THE EXPRESSION, EXPERIENCE AND TRANSCENDENCE OF LOW SKILLS IN AOTEAROA NEW ZEALAND

SKILLS, ECONOMIC CRISES AND THE LABOUR MARKET

ABOUT THIS RESEARCH PROGRAMME

Over half a million adult New Zealanders live with low literacy and/or numeracy (L+N) skills, with a strong over-representation of Māori and Pacific peoples. This has significant economic and social costs, including increased risk of unemployment and poverty, detrimental effects on physical and mental well-being, and decreased social and political attachment.

This programme applies a mixed-method approach to the following research aims: to build a detailed population-wide picture of those with low L+N skills; analyse their life-course pathways and effectiveness of interventions with respect to a range of economic and social outcomes; forecast future changes in population skill level; and develop an understanding of the barriers and enablers that build resilience to risk, along with pathway to transcend low skills.

For further information about our programme and other outputs, see http://workresearch.aut.ac.nz/low-skills

RESEARCH PARTNERS

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Skills, Economic Crises and the Labour Market

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Abstract

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 lockdown in 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 labor 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, the low skilled group experienced the largest wage drop when changing their employer during the GFC crisis. However, during the recent pandemic-induced lockdown period, we cannot detect differences in wage progression across skill levels.

JEL Code: J24, J31, O12
Keywords: Skills, Economic Crises, Wage progression, PIAAC, administrative data

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1 Introduction

The positive effect of skills on wages and employment has been well-documented in the economic literature (McIntosh and Vignoles, 2001; Murnane et al., 2000; Carneiro and Heckman, 2003; Hanushek et al., 2015). Moreover, empirical evidence points at skills helping foster a countries' economic growth (Hanushek and Woessmann, 2008). However, in most countries, a large fraction of the workforce only has acquired a basic set of skills, which makes *upskilling* a pressing policy topic. But skills might have not only a positive long-term labour market impact but also bolster against economic shocks (Hanushek et al., 2017). In this paper, we study two distinctively different economic crises–the Global Financial Crisis of 2008/2009 and the COVID-19 lockdown in 2020–to identify skill-related differences of economic shocks on wage progression in New Zealand.

Human capital and skills are interwoven and substantially determine labour market success and wages. The empirically challenging aspect of studying the interrelation of skills and labour market outcome lies in measuring the first. Many studies use educational attainment as a proxy for skill level. However, a wage premium is still empirically observable for individuals with similar education levels and different skills levels. This study uses the Organisation for Cooperation and Economic Development's (OECD) Programme for the International Assessment of Adult Competencies (PIAAC), which provides numeracy and literacy scores for New Zealand in 2014.

Surveys on skills typically only provide cross-sectional labour market information. We circumvent this limitation by linking the PIAAC survey with various New Zealand administrative datasets, including monthly Inland Revenue income data. This enables us to track earnings from wages & salaries of the PIAAC participants for a time window of two decades. Our study focuses on the following two periods: the years 2005-09, labelled as the Global Financial Crisis (GFC) period, and the period 2017-20, labelled as the COVID-19 period.

We use PIAAC's numeracy and literacy scores, measured on a 500-point proficiency scale, and tag someone as low skilled if both scores are below 200 and higher-skilled otherwise. Between 4 and 5 % are identified as low-skilled by this definition. Our outcome variable of interest is how monthly wages have progressed on an annual basis. To account for the effect of skills, we include (among others) a binary indicator of having higher skills, a year identifier and the interaction effect of both. This enables us to determine skill-specific differences in wage progression. As low-skilled workers are often low paid, we stratify our sample by conditioning it on those whose earnings from wages & salaries belong to the two lowest deciles in the previous year.

For the GFC sample, we find that across all skill levels, wage growth between 2007/08 and 2008/09 is significantly lower compared to the reference period 2005/06–and the drop intensifies for workers on low earnings. However, the interaction effects indicate that the wage reduction is further exacerbated for low-skilled workers. Between 2005/06 and 2008/09, wages decline, on average, for the low-skilled low-earning worker by -13.3% and by -4.8% for higher-skilled workers on low earnings 12 months before–and the difference of 8.5% points is statistically significant at the 5% level. To understand why the wages of low-skilled workers shrink during spells of economic downturn, we split the sample by those who stay at their current employer and those moving jobs. We do not find skill-specific differences in wage progression when restricting our sample to workers employed at the same employer as 12 months ago. However, low-skilled workers experience a substantial wage drop for those who change their employer. For example, in 2008/09, low-skilled workers wages declined, on average, 15.1% points larger than that of higher-skilled–and the difference grows to 33.1% points for workers on low earnings.

For the COVID-19 period, we do not find a variation in wage progression between the skill groups. One potential explanation is that the wage subsidy scheme–a newly introduced government policy to secure jobs during the pandemic–helped the low-skilled stay in their jobs. We find that workers whose employer received wage subsidies experience, on average, a substantial wage drop of 11.5% points. Further, higher skills seem only partially to reduce the wage decline.

The remainder of the paper is structured in the following way: Section 2 provides a literature review on the interrelation of skills and labour market performance, and a description of the Global Financial Crisis and the COVID-19 period in New Zealand; Section 3 introduced the datasets we use; Section 4 describes the empirical identification strategy; Section 5 discusses the findings, and finally Section 6 concludes.

2 Background

2.1 Human capital, skills and labour market outcome

According to the 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". Apparently, human capital can be shaped by several interrelated traits that include cognitive skills and non-cognitive attributes like personality characteristics, motivation, behavioural dispositions, and even physical appearance (OECD, 2013). However, several of these individual-level attributes that determine human capital are unobservable. As such, in empirical research, educational attainment is often used as a proxy for human capital. Consequently, to highlight the economic and wellbeing implications of human capital or skill, numerous studies have tried to empirically estimate the relationship between years of schooling and labour market performance (Bowen and Finegan, 1966; Leigh, 2008; Forbes et al., 2010). However, education might not reflect an individual's true human capital level perfectly. Moreover, individuals may improve their basic skills through alternative means (such as on-the-job training and life experiences) other than tertiary or vocational education. In their seminal paper, Blackburn and Neumark (1993), who use data on white males from the US National Longitudinal Survey of Youth, show that not all high school students profit from going to college and that labour market payoff depends on cognitive skills.[1]

In the past two decades, several studies have focused on the effect of individuals' numeracy and literacy skills on labour market return. 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) to 'demonstrate that cognitive skills are important determinants of subsequent earnings' [p. 562]. McIntosh and Vignoles (2001) explore UK-based evidence indicating that increasing literacy and numeracy skills improve wages and employment likelihood. Furthermore, cognitive ability measured using the Armed Forces Qualifying Test scores is positively associated with hourly wages (Carneiro and Heckman, 2003). Chiswick et al. (2003) find that participants of the 1996 Australian Aspects of Literacy Survey who perceive themselves to have good numeracy skills are less likely to participate in the labour force than those who perceive to have excellent numeracy skills. Using data from the Australian Adult Literacy and Lifeskills Survey, Shomos (2010) shows that improving literacy and numeracy skills increases labour force participation and hourly wages for both men and women. In a follow-up study, Shomos and Forbes (2014) find similar results for Australian men and women when using PIAAC data. Using the German Working and Learning in a Changing World Survey, Antoni and Heineck (2012) find empirical evidence supporting the international findings. Lane and Conlon (2016) further show that improving skills in other areas such as Information and Communication Technology (ICT) skills also results in a higher likelihood of employment and higher wages. Estimates show that low ICT skilled individuals with formal education have smaller returns than high ICT skilled individuals without formal education.

In a seminal study by Hanushek et al. (2015), the authors analyze the effect of skills on wages in 23 OECD countries. Consistent with the above findings, the authors show that higher cognitive skills–measured in terms of numeracy, liter-

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

acy, and problem-solving skills–are related to higher wages across all participating countries. Cross-country comparisons by Marius Vaag Iversen and Strøm (2020) show that improving numeracy and literacy also positively affects employment when controlling for age and country fixed effects. The magnitude of employment-skill estimates is larger across countries with centralized bargaining and strict employment rules than countries without those institutional characteristics.

At the macro level, the cognitive skill level of a labour force is positively related to GDP per capita, suggesting that countries with a more skilled workforce tend to experience more rapid growth (Hanushek and Woessmann, 2008; Vignoles, 2016). Additionally, Eckstein et al. (2016) find a positive association between cognitive skills and GDP.

So far, the number of New Zealand-related studies on the labour market relevance of skills are sparse. In a study conducted on behalf of the Department of labour, Maré and Chapple (2000) use the Adult Literacy Survey and find that improving literacy results in an increased likelihood of employment and earnings. Using the Adult Literacy and Lifeskills Survey, Earle (2009) finds that the difference of one standard deviation in literacy and numeracy accounts for a 20 percent difference in hourly earnings on average. These findings are confirmed by Dixon and Tuya (2010), who show that having a higher skill level is associated with higher average hourly earnings and longer job tenure. Alternatively, 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.

2.2 The GFC and its impact on New Zealand

The adverse economic implications of the global financial crisis of 2007-09 substantially affected the New Zealand economy as well. New Zealand experienced a sharp decline in employment, especially between the 2008-Q4 and 2009-Q4, exceeding even what most other OECD economies experienced (OECD, 2012). Not surprisingly, New Zealand also witnessed a 3.1 percent decline in its total output, which, however, was below the OECD average of -5.3 percent.

Like in most previous recessions, the economically vulnerable groups were the most severely affected. For example, unemployment among youth workers (15-24) went up from 11.9 percent in 2008-Q4 to 17.6 percent in 2009-Q4–and that for prime-age workers (25 and 54), the increase was by only 1.6 percentage points (2008-Q4: 3.2 percent, 2009-Q4: 4.8 percent).[2] Additionally, a substantial portion of workers with no/only school qualifications and those with a temporary contract were subjected to redundancies (OECD, 2012). The prevalence of job losses also varied across industries. According to Maré and Fabling (2013), the three most largely affected sectors were the construction, manufacturing, finance and insurance industries.

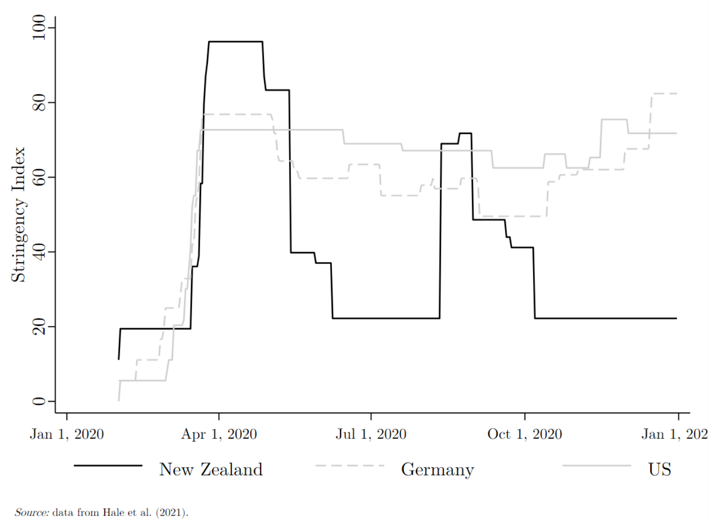
To reduce the adverse impact of the GFC, the New Zealand government introduced several one-off response tools. For instance, to maintain public trust in New Zealand's banking system, the government implemented a retail deposit guarantee scheme to ensure repayment for those who had monetary deposits in failed financial institutions (*Crown Retail Deposit Scheme*, 2008). For those losing employment, several different labour welfare programs were introduced: the *ReStart Transitional Relief Programme*, which provided limited transitional assistance for people who had lost their josb and were looking for other suitable work; *Redundancy Support* to support staff into alternative employment jobs or training; and *Job Support Scheme* that pays an allowance to workers who agree to work reduced hours. According to a Ministry of Social Development (2009) report, 4 500 people had received ReStart assistance and the Job Support Scheme saved over 400 jobs.

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

2.3 The COVID-19 period in New Zealand

To contain the spread of COVID-19, most OECD countries went into lockdown in early 2020. On 28 February 2020, the first Covid case was reported in New Zealand. In response, restrictions were imposed on all indoor gatherings of more than 100 people. Moreover, international borders were closed to all but New Zealand citizens and permanent residents on 19 March.[3] On 25 March, New Zealand went into a strict (Level 4) lockdown. The lockdown included working-from-home orders for non-essential workers, border closures, and restricted mobility (see Prickett et al., 2020). The stringency of the lockdowns varied across the countries (see Hale et al. (2021) and Figure 1) and with it the success to eradicate the virus (Kung et al., 2021). As the government's lockdown strategy was found to be effective to keep the spread under control, New Zealand eventually lifted almost all restrictions on 8 June 2020.

Figure 1: Stringency index on COVID-19 response in 2020 for selected countries



[3]Retrieved from (10 August 2021): https://covid19.govt.nz/alert-levels-and-updates/history-of-the-COVID-19-alert-system/

However, given that the provisions of the March lockdown implied temporary closure of numerous non-essential businesses, the strategy involved a risk of substantial job losses. This was primarily a major concern for businesses that cannot be conducted remotely (e.g., retail businesses or restaurants). Therefore, to protect employment, the New Zealand government introduced a large-scale nationwide *COVID-19 Wage Subsidy Scheme*[4] to help employers and self-employed individuals retain their businesses and, more importantly, keep financially supporting their workers.

Not surprisingly, the pandemic significantly impacted the New Zealand labour market. Application for the wage subsidy reached 400 000 by the end of March, increasing further into April. Importantly, given the differences in the nature of the shocks induced by the GFC and by the COVID-19 crises, the government's policy response during the COVID-19 period is comparatively much larger in size and had a wider reach than that of the strategy adopted to restore economic stability during the GFC (Maani et al., 2021).

Despite the wage subsidies by the government during the COVID-19 period, there were still incidences of permanent layoff and increases in job seeker support (Fletcher, 2020; Fletcher et al., 2021). Although the unemployment rate remained at around four percent in the March and June quarters, the rate of job loss dramatically increased to 5.3 percent in the September quarter of 2020, the highest since 2016 (Stats NZ, 2020b). For Auckland, the number of unemployed increased by 16 000 from the first to the third quarter of 2020. National employment would fall by 22 000, the third-largest drop in employment since employment was first tracked (Stats NZ, 2020b). However, recent Reserve Bank of New Zealand estimates shows that weekly hours, employment, and the under-utilisation rate, which had all been affected by the COVID-19 pandemic, have since all recovered to pre-Covid levels (Reserve Bank of New Zealand, 2021).

The COVID-19 response has globally induced structural changes in the na-

[4]Retrieved from (10 August 2021): https://www.workandincome.govt.nz/COVID-19/wage-subsidy/index.html

ture and composition of current business operations. For instance, large parts of the population routinely started working from home (e.g., Brynjolfsson et al., 2020). Moreover, the employment and wages effect is heterogeneous depending on the job type. For example, Graeber et al. (2021) in Germany, self-employed women are found to be significantly more likely to experience a wage loss than self-employed men . Foster (2020) finds that young workers in Australia are significantly more likely to drop out of the labour force. In Austria, Gulyas et al. (2020) find that "females, low paid workers, as well as for younger, smaller and worse-paying firms" [p. 90] were most adversely affected by the country's lockdown restrictions. This is confirmed by Hershbein and Holzer (2021), who find similar results for low-wage and minority workers in the US. Using Swedish data, Campa et al. (2021) look at the full population of registered unemployed individuals and find that the COVID-19-induced restrictions mostly affected the young and foreign-born individuals. Similarly, Casarico and Lattanzio (2020) show that young, temporary, low-skilled workers are at a much greater risk of losing their jobs during the COVID-19 pandemic in Italy.

3 Data and Descriptive Statistics

The PIAAC is a commonly used survey that documents measures of skill. The OECD administers PIAAC to assess and analyze skills of the working-age adult population (aged 16 to 65 years). The survey is conducted in over 40 countries and measures adults' proficiency in literacy, numeracy, and problem-solving in technology-rich environments. The survey is primarily designed to allow cross-country assessment of overall cognitive skill levels (Hanushek et al., 2015). In particular, the PIAAC aims at measuring three cognitive skills that are "broadly transferable (generic) in nature" (OECD, 2013, p. 102). However, the survey is not meant to portray inter- and intra-personal skills or personal attitudes.

New Zealand participated in the OECD's survey in 2014. To ensure that the survey is representative across multiple dimensions, specific groups like ethnic minorities are oversampled. Our primary variables of interest are the individuals' numeracy and literacy skills, separately measured on a 500-point proficiency score in PIAAC. We define an individual as 'low-skilled' if their numeracy and literacy scores are both below 200 and higher-skilled otherwise. Our strategy is similar to OECD's approach of categorizing the scores into different skill levels. The OECD identifies the group with scores literacy/numeracy below 176 as "Below Level 1" and individuals 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 also important note the empirical implications of the underlying assumption of constant skill levels. Since the PIAAC survey available for our analysis was conducted in 2014, the time-invariant nature of the information requires our analysis to rely on the assumption that skills do not vary during economic crises. As such, our findings may not be causally interpreted.

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 database hosted by Statistics New Zealand (Stats NZ). The database includes population-wide longitudinal microdata about individuals, households, and organisations. These data are sourced from government, non-government agencies, and Stats NZ surveys. The data are confidentialised by assigning a unique identifier to each individual, which can be used to link different datasets with each other.

To understand how the impact of economic shocks on wages differs across skill levels, we link the PIAAC (2014) dataset with recent and past labour market information from the IDI's Inland Revenue data. As noted in Section 4, we choose the period 2005-09 for the GFC-related analysis and 2017-20 for the COVID-19 analysis. We restrict the sample to full-time working age men aged between 25 and 60.

The Inland Revenue employer monthly schedule (IR-EMS) data provides monthly earnings and employment-related information. This allows us to create a monthly longitudinal panel. The IR EMS tax data are available from April 1999 onward for the entirety of the NZ workforce and document monthly information on all income sources. There are seven potential income categories, and we are particularly interested in information from earnings, measured in terms of wages & salaries. We use the monthly gross earnings across all employers for our analysis. With each job, a unique employer-id is linked. The employer-id covers all employers with at least one employee who receives wages and salaries. Attached to the employer-id is the Australian and New Zealand Standard Industrial Classification (ANZSIC) from 2006, which we use to account for industry-specific effects in wage progression. We further track each employer back to the first date they recorded in the IR tax data. The economic literature has shown that companies are most likely to drop out of the market during the initial years of their entry. We form a categorical variable that takes the value 1 if the employer is less than two years old; 2 if the duration is between two and four years old; and 3 if the duration is more than four years old. As the IR tax information holds information on the whole New Zealand workforce, we calculate the mean wage of its employees for each employer-month pair and rank them accordingly. This helps us determine low and higher-paying firms that might have genuinely different survival chances during an economic shock. We also identify the number of unique employees who received each month wages and salaries. This enables us to differentiate between very small firms (<10 employees), medium firms (up to 25 employees) and large firms (>25 employees). Individuals can hold multiple jobs in a month, and the individual's tax code allows us to separate the main employment from a second job.

For the purpose of our analysis, we exclude self-employed individuals from our analysis. Since the IR-EMS does not explicitly allow us to identify self-employment, we first remove all individuals who work at an employer with three or fewer employees to account 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 and are also observed to file an IR3 tax return (which must be completed by self-employed individuals subject to specific criteria[5]).

One limitation of the IR EMS data is that it does not contain information on the hours worked. As traditionally, working age-men aged above 25 are most likely to be in full-time employment, our primary analysis focuses on that group. However, we also provide findings for women.

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 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 remove the respective spells of individuals who are enrolled in tertiary education.

We also make use of two datasets that Stats NZ generates. The first one is the 'personal details file', which provides information on ethnicity. 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 prioritizing ethnicity. The ordering is the following: (1) Māori; (2) Pacific Peoples; (3) Asian; (4) Middle East, Latin America and America (MELAA); (5) Other; (6) NZ 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

[5]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)

data', which prioritizes the address history to provide a best-guess list of residential addresses. We use the regional indicator on the monthly level.

We then calculate for each individual the log value of the difference in the annually aggregated monthly wages and salaries (e.g., March 2006 and March 2007). We trim our dataset by removing the top and bottom 5% of the wage changes. Our final samples consist of 32 298 individual-month pairs for the GFC period and 23 382 individual-month pairs for the COVID-19 period. The fraction of low skilled workers is 5.2% for the GFC period and 3.7% 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 earnings. We see that the fraction of low skilled individuals is much higher among this earnings group: 14.3% for the GFC period and 9.7% for the COVID-19 period.

Table 1 presents the mean wage progression for low and higher skilled for both periods. The top panel (Panel A) indicates for the GFC period that low skilled experienced a larger wage progression before the crisis (2005/06 and 2006/07). Still, this relationship flips in the two following years. This pattern is further pronounced for the two latter years when looking at individuals with low earnings only (Panel B). For the COVID-19 period, we do not observe much differences in the wage progression between low and higher skilled, both before and after the economic shock, as well as for the full sample and those with low earnings.

4 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 Global Financial Crisis and the COVID-19 lockdown. For our analysis, we estimate the following model:

$$\Delta_{y_{i,t}} = \beta\, \mathrm{HS}_i + \sum_{\text{year}} \delta\, \text{year}_{i,t} + \sum_{\text{year}} \theta\, \text{year}_{i,t} \times \mathrm{HS}_i + \eta X_{i(t-12)} + u_{it} \qquad (1)$$

Table 1: Wage progression

	GFC period				COVID-19 period		
Δ_{year}	low skill	higher-skilled	diff	Δ_{year}	low skill	higher-skilled	diff
Panel A: ***Full Sample***							
2005/06	0.051	0.033	0.018	2017/18	0.028	0.032	-0.005
	(0.013)	(0.003)	(0.012)		(0.013)	(0.002)	(0.012)
2006/07	0.066	0.036	0.030***	2018/19	0.038	0.037	0.001
	(0.013)	(0.003)	(0.011)		(0.013)	(0.002)	(0.012)
2007/08	-0.007	0.034	-0.041***	2019/20	0.015	0.020	-0.005
	(0.012)	(0.003)	(0.000)		(0.015)	(0.003)	(0.013)
2008/09	-0.012	0.007	-0.019*				
	(0.011)	(0.002)	(0.011)				
Panel B: ***Low earnings***							
2005/06	0.183	0.159	0.024	2017/18	0.109	0.116	-0.007
	(0.02)	(0.142)	(0.024)		(0.019)	(0.007)	(0.021)
2006/07	0.172	0.142	0.030	2018/19	0.124	0.13	-0.006
	(0.021)	(0.008)	(0.022)		(0.019)	(0.007)	(0.021)
2007/08	0.080	0.144	-0.064***	2019/20	0.113	0.117	-0.004
	(0.018)	(0.008)	(0.022)		(0.023)	(0.007)	(0.024)
2008/09	0.046	0.111	-0.065***				
	(0.016)	(0.008)	(0.019)				

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 percent-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 2005-09 for the GFC analysis and 2017-20 for the COVID-19 analysis (excluding January and February for the latter one). This implies $t-12$ refers to the same month in the previous year. The outcome variable is the log wage difference of the same month in two consecutive years $\left(\Delta_{y_{i,t}} = \log(y_{i,t}) - \log(y_{i,t-12})\right)$. To reduce the impact of outliers, we remove the top and bottom 5% observations. Findings are hardly affected when moving to top/bottom 1% or 10%-cut-off points.

As explanatory variables, we have a higher-skilled indicator HS_i, taking the value 1 if the individual's numeracy or literacy 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.

$X_{i(t-12)}$ 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), duration of the firm (categorized 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: 2017/18) 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.

5 Results

5.1 Main specification

In Table 2, we present the estimated coefficients of interest for both the GFC and COVID-19 periods. To facilitate the interpretation, we first discuss the skill-specific changes of wage progression for the different years compared to the reference year (see Table 3).

First, we find that during the economic shock in 2008 and 2009, wages of the low skilled dropped, on average, by around 6-7%. The size of this drop rises to 10-13% when restricting the sample to low-skilled workers who were on low earnings in the preceding year ($t - 12$). We also detect a wage decline when looking at the higher-skilled. However, the magnitude is substantially smaller and only significantly negative for 2009. On average, we find a wage drop of 2% in general and of 5% for higher-skilled who received low earnings in the previous year. When moving to the COVID-19 period, the changes in wage progression between the years are minimal for the low skilled and not significantly different from zero. This is independent of the sample used. For the higher-skilled, we find a moderate drop of wages by 1% for the total sample–though this pattern is not detected anymore when moving to the group of low earners.

To understand whether the difference in the skill-specific wage progression is significantly different from zero, we turn to the interaction effects of Table 2. For the GFC period, the higher skilled have a significantly higher wage progression in 2007/08 and 2008/09, which gets further exacerbated when restricting the sample to low earners only. When switching to the COVID-19 period, none of the interaction effects significantly differ from zero.

However, one noteworthy difference between the two periods is that for the COVID-19 period, we find a significant positive impact of being higher-skilled on wage progression of about 5% for the full population. This magnitude drops to 3% and turns insignificant when restricting the sample to low earners. This aspect is underlined when calculating the marginal effects for the GFC period (Table 4):

Table 2: Regression results

	GFC period			COVID-19 period	
	total	low earnings		total	low earnings
HS	0.026	-0.011	HS	0.052***	0.031
	(0.017)	(0.028)		(0.017)	(0.025)
2006/07	0.014	-0.001	2018/19	0.015	0.014
	(0.024)	(0.035)		(0.024)	(0.036)
2007/08	-0.058**	-0.096***	2019/20	-0.001	0.019
	(0.026)	(0.033)		(0.025)	(0.035)
2008/09	-0.069***	-0.133***			
	(0.023)	(0.031)			
HS $\times$ 2006/07	-0.011	-0.013	HS $\times$ 2018/19	-0.008	0.003
	(0.024)	(0.038)		(0.024)	(0.038)
HS $\times$ 2007/08	0.062**	0.082**	HS $\times$ 2019/20	-0.008	-0.008
	(0.027)	(0.037)		(0.025)	(0.038)
HS $\times$ 2008/09	0.046**	0.085**			
	(0.023)	(0.034)			

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

higher skills do not necessarily provide a higher wage progression in general but are likely to safeguard against wage drops during an economic downturn. In Table 4, we find that during the COVID-19 period, the higher-skilled experiences a higher wage progression in general. However, this pattern is not observed for individuals with low earnings.

Table 3: Changes of wage progression over time

	GFC period					COVID-19 period			
	low skill		higher skill			low skill		higher skill	
Δ_{year}	total	low earnings	total	low earnings	Δ_{year}	total	low earnings	total	low earnings
2005/06			*reference*		2017/18			*reference*	
2006/07	0.014	-0.001	0.003	-0.014	2018/19	0.015	0.014	0.007*	0.017
	(0.024)	(0.035)	(0.005)	(0.015)		(0.024)	(0.036)	(0.004)	(0.012)
2007/08	-0.058**	-0.096***	0.003	-0.013	2019/20	-0.001	0.019	-0.009**	0.010
	(0.026)	(0.033)	(0.005)	(0.016)		(0.025)	(0.035)	(0.004)	(0.013)
2008/09	-0.069***	-0.133***	-0.023***	-0.048***					
	(0.023)	(0.031)	(0.005)	(0.015)					

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

Table 4: Marginal effects

Δ_{year}	GFC period total	GFC period low earnings		COVID-19 period total	COVID-19 period low earnings
2005/06	0.026	-0.011	2017/18	0.052***	0.031
	(0.017)	(0.028)		(0.017)	(0.025)
2006/07	0.015	-0.024	2018/19	0.045**	0.034
	(0.019)	(0.028)		(0.019)	(0.027)
2007/08	0.088***	0.071***	2019/20	0.044**	0.023
	(0.019)	(0.027)		(0.018)	(0.029)
2008/09	0.072***	0.074***			
	(0.019)	(0.025)			

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

5.2 Robustness tests

We perform several robustness estimations to test the validity of our key findings. First, we test how our findings are affected by the chosen skill-score cut-off to define low and higher skills. For this reason, we repeat our estimation starting at a score of 180 and moving up in 5-points until 230. We focus on the low earnings sample as findings are most pronounced in that group. 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. Concerning the interaction terms, we hardly find any significant effect for skill scores of 195 and below (although the sample size of the low-skilled shrinks substantially). However, the findings for higher skill scores remain relatively stable, especially for the interaction effect for 2008/09. For the Covid-19 period, we again do not find any significant effects.

We change the cut-off point to define the low earnings group as a second robustness analysis. We start at the lowest decile and move up by 0.05 percentage points until reaching the median (see Table A.2). For the GFC period, two observations are noteworthy: the magnitude of the year effect for 2007/08 and 2008/09 increases, in absolute terms, when choosing a lower cut-off point. Further, the respective interaction effect also increases with a lower cut-off point. This indicates that especially among the low earning group, the low skilled experience stronger wage losses while higher-skilled are not affected by this phenomenon. Finally, for the Covid-19 period, we find that the higher skilled coefficient turns significant with a higher percentile cut-off point.

In our analysis, we define someone as low-skilled if their numeracy and/or literacy proficiency score is below 200. To test whether one of our results vary when we create our low-skilled indicator by looking at the two skills separately, we re-estimate our regressions by individually focusing on each of the two skills. As an example, we present the esimation results for the low earnings group in Table A.3. The findings do not differ across the alternative specifications.

5.3 Mechanisms

One reason why wages progress differently across skill levels during an economic crisis can be explained by the option to move between employers. Inland Revenue assigns unique employer identifiers, enabling us to identify movements between different employers. As individuals might receive earnings from multiple employers in one 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 fraction of observations changing their employer between $t-12$ and t. We can see that the proportion of men changing their employer is larger among the low-skilled than the higher-skilled group. However, the difference between the skill levels for those on low earnings at $t-12$ is little for the GFC period.

We run separate regression for those staying at the same employer and those changing their employer. Table 6 shows that higher-skilled have, on average, a significantly higher wage progression when staying at the same employer for both periods. For the economic downturn periods 2007/08 and 2008/09, we can see a drop in wage progression, which is only compensated partly by the interaction effect for the higher-skilled. However, when moving to those individuals who

Table 5: Share changing their employer

	GFC period		COVID-19 period	
	total	low earnings	total	low earnings
low skilled	0.2353	0.2979	0.1763	0.1368
higher skilled	0.1608	0.2707	0.1466	0.2260

Note: Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI.

change their employer, findings are much more pronounced. We can find a strong wage drop during the GFC period, which is limited to the low-skilled workers. For the COVID-19 period, we find that low-skilled workers changing their employer experienced a larger wage drop in 2019/20. However, the effects are not statistically significant.

As previously mentioned, the government introduced a wage subsidy scheme to secure employment during the COVID-19 pandemic. The payment rates were at the minimum wage level for someone who worked full time. Once approved, the wage subsidies were transferred in the form of lump-sum payments to the employers, who then paid their employees' wages from the received amount. Thus, the Inland Revenue has records on the employers and the periods in which the employer received wage subsidies. However, the data does not allow us to identify the employees who benefitted from the wage subsidy scheme.

For this reason, we construct a marker that takes the value of 1 if the employer received wage subsidy in a particular month and 0 otherwise. We further add an interaction effect of the wage subsidy marker and the higher-skilled marker. Note that the wage subsidy scheme was introduced in 2020 and did not exist in the years before. Furthermore, the scheme was not limited to any specific industries or sectors.

Table 7 presents the estimated coefficients, both for the total sample and for men on low earnings at $t-12$. We can see a large wage progression in 2019/20– which is compensated if the employee was working at an employer who was part of the wage-subsidy pool. For low-skilled workers on low earnings, this results in

Table 6: Regression results by employer

	GFC period			
	Same employer		Changed employer	
	total	low earnings	total	low earnings
HS	0.043***	0.017	-0.040	-0.109**
	(0.016)	(0.030)	(0.041)	(0.052)
2006/07	0.021	-0.005	-0.047	-0.073
	(0.025)	(0.038)	(0.048)	(0.051)
2007/08	-0.027	-0.058	-0.182***	-0.241***
	(0.029)	(0.042)	(0.054)	(0.056)
2008/09	-0.040*	-0.084**	-0.165***	-0.316***
	(0.024)	(0.034)	(0.046)	(0.073)
HS $\times$ 2006/07	-0.018	-0.011	0.050	0.091
	(0.025)	(0.042)	(0.051)	(0.060)
HS $\times$ 2007/08	0.028	0.033	0.192***	0.267***
	(0.030)	(0.045)	(0.057)	(0.066)
HS $\times$ 2008/09	0.016	0.033	0.151***	0.331***
	(0.024)	(0.038)	(0.049)	(0.080)
	Covid-19 period			
HS	0.055***	0.047	0.012	-0.055
	(0.017)	(0.029)	(0.056)	(0.064)
2018/19	-0.012	0.030	0.111*	-0.052
	(0.025)	(0.041)	(0.062)	(0.092)
2019/20	0.008	0.030	-0.077	-0.095
	(0.023)	(0.041)	(0.075)	(0.102)
HS $\times$ 2018/19	0.019	-0.016	-0.102	0.079
	(0.025)	(0.042)	(0.064)	(0.097)
HS $\times$ 2019/20	-0.021	-0.020	0.084	0.132
	(0.024)	(0.043)	(0.076)	(0.107)

Note: Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI. Numbers in () are clustered std err. *, **, and *** signify statistical significance at the 10, 5, and 1 percent-levels, respectively.

Table 7: Wage subsidy scheme

	total	low earnings
HS	0.060***	0.054
	(0.020)	(0.037)
2018/19	0.023	0.007
	(0.025)	(0.040)
2019/20	0.087*	0.125*
	(0.045)	(0.074)
HS $\times$ 2018/19	-0.016	-0.019
	(0.025)	(0.043)
HS $\times$ 2019/20	-0.055	-0.083
	(0.046)	(0.078)
Wage subsidy	-0.115**	-0.169**
	(0.045)	(0.071)
Wage subsidy $\times$ HS	0.038	0.104
	(0.046)	(0.075)

Note: Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI. Numbers in () are clustered std err. *, **, and *** signify statistical significance at the 10, 5, and 1 percent-levels, respectively.

a wage decline by, on average, 4.4%. We find that the negative impact of working at an employer who received wage subsidies is partially cushioned for higher-skilled men when looking at the interaction effect. For higher-skilled workers on low earnings, wages grew, on average, by 3.1% and the difference to lower-skilled is statistically significant at the 5% level. Also, we do not find any significant difference between the skill levels for workers at an employer who did not receive wage subsidies.

5.4 Moving into benefits

Inland Revenue additionally provides information on whether an individual received benefits. As an additional outcome variable, we look at individuals who received earnings solely from wages & salaries in $t-12$ and construct a binary indicator that takes the value of 1 if the individual receives benefits at t and 0 if the individual still receives earnings from wages & salaries without receiving benefits. We repeat our analysis with the same set of covariates and continue to classify our regressions for the total sample and for low earning groups. To simplify the interpretation of the covariates, we use a linear probability model.

Table A.4 presents the relevant coefficients and Table A.4 provides skill-specific changes in the likelihood of entering benefit recipients over time for the GFC and the COVID-19 periods. As we can see from the latter table for the GFC period, the likelihood to move from employment into benefit dependency increases in 2008/09 compared to 2005/06–and the effect is significant for the higher-skilled. We find that the effect size increases for those with low earnings at $t-12$, but we do not detect a statistically significant effect. For the COVID-19 period, we also find that for the low-skilled, the probability of receiving benefits is higher in 2019/20 compared to the reference years 2017/18. The effect is insignificant and somewhat smaller when restricting the sample to previously observed low earners.

When we move back to the coefficient table, there are three noteworthy findings: first, having higher skills seems not to substantially lower the risk of entering benefit dependency in the GFC period and in the COVID-19 period. Second, the likelihood of receiving benefits increases for the GFC (2008/09, resp. 2019/20), and third, higher skills seem to reduce the impact of economic shocks. However, the effects described are not significant. One potential explanation for the small effects sizes is that we focus on prime-aged men between 25 and 60, who have the highest labour market integration.

5.5 Female

We finally replicate our analysis and look at women's wage progression and benefit receipts. However, since the Inland Revenue does not report the hours worked it is not clear whether a wage cut, when observed, is a result of a reduction in earnings or whether labour hours were reduced.

Table A.6 shows the coefficients and indicates that higher-skilled women generally experience larger wage progression than lower-skilled women, both in the GFC period and in the COVID-19 period. However, the magnitude is not significantly different from zero despite one exception. When turning to the year dummies for the GFC period, we see large effects, especially among women with earnings belonging to the two bottom deciles at $t-12$.[6] However, the interaction effects are all negative, indicating that wage growth was not experienced by higher-skilled. For the COVID-19 period, we see that there was no wage progression in the years 2019/20. Moreover, we do not detect any higher-skilled specific year effects. But for low earning women, we see a large positive effect of 9.6% for 2019/20, statistically significant at the 5% level. When turning to the interaction term, we see that the wage progression was significantly lower for low-earning higher-skilled women.

We also looked into the likelihood of becoming benefit recipients (Table A.7). For the GFC period, we find that higher-skilled women with low earnings at $t-12$ are less likely to become receive benefits. Further, the year dummies indicate that

[6] Note that position in the earnings distribution was calculated for both gender separately.

during the economic crises, the likelihood of moving into benefit recipients increased –especially in 2008/09–, but the interaction effect indicates that this was mainly for low-skilled women. The regression results for the COVID-19 period point towards a lower likelihood for higher-skilled women, which is only observable for 2017/18. After that, the difference between the skill groups disappears, which is indicated by the opposite signs of year dummies and the interaction effects.

6 Conclusion

Skills make up a critical component of human capital. Numerous studies have shown that higher numeracy and literacy skills are associated with better labour market performance and therefore with higher economic wellbeing. However, there is not much evidence in the empirical literature on whether cognitive skills are adequate safeguards during unanticipated adverse economic shocks. Focusing on the two most recent and major global economic setbacks–the GFC and the COVID-19 pandemic–our study is one of the first analyses to provide empirical insights into the labor market wellbeing implications of cognitive skills.

For our analysis, we focus on a New Zealand-based sample from the OECD's PIAAC survey of individuals' numeracy and literacy skills. We link those individuals to a high frequency administrative tax records that provide detailed labor market information of the entire workforce in New Zealand. The data allows us to longitudinally track the PIAAC sample's employment and earnings information during the two economic crises. We find that loss in earnings experienced by higher-skilled individuals is significantly less severe than the low-skilled group. However, these differences disappeared during the period of lockdown that the New Zealand government imposed during the COVID-19 pandemic. However, it is essential to note that our analysis rests on the assumption that skills distribution observed in New Zealand's PIAAC survey of 2014 does not vary over time, which may not be the case in practice.

Nonetheless, our analysis presents useful empirical evidence into the long-term relevance of upskilling initiatives (such as training and education programs) and governments' welfare interventions implemented to support the public during financial crises. Of particular interest is the contrast in our empirical findings on the differences in the wage progression observed across different skills levels over the two major economic crises. Our GFC-based results substantiate the empirical findings observed in the relevant literature that broadly indicate that higher cognitive skills are associated with better economic outcomes. However, our overall COVID-19 findings of insignificant differences in wage changes across different skills highlight several possibilities. For instance, one plausible explanation could be the governments' prompt and large-scale policy response in the form of a wage subsidy scheme adopted to mitigate job losses. The other underlying mechanism could be explained by the distribution of the different skill levels across industrial sectors (e.g., the allocation of various skill levels across essential and non-essential businesses). While we try to uncover some of these underlying mechanisms, our study opens up a substantial scope for future research. For instance, future analyses could more intuitively explore the social relevance of governments' preparedness to protect the wellbeing of the economically vulnerable population during unanticipated economic shocks and the evolution of various labour market trends and industry-specific focus of different skill levels over time.

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A Disclaimer

The results in this paper are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand. The opinions, findings, recommendations, and conclusions expressed in this paper are those of the authors, not Statistics NZ.

The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes. Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organisation, and the results in this paper have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI.

Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.

B Tables

Table A.1: Skill score cut-off

	GFC period										
Skill score	180	185	190	195	200	205	210	215	220	225	230
HS	0.015	0.018	0.003	0.009	-0.012	-0.023	-0.024	-0.014	-0.008	0.008	0.004
	(0.037)	(0.034)	(0.031)	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)	(0.026)	(0.026)	(0.025)
2006/07	0.010	0.033	0.025	0.026	-0.002	-0.007	-0.003	-0.018	-0.016	-0.010	-0.014
	(0.039)	(0.040)	(0.042)	(0.037)	(0.035)	(0.034)	(0.032)	(0.031)	(0.029)	(0.029)	(0.026)
2007/08	-0.100**	-0.077*	-0.081**	-0.065*	-0.098***	-0.094***	-0.086***	-0.083***	-0.070**	-0.047	-0.050*
	(0.045)	(0.044)	(0.038)	(0.034)	(0.033)	(0.032)	(0.031)	(0.028)	(0.028)	(0.031)	(0.029)
2008/09	-0.092**	-0.076*	-0.095**	-0.095***	-0.134***	-0.139***	-0.135***	-0.135***	-0.116***	-0.101***	-0.106***
	(0.043)	(0.042)	(0.038)	(0.033)	(0.031)	(0.031)	(0.029)	(0.028)	(0.029)	(0.027)	(0.025)
HS × 2006/07	-0.024	-0.049	-0.041	-0.044	-0.012	-0.006	-0.010	0.009	0.006	-0.003	0.004
	(0.042)	(0.043)	(0.045)	(0.040)	(0.038)	(0.037)	(0.035)	(0.034)	(0.033)	(0.033)	(0.031)
HS × 2007/08	0.082*	0.057	0.063	0.045	0.085**	0.081**	0.074**	0.071**	0.056*	0.029	0.033
	(0.047)	(0.046)	(0.041)	(0.037)	(0.037)	(0.036)	(0.034)	(0.033)	(0.032)	(0.035)	(0.033)
HS × 2008/09	0.036	0.018	0.040	0.040	0.086**	0.094***	0.090***	0.092***	0.070**	0.052*	0.062**
	(0.045)	(0.044)	(0.040)	(0.036)	(0.034)	(0.034)	(0.033)	(0.032)	(0.032)	(0.031)	(0.030)

	Covid-19 period										
Skill score	180	185	190	195	200	205	210	215	220	225	230
HS	-0.026	-0.016	0.000	0.020	0.031	0.020	0.035	0.038	0.023	0.038*	0.023
	(0.044)	(0.034)	(0.031)	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.023)	(0.022)	(0.021)
2018/19	-0.017	0.004	0.020	0.013	0.014	-0.003	0.002	0.005	-0.003	0.013	0.007
	(0.068)	(0.051)	(0.044)	(0.038)	(0.036)	(0.036)	(0.033)	(0.030)	(0.028)	(0.025)	(0.023)
2019/20	0.006	0.026	0.030	0.011	0.019	-0.003	0.010	0.026	0.016	0.031	0.014
	(0.064)	(0.052)	(0.048)	(0.036)	(0.035)	(0.034)	(0.032)	(0.030)	(0.027)	(0.026)	(0.025)
HS × 2018/19	0.035	0.013	-0.004	0.004	0.003	0.022	0.016	0.012	0.023	0.004	0.012
	(0.069)	(0.052)	(0.046)	(0.039)	(0.038)	(0.038)	(0.035)	(0.032)	(0.030)	(0.028)	(0.027)
HS × 2019/20	0.005	-0.016	-0.020	-0.000	-0.008	0.016	0.001	-0.017	-0.006	-0.024	-0.003
	(0.065)	(0.053)	(0.049)	(0.038)	(0.038)	(0.037)	(0.034)	(0.033)	(0.031)	(0.029)	(0.028)

Note: Data taken from the 2014 PIAAC survey and linked with administrative data from the IDI. Numbers in () are robust std err. *, **, and *** signify statistical significance at the 10, 5, and 1 percent-levels, respectively.

Table A.2: Percentile cut-off

	GFC period								
percentile	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
HS	-0.056	-0.043	-0.012	-0.001	0.007	0.001	0.005	0.009	0.012
	(0.048)	(0.031)	(0.028)	(0.027)	(0.025)	(0.024)	(0.022)	(0.021)	(0.020)
2006/07	-0.003	-0.011	-0.002	0.002	0.002	-0.004	0.010	0.012	0.010
	(0.070)	(0.046)	(0.035)	(0.031)	(0.030)	(0.029)	(0.027)	(0.027)	(0.027)
2007/08	-0.172***	-0.143***	-0.098***	-0.091***	-0.074**	-0.076**	-0.064**	-0.059**	-0.066**
	(0.046)	(0.040)	(0.033)	(0.031)	(0.031)	(0.030)	(0.029)	(0.028)	(0.028)
2008/09	-0.175***	-0.154***	-0.134***	-0.116***	-0.104***	-0.107***	-0.099***	-0.093***	-0.089***
	(0.059)	(0.037)	(0.031)	(0.027)	(0.026)	(0.025)	(0.024)	(0.023)	(0.023)
HS × 2006/07	-0.018	-0.002	-0.012	-0.017	-0.015	-0.004	-0.019	-0.021	-0.017
	(0.075)	(0.050)	(0.038)	(0.033)	(0.032)	(0.031)	(0.029)	(0.028)	(0.028)
HS × 2007/08	0.180***	0.144***	0.085**	0.075**	0.058*	0.065**	0.061**	0.059**	0.067**
	(0.053)	(0.044)	(0.037)	(0.033)	(0.033)	(0.032)	(0.030)	(0.030)	(0.030)
HS × 2008/09	0.139**	0.112***	0.086**	0.074**	0.061**	0.067**	0.062**	0.055**	0.052**
	(0.065)	(0.041)	(0.034)	(0.030)	(0.028)	(0.027)	(0.025)	(0.025)	(0.024)
	Covid-19 period								
percentile	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5
HS	0.011	0.014	0.031	0.023	0.037*	0.044**	0.051**	0.055***	0.052***
	(0.044)	(0.031)	(0.025)	(0.024)	(0.022)	(0.020)	(0.020)	(0.019)	(0.019)
2018/19	-0.022	-0.008	0.014	0.003	0.011	0.012	0.013	0.011	0.010
	(0.065)	(0.045)	(0.036)	(0.033)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
2019/20	0.023	0.018	0.019	-0.001	0.008	0.007	0.011	0.008	0.001
	(0.053)	(0.038)	(0.035)	(0.030)	(0.030)	(0.029)	(0.027)	(0.026)	(0.025)
HS × 2018/19	0.046	0.025	0.003	0.011	0.000	-0.002	-0.006	-0.002	-0.001
	(0.068)	(0.047)	(0.038)	(0.034)	(0.031)	(0.029)	(0.029)	(0.029)	(0.028)
HS × 2019/20	-0.001	-0.002	-0.008	0.006	-0.011	-0.010	-0.015	-0.014	-0.005
	(0.059)	(0.041)	(0.038)	(0.032)	(0.032)	(0.031)	(0.028)	(0.027)	(0.026)

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

Table A.3: Literacy & numeracy scores

	GFC period				Covid-19 period		
	base	numeracy	literacy		base	numeracy	literacy
HS	-0.012	-0.015	-0.012	HS	0.031	0.031	0.022
	(0.028)	(0.025)	(0.028)		(0.025)	(0.022)	(0.024)
2006/07	-0.002	-0.013	-0.010	2018/19	0.014	-0.002	0.021
	(0.035)	(0.027)	(0.033)		(0.036)	(0.026)	(0.034)
2007/08	-0.098***	-0.081***	-0.088***	2019/20	0.019	0.009	0.018
	(0.033)	(0.025)	(0.033)		(0.035)	(0.027)	(0.033)
2008/09	-0.134***	-0.131***	-0.130***				
	(0.031)	(0.025)	(0.030)				
HS $\times$ 2006/07	-0.012	0.001	-0.002	HS $\times$ 2018/19	0.003	0.021	-0.005
	(0.038)	(0.031)	(0.036)		(0.038)	(0.029)	(0.037)
HS $\times$ 2007/08	0.085**	0.071**	0.074**	HS $\times$ 2019/20	-0.008	0.003	-0.007
	(0.037)	(0.030)	(0.037)		(0.038)	(0.030)	(0.036)
HS $\times$ 2008/09	0.086**	0.090***	0.082**				
	(0.034)	(0.029)	(0.033)				

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

Table A.4: Entering benefits recipients

	GFC period			Covid-19 period	
	total	low earnings		total	low earnings
HS	-0.009	0.003	HS	0.008	0.005
	(0.029)	(0.045)		(0.022)	(0.060)
2006/07	-0.011	0.003	2018/19	0.010	0.028
	(0.031)	(0.054)		(0.033)	(0.075)
2007/08	0.007	0.033	2019/20	0.044	0.031
	(0.036)	(0.063)		(0.036)	(0.066)
2008/09	0.026	0.040			
	(0.040)	(0.059)			
HS $\times$ 2006/07	0.005	-0.030	HS $\times$ 2018/19	-0.001	-0.003
	(0.031)	(0.059)		(0.033)	(0.077)
HS $\times$ 2007/08	-0.009	-0.052	HS $\times$ 2019/20	-0.031	-0.016
	(0.036)	(0.067)		(0.036)	(0.068)
HS $\times$ 2008/09	-0.010	-0.020			
	(0.040)	(0.065)			

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

Table A.5: Changes of entering benefit recipients over time

	GFC period			
	low skill		higher skill	
Δ_{year}	total	low earnings	total	low earnings
2005/06		*reference*		
2006/07	-0.011	0.003	-0.006	-0.027
	(0.031)	(0.054)	(0.005)	(0.023)
2007/08	0.007	0.033	-0.002	-0.019
	(0.036)	(0.063)	(0.005)	(0.022)
2008/09	0.026	0.040	0.016**	0.021
	(0.040)	(0.059)	(0.006)	(0.025)
	Covid-19 period			
2017/18		*reference*		
2018/19	0.010	0.028	0.010***	0.025
	(0.033)	(0.075)	(0.004)	(0.016)
2019/20	0.044	0.031	0.013***	0.015
	(0.036)	(0.066)	(0.004)	(0.017)

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

Table A.6: Regression results (women)

	GFC period			Covid-19 period	
	total	low earnings		total	low earnings
HS	0.046	0.139*	HS	0.042	0.057
	(0.031)	(0.080)		(0.029)	(0.036)
2006/07	0.064*	0.230**	2018/19	0.025	0.049
	(0.037)	(0.100)		(0.034)	(0.064)
2007/08	0.079**	0.210***	2019/20	0.002	0.096**
	(0.035)	(0.080)		(0.037)	(0.039)
2008/09	0.024	0.209**			
	(0.038)	(0.089)			
HS $\times$ 2006/07	-0.055	-0.217**	HS $\times$ 2018/19	-0.014	-0.037
	(0.037)	(0.102)		(0.034)	(0.065)
HS $\times$ 2007/08	-0.071**	-0.202**	HS $\times$ 2019/20	0.000	-0.072*
	(0.035)	(0.081)		(0.037)	(0.041)
HS $\times$ 2008/09	-0.030	-0.212**			
	(0.038)	(0.090)			

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

Table A.7: Entering benefits recipients (women)

	GFC period			Covid-19 period	
	total	low earnings		total	low earnings
HS	-0.006	-0.043	HS	-0.125*	-0.241**
	(0.023)	(0.053)		(0.069)	(0.120)
2006/07	0.019	-0.004	2018/19	-0.123*	-0.270*
	(0.039)	(0.064)		(0.071)	(0.150)
2007/08	0.043	0.074	2019/20	-0.133*	-0.269**
	(0.048)	(0.094)		(0.073)	(0.133)
2008/09	0.041	0.193			
	(0.037)	(0.126)			
HS × 2006/07	-0.026	0.014	HS × 2018/19	0.128*	0.291*
	(0.039)	(0.065)		(0.071)	(0.151)
HS × 2007/08	-0.039	-0.050	HS × 2019/20	0.136*	0.281**
	(0.048)	(0.095)		(0.073)	(0.134)
HS × 2008/09	-0.029	-0.143			
	(0.037)	(0.127)			

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

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