	(0.022)
Observations	543	5,613			417	5,544	

Note: Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI. Numbers in () are std. err. *, ** and ***Signify statistical significance at the 10, 5 and 1 per cent-levels, respectively. Low earnings refer to the sample of workers whose earnings belong to the two bottom deciles 12 months ago.

with $i = 1, \ldots, N$ referring to the individual and t being a time-identifier. The time-identifier is on the monthly level and spans over the period 2005–2010 for the GFC analysis and 2018–2023 for the COVID-19 analysis. This implies $t{-}12$ refers to the same month in the previous year. The outcome variable is the log of the difference between wages earned in the same month of consecutive years $\left(\Delta_{y_{i,t}} = \log\left(y_{i,t}\right) - \log\left(y_{i,t-12}\right)\right)$. To reduce the impact of outliers, we remove the top and bottom 5 per cent observations. The results are robust to changes in the outlier threshold. Findings remain largely unchanged when adjusting the cut-off points to the top and bottom 1 per cent or 10 per cent.

As explanatory variables, we have a higher-skilled indicator HS_i, taking the value 1 if the individual's literacy or numeracy score is above 200 and 0 otherwise. Next, we control for year-specific effects, and we add an interaction effect between the higher-skilled indicator and the year. The interaction effects will help us identify heterogeneity in the impact of economic crisis across skill levels.

We do not include education as a control variable. Our objective is to estimate the total association between cognitive skills and wage progression, rather than the effect of skills conditional on education. Since education and skills are strongly correlated, including education as a control would absorb part of the variation in skills that is relevant for labour market outcomes. Moreover, while the relationship between education and labour market performance has been widely studied, our focus is to examine the direct association between skills and wage progression, particularly during periods of economic disruption.

$X_{i(t-12)}$ is a set of the following covariates measured at $t-12$. The vector includes information on prioritised ethnicity (time-invariant), age (linear and squared), binary indicator whether married/in a civil union, number of biological children below the age of 18 (top-coded at 4), region of residence, the log wage, industry classification, employer size (4–9, 10–24, 25+), percentile rank of the mean employee wage (linear and squared), age of the firm (categorised as <2 years, 2–4 years, 4+ years) and month fixed effects. u_{it} represents an idiosyncratic error term. The standard errors are clustered at the individual level in all our regressions.

We also calculate skill-group specific differences in wage progression compared to the base year of each crisis period (GFC: 2005/06; COVID-19: 2018/19) which is δ for the low-skilled and $\beta+\delta+\theta$ for the higher-skilled. Further, we calculate the marginal difference between low and higher skilled for each year as β for the base year and $\beta+\theta$ for the proceeding years.

VI Results

(i) Main Specification

In Table 2, we present the estimated coefficients of interest for both the GFC and COVID-19 periods. As outlined in Section III, the sample for the main specification is restricted to men aged between 25 and 60 years.

To aid interpretation, we first examine the skill-specific changes in wage progression across different years compared to the reference year (see Table 3). Specifically, these changes are represented by δ for the low-skilled and $\delta+\theta$ for the higher-skilled from Equations (1) and (2).

Relative to the base year of 2005/06, wage growth for the low-skilled group declined by approximately 5–6 per cent during the GFC years of 2007/08 and 2009/10 (column 1). Although wage growth also declined in 2009/10, this change was not statistically significant. For the higher-skilled group, wage growth remained unchanged in 2007/08 compared to 2005/06 but decreased by about 2 per cent in 2008/09 and 1 per cent in 2009/10 (column 3).

During the COVID-19 period, the changes in wage progression for the low-skilled group were smaller, with no statistically significant differences between 2018/19 and subsequent years (2019/20, 2020/21, 2021/22 and 2022/23) (column 5). For the higher-skilled group, wage growth relative to 2018/19 was lower in 2019/20, 2021/22 and 2022/23 by about 1–2 per cent (column 7).

For the low-earnings sample, the effects during the GFC period were more pronounced than for the total sample. Wage growth for the low-skilled group decreased by approximately 9–11 per cent in 2007/08, 2008/09 and 2009/10 relative to 2005/06 (column 2). For the higher-skilled group, earnings growth was also lower in these years, but the difference was much smaller (about 2–4 per cent) (column 4).

In the COVID-19 period for the low-earnings sample, there are almost no statistically significant differences for both the low-skilled and higher-skilled groups (columns 6 and 8). The one exception was 2022/23, when higher-skilled workers experienced a 3 per cent reduction in wage growth compared to the reference year of 2018/19 (column 8).

For example, the results for the GFC period are consistent with the idea that lower-skilled workers were less able to maintain wage progression due to factors such as lower productivity, weaker bargaining power and a higher likelihood of experiencing involuntary job changes. The muted differences in wage growth by skill level during the COVID-19 period may reflect how the Wage Subsidy Scheme helped preserve employment relationships, particularly for lower-skilled workers who would otherwise have been more vulnerable to displacement and wage losses.

We now turn to a comparison of wage progression between the higher-skilled and low-skilled group by examining the interaction term in Equations (1) and (2) (see Table 4). Specifically, earnings progression of the higher-skilled group relative to the low-skilled one is β in the base year and $\beta+\theta$ in subsequent years.

For the total sample, relative to the low-skilled group, the higher-skilled had higher

TABLE 2
Regression Coefficients for Wage Progression, Men Aged 25–60

	GFC period			COVID-19 period	
	(1) Total sample	(2) Low-earnings sample		(3) Total sample	(4) Low-earnings sample
Higher-skilled	0.030*	−0.004	Higher-skilled	0.040**	0.026
	(0.016)	(0.029)		(0.018)	(0.026)
2006/07	0.010	−0.008	2019/20	−0.014	0.012
	(0.021)	(0.035)		(0.026)	(0.033)
2007/08	−0.050**	−0.089***	2020/21	0.009	−0.005
	(0.025)	(0.031)		(0.019)	(0.030)
2008/09	−0.057***	−0.112***	2021/22	0.033	0.033
	(0.022)	(0.029)		(0.023)	(0.035)
2009/10	−0.028	−0.085***	2022/23	−0.002	0.015
	(0.024)	(0.033)		(0.025)	(0.036)
Higher-skilled × 2006/07	−0.006	−0.002	Higher-skilled × 2019/20	−0.001	−0.015
	(0.022)	(0.038)		(0.026)	(0.035)
Higher-skilled × 2007/08	0.049*	0.061*	Higher-skilled × 2020/21	−0.009	0.017
	(0.025)	(0.034)		(0.020)	(0.033)
Higher-skilled × 2008/09	0.036	0.069**	Higher-skilled × 2021/22	−0.048**	−0.051
	(0.022)	(0.032)		(0.023)	(0.037)
Higher-skilled × 2009/10	0.019	0.058	Higher-skilled × 2022/23	−0.021	−0.044
	(0.024)	(0.036)		(0.025)	(0.038)
Observations	40,710	6,156		38,736	5,961

Note: Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI. Coefficients from estimation of Equations (1) and (2). Coefficients represent the estimated change in the log wage difference from the base year for each period, relative to the base year (excluded category), which is 2005/06 for the GFC period and 2018/19 for the COVID-19 period. Coefficients for the interaction terms (higher-skilled × year) represent the difference in wage progression between higher-skilled and lower-skilled workers, conditional on the year. Numbers in () are clustered std. err. *, ** and ***signify statistical significance at the 10, 5 and 1 per cent-levels, respectively. Low earnings refer to the sample of workers whose earnings belong to the two bottom deciles 12 months ago. Base year (excluded category) is 2005/06 for the GFC period and 2018/19 for the COVID-19 period.

earnings progression during the GFC period. In 2007/08, 2008/09 and 2009/10, earnings growth for the higher-skilled group was between about 5–8 per cent higher than the low-skilled group (column 1). Restricting attention to the low-earnings sample yields similar results: earnings growth for the higher-skilled group was about 5–7 per cent higher than the low-skilled group in 2007/08, 2008/09 and 2009/10 (column 2).

In contrast, there are fewer differences between the low-skilled and higher-skilled groups during the COVID-19 period. For the total sample, the higher-skilled group had faster earnings progression than the lower-skilled group in 2018/19 and 2019/20 (i.e., in the pre-COVID-19 years). During the years when COVID-19 restrictions were in place, the higher-skilled group had higher earnings growth by about 3 per cent compared with the lower-skilled group, but the difference is statistically significant only at the 10 per cent level. There are no statistically significant differences between the higher-skilled and low-skilled groups in 2021/22 and 2022/23 (column 3).

Restricting attention to the low-earnings group yields even fewer differences. The only year where there is a statistically significant difference (at the 10 per cent level) is 2020/21, where the difference is about 4 per cent (column 4). In 2021/22 and 2022/23, the low-skilled group actually had faster earnings progression than the higher-skilled group, but the differences are not statistically significant.

TABLE 3
Marginal Earnings Progression: Relative to Base Year

	GFC period					COVID-19 period			
	Low skill		Higher skill			Low skill		Higher skill	
Δ_{year}	(1) Total	(2) Low earnings	(3) Total	(4) Low earnings	Δ_{year}	(5) Total	(6) Low earnings	(7) Total	(8) Low earnings
2005/06	*Reference*				2018/19	*Reference*			
2006/07	0.010	−0.008	0.004	−0.010	2019/20	−0.014	0.012	−0.015***	−0.003
	(0.021)	(0.035)	(0.005)	(0.015)		(0.026)	(0.033)	(0.004)	(0.014)
2007/08	−0.050**	−0.089***	0.000	−0.027*	2020/21	0.009	−0.005	0.000	0.012
	(0.025)	(0.031)	(0.005)	(0.015)		(0.019)	(0.03)	(0.004)	(0.014)
2008/09	−0.057***	−0.112***	−0.021***	−0.043***	2021/22	0.033	0.033	−0.015***	−0.018
	(0.022)	(0.029)	(0.005)	(0.014)		(0.023)	(0.035)	(0.004)	(0.013)
2009/10	−0.028	−0.085***	−0.009**	−0.028*	2022/23	−0.002	0.015	−0.023***	−0.029**
	(0.024)	(0.033)	(0.005)	(0.015)		(0.025)	(0.036)	(0.004)	(0.013)
Observations	2,181	543	38,529	5,613		1,692	417	37,044	5,544

Note: This table reports the marginal change in log wage progression for low-skilled and higher-skilled workers relative to the base year for each period (2005/06 for the GFC period and 2018/19 for the COVID-19 period). The estimate for each year, Δ_{year}, represents the change in wage progression relative to the base year for workers in the respective skill group. Earnings progression relative to the base year is δ for the low-skilled and $\delta + \theta$ for the higher-skilled, as described in Equations (1) and (2). Numbers in () are clustered std. err. *, ** and ***signify statistical significance at the 10, 5 and 1 per cent-levels, respectively. Low earnings refer to the sample of workers whose earnings belong to the two bottom deciles 12 months ago.

TABLE 4
Marginal Earnings Progression: Higher-Skilled Relative to Low-Skilled

Δ_{year}	GFC period			COVID-19 period	
	(1) Total	(2) Low earnings		(3) Total	(4) Low earnings
2005/06	0.030*	−0.004	2018/19	0.040**	0.026
	(0.016)	(0.029)		(0.018)	(0.026)
2006/07	0.024	−0.006	2019/20	0.039**	0.011
	(0.017)	(0.024)		(0.018)	(0.030)
2007/08	0.079***	0.057***	2020/21	0.031*	0.044*
	(0.017)	(0.022)		(0.018)	(0.025)
2008/09	0.066***	0.065***	2021/22	−0.008	−0.025
	(0.018)	(0.021)		(0.017)	(0.029)
2009/10	0.049**	0.054**	2022/23	0.019	−0.018
	(0.019)	(0.024)		(0.018)	(0.030)
Observations	40,710	6,156		38,736	5,961

Note: This table reports the marginal change in log wage progression of higher-skilled workers relative to low-skilled workers for each year in the respective crisis periods (2005/06 for the GFC period and 2018/19 for the COVID-19 period). The estimate for each year, Δ_{year}, represents the change in wage progression for higher-skilled workers relative to the low-skilled group, compared to the base year. Earnings progression for the higher-skilled relative to the low-skilled is β in the base year and $\beta + \theta$ in subsequent years, as described in Equations (1) and (2). Numbers in () are clustered std. err. *, ** and ***signify statistical significance at the 10, 5 and 1 per cent-levels, respectively. Low earnings refer to the sample of workers whose earnings belong to the two bottom deciles 12 months ago.

Overall, the earnings growth of those with low skill levels was more negatively affected during the GFC period compared to those with higher skill levels. This aligns with expectations that more vulnerable groups tend to fare worse during times of economic crisis.

In contrast, during the COVID-19 period, there was little difference in the earnings growth of those with low skills versus those with higher skill levels. In fact, during 2021/22, low-skilled workers experienced significantly faster wage progression than their higher-skilled counterparts – a finding that contrasts with the pattern observed during the GFC. This suggests that pandemic-era policy responses, including the wage subsidy scheme, together with general labour market policies such as increases to the minimum wage, may have helped to mitigate or even reverse expected skill-based disparities in wage growth during this period.

Evidence on earnings progression during the pandemic in New Zealand supports this notion, indicating that the COVID-19 shock did not necessarily have a disproportionately negative effect on more vulnerable groups. For instance, Meehan *et al*. (2024b) found that the gap in earnings progression between underemployed and fully utilised workers actually decreased during the COVID-19 period, suggesting that the pandemic may have had a levelling effect on earnings progression.

Several factors may have contributed to the distinct nature of the COVID-19 period. The government's wage subsidy scheme, paid at a flat rate, covered a higher share of wages for lower-paid workers. Since lower-paid workers are more likely to belong to vulnerable groups, such as the underemployed or those with lower skill levels, the scheme may have been more effective at protecting these workers compared to less vulnerable ones. Additionally, demand for jobs which are often undertaken by lower-skilled workers may have been more buoyant than other sectors of the labour market during the pandemic due to the high-demand for workers within businesses classified as 'essential' by the New Zealand government (e.g., supermarket workers, courier drivers). This trend may have allowed traditionally more vulnerable workers to increase their hours and/or hourly earnings to a greater extent than other workers. Finally, the significant increases in the minimum wage during this period likely provided further support to lower-paid workers. The minimum wage rose by 6.8 per cent in April 2020 and 5.8 per cent in 2021, outpacing general wage inflation at the time, which may have disproportionately benefited workers in lower-paying jobs.

(ii) Robustness Tests

We perform several robustness estimations to test the validity of our key findings. First, we assess the sensitivity of our results to the skill-score cut-off used to define low- and higher-skills. For this purpose, we re-estimate the model, adjusting the cut-off score from 180 to 230 in five-point increments (recall that the baseline model defines low-skilled individuals as those scoring below 200 in both literacy and numeracy scores) (see Table S1). This analysis focuses on the low-earnings sample, where the effects were more pronounced.

For the GFC period, we find that independent of the chosen skill score, wages drop significantly in the years 2007/08 and 2008/09 compared to the reference year. For the interaction terms, we observe minimal significant effects for skill scores of 195 and below, likely due to the reduced sample size of the low-skilled group. However, for higher skill scores, the findings remain relatively stable, particularly for the interaction effect in 2008/09. For the COVID-19 period, we again do not find any significant effects. For example, the results are generally robust to the cut-off score for defining low- and higher-skills.

We also examine the impact of changing the cut-off point for defining the low-earnings group. Starting at the lowest decile, we incrementally raise the cut-off by 0.05 percentage points until reaching the median (see Table S2). Two key observations emerge for the GFC period. First, the magnitude of the year effect for 2007/08 and 2008/09 increases, in absolute terms, when using a lower cut-off point. Second, the interaction effects also increase with lower cut-off points, suggesting that wage losses among the low-skilled are more severe in the lowest-earning group, while higher-skilled individuals are less affected. Finally, for the COVID-19 period, we find that the higher-skilled coefficient becomes significant with a higher percentile cut-off point. Despite these nuances, the overarching conclusion holds: the low-skilled group experienced greater wage losses relative to the higher-skilled group during the GFC, but this pattern was much less pronounced during the COVID-19 period.

Lastly, we test whether our results vary when numeracy and literacy proficiency are analysed separately rather than combined into a single low-skilled indicator. To do this, we re-estimate the regressions focusing on each skill independently and report the results for the low-earnings sample in Table S3. The findings remain consistent across these alternative specifications, further reinforcing the robustness of our conclusions.

(iii) Mechanisms

Employment stability

One explanation for the differing wage progression patterns across skill levels during economic crises is employment stability. Our data allow us to investigate those who change employers versus those who stay at the same employer. Inland Revenue assigns unique employer identifiers, enabling us to identify movements between different employers. As individuals might receive earnings from multiple employers in 1 month, we prioritise by the individual's tax code for the main employer (and by earnings level if in a month the tax code is the same).

Table 5 shows the proportion changing employers between $t-12$ and t. For the total sample of men aged 25–60, those with low skill levels are more likely to change employers than those with higher skill levels, suggesting that higher-skilled workers enjoy greater employment stability. This indicates that those with higher skill levels have more stable employment. However, among those on low earnings at $t-12$, the difference in employer change rates between the skill groups is much smaller.

We run separate regressions for those staying at the same employer and those changing their employer. Table S4 shows that higher-skilled workers have, on average, a significantly higher wage progression when staying at the same employer for both

TABLE 5
Share Changing Their Employer

	GFC period		COVID-19 period	
	Total	Low earnings	Total	Low earnings
Low skilled	0.218	0.279	0.226	0.277
Higher skilled	0.150	0.245	0.136	0.201

Note: This table reports the share of individuals who changed employers during the respective crisis periods (GFC and COVID-19) for both low-skilled and higher-skilled workers. Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI. Sample of men aged 25–60. Low earnings refer to the sample of workers whose earnings belong to the two bottom deciles 12 months ago.

periods. For the economic downturn periods 2007/08 and 2008/09, there is a noticeable decline in wage progression, which is only partially offset by the interaction effect for higher-skilled workers.

In contrast, the results are more pronounced for individuals who change employers. We can find a strong wage drop during the GFC period, which is limited to low-skilled workers. For the COVID-19 period, low-skilled workers who changed employers experienced a larger wage drop in 2019/20. However, these effects are not statistically significant.

A limitation of the data is that we cannot observe the reason behind employer changes and are, therefore, unable to distinguish between voluntary and involuntary job changes. Nonetheless, given that low-skilled workers who changed employers experienced greater wage declines during the GFC period compared with those who stayed with the same employer, it is reasonable to infer that much of this job movement was involuntary. This suggests that the slower wage progression observed for the low-skilled group relative to the higher-skilled group during the GFC was at least partly driven by their greater susceptibility to involuntary job loss, which forced them to change employers and accept lower wage progression.

Wage subsidy scheme

A possible reason for the differences between the GFC and COVID-19 period is that the government's response package during the COVID-19 period was much larger than its response during the GFC period. As noted earlier, the government introduced a wage subsidy scheme to preserve employment during the pandemic. This scheme was initially implemented in March 2020, with employers experiencing at least a 30 per cent decline in their revenue eligible to receive a 12-week wage subsidy, irrespective of industry or sector. In June 2020, the scheme was extended, with the eligibility threshold adjusted to a 40 per cent revenue decline and the payment period reduced to 8 weeks. It was extended again under the same 40 per cent revenue decline criterion, but for shorter periods (generally 2 weeks) in August 2020, March 2021 and September 2021.

The payment rates were capped at the equivalent of the minimum wage for full-time work, meaning they replaced a larger share of the wages for lower-paid workers. Once approved, wage subsidies were transferred as lump-sum payments to employers, who then used the funds to pay their employees' wages. Inland Revenue records detail the employers and the periods in which they received wage subsidies. However, the data do not allow us to identify the specific employees who directly benefited from the scheme.

For this reason, we construct an indicator that takes the value of 1 if the individual's employer received wage subsidy payments in a particular month and 0 otherwise. We also include an interaction term between the wage subsidy indicator and the higher-skilled indicator to examine differential effects by skill level.

Table S5 presents the estimated coefficients for both for the total sample of men aged 25–60 and for those on low earnings at $t-12$. The interaction terms between the year and higher-skilled workers are generally not statistically significant, except for 2021/22, when higher-skilled workers experienced approximately 6 per cent lower wage progression compared with lower-skilled workers. The wage subsidy coefficient reveals that wage subsidies had a positive impact on wage progression. However, the interaction term between wage subsidies and higher skill levels is negative, indicating that higher-skilled workers benefited less from wage subsidies compared to their lower-skilled counterparts.

This finding helps to explain why, in the descriptive statistics, low-skilled workers appeared to have experienced slightly faster wage growth during the COVID-19 period. The wage subsidy scheme and minimum wage adjustments may have temporarily boosted the earnings of low-skilled workers more than those of higher-skilled workers, especially in sectors with a high concentration of lower-paid roles. However, once we control for worker characteristics, sectoral differences and employer dynamics in the regression analysis, the wage progression advantage for low-skilled workers largely disappears, suggesting that these policy effects were not sufficient to generate sustained skill-based wage differentials beyond the crisis response period.

For the low-earnings sample, none of the year-higher-skilled interaction terms are statistically significant. However, similar to the results for the total sample, the wage subsidy coefficient is positive, while the wage-subsidy-higher-skilled interaction term is negative. This further confirms that higher-skilled workers benefited less from wage subsidies compared to their lower-skilled counterparts.

(iv) Results for Working-Aged Women

So far, we have focused exclusively on men aged 25–60. We now extend our analysis and examine the wage progression of women within the same age group.

Table S6 presents the regression coefficients for women aged 25–60. Overall, the patterns of wage progression are less pronounced and clear-cut for women compared with men. For the low-skilled group, wage progression during the GFC period was not significantly slower than in the base year of 2005/06, as the effects of δ and θ largely offset each other in both the total and low-earnings samples.[10] However, among higher-skilled women, wage progression was lower in 2008/09 and 2009/10 compared to 2005/06, with a decline of about 1–2 per cent. Interestingly, higher-skilled women exhibited slower wage progression than their low-skilled counterparts in some GFC years, contrasting with the findings for men. During the COVID-19 period, there were no statistically significant differences in wage progression across skill levels.

These results suggest that the impact of economic crises on women's wage progression may differ from their effects on men. As previously noted, one limitation of the data used in this analysis is the lack of information on hours worked or paid. Consequently, it is unclear whether changes in wages reflect reductions in hourly earnings or in hours worked or paid. Previous research on New Zealand highlights that mothers of young children experienced a decline in employment likelihood during the early stages of the COVID-19 pandemic, while fathers' employment rates remained largely unchanged (Dasgupta *et al.*, 2024). This is in line with expectations given early childhood education centres and schools were closed and mothers are likely to have taken on more of the resulting increase in the household childcare burden.

A possible reason why the impact of economic crises on women's wage progression is less straightforward compared to the effects on men's wage progression is the 'added worker' effect (Kletzer, 2002). When a husband experiences job loss or a reduction in working hours, wives—who are more likely to be out of the labour force or working part-time—may enter the labour market or increase their hours to help offset the household's income loss. This suggests that the mechanisms influencing women's wage progression may have been quite different from those affecting men.

VII Discussion and Conclusion

Skills make up a critical component of human capital. Numerous studies have shown that higher literacy and numeracy skills are associated with better labour market performance and therefore with higher economic wellbeing. However, there is limited empirical evidence on whether cognitive skills provide sufficient protection against unanticipated economic shocks. By

[10] Position in the earnings distribution was calculated separately for each gender.

focusing on two of the most recent and significant global economic disruptions—the GFC and the COVID-19 pandemic—our study is among the first to offer empirical insights into the role of cognitive skills in shaping labour market outcomes during economic crises.

For our analysis, we use a New Zealand-based sample from the OECD's PIAAC survey, which assesses individuals' literacy and numeracy skills. This survey data is linked to high frequency administrative tax records that provide detailed labour market information of the entire workforce in New Zealand. The linked dataset allows us to longitudinally track the PIAAC sample's employment and earnings information during the two economic crises.

Our findings reveal that during the GFC, earnings losses among higher-skilled individuals were significantly less severe than those experienced by the low-skilled group. However, this disparity disappeared during the COVID-19 period, when government-imposed restrictions were in effect.

Our analysis highlights the importance of the policy environment during economic crises. Specifically, the levels, conditions and timing of government interventions—such as the wage subsidy scheme during the COVID-19 period—played an important role in shaping the labour market outcomes observed across different skill levels. The large-scale government response during the pandemic helped mitigate disparities in wage progression that were more pronounced during the GFC. Particularly noteworthy is the contrast in wage progression trends observed across different skill levels during the two major economic crises. Our findings for the GFC align with the existing literature, substantiating the view that higher cognitive skills are associated with better economic outcomes. However, the COVID-19 results, which show no significant differences in wage changes across skill levels, highlight several potential explanations.

The size and scope of the government's response package during the pandemic may have been a key factor in this outcome, including the swift implementation of the wage subsidy scheme. This scheme, capped at the minimum wage level, disproportionately benefited lower-wage workers, who are also more likely to be low-skilled. Furthermore, the wages of low-skilled workers may have been supported by strong demand for workers in roles classified as 'essential' by the New Zealand government, such as supermarket employees and delivery drivers. Additionally, significant increases to the minimum wage in 2020 and 2021 would have further bolstered earnings among lower-skilled workers, reducing disparities in wage progression across skill levels.

While our study explores some of these mechanisms, it also highlights substantial scope for future research. In particular, the differing results for women compared with men warrant further investigation, as they suggest that the impacts of economic crises and government interventions may not be uniform across genders. Additionally, future research could examine the effectiveness of government interventions in protecting the wellbeing of economically vulnerable populations during unforeseen economic shocks. Similarly, studies could investigate the evolution of labour market trends and the industry-specific dynamics of different skill levels over time, providing deeper insights into these critical issues.

Conflict of Interest

The authors declare no conflict of interest.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Robustness results: Skill score cut-off, low-earnings sample.

Table S2. Robustness results: Low-earnings group percentile cut-off.

Table S3. Robustness results: Literacy and numeracy scores examined separately.

Table S4. Regression results: Same employer versus changed employer.

Table S5. Regression coefficients: Wage subsidy scheme.

Table S6. Regression coefficients, women aged 25–60.

REFERENCES

Adams-Prassl, A., Boneva, T., Golin, M. and Rauh, C. (2020), 'Inequality in the Impact of

Coronavirus Shock: Evidence from Real Time Surveys', *Journal of Public Economics*, **189**, 104245.

Antoni, M. and Heineck, G. (2012), 'Do Literacy and Numeracy Pay Off? On the Relationship Between Basic Skills and Earnings,' IZA Discussion Paper No. 6882.

Blackburn, M.L. and Neumark, D. (1993), '-Omitted-Ability Bias and the Increase in the Return to Schooling', *Journal of Labor Economics*, **11**, 521–544.

Bowen, W.G. and Finegan, T.A. (1966), 'Educational Attainment and Labor Force Participation', *The American Economic Review*, **56**, 567–582.

Brynjolfsson, E., Horton, J.J., Ozimek, A., Rock, D., Sharma, G. and TuYe, H.-Y. (2020), 'COVID-19 and Remote Work: an Early Look at US Data,' National Bureau of Economic Research Working Paper No. 27344.

Campa, P., Roine, J. and Strömberg, S. (2021), 'Unemployment Inequality in the Pandemic: Evidence from Sweden,' CEPR Discussion Paper No. DP16330.

Carneiro, P.M. and Heckman, J.J. (2003), 'Human Capital Policy,' IZA Discussion Paper No. 9495.

Casarico, A. and Lattanzio, S. (2022), 'The Heterogeneous Effects of COVID-19 on Labour Market Flows: Evidence from Administrative Data', *The Journal of Economic Inequality*, **20**, 537–558.

Chiswick, B.R., Lee, Y.L. and Miller, P.W. (2003), 'Schooling, Literacy, Numeracy and Labour Market Success', *The Economic Record*, **79**, 165–181.

Couch, K.A., Fairlie, R.W. and Xu, H. (2020a), 'Early Evidence of the Impact of COVID-19 on Minority Unemployment', *The Economic Journal*, **130**, F406–F437.

Couch, K.A., Fairlie, R.W. and Xu, H. (2020b), 'Early Evidence on the Impacts of COVID-19 on Minority Unemployment', *Journal of Public Economics*, **192**, 104287

Daly, M.C., Buckman, S.R. and Seitelman, L.M. (2020), 'The Unequal Impact of COVID-19: Why Education Matters', *FRBSF Economic Letter*, **17**(5), 1–5.

Dasgupta, K., Kirkpatrick, L. and Plum, A. (2024), 'Parental Employment at the Onset of the Pandemic: Effects of Lockdowns and Government Policies,' Federal Reserve Board Finance and Economics Discussion Series No. 2024-012.

Dixon, S. and Tuya, C. (2010), 'Workers with Low Literacy or Numeracy Skills: Characteristics, Jobs and Education and Training Patterns,' *Department of Labour*.

Dunn, T., Hamill, D. and Song, Z. (2023), 'Unmasking COVID-19's Economic Impact,' New Zealand Institute of Economic Research Working Paper 2023-01.

Earle, D. (2009), *Skills, Qualifications and Wages: An Analysis from the Adult Literacy and Life Skills Survey*. Ministry of Education, Wellington, New Zealand.

Eckstein, Z., Sarid, A. and Tamir, Y.Y. (2016), 'Do Cognitive Skills Impact Growth or Levels of GDP per Capita?' Centre for Economic Policy Research Discussion Paper 43-1469800205.

Erwin, C., Meehan, L., Pacheco, G. and Turcu, A. (2020), *An Empirical Portrait of New Zealand Adults Living with Low Literacy and Numeracy Skills*. New Zealand Work Research Institute, Auckland, New Zealand.

Fletcher, M. (2020), 'Government's Income Support Responses to the COVID-19 Pandemic', *Policy Quarterly*, **167**, 73–78. https://doi.org/10.26686/pq.v16i3.6560

Fletcher, M., Prickett, K.C. and Chapple, S. (2021), 'Immediate Employment and Income Impacts of COVID-19 in New Zealand: Evidence from a Survey Conducted During the Alert Level 4 Lockdown', *New Zealand Economic Papers*, **56**, 73–80. https://doi.org/10.1080/00779954.2020.1870537

Forbes, M., Barker, A. and Turner, S.A. (2010), 'The Effects of Education and Health on Wages and Productivity,' Productivity Commission Staff Working Paper.

Foster, G. (2020), 'Early Estimates of the Impact of COVID-19 Disruptions on Jobs, Wages, and Lifetime Earnings of Schoolchildren in Australia', *Australian Journal of Labour Economics*, **23**, 129–152.

Gibson, J. (2022a), 'Government Mandated Lockdowns Do Not Reduce COVID-19 Deaths: Implications for Evaluating the Stringent New Zealand Response', *New Zealand Economic Papers*, **56**, 17–28.

Gibson, J. (2022b), 'Hard, Not Early: Putting the New Zealand Covid-19 Response in Context', *New Zealand Economic Papers*, **56**, 1–8.

Graeber, D., Kritikos, A.S. and Seebauer, J. (2021), 'COVID-19: A Crisis of the Female Self-Employed', *Journal of Population Economics*, **34**, 1141–87. https://doi.org/10.1007/s00148-021-00849-y

Gulyas, A. and Pytka, K. (2020), 'The Consequences of the COVID-19 Job Losses: Who Will Suffer Most and by How Much?', *COVID Economics*, **1**, 70–107.

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S. and Tatlow, H. (2021), 'A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker)', *Nature Human Behaviour*, **5**, 529–538.

Hanushek, E.A. (2015), 'The Economic Value of Education and Skills', in Hanushek, E.A., Machin, S. and Woessmann, L. (eds), *Handbook of the Economics of Education*, vol. **5**. Elsevier, Oxford; 1–56.
Hanushek, E.A. and Woessmann, L. (2008), 'The Role of Cognitive Skills in Economic Development', *Journal of Economic Literature*, **46**, 607–668.
Hanushek, E.A., Schwerdt, G., Wiederhold, S. and Woessmann, L. (2015), 'Returns to Skills around the World: Evidence from PIAAC', *European Economic Review*, **73**, 103–130.
Hanushek, E.A., Schwerdt, G., Wiederhold, S. and Woessmann, L. (2017), 'Coping with Change: International Differences in the Returns to Skills', *Economics Letters*, **153**, 15–19.
Hershbein, B. and Holzer, H.J. (2021), 'The COVID-19 Pandemic's Evolving Impacts on the Labor Market: Who's Been Hurt and What we Should do,' IZA Discussion Paper No. 14108.
Hoynes, H., Miller, D.L. and Schaller, J. (2012a), 'Who Suffers during Recessions?', *Journal of Economic Perspectives*, **26**, 27–48.
Hoynes, H.W., Page, M.E. and Stevens, A.H. (2012b), 'Poverty in America: Trends and Explanations', *Journal of Economic Perspectives*, **26**, 3–28.
Hyslop, D.R., Maré, D.C. and Minehan, S. (2023), 'COVID-19 Wage Subsidy: Outcome Evaluation,' Motu Working Paper 23-04.
Iversen, J.M.V. and Strøm, B. (2020), 'Skills, Employment, and Labor Market Institutions: Evidence from PIAAC', *Labour*, **34**, 277–304.
Kletzer, K.T. (2002), 'Worker Displacement and the Added Worker Effect', *Journal of Labor Economics*, **20**, 722–744.
Lane, M. and Conlon, G. (2016), 'The Impact of Literacy, Numeracy and Computer Skills on Earnings and Employment Outcomes,' OECD Education Working Paper No. 129.
Leigh, A. (2008), 'Returns to Education in Australia', *Economic Papers: A Journal of Applied Economics and Policy*, **27**, 233–249.
Liang, X. (2022), 'The Impact of COVID-19 on Employment and Income of Vocational Graduates in China: Evidence from Surveys in January and July 2020', *China Economic Review*, **75**, 101832. https://doi.org/10.1016/j.chieco.2022.101832
Maani, S.A. (2021), 'COVID-19 Government Responses to Labour Market Disruptions and Economic Impacts: The New Zealand Model,' IZA Discussion Paper Series 14929.
Maré, D. and Chapple, S. (2000), *Literacy Formation and its Influence on Earnings and Jobs*. Department of Labour, Wellington, New Zealand.
Maré, D.C. and Fabling, R. (2013), 'The Incidence and Persistence of Cyclical Job Loss in New Zealand,' Motu Working Paper 13-08.
McIntosh, S. and Vignoles, A. (2001), 'Measuring and Assessing the Impact of Basic Skills on Labour Market Outcomes', *Oxford Economic Papers*, **53**, 453–481.
Meehan, L., Mitchell, L. and Pacheco, G. (2024a), *Workforce Vaccine Mandates: The Effect on Vaccine Uptake and Healthcare Workers' Labour Market Outcomes*. New Zealand Policy Research Institute, Auckland, New Zealand.
Meehan, L., Pacheco, G. and Turcu, A. (2024b), 'Underemployment and Wage Growth during COVID-19', *New Zealand Economic Papers*, 1–17, doi: https://doi.org/10.1080/00779954.2024.2394669
Ministry of Social Development (2009), 'Annual Report 2008/2009,' New Zealand Government.
Ministry of Social Development (2022), 'Who Received the 2021 COVID-19 Wage Subsidies?'.
Murnane, R.J., Willett, J.B., Duhaldeborde, Y. and Tyler, J.H. (2000), 'How Important Are the Cognitive Skills of Teenagers in Predicting Subsequent Earnings?', *Journal of Policy Analysis and Management*, **19**, 547–568.
OECD (1998), *Education at a Glance: OECD Indicators 1998*. Organisation for Economic Co-Operation and Development, Paris.
OECD (2012), *OECD Employment Outlook 2012*. OECD, Paris. https://doi.org/10.1787/empl_outlook-2012-en
OECD (2013), *The Survey of Adult Skills: Reader's Companion*. Organisation for Economic Co-operation and Development, Paris.
Prickett, K.C., Fletcher, M., Chapple, S., Doan, N. and Smith, C. (2020), 'Life in Lockdown: The Economic and Social Effect of Lockdown During Alert Level 4 in New Zealand,' Institute for Governance and Policy Studies Working Paper 20/03.
Reserve Bank of New Zealand (2022), *In Retrospect: Monetary Policy in New Zealand 2017 to 2022*. Reserve Bank of New Zealand, Wellington, New Zealand.
Shomos, A. (2010), 'Links Between Literacy and Numeracy Skills and Labour Market Outcomes,' Productivity Commission Staff Working Paper.
Shomos, A. and Forbes, M. (2014), 'Literacy and Numeracy Skills and Labour Market Outcomes in Australia,' Productivity Commission Staff Working Paper.
Vignoles, A. (2016), 'What is the Economic Value of Literacy and Numeracy?' *IZA World of Labor*, (229).