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Abstract

This paper uses Programme for International Student Assessment (PISA) data linked to administrative data to track the educational and labour market outcomes of young people. Students with lower skills have lower rates of participation in further education. While men with low skills out-earn their higher-skilled counterparts when they are very young, their earnings are overtaken by those with higher skills when they are in their early twenties and earn around 15 % less by the age of 25. The differences among women are substantially larger - women with low skills earn about 35 % less than their higher-skilled counterparts by age 25.

Keywords: PISA, cognitive skills, education, labour market, earnings
JEL Classification: J31, J24, I21, I26

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1 Introduction

Having a basic level of proficiency in reading and mathematics is widely seen as a key factor to fully participate in modern societies. Basic skills obtained at school can enable further learning, support success at the labour market and contribute to individuals' well-being. At the population level, a large share of students who do not have these skills is considered to threaten the long-term economic development of a country (OECD, 2016). The importance of basic skills is also reflected in the United Nations (UN) Sustainable Development Goal 4, which calls for inclusive and equitable quality education and the promotion of lifelong learning opportunities for all. As an indicator to monitor progress towards this goal, the UN (2018) monitors the share of children and young people who achieve at least a minimum proficiency level in reading and mathematics.

However, due to a scarcity of data linking competencies in reading and mathematics to individual outcomes later in life, there is only limited empirical evidence on the role of basic skills. Baldini Rocha and Ponczek (2011) analyse the effects of adult literacy in Brazil, and show that literate individuals have 21 % higher wages but the same employment rate compared to their illiterate counterparts. However, literacy in this study is self-reported, raising concerns about potential measurement error.[1] Polidano and Ryan (2017), in contrast, rely on data from the Programme of International Student Assessment (PISA) to measure skills. PISA is an international study to assess key competencies of 15-year old students, with a focus on reading, mathematics, and science (OECD, 2010a). Polidano and Ryan (2017) track Australian PISA participants over time, and find no relationship between full-time employment rates or earning capacity at age 25 and reading proficiency. However, this study uses longitudinal survey data with a high attrition rate of 75 %, which results in a relatively small sample size and raises the possibility of attrition bias.

In this paper, we follow Polidano and Ryan and use PISA data to assess students' literacy skills. However, we can link participants to administrative data from various New Zealand government agencies to track their outcomes for 11 years until they are 26 years old. Available information includes educational participation and attainment based on Ministry of Education data and earnings based on income tax data. The data allow us to explore the role of basic skills in the life course trajectories of young people, by comparing outcomes of those who reach baseline levels of proficiency in reading and mathematics, and those who do not. While our analysis is inherently descriptive, we also explore mechanisms that could contribute to differences in outcomes, including family formation and health.

We find substantial differences in the life-course trajectories of young people, at an age where they typically transition from formal education to the labour market. Those with low skills have lower rates of participation in, and completion of, further education. While men with low skills out-earn men with higher skills until their early twenties, they also have a much flatter earnings profile. By age 22, they are overtaken by men with higher skills, and earn around 15 % less at the age of 25. The differences among women are substantially larger, where those with low skills earn 35 % less than their higher-skilled counterparts by age 25. Part of this gap may be attributed to differences in care

[1] In Baldini Rocha and Ponczek (2011), only 2 % of the sample aged 25 to 60 and surveyed between 2002 to 2008 self-report as illiterate, compared to a literacy rate of 90 % reported by the UNESCO (2022) for the Brazilian population aged 15 years and older in 2008.

responsibilities because we find that those with low skills have more children earlier in life. We also find that young people with low skills are more likely to use health services, indicating they have poorer health status.

Our results contribute to the literature that links direct measurements of skills to labour market outcomes. While there is an established body of literature which examines the relationship between education and subsequent outcomes (e.g., Heckman et al., 2006; Clark and Royer, 2013), cognitive tests may offer a more direct measure of skills than educational attainment measures, which, for example, do not account for the quality of education. There is also evidence that skills are a more relevant measure of human capital for economic growth (OECD, 2010b; Hanushek and Woessmann, 2008). Next to the studies on basic skills discussed above, there is a somewhat larger literature that links continuous measures of cognitive skills derived from students' performance on standardised tests to labour market outcomes. In a review of this literature, Hanushek and Woessmann (2008) show that US studies suggest that a one standard deviation increase in student performance is associated with a 10-15 % increase in annual earnings when they enter the labour force. Similarly, Hanushek et al. (2015) use data from the Programme for the International Assessment of Adult Competencies (PIAAC) to explore the returns to skills measured in adulthood in 23 different countries, and find that a one standard deviation increase in numeracy skills is associated with a 18 % wage increase among prime-age workers. Additional research links literacy to other outcomes including health. For example, people with low literacy tend to be less responsive to traditional health education messages, are less likely to use disease prevention services and are less able to successfully manage chronic disease (Berkman et al., 2011; Dewalt et al., 2004).

This is the first study that we are aware of to explore labour market outcomes of PISA participants using administrative data, thereby making use of the strengths of both data sources. PISA was specifically designed to assess the extent to which young people have acquired the knowledge and skills to meet real-life challenges. It provides an indicator of whether students are reaching a baseline level of proficiency in reading and mathematics that allows them to participate effectively and productively in life. This baseline indicator is also used by the UN to monitor progress towards the Sustainable Development Goals (OECD, 2010a; OECD, 2017). The administrative data, on the other hand, allows us to track individuals effectively over time and provides high-quality, population-wide information on earnings and further outcomes. Previously, PISA data for England has been linked to contemporaneous Department for Education administrative data to study peer effects (Micklewright et al., 2012a) and survey response (Durrant and Schnepf, 2018; Micklewright et al., 2012b). However, we use longitudinal data from a linked administrative database that allows us to track educational, labour market as well as additional outcomes over time.

The paper proceeds as follows. Section 2 describes the PISA survey, data, method, and the population of interest. Section 3 presents our results structured into education, employment, earnings, and further outcomes.[2] Section 4 concludes.

[2]We focus here on further outcomes relating to family formation and health. See Meehan et al. (2022b) for additional outcomes including benefit receipt, NEET (not in employment, education or training) status and crime and justice outcomes.

2 Background

2.1 PISA survey and skill levels

PISA is a worldwide study to evaluate educational systems by assessing key competencies of 15-year-old students, with a focus on reading, mathematics and science. It aims to measure students' capacity to apply their knowledge in real-life settings and solve problems in a variety of situations (OECD, 2010a). PISA started as an initiative of the OECD in 2000, and is administered every three years. Initially, 32 countries/regions took part, with participation expanding to 88 countries/regions in 2022. In 2009, 4,643 students from 163 schools participated in New Zealand. Students and schools were randomly selected to ensure that the sample was representative (Telford and May, 2010).

The PISA 2009 reading assessment provides a reading literacy proficiency score for each student. These scores are divided into seven proficiency levels from Level 1b (the lowest level) to Level 6. Each level is associated with tasks that describe the skills and knowledge needed to achieve them. For example, at Level 2 some tasks "require the reader to locate one or more pieces of information, which may need to be inferred and may need to meet several conditions. Others require recognising the main idea in a text, understanding relationships, or construing meaning within a limited part of the text when the information is not prominent and the reader must make low level inferences" (OECD, 2010a, p. 84). The OECD considers Level 2 to be a baseline level of proficiency that enables students "to participate effectively and productively in life" (OECD, 2010a, p. 13). Across OECD countries, according to PISA 2009, 81.2 % of students can perform tasks at least at Level 2, while only 0.8 % reach the highest level (OECD, 2010a).

Similar proficiency levels summarise students' performance in mathematics. Here, students at Level 2 "can extract relevant information from a single source and make use of a single representational mode. Students at this level can employ basic algorithms, formulae, procedures, or conventions. They are capable of direct reasoning and literal interpretations of the results." (OECD, 2010a, p. 130). Again, the OECD describes Level 2 as a baseline level of proficiency (OECD, 2010a). The share of students who are proficient at Level 2 is lower than in the case of reading, with about 78 % being assessed at Level 2 or higher across OECD countries (OECD, 2010a).

Throughout this paper, students whose measured PISA proficiency is less than Level 2 in mathematics or reading (or both) are referred to as students with low skills. This is consistent with the OECD's categorisation of student performance into top, strong, moderate and lowest performers, with this last group being those who are proficient below Level 2 (OECD, 2010a). This threshold is also used by the UN to monitor progress towards the Sustainable Development Goals with PISA, where the proportion of children and young people at the end of lower secondary education who achieve at least minimum proficiency in reading and mathematics is assessed using PISA data (OECD, 2017). The residual group of students with skills above the baseline level forms our comparison group.

New Zealand performed well in PISA 2009 relative to other OECD countries. The mean reading proficiency score was 521, placing it fourth in the OECD behind Korea, Finland and Canada. New Zealand's performance in mathematics was somewhat lower, with a score of 519, placing it seventh in the OECD behind Korea, Finland, Switzerland, Japan, Canada and the Netherlands. One feature of New Zealand's performance that these mean scores hide is that the distribution of scores is wide, with relatively high shares of low-performing and high-performing students. About 14.3 % and 15.4 % of students were below the baseline proficiency Level 2 in reading and mathematics, putting the country in eighth place in the OECD ranking in both domains (OECD, 2010a).

2.2 Data and method

The Integrated Data Infrastructure (IDI) is a large research database managed by Stats NZ. It holds micro-data from various government agencies, organisations, and surveys with longitudinal information on education, income, health and other life events. Stats NZ links the data so that records from all sources can be assigned to the person they belong to, and de-identifies it before it is made available to researchers (Stats NZ, 2020).

The IDI includes the PISA 2009 for New Zealand. We can, therefore, follow the cohort of 15-year-olds who participated in PISA and study their outcomes using other data in the IDI until 2020, when they are in their mid-20s. We use multiple data sources to construct a range of outcome variables. Information on educational enrolment and attainment comes from the Ministry of Education. Income data comes from Inland Revenue (IR), occupation from the 2018 census, and data on births and marriages is sourced from the Department of Internal Affairs (DIA). We further use health-related information from the Accident Compensation Corporation (ACC) and the Ministry of Health (MoH). Table 6 provides details of the outcome variables of interest including their full descriptions.

The student proficiencies in PISA are reported in the form of plausible values (PVs). PVs are not test scores, but are rather random numbers drawn from the distribution of scores that could be reasonably assigned to each individual (OECD, 2012). Each student has multiple PVs for the same scale, which are derived from a student's answers to test and background questions using imputation methods (OECD, 2012). PISA 2009 provides five plausible values for mathematics and five for reading, which we use to estimate population parameters. PISA data also comes with sampling and replicate weights to account for the complex survey design when estimating population parameters. We provide estimates on mean outcomes using the Stata package Repest which accounts for both sampling weights and plausible values (Avvisati and Keslair, 2020).

2.3 Population of interest

Our population of interest is those who participated in PISA 2009 who can be linked to other data in the IDI. The vast majority (94 %) of the PISA 2009 participants are linked to the IDI, representing more than 51,700 15-year-old students in New Zealand.[3] This linkage rate is similar to that of Micklewright et al. (2012a), Micklewright et al. (2012b) and Durrant and Schnepf (2018) using PISA data for England linked to administrative data (94-97 %), and compares favourably to Polidano and Ryan (2017), which has a linkage rate between PISA 2003 and the Longitudinal Survey of Australian Youth of about 80 %. Within the population of linked students, 19 % have low skills, meaning they were assessed to be below Level 2 in either reading or mathematics (or both).

Given that PISA is designed to be representative of the population of 15-year-olds in 2009, we examined whether the 6 % of those who could not be linked to the IDI were different to the population

[3] Students are aged between 15-years-3-months and 16-years-2-months when participating in PISA. For brevity, we refer to all students as '15-year-olds' in 2009 throughout the paper.

that could be linked. Based on PISA information, Table A.1 in the Online Appendix shows that being born in New Zealand is positively associated with a link to the IDI. In terms of ethnicity, NZ European students are more likely to be linked while Asian students are less likely to be linked. The remaining differences between linked and not linked PISA participants are not statistically significant.

To compare students' outcomes over time, we construct an annual dataset of young people living in New Zealand in a given calendar year from 2009 to 2020. The use of administrative data means that, in contrast to existing research that uses longitudinal surveys to track young people over time, sample attrition is not an issue. For example, Polidano and Ryan (2017) reports a 75 % sample attrition rate by age 25 for the Longitudinal Survey of Australian Youth. However, we do exclude people from our population of interest if they died over the examined period or if they spent more than 100 days of the given year abroad based on administrative data on international arrivals and departures. The exclusion of those living abroad is necessary as information such as earnings based on IR records would be misleading for this group.[4]

2.4 Student characteristics

Table 1 summarises the characteristics of our population of interest by skill group based on the PISA 2009 background questionnaire. Females are underrepresented among those with low skills - about 40 % of students with low skills are female, compared to 51 % of students with above-baseline skills. Students with low skills are also more likely to have been born in New Zealand and be of Māori or Pacific Peoples ethnicity. These differences are consistent with Telford and May (2010), who provide a more detailed analysis of New Zealand's student performance using PISA 2009 data. They show that there are similar proportions of girls and boys at the lowest levels of mathematics proficiency, but many more boys do not reach Level 2 in reading.

Students' skills are correlated with parental characteristics. Parents of students with low skills have, on average, 0.78 fewer years of schooling and a lower occupational status compared with parents of students with a higher skill level.[5] Assuming that students' skills and educational achievement are correlated (which we analyse below), this difference is consistent with the large literature on the inter-generational transmission of education (Black and Devereux, 2011).

3 Results

This section tracks the outcomes of our population of interest for 11 years after they participated in PISA at 15-years-old in 2009. We first examine differences in education before turning to employment and earnings. Finally, we analyse patterns of family formation and health.

[4]Figure A.1 in the Online Appendix summarises this exclusion from the population of interest over time by skill group. In both groups, the share of excluded individuals increases as the population ages, peaking at 16-19 % in 2019. Exclusion from the population of interest is mainly driven by youth moving overseas, while the number of deaths is negligibly small in both groups. The smaller share of excluded students in 2020 is likely attributable to the COVID-19 pandemic, which severely limited international travel. The above-baseline skills group appears to have a slightly higher likelihood of moving overseas and therefore being excluded from the population from 2016 (age 22) onwards, but the difference is not statistically significant.

[5]PISA measures occupational status using the 'International Socio-Economic Index of occupational status (ISEI)' developed by Ganzeboom et al. (1992).

Table 1: Student characteristics by skill group

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
Female	0.40	0.51	-0.11	0.000
Born in NZ	0.76	0.80	-0.04	0.044
Socioeconomic status (ESCS)	-0.43	0.21	-0.64	0.000
Ethnicity				
NZ European	0.33	0.66	-0.32	0.000
Māori	0.31	0.15	0.16	0.000
Pacific Peoples	0.20	0.05	0.15	0.000
Asian	0.11	0.12	-0.01	0.369
Other	0.02	0.02	0.00	0.895
Highest parental				
Education in years	12.37	13.15	-0.78	0.000
Occupational status	42.51	54.35	-11.84	0.000

Notes: This table compares average characteristics of students with low skills (Column 1) and those with above-baseline skills (2). Column 3 shows the difference between skill groups, Column 4 shows the p-value testing the equality of the two means. The number of observations is 3,972 for highest parental education, 4,182 for parental occupational status because of missing information, and 4,356 for the remaining characteristics. ESCS is a standardised measure of socioeconomic status based on parents' highest occupational status, parents' highest educational level, and home possessions (see Avvisati, 2020).

3.1 Education

The left-hand panel of Figure 1 shows the share of PISA participants who are enrolled in any schooling, education or training over time. In 2009, when the cohort participated in PISA, 100 % are enrolled in some form of schooling or training. This is as expected since only those who are enrolled in school at the time PISA was administered are included in the survey. The share in any schooling or training starts to fall in 2011, when the participants are about 17 years old. However, it remains above 20 % even in 2020, when the participants are 26 years old. This reasonably high share likely reflects the fact that any schooling, education or training can be anything from full-time university study to short vocational courses. Two years after PISA in 2011 is also the point when differences between the low skills group and the above-baseline comparison group become apparent, with a higher share of those in the above-baseline group being enrolled in education. This gap increases over the next few years, reflecting that the above-baseline group are more likely to continue into higher education than the low-skills group. This difference starts to shrink in 2015 when participants are about 21 years old, which aligns with the age at which many in the above-baseline group may be finishing tertiary education (e.g. a three-year bachelor's degree). By 2019, at age 25, there is no statistically significant difference between the educational enrolment of the two groups.

The right-hand panel of Figure 1 compares the bachelor's degree enrolment over time of the two skill groups. As expected, this shows a more stark difference between the low-skills and above-baseline groups. In 2012, which for most participants would have been the year after they finished secondary school, the share of those in the above-baseline group enrolled in a bachelor's degree is over 40 %, with the share peaking at over 45 % in 2013 and 2014. In comparison, less than 10 % of the low skills group are enrolled in a bachelor's degree in 2012, and just over 10 % in 2013 and 2014.

Table 2 shows that low-skilled youth are more likely to enrol in other forms of post-secondary

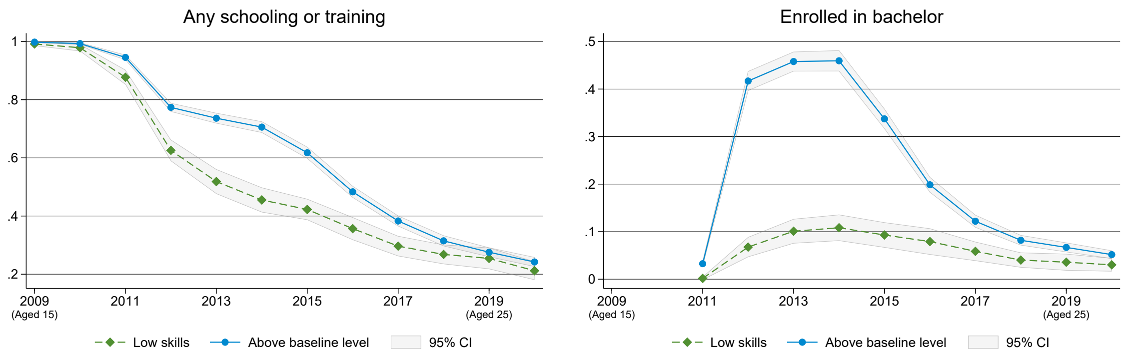

Figure 1: Share of young people enrolled in any education or training (left) and bachelor's (right). Estimation output in Table A.2 in the Online Appendix.

education. They are 7 percentage points (pp) more likely to ever participate in industry training, and 23 pp more likely to participate in targeted training. While industry training is on-job learning related to participants' work, targeted training programmes focus on people with low qualifications who are seeking work (TEC, 2008).

Table 2 also shows that there are large differences in terms of educational attainment. For the low-skills group, 80 % have attained at least Level 2 in the National Certificate of Educational Achievement (NCEA) and 56 % have attained Level 3 versus 94 % and 82 % respectively for the above-baseline group. Students in New Zealand typically begin formal school qualifications in Year 11 with NCEA Level 1. The final year of school is Year 13, when students will generally attempt NCEA Level 3, but it is possible for students to achieve NCEA levels earlier (Nusche et al., 2012). The differences are larger at higher qualification levels, with the above-baseline group being almost five times more likely to have gained university entrance (the minimum requirement to attend a New Zealand university) and more than four times as likely to have completed a bachelor's degree.

Table 2: Educational enrolment and attainment

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
Ever enrolled in				
Tertiary education	0.80	0.88	-0.08	0.000
Bachelor	0.17	0.55	-0.38	0.000
Industry training	0.35	0.28	0.07	0.002
Targeted training	0.41	0.18	0.23	0.000
Educational attainment				
NCEA Level 2 or higher	0.80	0.94	-0.14	0.000
NCEA Level 3 or higher	0.56	0.82	-0.27	0.000
University entrance	0.11	0.52	-0.41	0.000
Bachelor's degree	0.09	0.40	-0.31	0.000

Notes: This table compares average outcomes of young people with low skills (column 1) and those with above baseline skills (2). Column 3 shows the difference between skill groups, column 4 shows the p-value testing the equality of the two means. N=4356.

3.2 Employment and occupation

Employment and earnings are based on IR tax data, which is available on a monthly basis in the IDI. A limitation of IR data is that it does not include hours information for the time period under study. Therefore, we focus on months employed and total earnings without any adjustment for hours employed. Since women work, on average, fewer hours than men and there are relatively less women in the low-skills group, this inability to adjust for hours may, therefore, result in an underestimate of the earnings gap between the low-skills and above-baseline groups. Therefore, we also present results separately for men and women. Moreover, we can only observe whether or not a person is employed, and we cannot observe the reasons why they may not be in employment. For example, we do not know if it is due to being unemployed or because they are not in the labour force due to childcare responsibilities. Indeed, we expect that the earnings trajectories of men and women will differ since parenthood has, on average, a different effect on the employment and earnings of men versus women. For example, consistent with international evidence on the 'motherhood penalty' (such as, Anderson et al., 2002; Wilner, 2016), New Zealand research finds that most women are out of paid employment for a considerable length of time after becoming parents and upon returning to employment, mothers experience a decrease in earnings, while the employment and earnings of fathers do not fall (Sin et al., 2018).

The left-hand panel of Figure 2 shows that, as expected, the employment rate for both the low-skills and above-baseline groups increases over time, as young people complete their education and move into the labour market. In 2009, about 30 % of the PISA cohort were employed - that is, they had positive earnings in at least one month of the year. This is likely to be predominantly part-time employment while studying.

The employment rate of the above-baseline group is higher than the low-skills group throughout the 11 years examined. For the above-baseline group, the employment rate increases to just over 80 % by 2012, when the cohort are about 18 years old, and flattens off after reaching 90 % around three years later. It stays at about this level, with a slight dip in 2020, which may be (at least partly) due to the effects of the COVID-19 pandemic and the associated policy responses. For those with low skills, the employment rate is lower, and peaks in 2017 at just over 80 %, before falling slightly in 2018 and 2019, and dipping to below 80 % in 2020. Once again, this may be due to the effects of the pandemic. This may also suggest that COVID hit low-skilled youth harder than those with higher skill levels. However, the decrease is already evident in 2018 and 2019, before the pandemic, which suggests there may also be other factors underlining this trend.

The right-hand panel of Figure 2 shows the number of months during a year that an individual was employed. The above-baseline group are employed for a higher average number of months in every year. However, unlike the left-hand employment figure, the gap between the low-skills and above-baseline group increases from 2016 onwards. The 2020 dip in employment is also evident in the number of months of employment, but the dip for the low-skills group is more evident than with employment. However, as with employment, the dip for the low-skills group begins in 2019, before the COVID-19 pandemic.

Due to data limitations, we do not know the reasons for the lower employment rates among the low-skills group. One possibility is that unemployment rates are higher among the low skilled,

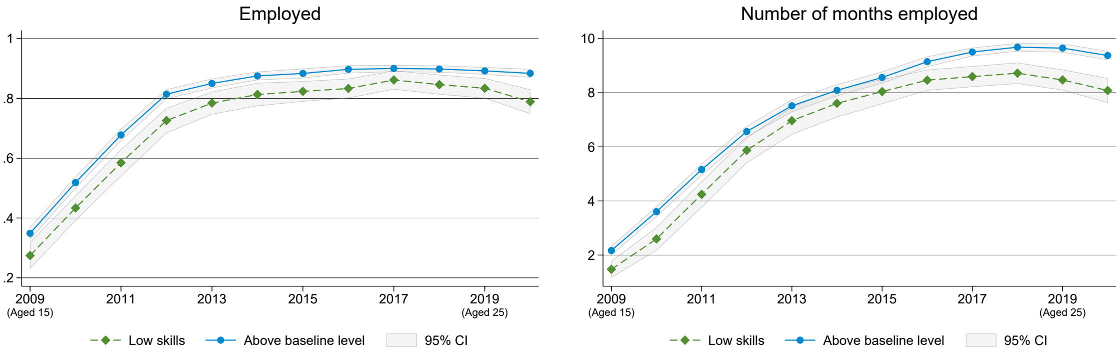

Figure 2: Employment indicators for full sample. Estimation output in Tables A.3 and A.4 in the Online Appendix.

which would be consistent with evidence that lower educated and skilled individuals have poorer employment outcomes. It may also be due to other factors, such as differences in family formation patterns and the opportunity costs of returning to work after having children (particularly for women). Therefore, we next decompose these results by gender. We also consider differences in patterns of family formation in Section 3.4.

Figure 3 shows that the employment differences between the low-skills and above-baseline comparison group reflects a much lower employment rate among low-skilled women compared with women in the comparison group. There is a much smaller difference between men in the low-skills group and men in the above-baseline comparison group.

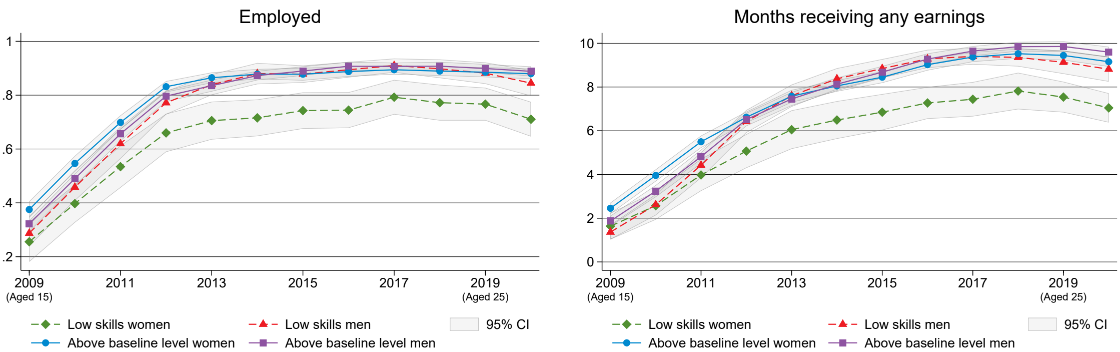

Figure 3: Employment indicators for men and women. Estimation output in Tables A.3 and A.4 in the Online Appendix.

Table 3 shows occupational differences between skill groups. This information comes from Census 2018, and therefore only includes those who were employed in the week prior to the census.[6] Those in the low-skills group are more likely to be labourers and machinery operators and drivers than the above-baseline group. They are less likely to be professionals and clerical and administrative workers, which is as expected as these are the types of roles that require proficiency in the kind of reading and mathematics skills measured by PISA. Decomposing these results by gender reveals that there are some differences for women. Women with low skills are more likely to be labourers and sales workers and less likely to be professionals than women in the above-baseline group.

[6]In addition, the Census has a lower linkage rate than administrative data sources in the IDI, and occupation was deemed to be of poor quality by the external data quality panel and of moderate quality by Stats NZ Stats NZ (2019).

Table 3: Occupations

	All		Women		Men	
	(1) Low s.	(2) Above b.	(3) Low s.	(4) Above b.	(5) Low s.	(6) Above b.
Labourers	0.19*	0.07	0.14*	0.04	0.23*	0.11
Technicians and Trades Workers	0.16	0.13	0.05	0.06	0.22	0.20
Sales Workers	0.12	0.12	0.22*	0.13	0.07	0.10
Managers	0.12	0.11	0.08	0.09	0.14	0.12
Community and Personal Service Workers	0.12	0.11	0.20	0.15	0.07	0.08
Machinery Operators and Drivers	0.11*	0.04	0.01	0.01	0.17*	0.06
Professionals	0.11*	0.31	0.17*	0.37	0.08*	0.25
Clerical and Administrative Workers	0.07*	0.11	0.13	0.16	0.03*	0.07

Notes: This table compares average outcomes of young people with low skills and those with above baseline skills for different groups of the population. * indicates that the difference between skill groups is statistically significant at the 5 % level. Occupational information for 1362 women and 1500 men comes from the 2018 Census.

3.3 Earnings

Figure 4 shows differences in earnings. The left-hand panel including both genders together shows that the average earnings of those in the low-skills group are slightly higher than those in the above-baseline group when they are very young, likely reflecting that more of the low-skills group would have been working full-time while many of those in the above-baseline group would have been studying and therefore not working or working part-time. However, those in the above-baseline group begin to out-earn their lower-skilled compatriots when they are about 22 years old. This roughly aligns with the education results presented in Section 3.1, whereby rates of study begin to fall at about age 21 for the above-baseline group as young people begin to complete their tertiary studies and enter the labour market. The earnings gap between these groups continues to grow over time, with the above-baseline group earning approximately 27 % more than the low-skills group by the time they are 25 in 2019.

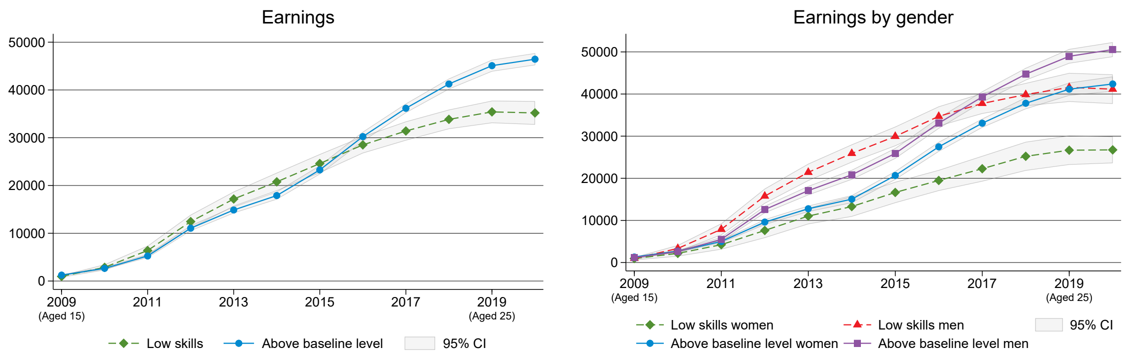

Figure 4: Earnings. Estimation output in Table A.5 in the Online Appendix.

Decomposing earnings by gender once again highlights that the differences for women are larger. The right-hand panel of Figure 4 shows men in the low-skills group out-earn men in the above-baseline group until they are about 23 years old in 2017. After this point, above-baseline men have higher average earnings than low-skilled men, with the gap increasing over time. In contrast, low-skilled women have lower earnings than above-baseline women throughout the whole time period, with the gap widening from when they are about 21 years old in 2015. At 25 years of age, women and men with low skills earn approximately 35 % and 15 % less than their counterparts.

Since part of this pattern for women may reflect the lower employment rates among low-skilled women (discussed above), we further examine earnings only for those who are working. Online Appendix Table A.6 reveals very similar patterns as the results for the full sample. Low-skilled women earn a similar amount to above-baseline women until 2015, at which point a gap between the low-skilled and above-baseline group opens up and increases over time. Again, we find that the gaps in earnings in both absolute and relative terms is larger among women than men.

3.4 Family formation and health

Some of the differences in labour market outcomes may reflect family formation patterns, particularly given the observed gender differences. Therefore, this section examines childbearing and marriage patterns. Childbearing is based on Department of Internal Affairs birth records. We record an individual as having had a child if they are listed as parents on a child's birth certificate. This does not, however, necessarily align with child-rearing since a child's biological parents may not be their primary caregiver/s. Moreover, while mothers are always recorded, fathers are not recorded for about 5 % of births (Staninski, 2021). However, it is the only population-wide measure of childbearing available in the IDI. We also use Department of Internal Affairs information to identify whether individuals have ever been married or in a civil union.

Table 4 shows that men in the above-baseline skills group have the lowest average number of children, with less than 0.2 by age 26 in 2020. Women in the low-skills group have the highest average number of children, with over 0.8 by 2020. Furthermore, low-skilled women who have had at least one child by the age of 26 are on average 21.3 years old when their first child is born, while the average age for above-baseline women is 22.6 years. The lower employment and earnings of women in the low-skills group is, therefore, likely to at least partly reflect higher rates of childbearing and time spent out of the workforce to raise children. In the other direction, the choice to have children earlier may also reflect the lower opportunity cost of doing so compared with women in the above-baseline group given lower employment and earnings opportunities. We find no statistically significant difference between the share of low-skilled and above-baseline individuals who were ever married by 2020.

Table 4: Further outcomes - family formation

	All		Women		Men	
	(1) Low s.	(2) Above b.	(3) Low s.	(4) Above b.	(5) Low s.	(6) Above b.
Number of children in 2020	0.68*	0.29	0.82*	0.40	0.59*	0.17
Age at first birth	21.89*	22.96	21.27*	22.61	22.41*	23.63
Ever married	0.13	0.14	0.15	0.18	0.12	0.10

Notes: This table compares average outcomes of young people with low skills and those with above baseline skills for different groups of the population. * indicates that the difference between skill groups is statistically significant at the 5 % level.

Given that poor health status is generally associated with worse labour market outcomes (O'Donnell et al., 2015), Table 5 explores differences in health care utilisation. It shows that the low-skills group is 13 percentage points more likely to experience a hospitalisation between 2009 and 2020.

Part of the reason for higher rates of hospitalisation among the low-skills group could be higher birth rates, as discussed above. To examine this possibility, Table 5 also shows results when childbirth is excluded from the hospitalisation statistics and finds the magnitude of the difference between the low-skills and above-baseline group is similar, and remains statistically significant.

In terms of non-admitted secondary care events, the low-skills group have higher rates of emergency department visits, with 69 % having visited the emergency department at least once between 2009 and 2020 versus 59 % of the above-baseline group. While this may indicate poorer health outcomes, it may also partly be due to lower access to primary healthcare resulting in more emergency department visits (Dolton and Pathania, 2016).

Furthermore, there are also significant differences in the use of mental health services. Among the low-skills group, 12 % have used mental services in the observation period, compared to 7 % of the above-baseline group. As with other health care utilisation, these data likely reflect a combination of the prevalence of mental health disorders and differences in the propensity to access health services across groups. With mental health, this is could be particularly important among groups where mental health disorders may be stigmatised, making it more difficult to seek medical treatment.

Table 5: Further outcomes - health care utilisation and injuries

	(1) Low-skills	(2) Above baseline	(3) Difference	(4) p-Value
Health care utilisation				
Hospitalisation	0.59	0.46	0.13	0.000
Hospitalisation (excl. childbirth)	0.52	0.41	0.11	0.000
Emergency department visits	0.69	0.53	0.15	0.000
Mental health service	0.12	0.07	0.05	0.002
Injuries				
Any injury	0.84	0.83	0.01	0.328
Injuries at home	0.59	0.56	0.04	0.097
Work injuries	0.43	0.29	0.14	0.000
Road accidents	0.15	0.11	0.04	0.032
Sport injuries	0.50	0.56	-0.06	0.004

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

Table 5 also shows the share of injuries in the low-skills and above-baseline groups over the entire 2009-2020 period by injury type. There is no statistically significant difference between the low-skills and above-baseline group in the total rate of injuries, with the majority in both groups having experienced at least one injury during this time period (84 % of low-skills group and 83 % for the above-baseline group). There is also no statistically significant difference in the rate of injuries occurring in the home. However, those with low skills are more likely to have had at least one work injury (43 % versus 29 %). This likely reflects that the low-skills group are more likely to be employed in manual jobs with higher risk of injury. Interestingly, the above-baseline group have a higher rate of sports injuries (56 % versus 50 % for the low-skills group).

Similar to the mental health data, one factor to consider that we cannot account for is that injuries are based on ACC claims data and therefore likely reflect a combination of actual injury rates and medical care access. Since ACC claims are submitted via medical providers, if the rate at which the low-skills group seeks medical treatment in the event of an injury is lower than for the above-baseline group, the observed injury rates as measured by approved ACC claims may underestimate the true difference between the two groups. This may be the case, for example, because those with lower skills are less aware of and/or less able to access information about their entitlements or have lower access to medical care.[7]

4 Discussion and conclusion

This paper examines the life-course trajectories of a cohort of NZ youth who participated in PISA 2009 when they were 15-years old by tracking their outcomes until 2020, when they are about 26 years old. Our results highlight the importance of reading and mathematics skills. The group of students with below Level 2 proficiency have lower rates of participation in, and completion of, further education compared with the above-baseline skills group. They also have less favourable labour market outcomes. For young men, the employment rate of those in the low-skills group is similar to that of the above-baseline group throughout the 11 years examined. However, men in the low-skills group out-earn men in the above-baseline group until they are about 23 years old. After this point, above-baseline men have higher average earnings than those in the low-skills group, with the gap increasing over time. For young women, the labour market differences by skill level are larger. Women in the low-skills group have much lower employment rates than above-baseline women. They also have lower average earnings throughout the 11 year period examined, with the gap widening over time.

Our results contrast with those of Polidano and Ryan (2017), who use 2003 PISA data linked to the Longitudinal Survey of Australian Youth (LSAY) to track the employment outcomes of Australian PISA participants at age 25. They find that those with low-reading proficiency at age 15 and those with medium-reading proficiency have the same full-time employment rates and are employed in jobs with similar earnings capacity at age 25. One explanation is that Polidano and Ryan use low reading proficiency rather than low reading and/or mathematics proficiency as we do here. Indeed, Polidano and Ryan find that low proficiency in mathematics at age 15 is associated with a higher probability of full-time employment at age 25, and suggest that there is no direct labour market payoff to mathematical proficiency. It may also be due to a relatively lower linkage rate between PISA and LSAY (about 80 % versus 94 % in the present paper) and high sample attrition of LSAY whereby only 25 % of original 2003 respondents remained in the sample by age 25.

Although we find large differences in labour market outcomes between the skill groups, it is difficult to assess the potential impact of policies aimed at improving the skills of young people. Unobserved factors such as family background or personality traits may be correlated with both

[7] As far as we are aware, there is little research comparing actual injury rates with ACC claim rates, and none that compares these rates by skill levels. Poland (2018) appears to be one of the only pieces of NZ research comparing actual injury rates with ACC claim rates. This research links self-reported injuries from the Survey of Family, Income and Employment to ACC claims and finds that about a third of those who report having an injury that stops them doing their usual activities for more than a week do not appear to have received any form of accident compensation (including medical treatment costs). In addition, the degree of under-reporting varies by age and ethnicity, likely reflecting differences in attitudes and access to healthcare treatment.

skills and labour market outcomes. A convincing identification strategy on the causal effects of skills would therefore require some form of exogenous variation in skills. Hanushek et al. (2015) provide a number of different explorations into causality in the context of returns to skills, including using parental education and changes in compulsory schooling laws as instrumental variables for skills. While Hanushek et al. note that these approaches do raise further concerns, their results support the underlying importance of skills to labour market outcomes.

Due to the lack of a convincing identification strategy in our setting, we do not provide causal estimates on the effect of skills. However, we explore factors that may contribute to the observed labour market differences. At age 26, women in the low-skills group have the highest average number of children, followed by men in the low-skills group, which could partly explain a weaker labour market attachment. Those in the low-skills group also have higher rates of health care utilisation, including hospitalisations, emergency department visits, and mental health service use. A worse health status is typically associated with worse labour market outcomes (O'Donnell et al., 2015). While poor health can reduce employability, we also find higher rates of work injuries among low-skilled groups, indicating that some of the observed health differences can be attributed to the fact that low-skilled workers are employed in more dangerous jobs.

A natural question is if the gaps in labour market outcomes would continue to increase as the cohort enters their prime-earning years. Indeed, Meehan et al. (2022a) follows adults with low literacy and numeracy skills (as measured by the OECD's Programme for the International Assessment of Adult Competencies, PIAAC) and this widening of the earnings gap by age between the low-skills and above-baseline groups is even more evident. Similarly, Hanushek et al. (2015) and Lin et al. (2018) find that labour market returns to cognitive skills rise with age.

While PISA data is used widely to compare education outcomes, it is important to recognise its limitations. Specifically, PISA was administered only in English in NZ, which raises the possibility that the PISA assessment may not reflect the true reading and mathematics skills of students whose first language is not English (noting that the mathematics assessment also requires English reading ability to interpret the questions). More generally, PISA only measures certain skills and the partiality of the notion of skills used in international tests such as PISA is in contrast to the diversity of skills used by people in their lives (Cochrane et al., 2020). In addition, while the approach of examining one cohort offers the advantage that all face the same macroeconomic conditions, a potential disadvantage is that the cohort being investigated may not be representative of other cohorts. One particular issue for the PISA 2009 cohort may be the effect of the global financial crisis (GFC). The GFC meant that these individuals were facing tough economic conditions when they were in their last years of secondary school, and some of them would have been entering the workforce during a downturn, and, as research highlights, this can have long-term negative consequences for employment and earnings outcomes.[8] The timing may have particularly impacted the low-skills group, who would have been more likely to enter the workforce straight from school rather than going on to tertiary education.

[8] See Borland (2020) for a recent review of the literature. Further, Dasgupta and Plum (2022) find that adults with low literacy and numeracy skills in New Zealand experienced the largest wage falls when changing employer during the GFC.

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Table 6: Definition of outcome variables

Outcome	Description
Education enrolment and attainment	
Tertiary education	Enrolled in any tertiary education (Source: MoE tertiary qualification enrolment).
Bachelor's enrolment	Enrolled in bachelor type tertiary education (MoE tertiary qualification enrolments).
Industry training	Indicator for workplace-based training (MoE industry training data).
Targeted training	Enrolled in targeted training programmes (Gateway, Skill Enhancement, Training Opportunities, Foundation Focused Training, Youth Training; MoE trageted training data).
Any schooling or training	Enrolled in compulsory education, tertiary education, industry training, or targeted training (MoE enrolment data).
Level 2/3 or higher	Attained NCEA level 2/3 or higher (MoE student qualifications).
Bachelor's attainment	Completion of bachelor's programme (MoE tertiary completions).
University entrance	Students met the minimum requirement to go to a New Zealand University (MoE university entrance information).
Income and employment	
Earnings	Sum of wages, salaries and income from self-employment, adjusted to 2020 prices using the consumer price index (Inland Revenue (IR) derived income data).
Employed	Indicator for having any earnings (IR).
Months receiving earnings	Number of months receiving any earnings (IR).
Occupations	Working in an occupation classified according to ANZSCO v 1.2 major groups (Census 2018).
Family formation	
Number of children	Number of children born, where respondent is recorded as a parent (Department of Internal Affairs (DIA) life events).
Age at first birth	Parent's age at the time of the first birth (DIA).
Married	Having married or entered a civil union (DIA).
Health	
Any injuries	Indicator for injuries after accidents (Source: Accident compensation corporation (ACC) injury claims).
Injuries at home	Accidents that occurred at home (ACC).
Work injuries	Paid from ACC work account or claim occurred at place of work (ACC).
Road accidents	Paid from ACC motor vehicle account (ACC).
Sport injuries	Engaged in recreation/sporting activity at the time of the accident (ACC).
Mental health services	Utilisation of any service related to mental health (Programme for the Integration of Mental Health Data (PRIMHD), MoH).
Hospitalisation	Indicator for publicly funded hospital events (Ministry of Health (MoH) national minimum dataset).
Hosp. excluding childbirth	Hospitalisation excluding Major Diagnostic Categories (MDC) 14 and 15.
Non-admitted secondary care events	Indicator for any non-admitted secondary care event (MoH National Non-Admitted Patient Collection (NNPAC)).
Other outpatient visits	Outpatient and community referred events (NNPAC).
Emergency department visits	Emergency department event types (NNPAC).

A Online Appendix

This Online Appendix provides additional material discussed in the manuscript “Basic reading and mathematics skills and the labour market outcomes of young people: Evidence from PISA and linked administrative data”.

Table A.1: Characteristics of students with a link and no link to the IDI spine

	(1) Linked	(2) Not linked	(3) Difference	(4) p-Value
Female	0.49	0.52	-0.03	0.257
Born in NZ	0.79	0.63	0.16	0.000
Index of economic social and cultural status	0.09	-0.01	0.10	0.151
Ethnicity				
NZ European	0.59	0.45	0.15	0.000
Māori	0.18	0.21	-0.03	0.279
Pacific Peoples	0.08	0.13	-0.05	0.123
Asian	0.12	0.19	-0.07	0.001
Other	0.02	0.02	-0.00	0.792
Highest parental				
Occupational status	13.02	12.91	0.11	0.486
Education in years	52.29	50.06	2.23	0.066

Notes: This table compares average characteristics of students with a link to the IDI spine (Column 1) and those without (2). Column 3 shows the difference between skill groups, Column 4 shows the p-value testing the equality of the two means. The number of observations is 3,972 for highest parental education, 4,182 for parental occupational status because of missing information, and 4,356 for the remaining characteristics.

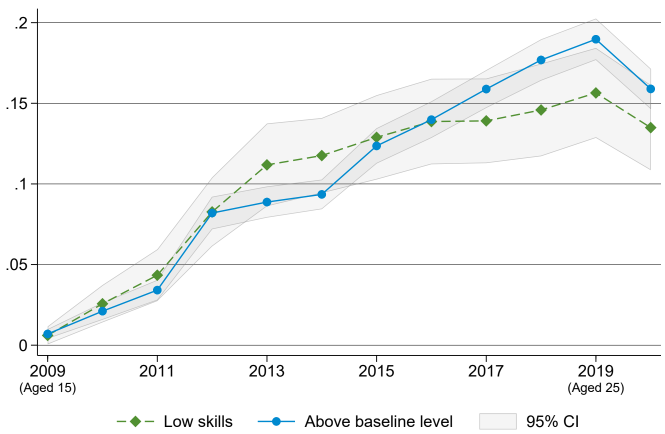

Figure A.1: Share of individuals excluded from the population of interest

Table A.2: Enrolment in education

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
Enrolled in any schooling or training				
2009	0.99	1.00	-0.01	0.089
2010	0.98	0.99	-0.01	0.045
2011	0.88	0.95	-0.07	0.000
2012	0.63	0.77	-0.15	0.000
2013	0.52	0.74	-0.22	0.000
2014	0.46	0.71	-0.25	0.000
2015	0.42	0.62	-0.19	0.000
2016	0.36	0.48	-0.13	0.000
2017	0.30	0.38	-0.09	0.000
2018	0.27	0.31	-0.05	0.009
2019	0.25	0.28	-0.02	0.293
2020	0.21	0.24	-0.03	0.096
Enrolled in bachelor's				
2011	0.00	0.03	-0.03	0.000
2012	0.07	0.42	-0.35	0.000
2013	0.10	0.46	-0.36	0.000
2014	0.11	0.46	-0.35	0.000
2015	0.09	0.34	-0.24	0.000
2016	0.08	0.20	-0.12	0.000
2017	0.06	0.12	-0.06	0.000
2018	0.04	0.08	-0.04	0.000
2019	0.04	0.07	-0.03	0.002
2020	0.03	0.05	-0.02	0.020

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

Table A.3: Indicator for any employment

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
All				
2009	0.27	0.35	-0.07	0.004
2010	0.43	0.52	-0.09	0.000
2011	0.58	0.68	-0.09	0.000
2012	0.73	0.81	-0.09	0.000
2013	0.78	0.85	-0.07	0.001
2014	0.81	0.88	-0.06	0.004
2015	0.82	0.88	-0.06	0.001
2016	0.83	0.90	-0.06	0.000
2017	0.86	0.90	-0.04	0.027
2018	0.85	0.90	-0.05	0.003
2019	0.83	0.89	-0.06	0.001
2020	0.79	0.88	-0.09	0.000
Women				
2009	0.26	0.38	-0.12	0.004
2010	0.40	0.55	-0.15	0.000
2011	0.53	0.70	-0.16	0.000
2012	0.66	0.83	-0.17	0.000
2013	0.71	0.86	-0.16	0.000
2014	0.72	0.88	-0.16	0.000
2015	0.74	0.88	-0.14	0.000
2016	0.74	0.89	-0.14	0.000
2017	0.79	0.89	-0.10	0.003
2018	0.77	0.89	-0.12	0.001
2019	0.77	0.89	-0.12	0.000
2020	0.71	0.88	-0.17	0.000
Men				
2009	0.29	0.32	-0.03	0.241
2010	0.46	0.49	-0.03	0.256
2011	0.62	0.66	-0.04	0.248
2012	0.77	0.80	-0.02	0.336
2013	0.84	0.84	0.00	0.856
2014	0.88	0.87	0.01	0.741
2015	0.88	0.89	-0.01	0.530
2016	0.89	0.91	-0.01	0.420
2017	0.91	0.91	0.00	0.816
2018	0.90	0.91	-0.01	0.617
2019	0.88	0.90	-0.02	0.462
2020	0.84	0.89	-0.04	0.117

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

Table A.4: Months receiving any earnings

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
All				
2009	1.47	2.17	-0.70	0.000
2010	2.60	3.60	-1.00	0.000
2011	4.24	5.16	-0.92	0.001
2012	5.87	6.57	-0.69	0.007
2013	6.97	7.52	-0.55	0.052
2014	7.61	8.09	-0.48	0.081
2015	8.04	8.56	-0.52	0.040
2016	8.47	9.15	-0.68	0.001
2017	8.60	9.51	-0.91	0.000
2018	8.72	9.68	-0.96	0.000
2019	8.47	9.65	-1.18	0.000
2020	8.08	9.38	-1.29	0.000
Women				
2009	1.64	2.46	-0.82	0.017
2010	2.57	3.96	-1.38	0.000
2011	3.98	5.50	-1.52	0.000
2012	5.07	6.62	-1.55	0.000
2013	6.05	7.58	-1.53	0.001
2014	6.49	8.05	-1.56	0.001
2015	6.85	8.45	-1.60	0.000
2016	7.27	9.02	-1.75	0.000
2017	7.44	9.37	-1.93	0.000
2018	7.82	9.52	-1.71	0.000
2019	7.54	9.44	-1.90	0.000
2020	7.05	9.16	-2.11	0.000
Men				
2009	1.36	1.87	-0.51	0.018
2010	2.62	3.24	-0.62	0.019
2011	4.42	4.81	-0.39	0.233
2012	6.43	6.51	-0.09	0.772
2013	7.60	7.46	0.15	0.610
2014	8.38	8.13	0.25	0.368
2015	8.84	8.68	0.16	0.531
2016	9.29	9.28	0.01	0.967
2017	9.40	9.64	-0.24	0.286
2018	9.36	9.85	-0.49	0.046
2019	9.13	9.85	-0.72	0.019
2020	8.81	9.60	-0.78	0.023

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

Table A.5: Earnings

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
All				
2009	967.35	1240.16	-272.82	0.046
2010	2869.43	2655.26	214.17	0.531
2011	6395.07	5243.47	1151.60	0.030
2012	12444.91	11059.71	1385.20	0.085
2013	17174.49	14877.86	2296.63	0.006
2014	20769.15	17892.86	2876.29	0.006
2015	24600.43	23267.49	1332.94	0.251
2016	28502.80	30235.53	-1732.73	0.092
2017	31409.59	36169.71	-4760.13	0.000
2018	33847.86	41253.84	-7405.98	0.000
2019	35411.32	45089.23	-9677.92	0.000
2020	35193.64	46442.81	-1.1e+04	0.000
Women				
2009	955.42	1313.64	-358.22	0.121
2010	2166.55	2704.59	-538.04	0.192
2011	4234.91	4991.23	-756.32	0.230
2012	7621.60	9607.72	-1986.12	0.046
2013	11032.69	12765.68	-1732.99	0.093
2014	13289.43	15046.17	-1756.75	0.193
2015	16636.86	20666.50	-4029.64	0.004
2016	19485.21	27471.34	-7986.13	0.000
2017	22271.26	33076.67	-1.1e+04	0.000
2018	25220.50	37812.79	-1.3e+04	0.000
2019	26670.06	41154.39	-1.4e+04	0.000
2020	26744.32	42381.91	-1.6e+04	0.000
Men				
2009	976.00	1164.09	-188.09	0.321
2010	3348.05	2604.54	743.51	0.075
2011	7888.65	5504.59	2384.06	0.001
2012	15773.10	12576.91	3196.19	0.001
2013	21418.28	17068.47	4349.81	0.000
2014	25899.06	20830.57	5068.49	0.000
2015	29950.16	25898.86	4051.30	0.004
2016	34709.82	33084.06	1625.76	0.244
2017	37759.65	39322.71	-1563.06	0.268
2018	39870.07	44717.90	-4847.83	0.002
2019	41578.46	48959.92	-7381.46	0.000
2020	41156.84	50553.92	-9397.08	0.000

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

Table A.6: Earnings conditional on working

	(1) Low skills	(2) Above baseline	(3) Difference	(4) p-value
All				
2009	3521.00	3553.28	-32.28	0.903
2010	6615.16	5120.28	1494.87	0.010
2011	10932.23	7734.86	3197.37	0.000
2012	17138.67	13581.53	3557.15	0.000
2013	21892.34	17499.04	4393.30	0.000
2014	25537.21	20439.25	5097.97	0.000
2015	29864.41	26330.36	3534.04	0.002
2016	34204.65	33692.32	512.33	0.611
2017	36448.54	40175.66	-3727.12	0.001
2018	39997.77	45915.32	-5917.55	0.000
2019	42457.41	50540.05	-8082.64	0.000
2020	44597.70	52536.01	-7938.31	0.000
Women				
2009	3729.43	3500.42	229.01	0.630
2010	5449.16	4949.99	499.17	0.510
2011	7915.85	7143.28	772.57	0.345
2012	11544.23	11555.61	-11.39	0.992
2013	15636.71	14763.20	873.50	0.414
2014	18559.39	17135.14	1424.25	0.304
2015	22394.50	23542.41	-1147.92	0.369
2016	26179.56	30951.43	-4771.86	0.001
2017	28103.20	36981.86	-8878.66	0.000
2018	32660.41	42521.69	-9861.28	0.000
2019	34786.84	46491.43	-1.2e+04	0.000
2020	37641.40	48186.87	-1.1e+04	0.000
Men				
2009	3393.98	3616.99	-223.01	0.619
2010	7302.68	5315.66	1987.02	0.005
2011	12729.57	8386.72	4342.84	0.000
2012	20439.77	15791.47	4648.30	0.000
2013	25526.53	20436.71	5089.81	0.000
2014	29428.95	23870.15	5558.80	0.000
2015	34110.27	29113.74	4996.52	0.000
2016	38804.77	36454.77	2350.00	0.075
2017	41496.27	43388.59	-1892.33	0.197
2018	44401.66	49262.07	-4860.41	0.005
2019	47162.48	54461.51	-7299.03	0.000
2020	48729.71	56894.25	-8164.54	0.000

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