Human Capital Effects for Productivity and Income: A New Zealand Perspective

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Economics at Massey University

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November 2023

Acknowledgements

I would like to thank my supervisors, Professor Xiaoming Li and Professor Rukmani Gounder, for their immeasurable encouragement, support, patience, guidance, and tuition in the development of my thesis.

I would also like to thank the academic staff and administrative staff of the School of Economics and Finance at Massey University for their support, encouragement, and advice.

Abstract

The overarching purpose of this dissertation is to identify factors crucial for improving the performance of the New Zealand economy and in turn, for raising standards of living. Within this overall aim, I investigate whether and/or how human capital affects the key growth driver of labour productivity, and flowing from this, worker income. The findings of my research suggest several policy measures to support existing government initiatives as well as identifying further avenues for research into the contribution of human capital to economic growth.

In my first study I examine the effects of industry skill on labour productivity. I find gains in labour productivity from increases in capital intensity. Capital intensity is particularly effective for raising labour productivity in lower to medium-skilled industries, relative to lower-skilled. This result indicates possible skill-capital complementary effects. I also observe significant improvements in labour productivity from increases in total factor productivity. This result indicates the importance of technology adoption in New Zealand production. For input substitution effects, I observe a negative relationship between labour cost and capital intensity. This indicates that firms may reduce capital investment when managing labour cost increases. Additionally, low sensitivity is observed from increasing physical capital returns for capital investment. The latter two results are likely to be negative for productivity in the relatively labour-intensive New Zealand economy.

In my second study I build on the established human capital measure of years of schooling, drilling down further to examine the impacts of the core cognitive skills of literacy, numeracy, and Information and Communications Technology (ICT) problem-solving on worker income. I find a positive relationship between proficiency in each of

these three core skills and worker earnings. This result indicates demand in the New Zealand labour market for greater cognitive skill proficiency. A further important finding is that earnings are improved from greater use of ICT problem-solving skills in the workplace. This result indicates the importance of the continuing integration of technology into industries for lifting worker productivity and income. There are also significant earnings benefits from further adult education and training, after completion of foundation studies. For occupational effects, I observe a fall in the relative value of the skills of white-collar workers. However, this may be offset by greater use of numeracy skills, for each occupational skill level group. Further findings for the New Zealand labour market include that the peak level of earnings for New Zealand workers occurs for the 35 to 44-year age group and an expected negative gender earnings gap is observed for female workers. These findings indicate a loss of earnings potential for many workers, restricting the performance of the New Zealand labour market and economy.

In my third study I evaluate similarities and differences in the impacts of the core cognitive skills on worker earnings internationally. I find a positive relationship between proficiency in numeracy skills in particular, and worker income. Increased usage of ICT problem-solving skills in the workplace is the most significant of the skill use variables for raising earnings internationally. This also indicates the earnings potential from greater development of this key infrastructure for economies. The results also show significant gains to worker earnings from investment in job-related adult education and training for countries with less developed programmes. I find that countries providing the strongest worker protection show the smallest range in earnings by occupational skill and by gender and age. In contrast, increasing numeracy skill improves earnings by occupational skill, with the greatest benefit for countries with more flexible labour markets. Similarly, increasing numeracy and ICT skill proficiency improves earnings for workers in the lower three age bands. This is found for numeracy proficiency in flexible labour markets. Rather than through regulation, earnings and living standards for individuals may instead be improved through greater cognitive skill proficiency in flexible labour markets.

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Chapter 1

1. Introduction

1.1 Background and Research Rationale

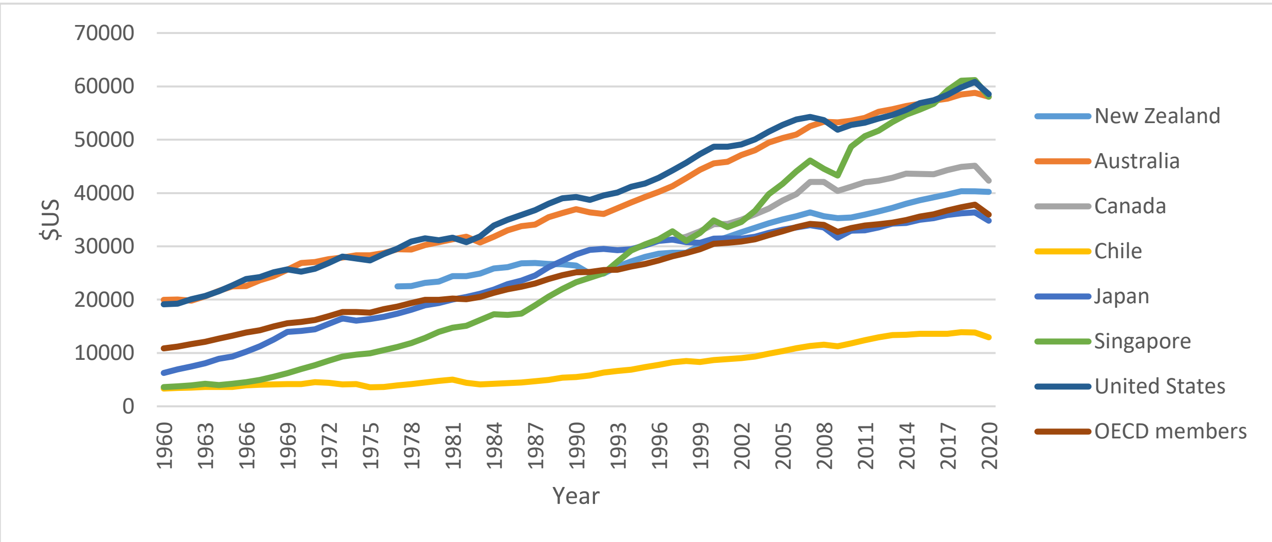
A key objective in economic research is to seek quantifiable results that support policy to improve standards of living for individuals and households. Important measures of progress in this aim include increasing real national and household income. A number of factors contribute to raising income levels, with gains to productivity being a key driver[1]. The focus of international attention is on lifting the economic performance particularly for developing countries, on which a large body of practical work exists in the development economics literature (see, for example, Sen, 2001, Argawal, 2018). However, there are also economies within the developed country grouping where performance may be lower than expected and where data allows the opportunity to further understanding of the underlying causes. The results from such study are important for the development of policy to enhance global economic performance, supporting improvements in living standards.

One such developed economy where performance has been lower, relative to comparable countries, is arguably New Zealand's. With the stylised feature of a small, open economy, there has been concern for many years for New Zealand's per capita income performance. This has created an income gap, contributing to a fall in the relative standard of living. This gap can be seen through level trends from the

[1]The Organisation for Economic Cooperation and Development (OECD, 2021, Labour Income and Productivity) note that labour income is the most direct mechanism through which the benefits of productivity gains, and thus economic growth, are transferred to workers. An employer's ability to increase wages and other forms of labour income depends on increases in labour productivity, highlighting the welfare implications of productivity growth.
https://www.oecd-ilibrary.org/sites/f8c31e3c-en/index.html?itemId=/content/component/f8c31e3c-en

Organisation for Economic Co-operation and Development (OECD) which I present in Figure 1.1. Established in 1961, the OECD comprises 37 member countries and more than 70 non-member countries (OECD, 2021a). Member countries include Australia (New Zealand's nearest neighbour and major trading partner), Canada, Singapore, Chile, Japan, and the United States. New Zealand joined in 1973. A significant function of the OECD is that it allows countries to measure their performance against each other across a range of metrics important to improving overall levels of well-being. The widening gap in real GDP per capita ($US) for New Zealand can be seen in Figure 1.1, relative to selected member countries. New Zealand's level of GDP per capita is less than Australia, Singapore, the United States, and Canada. New Zealand has, however, maintained higher levels of real GDP per capita than the OECD average, and Japan. For the developing economy of Chile, real income levels are lower but improving.

Figure 1.1. Real GDP per Capita Comparisons, 2015 US$. Selected Countries.



Source: https://data.worldbank.org/indicator/NY.GDP.PCAP.KD?locations=NZ-AU-CA-CL-JP-US-OE

In Appendix A.1, I present GDP per capita data based on purchasing power parity (PPP) at constant 2011 US dollars for selected countries and groupings of countries. From data sourced from the World Bank for the period 1990 to 2016, New Zealand has maintained approximately 80 per cent of Australia's purchasing power income. It has increased its relative purchasing power from 75 to 83 per cent of Canada's and maintained a PPP of 65 per cent of the United States' per capita income. New Zealand's purchasing power is 92 per cent of the OECD average. The economy's PPP GDP per capita has grown at a robust 4 per cent, but below an average of 5.3 per cent for the countries examined. Overall, New Zealand's relative purchasing power is not improving.

Examining further performance indicators, I present Penn World Table data in Table 1.1. The data shows New Zealand's economic performance relative to selected OECD member economies, from 1950 to 2017. The New Zealand economy has performed below the country average on each measure: the lowest average annual increase in real GDP per capita over the period at 1.94 per cent, shown in Column 1; the lowest average annual increase for the human capital index at 0.32 per cent over the period, in Column 2; the second-lowest average annual increase in total factor productivity at 0.37 per cent, following Singapore at 0.23 per cent, in Column 3; the largest average annual fall in labour's share of GDP (at current prices) at 0.37 per cent; and the third-lowest average increase in capital stock at 3.44 per cent per annum.

In Table 1.2, I present OECD data for average annual growth rates of real GDP per capita over a shorter time period, from 1970 to 2018, split into two time periods, and for a greater range of countries. New Zealand records the second-lowest average annual growth rate ahead of the Swiss economy at 5.10 per cent over the full period 1970 to 2018 in Column 1, and also for the 1970 to 1990 period in Column 2 at 6.9 per cent. New Zealand's growth rate for the more recent period from 1991 to 2018 in Column 3 is similar to several countries at 3.81 per cent and broadly in line with the

Table 1.1. Average Annual Growth Rates, Selected Economic Indicators by Country, 1950 to 2017.

Country	Real GDP per capita % (1)	Human Capital Index % (2)	Total Factor Productivity % (3)	Labour's Share of GDP (current prices) % (4)	Capital Stock % (5)
New Zealand	1.94	0.32	0.37	- 0.37	3.44
Australia	2.11	0.42	0.58	-0.25	3.75
United States	2.05	0.56	0.71	-0.072	2.84
Canada	2.11	0.61	0.83	-0.33	3.76
United Kingdom	2.23		0.54	0.25	3.02
Germany	3.64	0.63	1.62	-0.32	3.83
Japan	4.36	0.68	1.17	-0.26	5.36
Singapore	6.37	1.82	0.23	0.39	7.53

Source: Penn World Table, version 9.1. https://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt9.1

OECD average of 3.68 per cent. This provides some optimism for a catch-up in New Zealand's growth path of real GDP per capita. However, this rate is still below that of Australia at 4.1 per cent, South Korea at 5.96 per cent and Ireland at 6.9 per cent for the 1991 to 2018 period.

While GDP per capita expresses the value of national income if it were shared equally across the population, the Gini coefficient measures inequality in the income distribution. OECD Gini coefficients for household income distribution are presented in Appendix A.2 for the period 2014 to 2020. These were recently updated to the 2020-2021 period. Previously, only one data point was available for New Zealand, for 2014. The data show that New Zealand has a similar income distribution to Australia and Canada, in the lower to mid-range 0.3 level. New Zealand's median Gini coefficient value is 0.33. This is just above the median value of the recorded countries for the period of 0.31. Based on median values, New Zealand has less income inequality than the United States at 0.39 and 0.36 for the United Kingdom, but higher income inequality than the European countries of Denmark, Finland, and Norway, with mid to upper 0.20 Gini coefficient values.

Table 1.2. Average Annual Growth Rates - Real GDP per Capita ($US) – Country Comparison, 1970 to 2018.

Country	1970 to 2018 % (1)	1970 to 1990 % (2)	1991 to 2018 % (3)
Australia	5.28	7.01	4.10
Canada	5.16	7.74	3.32
Denmark	5.61	7.58	4.20
Germany	5.62	8.20	3.77
Ireland	7.80	9.05	6.90
Japan	5.50	9.35	2.75
South Korea	9.32	14.03	5.96
Netherlands	5.54	7.64	4.05
New Zealand	5.10	6.90	3.81
Norway	6.60	8.93	4.94
Poland	-	-	*6.01
Sweden	5.19	7.42	3.60
Switzerland	4.90	6.70	3.42
United Kingdom	5.55	8.06	3.75
USA	5.36	7.90	3.54
Chile	**6.54	-	6.21
Estonia	-	-	***7.84
OECD	5.51	8.08	3.68

Source: https://data.oecd.org/gdp/gross-domestic-product-gdp.htm. Note: *Polish data only available from 1990. ** Chilean data available from 1986. *** Estonian data available from 1993.

As stated, a key driver of income growth is productivity. In Table 1.3 I present OECD data showing the average annual percentage change in labour and total factor productivity rates between 1971 and 2020 for seven OECD countries. The overall period for average annual labour productivity growth is from 1971 to 2020. This is then split into two periods to identify differences in trends for the 1996 to 2020 period compared with the earlier 1971 to 1995 period. New Zealand has experienced the lowest average annual growth rate for labour productivity over the full period at 1.19 per cent and for both of the split time periods with 1.35 per cent growth in the 1971 to 1995 period and 1.03 per cent annual growth for the 1996 to 2020 time period. Average labour productivity growth rates fall in the latter period for all countries except the United States. For total factor productivity (TFP), growth rate data starts in 1985. For the full period to 2020, New Zealand has a similar annual average growth rate to Australia at

0.55 per cent per year, with both below that for other countries shown. New Zealand TFP grows at a 1.0 per cent annual rate for the 1985 to 2004 year period, but is much lower during the 2005 to 2020 year period at 0.15 per cent per annum.

Table 1.3 Average Annual Percentage Change in Productivity, Selected OECD Countries. 1971 to 2020.

		New Zealand %	Australia %	Canada %	United States %	Japan %	Chile %	Germany %
Average annual labour productivity growth	1971 to 2020	1.19	1.48	1.39	1.57	2.52	3.36	1.98
	1971 to 1995	1.35	1.50	1.40	1.47	3.77	4.63	2.93
	1996 to 2020	1.03	1.46	1.38	1.68	1.28	2.90	1.07
Average annual total factor productivity growth	1985 to 2020	0.55	0.50	0.60	0.83	0.70	-	0.89
	1985 to 2004	1.0	0.69	0.67	0.96	1.31	-	1.35
	2005 to 2020	0.15	0.31	0.54	0.34	0.70	-	0.43

Notes: Data for labour productivity growth rates available from 1971 to 2020. https://data.oecd.org/lprdty/labour-productivity.htm Data for total factor productivity available for 1985 to 2020. https://data.oecd.org/lprdty/total factor-productivity.htm

In 2008, the then-incoming Government established a taskforce named The New Zealand Productivity Commission. The Commission's objective was to provide policy recommendations to address New Zealand's relative economic performance, as highlighted so far in my introduction. Their first report entitled 'Answering the $64,000 Question - Closing the Income Gap with Australia by 2025' (NZ Productivity Commission, 2009) - provided a series of recommendations including changes to fiscal policy settings. These were aimed at improving New Zealand's fiscal efficiency, growth levels, and raising household disposable income[2]. Changes subsequently implemented by the New Zealand Government towards meeting these aims included reductions in direct income tax rates in 2010, offset by an increase in the rate of Goods and Services taxation from 12.5 to 15 per cent. These fiscal policy adjustments were intended to maintain overall neutrality in tax settings.[3] The Productivity Commission's (2020) final report to the Government was released in March 2020 and presented a significant shift in focus from earlier reports towards recognising the need for greater technological integration by firms. Other recommendations included removing barriers to worker mobility, improving career advice, and making training systems more flexible and accessible. The importance of technology for growth in the New Zealand economy is a significant theme identified in my study.

The Productivity Commission's study complemented on-going work in this area, including a series of discussion papers developed by the New Zealand Treasury. These include those by Kidd (2008), who considered factors underlying productivity levels in the New Zealand economy. Kidd identified the drivers of productivity as enterprise, innovation, skills, investment, and natural resources. For natural resources, the New Zealand economy has traditionally held a comparative advantage in agricultural products as a result of favourable production factors, including climate and soil conditions. These attributes attracted early European settlers with farming skills and experience associated with these resources. Agricultural and horticultural products

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[2] New Zealand Productivity Commission, First Report, p.7.
Source: https://www.treasury.govt.nz/sites/default/files/2017-11/2025tf-summary-nov09.pdf

[3] As detailed in the 2010 New Zealand Government Budget. The bottom tax rate was lowered from 12.5% to 10.5%, the 21% rate was lowered to 17.5%, the 33% rate was lowered to 30%, and the highest rate was lowered from 38% to 33%. This was offset by an increase in the rate of Goods and Services tax from 12.5% to 15%. Source: https://www.treasury.govt.nz/resources/budget-speech-11#section-3, p.6.

make up a significant proportion of New Zealand's tradeable economy[4]. For enterprise and innovation, New Zealand is regarded as having a strong supply of entrepreneurs with new ideas developing innovative products. This may, in part, stem from the early European settlement practice of having to 'make do' that existed for many years due to resource availability and which is embedded in the colloquial expression known as the 'number eight fence wire' approach (English-Lueck, 2003). Resource constraints are an issue for many smaller, isolated economies, as was the case for New Zealand's earlier development. In modern New Zealand, it may now manifest itself in the area of financial capital constraint. This in turn affects the key driver of investment, as identified by Kidd (2008). Capital intensity in production is identified in this study as a significant factor affecting productivity.

For skills, Kidd discusses the identification of low literacy levels for a significant proportion of the New Zealand domestic working-age population (Kidd, 2008). This is amplified in the 2015 report of the New Zealand Tertiary Education Commission in their consideration that approximately 40 per cent of individuals in the New Zealand workforce do not have sufficient literacy and numeracy skills to function will in a knowledge society and information economy[5]. The importance of human capital is well established in the literature as providing the skills, knowledge, and creativity organisations need to drive innovation, productivity, and economic growth. As for

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[4]For the full 2019 calendar year, agricultural products made up approximately 40 per cent of New Zealand's overseas exports, with horticulture at 17 per cent, seasonally adjusted. Source: Statistics NZ Overseas merchandise trade, 2020. [5]The Tertiary Education Commission is a New Zealand Government Crown Agency with responsibility to lead the Government's relationship with the tertiary education sector and to provide career services from education to employment. https://www.tec.govt.nz/assets/Publications-and-others/c74aff1b80/Literacy-and-Numeracy-Implementation-Strategy-2015-2019.pdf

physical capital, a certain level of human capital accumulation is required to maintain existing levels as skills depreciate through lack of use and industry demand (Dinerstein, Megalokonomou, and Yannelis, 2022). For outputs, in their annual publication, Education at a Glance, the OECD (2013) consider that investment in education provides employment opportunities, lifts income levels and standards of living, as well as improving social cohesion and equity[6]. I present in Table 1.4 New Zealand's comparable educational attainment from OECD compilation data. The proportion of New Zealand's adult working age population with upper secondary level education is 41 per cent, comparable with the United States and the OECD average level. The proportion of the population aged 25 to 64-years with tertiary education is in line with the OECD average at 39 per cent, but below comparable countries. These include Australia, with a 47 per cent proportion and Canada, at 59 per cent. While a comparative level of secondary attainment may support the development of literacy and numeracy skills, it is at tertiary level that important cognitive skills are developed further (Kollo, 2006, Guerra-Carrillo, Katovich, 2017). New Zealand's tertiary attainment lags behind comparable economies. Additionally, like many developed countries, New Zealand is facing an ageing population and has sought to address this issue through measures aimed at increasing the size of the workforce. New Zealand's population has increased through the last ten-year period, driven largely by changes to net migration[7,8]. This has introduced greater diversity and skills to the New Zealand

[6]Education at a Glance, 2023:OECD Indicators. https://doi.org/10.1787/e13bef63-en [7]New Zealand's average annual population increased by 1.17% for the 1991 to 2009 period and by 1.35% for the 2010 to 2019 period. [8]Annual average net migration increased by 53% for the period 1989 to 2009 and by 202% for the 2010 to 2019 period. Source for footnotes 8 and 9: Statistics NZ. Infoshare. Permanent and long-term migration key series.

workforce and poses questions on the effects of these trends for human capital - a key driver of productivity growth.

Table 1.4. Highest Adult Education Level for the Population aged 25 to 64-years. Four Year Average, 2017 to 2020. Selected Countries

	New Zealand %	Australia %	Canada %	United Kingdom %	Japan %	United States %	Germany %	Chile %	OECD Average %
Below Upper Secondary Level	19.8	17.6	8.2	19.5		9.0	13.5	32.6	21.5
Upper Secondary Level	41.2	35.5	33.3	33.5		43.0	56.8	42.3	41.5
Tertiary	39.1	46.9	58.5	47.03	52.02	48.1	29.7	25.2	37.4

Source: https://data.oecd.org/eduatt/adult-education-level.htm Chilean data for 2017 only.

1.2 Motivation for this Study

My findings for the continued lower relative performance of the New Zealand economy when compared to similar developed economies, together with the importance of human capital for driving improvements in productivity and income provide the motivation for this study to identify and analyse relationships between human capital measures and other key variables with the aim to provide policy suggestions to raise economic performance. The key performance measures for my study are labour productivity and labour income. Human capital measures to be included in my study are years of schooling, educational attainment, training, cognitive skill, and occupational skill. Broader factors will include macro-economic and demographic variables. This analysis and the resulting policy implications have the objective of closing New Zealand's relative economic performance gap. The findings may also be transferable to other economies for enhancing international economic performance.

1.3 Main Findings and Contribution to the Literature

This section outlines the gaps in the literature my research will fill, and sets out my key contributions, developed in Chapters 3, 4, and 5. These chapters comprise the core empirical sections of this thesis. In Chapter 3, within a neoclassical growth framework, I seek to understand the impacts of existing human capital levels on average labour productivity and real GDP, or earnings, for the New Zealand economy. This work adds to the micro-economic literature on human capital and labour productivity. Partly through data availability issues - particularly for schooling measures at the industry level - my study takes a novel approach in comparing productivity and earnings for industry sectors when grouped by average occupational skill. Rather than necessarily establishing causality, this approach results in the observation of industry trends from which inferences are made for human capital effects.

For the significant relationships identified, in a relatively labour-intensive economy, I find gains in labour productivity from increases in capital intensity. This finding builds on the work of Hall and Scobie (2005), Black, Guy, and McLellan (2009) and others in evaluating New Zealand labour productivity performance for earlier periods. Capital intensity is particularly effective for raising labour productivity for the lower to medium-skilled industries, relative to lower-skilled. This result indicates possible skill-capital complementary effects. Building on the work of Razzak (2007), I also observe significant improvements in labour productivity from higher total factor productivity. This result indicates the importance of a focus on increasing the level of technology adoption in New Zealand production. Considering input substitution effects, I observe a negative relationship between rising labour cost and capital intensity. This may indicate that firms reduce capital investment when costs rise. Low sensitivity is observed from increasing physical capital returns to capital investment. The latter two effects are likely to be negative for productivity in the relatively labour-intensive New Zealand economy.

My study in Chapter 4 draws on the traditional measures of human capital of years of schooling, qualifications, and experience to evaluate their effect on worker earnings in the New Zealand labour market. This is made possible by the availability of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) skills dataset. The findings support the educational labour returns literature and foundational work of Mincer (1974). The main contribution of this chapter is its extension from the existing human capital measures to an evaluation of the impacts of the core cognitive skills - literacy, numeracy, and a technology component: ICT problem-solving - for lifting New Zealand worker income. These are essential skills for improving workplace productivity. This work departs from applications of the PIAAC dataset which focus predominately on skills mismatch effects (Pellizzari and Fichen, 2013; McGowan and Andrews, 2015, 2017).

I examine the impacts of proficiency in the core skills together with a novel approach in examining the impact of greater usage of these core skills in workplace tasks on average earnings. The main findings are that greater proficiency in numeracy proficiency, in particular, has a positive effect on earnings, indicating the demand for this skill in the New Zealand labour market. For the effects of frequency of use of the core skills on earnings, the strongest positive effects are observed from greater use of ICT problem-solving, and from writing skills in the workplace. For ICT usage, this result highlights the importance of continued integration of technology into industry for lifting worker income. In examining the effects of occupational skill on income, I further contribute to the literature in finding labour earnings improvements from greater use of numeracy skills for each of the occupational skill groupings, and for all but use of ICT skills at work for skilled workers. Improved numeracy skill proficiency also raises worker income by age group and gender. This is particularly so for the prime working age group of those aged 25 to 54-years old. A relatively new finding and contribution from my study involves peak earnings by worker age. Peak earnings are found to occur for the 35 to 44-year age group of New Zealand workers. This contrasts with the existing literature such as Mincer (1974) and Thornton, Rodgers and Brookshire (1997) finding peak earnings for higher age groups. This result may indicate a possible loss of earnings potential for many in the workforce resulting from a factor they cannot control. In turn, this may restrict the income per capita performance of the New Zealand economy.

In my third empirical study in Chapter 5, I contribute to the literature through an international comparative evaluation of the effects of proficiency and use of the core cognitive skills on worker earnings. This work aims to identify broad trends and points of difference in the results across countries and to analyse underlying reasons for these trends. My contributions to the literature include the finding of a significant positive relationship between improvements to proficiency in numeracy skills and worker income. Further, increased usage of ICT problem-solving skills in the workplace raises worker earnings across countries. This indicates the international demand for this technology skillset and the importance of well-developed ICT infrastructure. These results also align with the cross-country work of Kollo (2006) and Nikoloski and Ajwad (2014) who emphasise the critical value of cognitive skills for income and employability.

In considering occupational skill effects, my findings add to the debate on the benefits of flexible labour markets versus a level of State protection for workers. Specifically, those countries offering the greatest protection for workers, typically northern European Union member countries, experience the smallest differences in occupational skill level earnings relative to skilled occupations. These findings add to the work of Flassberg (2013) and others on the tendency of flexible labour markets to grow wage inequality. However, when examining the ability of cognitive skills to reduce occupational income differences, those countries with more flexible markets see the greatest gains from increased numeracy skill.

As for my study in Chapter 4 on the New Zealand labour market, and in contrast to the literature, the results show a trend for peak earnings to occur for workers internationally in the 35 to 44-year age group rather than for those in older age brackets. This adds to the literature in identifying international labour market age constraints for worker income. Differences in earnings by age are similar in both protected and flexible labour markets. In examining impacts for earnings from greater cognitive skill by age group, I find that increased numeracy and ICT problem-solving proficiency improve income for workers in the lower three age brackets. For numeracy skills, it is those countries with more flexible labour markets that experience the higher income gains. This indicates that regulation is not always the most effective way to deliver higher income growth. The results found consistently in the literature for gender earnings differences are also observed in my study. Female workers experience lower average earnings relative to male workers across all age groups. My findings indicate and support the potential to raise international standards of living through policy to lift female labour market participation and income and better recognise the value of workers of all ages.

1.4 Chapter Outline

In Chapter 2, I review the significant empirical studies related to human capital and its relationship with productivity and earnings. This includes a review of the theoretical underpinnings for human capital in neoclassical growth theory, and of the education-labour market literature. The relevant literature highlights the importance of the key human capital factors of education and experience and expands to examine complementary and substitution effects of labour skills with capital and technology. I also study the empirical industry literature for the effects of occupational skill on productivity and earnings.

In Chapters 3 to 5, I empirically examine relationships between human capital, labour productivity, and worker earnings using panel and cross-sectional data. In Chapter 3, I employ Statistics New Zealand data to examine factors affecting average labour productivity for the New Zealand economy, using dynamic panel data modelling methodology. From the literature, I develop equations utilising relevant explanatory variables to gauge the effect of skills on labour productivity, together with equations examining capital intensity and input substitution effects. Policy implications are derived from the results. Diagnostic tests are undertaken for each equation and robustness checks are conducted to assess the reliability and robustness of the results.

In Chapter 4, I investigate the relationship between core cognitive skill proficiency, and frequency of their use and earnings in the New Zealand labour market. Here, I employ data from the OECD's survey of adult skills: the Programme for the International Assessment of Adult Competencies (PIAAC) for the New Zealand population and economy, in a cross-sectional study. This data additionally allows for an analysis of the effects on earnings from a wide range of skill factors for a broad cross-section of the New Zealand population. Again, the results allow for the development of policy suggestions. Appropriate diagnostic tests are performed, and robustness checks are undertaken to assess the reliability and robustness of the results.

In Chapter 5, I evaluate international similarities and differences in the relationship between human capital factors and worker income in a comparative study for 13 OECD member countries, including New Zealand. This analysis employs cross-sectional data from the PIAAC surveys for each country included in my study. An objective is also to demonstrate the robustness of the results obtained for the single-country study in Chapter 4.

In Chapter 6, I present a summary of the contributions of my research. I provide overall policy recommendations, set out the limitations of my research, and provide suggestions for further research that arise from my findings.

Appendix A

Appendix A.1.

Table 1.5. presents purchasing power parity data in $US for a number of OECD member countries, over the period 1990 to 2016. For this period, New Zealand has maintained 80 per cent of Australia's purchasing power and 65 per cent of that for the United States. New Zealand's purchasing power has grown at 4 per cent over the period compared to a mean growth rate of 5.3 per cent. The performance indicators show that New Zealand's purchasing power has not improved to match comparative economies.

Table 1.5. GDP per capita, Purchasing Power Parity (constant 2011 US$), 1990 to 2016.

	1990	2000	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
New Zealand	23,671.3	27,620.5	32,657.6	31,881.1	32,168.8	32,119.2	32,734.5	33,369.3	33,782.1	34.455.3	35,309.8	35,776.6
Australia	28,658.4	35,377.7	40,680.2	41,331.5	41,266.9	41,464.0	41,894.2	42,754.5	43,118.1	43,547.2	43,923.3	44,493.5
Canada	31,299.7	37,431.9	41,647.4	41,611.3	39,924.2	40,699.4	41,565.3	41,794.5	42,339.4	43,079.1	43,149.5	43,238.3
Singapore	34,344.7	51,706.4	68,432.7	66,046.1	63,697.3	72,115.8	75,113.2	76,285.6	78,896.6	80,903.5	81,741.1	82,621.5
Japan	30,582.4	33,871.9	36,697.2	36,278.4	34,317.7	35,749.8	35,774.7	36,367.6	37,148.6	37,337.3	37,883.0	38,282.5
Korea. Republic	11,632.6	20,756.8	28,013.7	28,588.4	28,642.8	30,352.1	31,228.5	31,776.9	32,548.7	33,425.7	34,177.7	35,020.4
Chile	8,991.8	14,315.4	18,572.6	19,031.6	18,547.5	19,442.1	20,437.7	21,330.2	21,998.3	22,195.3	22,516.6	22,614.4
United Kingdom	26,827.8	33,266.1	38,384.3	37,903.4	36,042.4	36,367.0	36,608.0	36,892.9	37,398.8	38,251.8	39,839.2	39,309.3
Germany	31,287.1	36,764.6	40,473.5	40,989.4	38,784.5	40,428.7	42,692.5	42,822.1	42,914.5	43,560.6	43,938.0	44,431.8
European Union	24,875.0	30,325.5	34,998.9	35,110.5	33,502.6	34,102.7	34,720.7	34,498.5	34,495.6	35,007.9	35,737.6	36,357.1
OECD Members	26,932.3	32,809.3	36,923.4	36,738.3	35,207.1	36,023.1	36,562.4	36,819.4	37,131.0	37,464.8	38,646.8	38,724.8
United States	37,062.1	45,986.1	51,011.4	50,383.8	48,557.9	49,374.2	49,793.7	50,520.3	51,003.7	51,922.0	53,005.6	53,399.4

Notes: Purchasing Power Parity (PPP) GDP is gross domestic product converted to 2011 US dollars using purchasing power parity rates. Under PPP, an international dollar has the same purchasing power over GDP as the U.S. dollar has in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Source: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

Appendix A.2.

Table 1.6. presents Gini coefficient results for 25 OECD member and non-member countries for the period 2014 to 2020. Non-member countries are economies the OECD has working relationships with. For 2020, Mexico has the highest income inequality value at 0.420, followed by the United States at 0.377. Chile's last value in 2017 is 0.46. Slovakia has the lowest income inequality for the majority of the time period, with a Gini coefficient of 0.222 in 2019, followed by the Czech Republic at 0.248. New Zealand is placed just above the median value for the period of 0.306, with a median Gini coefficient of 0.33.

Table 1.6. OECD Gini Coefficients for Member and Non-Member Countries, 2013 to 2019.

	2014	2015	2016	2017	2018	2019	2020
Australia	0.337		0.33		0.325		0.318
Belgium					0.258	0.262	0.248
Canada	0.312	0.318	0.307	0.310	0.304	0.30	0.28
Chile		0.454		0.460			
Czech Republic	0.257	0.258	0.253	0.249	0.249	0.248	0.255
Denmark	0.256	0.263	0.261	0.264	0.263	0.268	
Estonia	0.346	0.330	0.314	0.309	0.305	0.305	0.305
Finland	0.257	0.260	0.259	0.266	0.269	0.273	0.265
France	0.293	0.295	0.291	0.292	0.301	0.292	
Germany	0.289	0.293	0.294	0.289	0.289	0.296	
Ireland	0.298	0.298	0.309	0.295	0.292	0.293	0.282
Italy	0.326	0.333	0.327	0.334	0.330	0.325	0.331
Japan					0.334		
Luxembourg		0.306	0.305	0.327	0.318	0.305	0.290
Mexico	0.459		0.459		0.418		0.420
Netherlands	0.305	0.305	0.292	0.298	0.295	0.312	0.295
New Zealand	0.341	0.325	0.333	0.335	0.330	0.326	0.320
Norway	0.257	0.272	0.262	0.262	0.262	0.261	0.263
Poland	0.297	0.291	0.285	0.275	0.281	0.268	0.265
Slovakia	0.247	0.250	0.241	0.220	0.236	0.222	
South Korea	0.363	0.352	0.355	0.354	0.345	0.339	0.331
Spain	0.343	0.344	0.341	0.333	0.330	0.320	0.329
Sweden	0.272	0.276	0.280	0.282	0.273	0.277	0.276
United Kingdom	0.356	0.360	0.351	0.357	0.366	0.366	0.355
United States	0.394	0.390	0.391	0.390	0.393	0.395	0.377

Source: OECD Statistics. https://data.oecd.org/inequality/income-inequality.htm

Chapter 2

Literature Review

2.1 Introduction

In Chapter 2, I review the significant literature examining the relationship between human capital, productivity, and earnings. The aim of this chapter is to identify key theoretical underpinnings and evaluate the existing empirical evidence to provide a framework for the empirical analysis I will undertake in my study. This review also identifies the gaps in the literature my study will seek to fill. From the introductory chapter, I identify productivity as a key driver for lifting the performance of the New Zealand economy, with human capital, or skills, a central factor impacting on performance. The importance of physical capital and technology are also firmly recognised where skills are heavily intertwined with capital and technological change. I now study the literature on human capital and its related strands in greater detail to understand the importance of its contribution to past and future economic growth.

Chapter 2 is organised as follows. In Section 2.2, I discuss the theoretical foundations for human capital embedded within the neoclassical growth theory literature. In Section 2.3, I examine the literature on human capital measurement and its empirical treatment. Section 2.4 presents the literature on productivity, its measurement, causes of change, and trends. In Section 2.5, I examine findings on the impacts of technology on skill demand, earnings, and employment. Section 2.6 considers the importance of managerial skills. In Section 2.7, I explore the effects of education and skills matching for earnings and productivity. Section 2.8 examines the literature on the impacts of the core cognitive skills of literacy, numeracy, and ICT problem-solving skills on earnings and productivity. I present the conclusions for this chapter in Section 2.9

2.2 Human Capital and Economic Growth Theory

The theoretical foundations for my study evaluating the importance of human capital for growth in the New Zealand economy are established in the growth theory literature within a neoclassical economic framework. The Solow-Swan (Solow, 1957) exogenous growth model uses a Cobb-Douglas-type production function to explain that, in the long run, economies converge to their steady state equilibrium growth rate. Shifts in savings and population growth cause only level effects and permanent growth is only achievable through technological progress. A key assumption is that capital is subject to diminishing returns. The basic equation takes the following Cobb-Douglas form:

$$Y_t = K_t^{\alpha} A_t L_t^{1-\alpha}$$

where Y at time *t* is output, A at time *t* is total factor productivity, K at time *t* is physical capital, and L at time *t* is labour input. Within this model, technology is labour-augmenting. Labour productivity and total factor productivity (TFP) are measured through the extension to growth accounting, dividing the components by labour and taking logs:

$$\Delta \ln\left(\frac{Y}{L}\right) = \alpha\Delta\ln\left(\frac{K}{L}\right) + \Delta lnA$$

Solow contended that because saving and population growth rates vary across countries, they may reach different steady states. The higher the rate of saving, the richer the country, the higher the rate of population growth, the poorer the country. The prediction is interesting for this current study in that the New Zealand economy has the stylised facts of having a relatively low level of savings and has seen an increase in population level in the last ten-year period, with the question of what these trends mean for income per capita. Also under growth theory, poorer countries, with higher rates of return to capital, should experience higher growth rates, as capital flows are shifted away from wealthier nations. However, the theory for capital flows is not borne out by empirical evidence due to factors such as the level of risk to capital, as set out theoretically as the Lucas' Paradox (Lucas, 1990). Some element of Lucas' Paradox may apply to the New Zealand economy, given the interest rate differential experienced with economies such as Australia (adjusted for through uncovered interest parity). New Zealand's capital inflows are relatively smaller.

Mankiw, Romer, and Weil (1992) introduce human capital into the production function. They find that although Solow's model correctly predicts the direction of the effects of saving and population growth on income, the impacts are too large. Mankiw et al. (1992) propose the inclusion of accumulated human capital as well as physical capital to correct for this. Their extended Solow model including human capital as *H* is:

$$Y_t = K_t^{\alpha} H_t^{\beta} (A_t L_t)^{1-\alpha-\beta}$$

A measure of per effective units of labour is achieved by dividing through by AL. This model provides a greater representation of the input share of human capital for income. Romer's work (1990) in endogenous growth theory contends that investment in human capital, innovation, and knowledge are significant contributors to economic growth. He considers that human capital, as well as technology, are endogenous rather than exogenous inputs and that the stock of human capital is a key factor in determining the rate of growth. Growth is seen to arise from the positive externalities and spillovers of a knowledge-based economy. In a similar but also diverging view, Schumpeter's earlier theory focuses on long-run growth resulting from innovation. Innovations are motivated by the prospects of monopoly rents, with new innovations leading to the creative destruction or replacement of older technologies (Aghion and Howitt, 1992). Two competing approaches for my study are exogenous and endogenous methodologies, with merit for both approaches. For endogenous growth, positive spillovers arise from technological innovation. It may be argued that while human capital is endogenous, New Zealand 'imports' a quantity of the innovation and technology required for knowledge spillovers from abroad. This may favour the Mankiw, Romer, and Weil 91992) exogenous model as more appropriate in the New Zealand setting. This approach using a Cobb-Douglas production function framework will be adopted in my study, however it is acknowledged that both methodologies may be considered for modelling work.

2.3 Human Capital – Theory and Measurement

The Organisation for Economic Co-operation and Development (OECD) defines human capital as the "knowledge, skills, competencies, and attributes embodied in individuals that facilitate the creation of personal, social, and economic well-being" (OECD, 2001). Measures for the accumulation of human capital are generally centred on individual and aggregate attainment in education and skill. Early human capital models (Schultz 1961; Becker 1964; Mincer 1974) postulate that human capital helps individuals increase their labour income through its effects on increasing worker productivity. The more skilled the labour force, the more efficient and productive firms should be, allowing greater profit to be shared between the organisation owners and employee stakeholders. In addition to education levels, the productive value and quality of human capital is built from components including experience and job-related skills.

Le, Gibson and Oxley (2003), Morrissey (2018) and others note three major approaches to measuring human capital. These are a cost-based approach; an income-based approach; and an educational stock-based approach. Each measure has strengths and weaknesses and all three focus on education-based outcomes. The cost-based approach originates in Engel's (1883) cost-of-production method estimating human capital based on aggregating the cost to parents to rear a child and provide schooling and healthcare from conception to the age of 25. It was considered a person was not fully 'produced' until the age of 26. This approach is not widely used in the literature because the cost of providing education bears little relationship to the labour market returns of higher qualifications (Morrissey, 2018).

A more realistic measure may be the income-based approach which values the stock of human capital by the income generated from each qualification type over the lifetime of the individual holding the qualification. Foundational work for this approach is established by Jorgenson and Fraumeni (1989). Their methodology considers two important effects: that formal schooling will generate income throughout the lifetime of an educated individual and that education also enhances the value of activities outside of labour market activities. In their study applying this approach for the New Zealand labour market, Le, Gibson and Oxley (2006) find a partial positive effect. Using data from the Census from 1981 to 2001, they find the value of New Zealand's human capital stock, as measured by labour income growth, grew by approximately 50 per cent between 1981 to 2001.The value of the stock of human capital is more than double that of physical capital. Le et al. (2006) depart from Jorgenson and Fraumeni's approach in excluding the human capital of those individuals who are out of employment as well as the contribution that employed individuals make outside paid work. They contend the Jorgenson and Fraumeni approach overestimates a country's stock of human capital.

The educational stock-based approach is arguably a more focused measure of the labour market returns to human capital. This is the more commonly used measurement method for human capital employed in the literature and the method I will adopt in this research. This method controls for additional factors including experience. Discrete measures of educational attainment are typically years of education and qualifications used to explain individual and country labour earnings performance. Pioneering work with this method date back to Denison (1962) and Mincer (1974), and to the constructed data sets and empirical research of Barro and Lee (1996). Using descriptive statistics, Denison (1962) established a positive contribution to economic growth from aggregated investment in human capital through education. Using data for United States (U.S.) male workers, Denison calculated that education, using years of schooling, contributed 0.35 percentage points to the growth rate of total real national income over the period 1909 to 1929. This increased to 0.67 percentage points for the 1929 to 1957 period. Forecasting for the period 1960 to 1980 resulted in a similar 0.64 percentage point contribution to real national income. Building on this work, Chiswick and Mincer (1972) developed an econometric framework for studying the relationship between human capital and earnings in a relatively simple model measuring income effects from years of schooling and age. Chiswick and Mincer employed a time-series econometric analysis of income inequality for U.S. males for the period 1939 to 1969 and then projected the results to 1985. They found that schooling and age had a measurable effect on increasing income inequality.

Mincer's (1974) prominent work established the key human capital-earnings econometric model measuring the positive effects of years of schooling and work experience on individual worker earnings. This approach forms the foundation for the empirical work I undertake in Chapter's 4 and 5. In contrast to the earlier Chiswick and

Mincer (1972) work, Mincer presented years of work experience, rather than age, as a key explanatory factor for earnings. The education stock-based approach is also useful, as Morrissey (2018) contends, because data for these measures has been collected for a sufficient time duration to allow long-term time series to be constructed. This allows for trend analysis and cross-country comparison of human capital effects for earnings, the latter which I will undertake in Chapter 5.

For further human capital attributes, among New Zealand studies, Szeto and McLoughlin (2008) draw on approaches from the United States' Bureau of Labour Statistics (1993) 'estimated wage model' to show the importance of labour quality for labour productivity since 1988[9]. This is attributed to increasing qualification levels, particularly at the university degree level. In their study, labour quality has increased by an average of 0.6 per cent annually from 1988 to 2005. This result is considered comparable to the experience of Australia, the United States, and the European Union. Szeto and McLoughlin (2008) find, however, that although New Zealand labour quality rises yearly during the sample period, the increase is not constant over time. There is a greater gain in the first half of the period (1988 to 1997) than in the second half (1997 to 2005). Szeto and McLoughlin (2008) consider that by drawing a large number of lower-skilled workers into the New Zealand labour market during the latter period, the strength of employment growth may have dampened growth in labour quality. More

[9]The Bureau of Labour Statistics (1993) estimate labour quality in the private business sector of the United States using the following methodology: Firstly, they cross-classify hours worked by educational attainment, work experience, and gender. Secondly, they identify the impact of these sources of change in labour composition through estimating wage equations for cross-categorised groups using unit-record data. Thirdly, after estimating wage equations, they create Tornqvist indexes of labour input, weighting the hours worked of each group by the wage of the group. https://www.bls.gov/productivity/articles-and-research/labor-composition-us-productivity-growth-1948-1990.pdf

positively, they find that the overall rise in labour quality over the full period has been beneficial for labour productivity. Approximately half of the labour productivity growth of 1.4 per cent per annum since 1988 is attributed to the rise in labour quality. Labour productivity measured as output per quality-adjusted working hour rose by 0.8 per cent per annum on average from 1988 to 2005.

Human capital has a positive signalling effect for employment. Spence (1973) postulates that a United States college education helps a worker signal to firms that he/she has a higher innate ability than a high school graduate, although the education itself is unproductive. Under signalling theory, Ge and Haller (2017) find positive effects on income from education which is supported by the impact of technological change in facilitating job sorting. However, labour markets do not always function efficiently to fully transmit the positive effects of human capital. This can be seen through the research into skills mismatch effects. One of many examples is provided by McGowan and Andrews (2018), where the authors find that skill and qualification mismatch may reduce labour productivity, particularly where skill and qualification levels are lower than required for the position.

While human capital is an important component in driving economic growth, its' measurement continues to be imprecise. Temple (1999) is one of many to note that "the literature uses somewhat dubious proxies of aggregate human capital". Proxies such as years of schooling or formal educational attainment may not fully account for an individual's productivity or earnings capacity. This includes that learning and the acquisition of skills are increasingly expected to take place throughout life, beyond formal education, as embodied in the concept of 'lifelong learning'. Marginson (2017) contends that modelling techniques may fail to capture all the shifting human capital influences for earnings. Earnings often are not linear, as witnessed by extreme differences between the top and bottom percentiles of income distribution.

Notwithstanding issues of measurement, over time, human capital theory has broadened to reflect the economic value of a large range of worker attributes. These include not only educational and experience factors but also additional skill development and training, health, cultural, and social capital, and other factors employers value such as loyalty and punctuality. Boris, Gyyazov, Kuzmenko, and Anopchenko (2019) are among many to stress the economic value these wider factors provide to firms and the economy as a whole. A generally accepted principle is the belief that an organisation is only as good as its people, where the directors, leaders, and employees who make up an organisation's human capital are critical to its success. Human capital is perceived to increase productivity and, thus, profitability; therefore, the more a company invests in its employees (i.e., in their education and training), the more productive and profitable it may be. To capture the impacts of these broader variables, in my study I seek to assess as many relevant human capital measures as data will allow. These include in Chapters 4 and 5, further educational investment factors as explanatory variables in measuring human capital effects for earnings.

2.4 Productivity Theory and Trends

As discussed, productivity is considered a major source of longer-term income growth and is a key driver of improvements in standards of living. This makes productivity an important measure for this study. As Paul Krugman famously noted, “Productivity isn’t everything, but in the long run it is almost everything” (Krugman, 1997, p.11). Productivity, of course, measures the efficiency of input use in generating output. For labour input, efficiency gains occur through multiple avenues including improvements to the quality of human capital and the efficient deployment of labour (Koch and McGrath, 1996). For physical capital, improvements to productivity may occur through higher capital-to-labour ratios and increased fixed capital formation (Jorgenson, 1986). Other sources of productivity improvement include competitive effects from international trade (Alcala and Ciccone, 2004) and business cycle impacts on labour productivity (Baily, Bartelsman and Haltiwanger, 2001).

The first two-thirds of the twentieth century were a period of fast-growing productivity. An overall upward secular trend occurred from 1869 to 1969 for the United States and other developed economies, driven in large part by the rising pace of trade (Kendrick, 1973, International Monetary Fund - Annual Report, 2017). This trend was only intermittently interrupted by the significant events of the two world wars and the Great Depression. A decline in productivity is observed since the 1970s. Reasons put forward for this downward trend include Lindberg's (1983) findings of negative impacts from inflation and capital diversion through taxation systems, at the macro-economic level. The significant developments in computing technology lifted productivity through the 1980s and 1990s, before a further slowing to the present time (IMF, 2017).

For productivity measures, labour productivity is the key measure of focus in this study due to its strong relationship with human capital. Human capital quality improvements achieved through higher worker qualifications and skill levels is a key driver of gains to labour productivity. At the firm level, Koch and McGrath (1996) are amongst those to find that firms investing in their human capital in ways other than through compensation alone often obtain higher workforce labour productivity. This is accomplished through taking a proactive approach to human resource processes which includes securing and retaining the labour skills required through effective screening of applicants, investment in training, and recognition of employee contributions. Koch and McGrath find human resource management is particularly important in capital-intensive organisations where a relatively small labour force may operate large, costly fixed assets. In this setting, a poorly chosen and/or under-skilled employee could do significant harm. In the labour-intensive construction industry, Ng, Skitmore, Lam, and Poon (2004) estimate that site labour accounts for up to 40 per cent of the direct capital cost of large construction projects, making it important to maximise the productivity of labour resources. In their survey of Hong Kong-based construction workers, they find that motivation is a significant factor in the level of worker productivity for engineering projects. It is not just compensation but workplace challenges and a lack of recognition that may hamper performance. A wider view of human capital may lead to a more capable workforce able to drive efficiency gains.

Labour productivity may be improved through higher capital intensity in production, resulting from investment in machinery and equipment. Rao, Tang, and Wang (2003) find stronger labour productivity for the United States relative to Canada through the 1990s. This is attributed to higher capital intensity driving efficiency gains for the United States. Advances in technology will also increase the efficiency and capability of physical capital to deliver productivity improvements. Impacts from capital intensity for labour productivity is an important topic for my study. Strongly linked for this thesis is the stylised fact that production in New Zealand is currently relatively labour-intensive. This has important implications for rates of productivity. In this regard, in a country comparison, Mason and Osborne (2007) find that lower capital intensity for the overall New Zealand economy has contributed to lower aggregate productivity in comparison to the United Kingdom. Black, Guy and McLellan (2009) study differences in labour productivity between the New Zealand and Australian economies for the period 1988 to 2002. They find that while market sector total factor productivity growth has been similar in both countries over the sample period, since 1994, average labour productivity growth has been higher in Australia. This is attributed to a lower rate of physical capital accumulation in New Zealand after 1993. Partially offsetting this, New Zealand's capital productivity growth has been higher than Australia's since 1994. This reflects relatively higher growth in hours worked in New Zealand.

The substitutability of labour/skill levels and physical capital also have important impacts on productivity. Dupuy and de Grip (2006) show the larger the substitution parameter between skilled and unskilled labour, the larger the labour productivity gain is as skilled labour is substituted for the less skilled. Alvarez-Cuadrado, Long, and Poshke (2017) show that sectoral differences in the degree of capital-labour substitutability are a driving force for structural change and factor income shares. Similarly, Chen (2020) finds as capital becomes more abundant relative to labour in the U.S. economy, lower-skilled labour is substituted by capital, leading to faster growth of capital intensity and hence labour productivity in the goods sector relative to the service sector. For long run aggregate growth, Klump and de La Grandville (2000) find that, in drawing back to the neoclassical growth theory work of Solow, the higher the labour input cost elasticity of demand, the higher is income per capita in the steady state as capital is substituted for labour.

The degree of capital intensity in production is also an important determinant of the share of income attributed to capital and labour input. Fleck, Glaser and Sprague (2011) discuss that, since the 1970s, hourly compensation has lagged behind labour productivity growth in what is referred to as the wage gap. The OECD (2021) contends there has been a decoupling of labour productivity from real labour income growth for approximately two-thirds of OECD countries since the mid-1990s. This is reflected in the decline in labour shares observed for these countries[10]. Causes include the effects of technological progress and the impacts this has on the more routine-tasked occupations (Dao, Das, Koczan and Lian, 2017). Alyan (1999) is amongst those to find that greater capital deepening, particularly in investment in computer technology, is positively related to the wage share of skilled workers in a U.S. industry study. The decline in the labour share of income has also been concomitant with an increase in income inequality, with lower-skilled workers bearing the brunt of the income share changes. This trend is related to the rich capital-skills complementarity literature, finding widening income inequality from higher skill and capital complementary wage effects (Correa, Lorca and Parro, 2019; Chen, 2020).

Total factor productivity (TFP) is an important measure in determining the impacts of technology and efficiency on labour productivity in the New Zealand economy. I will assess the impacts of TFP on labour productivity in Chapter 3. TFP is a residual not explained by labour and capital productivity. Also referred to as the 'Solow Residual' (Ahmed and Bhatti, 2020), there has been significant debate on the components that make up this measure. In his original model, Solow (1957) uses the term 'technical change' to describe TFP as consisting of factors that may shift the production frontier, including education of the labour force and slowdowns and speed-ups in activity. Lipsey and Carlaw (2004) argue that technology may be just one component and summarised TFP as (a) a measure of all improvements in technology and increases in efficiency over time and (b) the factors of productivity not already

[10]As detailed in the OECD's Compendium of Productivity Indicators, Labour Income and Productivity. https://www.oecd-ilibrary.org/sites/f25cdb25-en/index.html?itemId=/content/publication/f25cdb25-en

identified. The second definition is famously described by Abramovitz (1956) as "a measure of our ignorance". Measurement approaches such as frontier models attempt to divide total factor productivity into the proportion that is technological change and the portion that is technical efficiency change. The OECD's (2019) approach summarises TFP as a measure of the overall efficiency with which labour and capital inputs are used together in the production process. It is acknowledged that the measure will also reflect the effects of changes in factors including technology, management practice, economies of scale, market structure effects, spillovers, and measurement errors[11]. Whilst a broader measure than is preferred, I will adopt the OECD's measure of TFP in this study.

Razzak (2007) finds that more than eighty percent of labour productivity gaps between the New Zealand and Australian economies are explained by endogenous technology shocks (TFP) and capital intensities. Over the sample period 1989 to 2003, real GDP per capita and real GDP per hour worked are lower for New Zealand than Australia. These results reveal New Zealanders to be less productive than Australians. Razzak also investigates a widespread belief that Australia's productive superiority is due to having a vast mining industry, which has large capital investments delivering a higher marginal product of labour (Matheson and Oxley, 2004). Removing the GDP of the mining industry from Australian output makes only a small difference to the GDP per hour worked, indicating higher capital intensity overall for the Australian economy. In a similar vein, Margaritis, Scrimgeour, Cameron and Tressler (2005) investigate the growth experience of Australia, New Zealand, and Ireland over the period 1979-2002.

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[11]As described in the OECD's Compendium of Productivity Indicators (2019), p.12. https://www.oecd-ilibrary.org/industry-and-services/oecd-compendium-of-productivity-indicators-2019_b2774f97-en

They find that Ireland has outperformed Australia and New Zealand in terms of economic and productivity growth. Ireland's higher productivity growth is driven by total factor productivity increases, due to improvements particularly in Ireland's 'high-tech' manufacturing and services sectors. These gains are considered to have originated from research and development, innovation, and technology spillovers as a result of significant foreign direct investment.

2.5 Impacts of Technology on Skill Demand, Labour Earnings, Productivity, and Employment

2.5.1 Impacts of Technology on Labour Earnings and Productivity

An important issue in understanding the impact of skills on income and productivity in the New Zealand economy is how effectively New Zealand workers' skill levels are changing and adapting to match labour demand shifts created though changes in technology. A stock of human capital is important, but it is also essential that this stock provides the skills required to complement and augment continual technological development. For a relatively small economy such as New Zealand's, and with some geographical distance from markets, there can be a danger of a) not keeping up with peer-country technological improvements in production and, as a result of this, b) seeing a further lag in developing the skills required to compete effectively. The strengthening relationship between human capital and technological advances in recent decades has led to the development of another important theory for this study - that of skill-biased technical change. This theory centres around the expectation that changes in technology have increased demand for those with higher skills at the expense of those with lower skills, contributing to wage inequality and labour employment effects. These changes are set out in the canonical model of Acemoglu and Autor (2011), where the labour force is considered to comprise two distinct imperfectly substitutable skill groups.

Technology is assumed to take a factor-augmenting form and complements either high or low-skilled workers. Changes to factor-augmenting technology and its relationship with labour skill cause skill-biased technical change. My study will contribute to the literature in examining technology-skill effects for earnings in the New Zealand labour market, including through occupational skill impacts.

A significant proportion of the gains in productivity and wage growth through the 1980s and 1990s has been attributed to the birth and development of the microcomputer in what is known as the Information Age[12]. The gains from technological advancement have been achieved in numerous ways, including the further automation of routine tasks, automating and systemising workflows and processes, and improving communication links. Early studies such as Krueger (1993) observed that the more highly skilled workers are, the more likely they are to use computers on the job. This suggests that computer technology is complementary with improving human capital. However, the effects of these developments have not all been positive. A series of studies by authors including Katz and Murphy (1992), Levy and Murnane (1992), and Juhn, Murphy, and Pierce (1993) point to the development of microcomputers as a key cause to explain the rise in wage inequality since the 1980s[13]. Johnson (1997) contends that the inequality literature has "reached virtually unanimous agreement" that relative demand for highly skilled workers increased in the 1980s, causing earnings inequality to rise: the skill-biased technical change theory. Assessing the impact of technology on wage inequality

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[12]A term espoused by many including Castells (1996) and Zimmerman (2017) to describe the shift from industry established by the industrial revolution to the modern economy shaped by the development of computer technology and dependent upon information technology. [13]Bluestone and Harrison's (1988) earlier study of rising wage inequality focused on changing industry composition and institutionally based explanations for rising wage inequality in the early 1980s, rather than the technology cause pointed to here.

in the New Zealand labour market, Hector (2004) uses data from the Household Labour Force Survey to find a strong relationship between the two variables for New Zealand workers in the lower half of the qualification range. Controlling for education and occupation, Hector further contends that it is not so much industry use of technology driving the wage premium as the industry need for a better educated and more appropriately qualified workforce.

For occupational effects, Autor and Dorn (2013) consider that workers who undertake abstract thinking tasks will continue to benefit from technological advancement via strong complementarities between cognitive skill and technology. Such skills are typically found in professional and technical occupations. For these workers, earnings are supported by inelastic demand for their labour services, and because of lengthy training requirements, they experience inelastic labour supply conditions over the short and medium term. By contrast, for workers in jobs with a greater proportion of manual tasks, these same synergies may not apply. These types of tasks are typically found in lower-skilled occupations including as janitors and cleaners, vehicle drivers, security guards, flight attendants, food service workers, and home health aides. While such jobs are in demand, most manual, task-intensive occupations use minimal information or data processing in their core tasks. This provides limited opportunities for positive complementary technology and earnings effects.

These income-widening effects of technology - particularly for lower skilled workers - support the use of policy to address wage inequality. This is of importance for the New Zealand workforce, which, as this study will show, comprises a significant proportion of lower-skilled occupations. Lankisch, Prettner, and PrskaItz (2019), in their theoretical paper entitled ‘How can robots affect wage inequality?’, show a rising automation level contributing to per capita GDP growth but an increasing skill premium and falling wages for lower-skilled workers. They recognise the difficulty in offsetting the effects on lower-income earners and instead recommend policy to increase the share of higher-income earners in the workforce through a central policy setting of greater investment in higher education.

For productivity effects, Sorbe, Gal, Nicoletti, and Timiliotis (2019) find that it is increasingly technology adoption affecting employment, wages, and productivity across industries. The most productive firms have connected with and benefit relatively more from digitalisation. This contributes to a widening firm and industry productivity gap. Sorbe et al. (2019) consider that policies should create the conditions for the efficient adoption of digital technology by less productive firms to help them to catch up. They consider this will achieve a double dividend in terms of growth and inclusiveness. Greater use of technology across industries supports and enhances skill quality and reduces skill shortages. Encouragement of specific skills and occupations may help in increasing worker earnings and productivity. Roberts and Wolf (2018) use 2016-year data from the Bureau of Labour Statistics in their descriptive statistical analysis of employment, wages, and output for U.S. high-tech industries. They find that median wages for workers with Science, Technology, Engineering, and Mathematics (STEM) training were higher than the average, but that in a comparison of wages by occupational group, workers of all types, not just STEM workers, had higher wages if they were in high-technology industries. They contend that productivity in high-technology goods-producing industries is projected to increase by 34.3 per cent between 2016 and 2026.

2.5.2 Impacts of Technology on Employment

Similar to wage inequality concerns, there is a threat to the New Zealand workforce that technology may reduce employment in certain occupations. Concern over technology's impact and ability to take over jobs is not new. Early examples include the Luddite movement of the early nineteenth century, in which a group of English textile artisans protested the automation of textile production by seeking to destroy some of the machines (Rude, 1971). What is apparent is that the degree of substitutability and complementarity between labour and physical capital has a significant impact on whether automation may replace or enhance labour.

In their widely discussed book, The Second Machine Age, MIT scholars Brynjolfsson and McAfee (2014) contend that technological progress may leave many people behind as it races ahead. They consider there has never been a better time to be a worker with special skills or the right education. These people are able to use technology to create and capture value. Conversely, there's never been a worse time to be a worker with only 'ordinary' skills and abilities because computers, robots, and other digital technologies are acquiring these skills and abilities at an extraordinary rate. Changes in technology do alter the types of jobs available and what those jobs pay. Whereas the income effect has been discussed as widening, for employment another noticeable change in the last few decades has been what is referred to as "job polarisation" of the labour market (Goos and Manning, 2003, Acemoglu and Autor, 2012, and Goldin and Katx, 2007). This has meant greater demand for cognitive and problem-solving skills found in fields including information technology, technical, education, financial services, and marketing, and for certain manual skills typically found in jobs in healthcare, hospitality, and cleaning services. For the former, technology is often complementary, for the latter, technology may not be able to substitute. Conversely, automation has led to a reduction in demand for certain tasks which may be substitutable. These tasks are found in data processing, bookkeeping, manufacturing, and clerical roles. With perhaps the exception of manufacturing, many of these tasks are performed in middle management or white-collar positions. They may be considered mid-level skilled tasks and illustrate how automation has led to a polarisation effect with a 'hollowing out' in this employment grouping (also discussed in Autor and Dorn, 2013, and Guo, 2022). Dao et al. (2017) find evidence of a persistent decline in middle-skilled occupations with routine tasks in advanced economies. Evidence for this effect in the New Zealand labour market will be undertaken in my study.

Technology may also support the creation of further 'white-collar' tasks, replacing those that are 'lost' with activities of higher value. Bessen (2019) draws upon the introduction of automated teller machines (ATMs) in the U.S. banking industry. While the number of workers involved in bank teller services has fallen, information technology has enabled growth in a broad range of 'relationship banking' services including the provision of an increasing variety of credit and investment products. This has led to higher-valued employment opportunities.

2.6 The Importance of Managerial Skills for Productivity and Labour Market Earnings

Managerial skill is an ability critical for driving improvements in organisational labour productivity. Adam Smith (1776) sets out foundation work for managerial organisational practice in his treatise 'The Wealth of Nations'. Smith's famous example of the manufacture of pins shows labour productivity improvements through the division of labour, with worker production of separate components. This is in comparison to a production method where each person produces units of output separately. Sayer (1803) extended Smith’s work in considering productivity gains arising from managerial advances in the use of other inputs to production including capital deployment and the more efficient use of natural resources. Lucas (1978) proposed a model where managerial skill improves productivity but that there are diminishing returns to scale as firms increase in size. The skills of good managers are spread thinner as firms grow. Jovanovic (1982) considers that effective managers have an intrinsic ability, learned over time, to respond to productivity shocks which allow firms to decide whether to expand or contract. In contrast, Caves and Barton (1990) are among those with a less favourable view of managerial performance. They contend that managers do not always perform to the upper limit of their abilities. This can lead to a cycling of firm productivity where they move down to the bottom of the productivity distribution. Changes are then made to allow productivity to improve again. This brief review in the context of this study highlights the importance of managerial human capital skill for firm-level and aggregate economic growth.

2.7 The Effects of Education and Skills Matching for Labour Earnings and Productivity

The importance of skills for earnings has resulted in a drive for greater individual educational attainment. However, higher qualification levels do not in themselves guarantee higher individual income. The literature on skills mismatch examines the success in matching worker education and skills with the requirements of the job. Through probit modelling, Duncan and Hoffman (1981) predict the earnings for those who have more skills than are required for their position (over-educated), the right level of skills, or fewer skills than are required (under-educated) Also known as the ORU specification, their work studying the effects of over-education on earnings for the U.S.

workforce finds that nearly 40 per cent of workers had more education than required for their jobs, but also that ‘surplus’ education does have economic value. The individual return to an additional year of surplus education is positive and significant for the demographic groups examined. Further demonstrating inefficiencies in the labour market, Hartog (2000) shows in a five-country study that the predicted return to required education is higher than the actual return.

Yeo and Maani’s (2017) study on the effects of educational mismatch on earnings for the New Zealand economy for the period 2004 to 2007 reaches similar conclusions. They use Statistics New Zealand’s HLFS/NZIS cross-sectional dataset to study probabilities for labour earnings from education for full-time employed males and females, aged 25 to 59-years. Significant earnings penalties are predicted for under-education. This is estimated at approximately 4.5 per cent less for each year of under-education relative to the level required for the job. For over-education, each additional year of education above that required for an occupation generates returns that are 3.5 per cent to 4 per cent per year lower than expected for the level of education. This demonstrates that it is important to match workers in the New Zealand labour market with jobs appropriate for their skill level to avoid inefficiencies and to reward individuals equitably.

In more recent studies, Pellizzari and Fichen (2013) make use of the Organisation for Economic Co-operation and Development (OECD)’s Programme for the International Assessment of Adult Competencies (PIAAC) data, on which my study will draw in Chapter’s 4 and 5, to include the skill domains of literacy and numeracy as measures of skills mismatch. They find for a range of countries that approximately 86 per cent of employees are well-matched in literacy for their jobs, and of these, 94 per cent are also well-matched for numeracy skills. The authors contend however, that for general skill matching, a better match of the workers' skills to the requirements of their jobs can reduce the waste of skills among the over-skilled and improve the efficiency of the under-skilled at the same time. Far less empirical research is observed showing the effects of skill mismatch on productivity, with data availability likely to be a key reason for this. Work by Kampelmann and Rycx (2012), Grunau (2014) and McGowan and Andrews (2015, 2017) examine the link between firm productivity and over and under-education. McGowan and Andrews find that higher skill and qualification mismatch is associated with lower labour productivity through a less efficient allocation of resources. They find an over-supply of workers with higher education levels than is required for their current job.

2.8 Literacy, Numeracy, and ICT Problem-Solving Skill Effects on Labour Earnings

My study will contribute to the existing literature on human capital through examining the effects of the core cognitive skills of literacy, numeracy, and information communication technology (ICT) problem-solving on worker earnings, in addition to the traditional measures of schooling and experience. This research will be for the New Zealand labour market and an international comparative study. Nikoloski and Ajwad (2014) discuss cognitive skills as allowing for the development of memory, literacy, and numeracy skills. Greater use of cognitive skills may be found in jobs that require above-average, non-routine cognitive and analytical skills and above-average, non-routine interpersonal skills needed in the 'new' economy. The use of non-cognitive skills may be found, to a greater extent although not exclusively, in vocational-type jobs including the trades and occupations making greater use of manual tasks. Nikoloski and Ajwad (2014) analyse the relationship between skills and labour market outcomes for the two

Central Asian countries of Tajikistan and Uzbekistan, applying data from primary surveys conducted jointly by the World Bank and the German Society for International Cooperation in 2013. They find a strong positive link between employability and cognitive skills. They also provide evidence that stronger cognitive skills are associated with higher wage rates and labour productivity and that there is evidence of a robust and positive association between skills and job satisfaction.

In earlier work, for literacy skills, Hartog and Jonker (1996) use Adult Literacy Survey (IALS)[14] data to find that while there are overall positive effects on income for both men and women from an increase in education and work experience, the likelihood of under-schooling is significantly increased with relatively low levels of quantitative literacy. Denny, Harmon and O'Sullivan (2003) also make use of the IALS data to find that the returns to the broader 'years of schooling' variable and the returns to a more specific skills variable of functional literacy are not correlated, implying there may be differences in the effects of each for labour earnings. The effects of literacy skills on earnings vary across countries but are generally economically significant. In most countries, a one standard deviation increase in literacy skill increases wages by more than that for a year of schooling. Denny et al. (2003) find a further effect of literacy skills where, in general, these skills have a robust positive effect on social skills, particularly volunteering. A one standard deviation increase in literacy skill is associated with a higher probability of volunteering in the range of 3 to 10 per cent.

The OECD's Programme for the International Assessment of Adult Competencies

[14]The IALS represented a first attempt to assess the literacy skills of entire adult populations in a framework that provided data comparable across cultures and languages. This survey was carried out in two waves: in 1994 and 1996 for 13 member countries, and a third wave in 1998, adding a further nine countries. https://nces.ed.gov/statprog/handbook/pdf/ials.pdf

(PIAAC) provides access to a further rich data set to allow continued research into the impacts of the core cognitive skills, which my research utilises. The PIAAC skills programme provides extensive skills and demographic data, including worker earnings. In addition to literacy and numeracy measures, the PIAAC data allows for measurement of a third important skill proficiency variable, that of ICT problem-solving. This latter variable captures the effects of demand for technology skills in the modern workplace.

Studies making use of this dataset include Pellizzari and Fichen (2013). They find in examining skills mismatch that overlap between the skill domains of literacy and numeracy is substantial: 94 per cent of workers who are well-matched in literacy are also well-matched in numeracy. Key literature for my study in Chapter 4 and 5 include the studies of Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), and De la Rica, Gortazar, and Lewandoswski (2020). Hanushek et al. (2015) utilise PIAAC data to assess labour market returns to proficiency in cognitive skills for 23 countries, establishing a positive relationship between numeracy skills, in particular, and labour returns. De la Rica et al. (2020) utilise the PIAAC data to examine the empirical relationship between abstract, routine, and manual tasks and wages. They find a positive relationship between abstract task usage and labour returns.

Much of the existing research using the PIAAC dataset explores skills mismatch effects on worker earnings (examined previously, including Kampelmann and Rycx, 2012; Pellizzari and Fichen, 2013; Grunau, 2014; and McGowan and Andrews, 2015, 2017), with little evidence in the literature for studies examining the effects from usage of these core skills, in either single country or comparative country studies. This gap in the literature provides motivation for my study to contribute to the human capital literature through research into the impacts of greater proficiency and use of the three core cognitive skills of literacy, numeracy, and ICT problem-solving for worker earnings. I examine these relationships for the New Zealand labour market in Chapter 4, and for international labour markets in Chapter 5, together with other earnings-related explanatory factors.

2.9 Conclusion

In this chapter I survey the relevant literature examining the role of human capital as a key driver of economic performance. This review identifies gaps in the literature for the New Zealand economy, which my study will seek to fill. These include an examination of the relationship between industry level skill and labour productivity and earnings, and a drilling down to the impacts of the core cognitive skills on labour earnings. The literature informs on the theoretical underpinnings, establishing a neoclassical Solow-Swan (1957) growth framework with human capital for factors impacting labour productivity. The education-labour returns literature is also important for my study, with the work of Mincer (1974) establishing the underlying econometric framework to examine the relationship between cognitive skills and worker income.

The literature on growth theory also informs me on the importance of key explanatory factors in capital intensity, through the work of Rao, Tang, and Wang (2003) and others, and total factor productivity such as through Razzak's (2007) comparative study between the New Zealand and Australian economies. Lower performance is identified for the New Zealand economy for both variables in the literature, reinforcing the importance of my research to a more up-to-date time period. The skills-capital complementarity literature finding substitution effects between skilled and unskilled labour with fixed capital (Dupuy and de Grip, 2006, Chen, 2020) supports the need for a similar examination in my study, in relation to input prices and labour skill, as data allows. Further, the skill-biased technical change literature examines the role of technology as a driver of wages and employment for differing skill groups. These include the hollowing out of employment for those with middle skill positions discussed by Autor and Dorn (2013), and Guo (2022). These will be important skill-related issues to examine for the New Zealand economy and labour market.

Temple (1999) and others consider that measures of human capital such as years of schooling and qualifications can be imprecise measures of skill. As discussed, subsequent work finds evidence for influence from a wider range of factors, including cultural and family background effects (Boris, Gyyazov, Kuzmenko and Anopchenko, 2019). Data development, through the OECD and Statistics Canada's (1995) International Adult Literacy Survey and more recently the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) allows for further research into the economic impacts of the core cognitive skills of literacy and numeracy. The PIAAC data set provides a third core skill of problem-solving in an ICT-rich environment. This is an important skill variable which allows for the evaluation of worker-technology skill level effects on income. The availability of this rich dataset allows my study to further contribute to the literature in analysis of the ability of the core cognitive skills to lift labour income in the New Zealand economy. It also allows for country-comparative study to assess international trends and differences in the relationship between key variables of interest.

The human capital literature provides a strong theoretical and empirical base on which to undertake my research. In addition to the research topic, this includes for the development of appropriate empirical frameworks, data selection, and in the identification of key explanatory variables. The literature guides me on the use of appropriate modelling methodology to apply to the data, including dynamic panel data and cross-sectional modelling. In addition, it supports the choice of appropriate diagnostic and robustness tests to strengthen the reliability of the results I obtain.

Chapter 3

New Zealand Industry Skill Level Effects on Average Labour Productivity

3.1 Introduction

The review of the literature on human capital in Chapter 2 has shown the significance of labour skill to economic performance and identifies important factors human capital interacts with and impacts on. The quality of human capital is built from a number of components including the quality of educational institutions, educational attainment, experience, job-related skills, and cultural factors. The more skilled the labour force, the more efficient and productive firms should be, and the more profitable. This in turn will generate higher levels of income to be shared by organisation owners and employee stakeholders. The New Zealand economy is shown to have lower performance on key metrics including labour productivity, relative to peer countries including Australia and Canada. In Chapter 3, I contribute to the literature in evaluating the impacts of human capital on labour productivity in the New Zealand economy. Using a neoclassical growth framework, I disaggregate skill effects to the industry or sector level. Data is not available for the human capital attainment of individuals at the sector level which necessitates a measure of average industry skill level. In the course of this analysis, I identify other factors important for labour productivity, and assess their relationship through sectoral interactions. These include for capital intensity and input prices. I also examine factors impacting on labour market earnings, including productivity, however, I have limited success in identifying significant relationships.

For the key empirical findings in this chapter, I find evidence that greater capital intensity, through the proportion of physical capital used in production relative to labour input, significantly increases aggregate New Zealand average labour productivity. This result builds on the findings of Mason and Osborne (2007) and Black, Guy, and McLellan (2009) for the New Zealand economy. Secondly, I find a strong positive relationship between total factor productivity and the technology component this may incorporate, and labour productivity. This latter finding supports the results of Razzak (2007) but updated to the current time period. Next, and flowing from the result for capital intensity, I examine the relationship between individual industry or sector capital intensity and labour productivity. Controlling for two separate measures of labour cost, I find a positive relationship between capital intensity and labour productivity for the majority of New Zealand industries studied. For individual industry average skill, the strongest economic effects are for the lower-to-medium-skilled sectors, encompassing the capital-intensive industries of utilities and wholesale trade. When grouping industries by average skill level, I find significant positive effects also for the medium-to-higher-skilled industries, relative to the lower-skilled. These results suggest skill-capital complementary effects, where increased physical capital will support labour efficiency as labour skill rises in the New Zealand economy. For lower-skilled industries such as hospitality and construction, the results, while positive, may indicate a greater importance for the input of labour in production.

Thirdly, stemming from the results obtained for capital intensity effects on labour productivity, I examine the relationship between input cost and capital intensity by industry. I find a negative relationship between labour cost and capital intensity for most industries, regardless of average skill level. This is evidence against a substitution effect from increasing labour costs to greater physical capital use in production. With rising input costs, New Zealand firms may be reluctant to invest further in physical capital. This in turn, may impact negatively on labour productivity in a labour-intensive economy. For the other key input to production, I observe a positive relationship between returns to physical capital and capital intensity for the majority of New Zealand industries. Higher returns may support physical capital use or indicate substitution of capital for labour in production. However, while the results are statistically significant, they are economically small. For further variables of interest, an increase in full-time equivalent employment reduces capital intensity, showing a tendency to labour intensive production. Growth in fixed capital formation has an economically modest effect in lifting capital intensity in production.

Fourthly, I find no evidence to support an efficiency wage effect on average labour productivity in the New Zealand workforce. Given the mixed results found in the literature, such as by Huselid (1995), this may be expected as higher wage rates may only have a short-term effect in lifting worker motivation to improve productivity. This result also indicates that productivity growth for the New Zealand economy is not being directly constrained by the level or growth of wage rates. For the final relationship in the chain - that of a link from labour productivity to earnings in the workforce – I find no significant empirical evidence in this study. The results of this empirical work with earnings as the dependent variable are presented in Appendix B.6. However, as reviewed, previous studies such as Krugman (1997) have demonstrated that productivity is an ultimate driver of gains to income.

Literature Review and Hypotheses Rationale

From a starting point of the base production function with capital and labour inputs, the literature points to human capital, when incorporated into the model, contributing significantly to productivity performance. This includes through Mankiw, Romer, and Weil's (1992) work integrating human capital into the Solow-Swan exogenous growth model, Romer's (1990) endogenous growth model incorporating human capital, and

Krugman's (1997) empirical work on labour productivity. Mate (2015) finds a positive relationship between human capital in four different labour-skill branches and productivity for various OECD countries, for the period 1985 to 2007. For the New Zealand economy, Szeto and McLoughlin find a fall in the rate of increase in labour quality from 1998 to 2005, compared with the 1987 to 1997 period. Almost half of the labour productivity growth of 1.4 per cent per annum during the 1987 to 1997 period is attributed to rising labour quality. For the 1998 to 2005 period this reduces to a 0.8 per cent annual increase. Szeto and McLoughlin (2008) consider that drawing a relatively large number of lower-skilled workers into the New Zealand labour market during the latter period may have dampened growth in labour quality and in turn, labour productivity. These findings provide motivation for my research to evaluate the impacts of human capital on productivity to the current time period.

From the Solow-Swan growth model, other important variables affecting output, labour productivity, and income include the level of physical capital, capital intensity, and total factor productivity as a residual. In Appendix B.3, I present trends for the levels of capital intensity, or the capital-to-labour ratio, for each of the fourteen industries I study, for the period 1995 to 2020. The trends show an overall significant increase in capital intensity amongst industry over the full time period. Industries showing a rising trend are the retail, wholesale trade, transport and warehousing, information and communication media, financial and insurance, professional and scientific, and education sectors. Other sectors experience an increase, followed by a plateauing in capital intensity. These are the construction, manufacturing, rental and real estate, utilities, health and social services, and the arts and recreation sectors. The hospitality sector has seen an increase in capital-to-labour ratio from the 2004 to 2010 period, followed by a fall. The overall increasing industry capital intensity should support productivity growth in the New Zealand economy.

The literature guides on skill-capital complementarities affecting productivity and income. Improvements to physical capital through technological change have increased demand for those with higher skills at the expense of those with lower skills (Acemoglu and Autor, 2011). Krusell et al. (2000) in assessing impacts of physical capital change on real wage rates for the U.S. economy find the relative quantity of skilled labour, or skill premium, has increased substantially for the U.S. economy since the 1980s. While educational attainment data is not available at the industry level for the New Zealand economy, in my study a partial analysis of skill premium trends can be undertaken using hours worked and real wage rates for industry grouped by average skill level. Figure 3.1.a shows the ratio of total paid hours worked over the period 1996 to 2020 for skilled versus unskilled workers. For the ratio calculation, industries classified as having skilled workers are the professional, scientific, technical and support sector, education and training, and the arts and recreation sectors. Unskilled labour industries are construction, hospitality, and the retail trade sectors. Despite a fluctuating pattern, figure 3.1.a shows there is not a shift to greater paid hours worked in higher skilled occupations in the New Zealand economy over the full time period. The fluctuation is counter-cyclical to the business cycle. A fall in the ratio occurred in the mid-2000s likely due to increased overall employment during the economic ‘boom’ period. Rising unemployment during the global financial crisis resulted in increased relative demand for higher skilled workers. The pattern ‘flattens’ out in the later period as total employment increased again. This trend is also reflected in the skill premium, presented in figure 3.1.b, which shows the ratio of real wage rates for skilled relative to lower-skilled workers. Construction is dropped from the calculations with average wage rates that do not reflect skill level. This is due to factors such as likely conditions payments in construction. There is a rise in the skill premium till the mid-2000s which has declined back towards its starting point by 2020. Absolute real wage rates for higher-skilled workers are higher than lower-skilled in the New Zealand labour market, but the wage rate ratio is now similar to the 1996 level. I also present employment shares by industry in Table 3.1. Column 1 shows employment shares as an average for the 1996 to 2000 period, Column 2 presents industry shares for the later 2016 to 2020 period. Column 3 shows industry employment shares over the full 1996 to 2020 time period. The employment shares are broadly similar between the two five-year periods. Exceptions are for manufacturing, where the share falls from 19 per cent to 12 per cent in the 2016 to 2020 period, and for the higher skilled professional, scientific and technical sectors with an increase from 9 to 15 per cent. Overall, these findings do not provide evidence of shifting skill employment shares or a skill premium effect in the New Zealand economy.

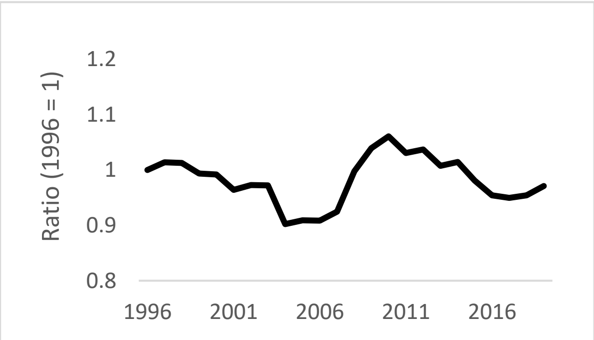

Figure 3.1.a. The labour input ratio: Skilled vs. unskilled paid hours worked (normalised with 1996 = 1).

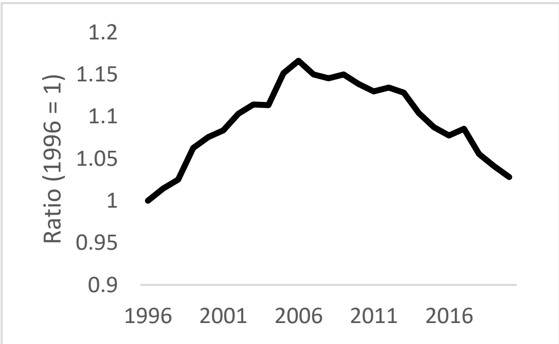

Figure 3.1.b. The skill premium: Skilled vs. unskilled real wage rates (normalised with 1996 = 1).

For the impacts of skill level on labour productivity, a fuller understanding requires study at the microeconomic level. This necessitates an analysis of skill at the industry level for the New Zealand economy. However, as discussed, skill level data through established measures such as years of schooling (Mincer, 1974) is not readily available for New Zealand industry. This necessitates a new approach for my study where I group industries by occupational skill level. Although a broad measure, this method should allow a partial comparative analysis of skill quality trends by industry. Firms and industries have differing human capital needs in the delivery of their products. Studies such as that of Mason, O'Leary, and Vecchi (2012) show a positive relationship between human capital and average labour productivity for industries where skills are measured as certified (educational qualifications) and uncertified (on-the-job training).

Table 3.1. Employment Shares by New Zealand Industry, 2016 to 2020.

Industry	(1) 1996 to 2000 Average	(2) 2016 to 2020 Average	(3) 1996 to 2020 Average
Retail Trade	10.0	9.0	10.0
Hospitality	5.0	6.0	6.0
Construction	6.0	9.0	8.0
Forestry and Mining	1.2	0.8	1.0
Manufacturing	19.0	12.0	14.0
Wholesale Trade	7.0	6.0	6.0
Utilities	1.3	0.9	0.9
Rental and Real Estate	1.3	1.5	1.4
Transport and storage	5.0	5.0	5.0
Information Media and Telecommunications	2.0	2.0	2.0
Financial and Insurance	4.0	3.0	3.0
Public Administration and Safety	5.0	6.0	6.0
Healthcare and Social Services	9.0	11.0	10.0
Professional, Scientific, Administrative and Support Services	9.0	15.0	12.0
Education	11.0	9.0	10.0
Arts and Recreation	5.0	5.0	5.0

Notes: Full-time equivalent employment. Beginning and end of period five-year weighted averages of total employment. Source: Statistics New Zealand. Infoshare: Filled Jobs by Industry, ANZIC06 series, from the earnings and employment survey (QEM). This includes both fulltime and part-time employment.

Koch and McGrath (1996) find gains to labour productivity through effective recruitment and selection processes to capture the human capital firms require.

Capital intensity is also influenced by the characteristics of individual industry sectors. Higher relative labour use may be required in construction (Ng, Skitmore, Lam, and Poon, 2004) and the retail and hospitality sectors. Greater physical capital and labour complementary effects may be observed in the utilities sector and higher-skilled industries. Overall, increased use of physical capital in production is found empirically to result in more efficient production and higher output levels than more labour-intensive methods (Rao, Tang, and Wang, 2003). Mason and Osborne (2007) find that production in New Zealand is relatively labour-intensive and that lower capital intensity for the overall New Zealand economy has contributed to lower aggregate productivity in comparison to the United Kingdom. These findings form the rationale for examining the relationship between capital intensity and worker skill levels in New Zealand industry, and the impact this relationship may have on average labour productivity for the recent period. From this, I will evaluate in hypothesis one that *average labour productivity will rise with industry skill and physical capital complementarities in the New Zealand economy*.

An examination of capital intensity effects also requires exploration of impacts from changes to the costs and returns of labour and capital inputs. Changes in input values may impact on the capital-to-labour ratio decisions for firms. The literature is scarce on such study for New Zealand industry, which provides the opportunity for my contribution in this research. Long and Poshke (2017) show that sectoral differences in the degree of capital-to-labour substitutability are a driving force for structural change and factor income shares. Chen (2020) finds as capital becomes more abundant relative to labour in the U.S. economy, capital is substituted for lower-skilled labour, leading to faster growth in capital intensity and in turn labour productivity in the goods sector relative to the service sector. This has resulted in an increase in income inequality, with lower-skilled workers bearing the brunt of shifts in income share. For long run aggregate growth, Klump and de La Grandville (2000) find that, in drawing back to the neoclassical growth theory work of Solow, the higher the labour input cost elasticity of demand, the higher is income per capita in the steady state as capital is substituted for labour. These findings point to the need for further understanding of the effects of input cost and returns on capital intensity for New Zealand industry, and impacts from industry skill level on these relationships. Flow-on effects for industry labour productivity will be inferred from the results. These relationships will be examined through hypothesis two, that *skill level-related input substitution effects drive capital intensity change in New Zealand industry.*

Labour productivity and wage rate variables within the models allow the evaluation of efficiency wage effects in the New Zealand economy. This theory, as discussed by Yellen (1984) and others, is the incentive for managers to pay their employees more than the market-clearing wage to increase productivity or efficiency or to reduce costs associated with staff turnover. For New Zealand, as a relatively low-wage economy in comparison with peer economies, this will be an important relationship to evaluate. Huselid (1995) and Shaw, Delery, Jenkins, and Gupta (1998) show the empirical evidence for such effects is mixed. In Appendix B.2, I present growth rate trends of labour productivity and real wage rates for the fourteen countries examined in this study. Although there are differing relationships between the two variables for some individual industries, a rising trend is observed for both variables over the full time period of 1995 to 2020. Through regression analysis, my study allows the opportunity to contribute further to the literature on efficiency wages through evaluating hypothesis three, that a*verage labour productivity will rise with increases in real wage rates in the New Zealand labour market.*

3.3 Data and Methodology

3.3.1 Data and Variables

The time period to be examined for this study is 1996 to 2020. I have collected and processed economic time series data from Statistics New Zealand (Statistics NZ), the official national source. The data frequency is annual rather than a preferred quarterly duration due to availability constraints for some variables. These include the productivity series and data required for the calculation of the real rate of return to physical capital. I include fourteen New Zealand industry sectors as category variables. Industry$_i$ is the unit of analysis in this study. The aim is to represent overall New Zealand industry economic activity. However, some desired sectors, particularly agriculture and the technology field, are not able to be included due to data availability. In defence of agriculture's non-inclusion in this study, while a key export earning sector, agriculture has contributed a reducing share of total annual real GDP and contributes 5 to 6 per cent of New Zealand's total output today. The economy has sought to diversify over time with expansion into technology, niche industries and other value-added activities. Additionally, agriculture contributes only a small share of total employment to the economy, at 5.6% in 2019, with many in this industry being self-employed[15].

For evaluating hypothesis one, the dependent variable is labour productivity, in

[15]Sources for export information are from the value of exports, annual-June; GDP – actual value-added output, ANZSIC06 industry groups, annual-March; filled jobs by industry, ANZIC06 series, from the earnings and employment survey (QEM). All Statistics NZ.

logarithmic form: log (labour productivity). Using data from Statistics NZ's productivity series, labour productivity is calculated as an index of real value-added output in period *t* relative to an index of labour volume input in period *t*, for each industry$_i$[16].

Labour input is calculated using total paid hours worked in producing that output. This measure is used instead of the generally preferred actual hours worked as the source, Statistics New Zealand, considers there are issues of data availability and consistency with the latter measure[17]. I utilise real variables in this study to eliminate price level effects.

Traditional measures of human capital for econometric analysis are established in the early work of Schultz (1961), Becker (1964), and the foundation study of Mincer (1974) using years of education as the principal measure. Availability issues arise when seeking educational skill data for individuals linked to New Zealand industry. Data through prominent sources, including Barro and Lee, are not available. This has resulted in the need for an alternative methodology. For this, I group New Zealand industries into four broad occupational skill categories. The categories are based on the Australia New Zealand Standard Classification of Occupations (ANZSCO) skill level classification system developed by the Australian Bureau of Statistics and Statistics New Zealand[18]. Esposto and Abbott (2011) draw similarly on this skill classification

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[16]As set out in Statistics New Zealand's (Statistics NZ) Productivity Statistics: Sources and Methods Manual p.11. [17]Statistics NZ Productivity Statistics: Sources and Methods Manual, p.33. [18]The Australian and New Zealand Standard Classification of Occupations (ANZSCO) is the product of a development program undertaken jointly by the Australian Bureau of Statistics, Statistics New Zealand and the Australian Government Department of Employment and Workplace Relations. The program sets out to classify all occupations and jobs in the Australian and New Zealand labour markets on the basis of average required skill level to complete overall job tasks.

system in their comparative study of knowledge and skill intensity in the New Zealand and Australian labour markets.

The ANZSCO methodology involves the collection of data from Statistics New Zealand's Household Labour Force Survey (HLFS): Approximately 30,000 households are interviewed each quarter with an estimated 18,000 of those having individuals in employment. Respondents are asked for information on their occupational title, the industry they are employed in, and their main tasks or duties. Individuals are then assigned to an occupational skill level. Table 3.2. shows the skill level ANZSCO assigns to the main types of jobs by occupation and industry.

Table 3.2. Average Skill Level by New Zealand Occupation and Industry.

	Occupation and industry
1 Highly skilled	Managerial and professional roles mainly in these industries: Education and training (teachers), professional and technical services, health and social assistance, agriculture (farmers and farm managers).
2	Managerial roles in the accommodation and retail industries, support workers in the health and social assistance industry.
3 Skilled	Technicians and trade workers in the construction, manufacturing, and other services industries.
4	Carers and receptionists in the health industry, road and rail drivers in the transport industry, clerks, operators, storage workers, process workers in the manufacturing industry.
5 Lower skilled	Sales workers in the retail industry, accommodation workers, farm, forestry, and garden workers in agriculture, construction workers, cleaners and laundry workers.

Source data: https://www.stats.govt.nz/methods/australian-and-new-zealand-standard-classification-of-occupations-anzsco

Based on these classifications, I group New Zealand industries into four average skill level categorical variables in this study:

1) Lower-skilled sectors: Construction; Retail Trade; Hospitality (Accommodation and Food Services).

2) Lower to medium-skilled sectors: Manufacturing; Wholesale Trade; Utilities; Transport, Postal and Warehousing; Rental, Hiring and Real Estate Services.

3) Medium to higher-skilled sectors: Information Media and Telecommunications; Insurance and Financial Services; Healthcare and Social Services.

4) Skilled sectors: Professional, Scientific and Technical Services; Education Services; Arts and Recreation.

For the base production function, I include variables for capital and technology. I establish a variable to measure the degree of capital intensity both by industry and in aggregate. This variable: capital relative to labour, is calculated using Statistics New Zealand's productivity input series[19]. For technology, I utilise Statistics New Zealand's total factor productivity (TFP) index measure, calculated as part of their productivity series[20]. I also undertake regressions using the regression residuals as the TFP measure, but with less consistent results achieved. These are discussed further in the empirical section. Lipsey and Carlaw (2004) amongst others, consider TFP provides a measure of all improvements in technology and increases in efficiency over time, together with a residual of factors not already identified (the Solow residual, Ahmed and Bhatti, 2020). I also included capital productivity as an explanatory variable in regressions, however, this measure is omitted due to confounding variable effects. The capital and total factor productivity variables were also each estimated in regressions as dependent variables, with no significant results.

For further variables of interest, I include three measures of labour cost, or

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[19,20]Source: http://infoshare.stats.govt.nz/ Economic indicators, productivity statistics.

compensation. These measures will evaluate the relationship between labour cost and productivity, labour cost and capital intensity- for hypothesis two; and wage efficiency effects (Yellen, 1984) from labour compensation - for hypothesis three. The three measures are real hourly wage rate: log wage rate; real weekly earnings: log weekly earnings; and total real employee compensation: log total employee compensation. Each in logarithmic form. Real hourly wage rates are calculated as the hourly wage rate with no overtime included. Real weekly earnings are calculated as ordinary time plus overtime hours on a full-time equivalent basis. Real total employee compensation is total annual employee compensation paid, as measured in the New Zealand National Accounts[21]. In an examination of the determinants of labour productivity in Middle East and North Africa (MENA) countries, Samargandi (2018) finds a negative relationship between size of employment, labour compensation and labour productivity. Including the three income/cost measures provides a robustness check, as well as evaluating their relationship with other explanatory variables in the separate regressions. The measures represent a widening out of income, from hourly wage rates to total employee compensation paid. I deflate each measure using the consumer price index. The three measures are also examined in regressions as dependent variables, but with no reliable results produced. These results are presented in Appendix B.6.

In addition to labour cost measures, I include further labour market explanatory variables that may impact on labour productivity. These are: total labour supply as log labour supply. This is an aggregate measure for all industries, as separate industry data was not available. Neoclassical growth theory informs that increases to labour supply

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[21]Source: National Accounts, GDP(Income), ANZSIC06 industry groups. www.infoshare.stats.govt.nz

are expected to reduce labour productivity, as expressed in the simple labour productivity equation, holding output constant: $LP = Y/L$. To capture labour market demand effects, I include variables for the aggregate unemployment rate, and industry full-time equivalent employment: log full-time equivalent employment. The full-time equivalent employment measure is intended to reduce measurement issues arising from differences in paid hours for full-time and part-time workers. Baily, Bartelsman, and Haltiwanger (2001) show labour demand cyclicality dynamics with long-run downsizing firms exhibiting significantly greater procyclicality of productivity than do long-run up-sizing firms. The unemployment rate is in levels form; industry full-time equivalent employment and aggregate labour supply are both in logarithmic form.

I also include variables to estimate the impact on capital intensity from changes in the cost and return to the two key inputs to production of labour and physical capital. These are the three labour price/cost variables presented above, and a variable for the real rate of return to physical capital, in logarithmic form: log return to physical capital. I provide information on the detailed methodology employed in calculating the capital rate of return variable and the rationale for its use further in this section. Further, capital intensity may be impacted by the quantity of fixed capital available, as De la Escosura and Roses (2010) find for the Spanish economy. I include a measure for annual industry real gross fixed capital formation, in logarithmic form. This measure is deflated using a GDP deflator.

Further variables of interest are as follows: A measure of trade openness, in levels form: trade openness; the real trade-weighted index (TWI) to measure exchange rate effects log TWI; and for price level effects, the producer price index in level form: producer price index. Each of these measures are at the aggregate level. Trade openness is an important measure for a small open economy such as New Zealand, where the competitive forces of trade may affect productivity, earnings, and profitability. Trade openness is the value of tradeable goods as a share of real GDP. This measure is calculated using the methodology recommended by Blanchard (2017) as the real value of export output plus import output plus the product of domestic firms exposed to foreign competition, relative to total real GDP. Blanchard considers this measure better represents trade effects than the narrower measure of exports plus imports relative to GDP, as used by Ulasan (2015) and others. It captures the trade effect of the value of product produced and sold by import-competing domestic firms. By being competitive, these firms are able to maintain their domestic market share against similar imported products.

I include the real TWI variable to capture exchange rate effects on productivity and capital intensity. It is an overall measure of changes to the New Zealand currency relative to those of the economy's major trading partners. The real TWI may affect capital intensity through its impact on the cost of imported capital, with flow-on effects for productivity and earnings. The producer price index is included to assess price level effects on capital and labour productivity. The producer price index may better capture impacts of price change within the supply chain compared with the final product consumer price index. Such effects may include where rising prices impact on competitiveness and result in changes to production methods and productivity. Studies such as Freeman and Yerger (2000) have found that even low rates of inflation create distortions in capital allocation, which can result in lower productivity growth rates. I include year dummies to control for time fixed effects. I undertake panel unit root tests as the variables are economic time series with tendency to non-stationarity. These are the Levin-Lin-Chu aic, bic, and hqic and Dickey-Fuller test for stationarity. For both level and logged variables, the tests indicate the presence of unit root. When first-differenced, the series are I(1) stationary. Accordingly, all variables require to be first-differenced, whether in level or log form in this study.

Calculating the Cost/Return of Physical Capital

For evaluating impacts on capital intensity arising from changes in the cost, or price of the two key inputs of physical capital and labour, an issue may arise in the calculation of a measure for the price, or return to, physical capital. This is particularly so when it is a measure based on the value of a collection of assets used within a firm or industry, rather than for a single piece of equipment. For asset aggregation, the OECD (2009) notes that constructing price indices for the value of fixed assets is problematic because many capital goods are unique, making it difficult to observe aggregate price changes from one period to the next[22]. This raises questions as to an appropriate measure and the factors to combine in constructing this measure. A preferred method may be to value or price aggregate physical capital based on user cost in rental markets. However, an issue with this approach is that many assets are owner-used and sufficient and/or adequate rental markets do not exist in the New Zealand economy to allow for market-based values for the user cost of these physical assets. Further, lessor costs include labour and overheads associated with the leasing service, which may not be obtainable for valuations of business-owned assets. These factors result in situations of under or over-estimation in the valuation of physical capital using a rental market methodology.

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[22]OECD Manual for Measuring Capital (2009), p.12.
https://www.oecd.org/publications/measuring-capital-oecd-manual-2009-9789264068476-en.htm

The literature shows alternative approaches to addressing aggregate capital good are an ex-ante exogenous method, and ex-post endogenous approach. The latter is more valuation based on the return generated by the assets. The two main approaches commonly applied in empirical research (OECD, 2009). Each measure incorporates the element of the expected rate of return in the construction of user costs and applies an opportunity cost interpretation to rates of return. Krusell et al. (2000) is one such study that, in finding no standard measure of rental rates for equipment and structures, constructs a proxy for price as the expected net rate of return on investment. For the ex-ante method, with functioning capital markets one can apply and expect a rate of return on fixed assets that is comparable to that obtained on alternative assets with a similar risk profile. This may typically be the return available to capital in financial markets. One method here may be to apply the return to corporate bonds. For New Zealand firms, however, this may not be a suitable approach as the New Zealand corporate bond market is relatively shallow (RBNZ, 2014)[23]. Alternatively, the ex-post method measures the return to capital goods as an internal rate that estimates the value of capital services as income generated relative to the productive stock employed. Income is measured as gross operating surplus plus the capital element of gross mixed income and assumes these components will exactly exhaust the cost of capital services. This is an endogenous approach as set out by the OECD in their 2009 manual on measuring capital and is the methodology which I will employ in this study[24]. The method uses the return to the

[23]As discussed in the RBNZ 2014 Financial Report: The role of capital markets in the New Zealand financial system. https://www.rbnz.govt.nz/financial-stability/financial-stability-report/fsr2014-11/the-role-of-capital-markets-in-the-new-zealand-financial-system

[24]As set out in Section 8.3.1 on endogenous and exogenous rates of return. Measuring Capital: OECD Manual 2009, p.68. Calculation: p.137.

productive stock – a measure of capital services – rather than capital stock, which is a measure of wealth, to better estimate the value of the return generated from productive assets employed[25].

The OECD (2009) note several advantages in using this methodology, in addition to income exhausting the user costs. First, theoretically it appears consistent with a fully competitive economy and production processes under constant returns to scale. Secondly, intuitively, firms will base their physical capital input selection on the return generated by the assets. Thirdly, it is relatively straightforward to calculate, based on endogenous returns produced from an integrated system within firms and industries. For this study, the rate of return to industry physical capital is calculated using the OECD's (2009) methodology, given in equation (1) below:

$$r_t = \frac{N_t + T_{tK} + R_t}{P_{k,t}K_t} \qquad (1)$$

where:

r_t - the rate of return that applies at the beginning of period t

N_t - net operating surplus = $G_t - D_t$. This is the difference between gross operating surplus G_t (including the capital part of mixed income) minus depreciation D_t.

T_{tK} - capital related taxes on production

R_t - revaluation of assets

[25]The data series for productive stock by industry required for this formula is not available in Statistics NZ's publicly available data and was generously provided to the candidate by their productivity analysis department upon request.

$P_{k,t}\, K_t$ - the value of the productive capital stock of assets K during period t, at beginning of period prices $P_{k,t}$[26]

The producer price index p_t is subtracted from r_t and divided by $1 + p_t$ to yield the real rate of return r_t.

3.3.2. Methodology

I establish the framework for econometric analysis in this chapter as a Solow-Swan constant-returns-to-scale Cobb-Douglas production function. The model is a Mankiw, Romer, and Weil (1992). exogenous growth model augmented to include human capital accumulation. The base production function is set out in Equation 2:

$$Y/L_t = K/L_t^{\propto}(AH)_t^{1-\propto} \qquad (2)$$

where:

Y/L_t is output relative to labour,

K/L is physical capital relative to labour, or capital intensity,

AH is labour augmenting technology.

The unit of analysis is industry i

The base growth model is expanded to include further explanatory variables that may impact on labour productivity. This begins with the equation in level form in Equation (3):

$$y_{i,t} = \beta_0 + \emptyset y_{i,t-1} + \beta_x X_{i,t-1} + \nu_i + \varepsilon_{i,t} \qquad (3)$$

[26]The OECD's 2009 methodology for measuring capital has developed to better measure not only the consumption of fixed capital to derive net measures for national accounts but also for establishing balance sheets for economic sectors and measuring capital services for the analysis of production and productivity as is important for this study. The ex-post approach is considered to better align with the national accounts in employing attained values, where the estimated value of capital services exactly corresponds to the value of gross operating surplus plus the capital element of gross mixed income, rather than the ex-ante approach of choosing a rate of return for capital that may at best reflect economic agents' expectations about the return from investment.

where:

y_{it-1} is the lagged dependent variable,

X_{it-1} is a vector of explanatory variables,

ν_i are time invariant fixed effects,

$\varepsilon_{i,t}$ is the error term.

Equation 3 with variables in levels form are first-differenced using GMM Difference estimation. This removes time-invariant fixed effects to obtain Equation (4):

$$\Delta y_{i,t} = \emptyset \Delta y_{i,t-1} + \beta_x \Delta X_{i,t} + \Delta \varepsilon_{i,t} \quad (4)$$

At T = 24 annual observations and sector panels N =14, a panel data estimation method is necessary. Additionally, the economic variables, including capital intensity and productivity, are likely to exhibit serial correlation and endogeneity. To address this, I employ a dynamic panel data generalised method of moments (GMM) estimation method using xtabond2. The model comprises a lagged dependent variable with lagged explanatory variables and instrument variables. I evaluated a number of possible estimators for the features of my dataset. These included ordinary least squares (OLS) panel data, generalised least squares (GLS), and dynamic panel data GMM estimators. The results obtained from OLS, GLS, and GMM estimation are broadly similar. However, OLS and GLS have less ability to adjust for serial correlation and endogeneity amongst variables. In comparison, GMM estimation allows for lagged explanatory variables as instruments, eliminating the need to source separate proxy measures. As stated, I estimate the regression equations with variables in levels, using xtabond2 GMM Difference to first-difference the data. This corrects for unit-root and removes fixed effects. I present the Stata command code and raw results for my labour productivity regression as a regression example in Appendix B.5.A. In Appendix B.5.B, I also present the Stata raw results for the OLS panel data regression for the baseline equation for comparison with the dynamic panel model results. Results are similar from the two estimation methods.

A limitation found in the use of Difference GMM estimation is that while the Arellano-Bond test for autocorrelation is provided, the post-estimation Sargan and Hansen tests Roodman (2009) for instrument overidentification are not. Additionally, Roodman (2009) notes that GMM estimators can generate moment conditions prolifically, with an instrument count quadratic in the time dimension of the panel T. Finite samples may lack adequate information to estimate such a large matrix well. It is then not uncommon for the matrix to become singular, forcing the use of a generalised inverse. This result occurs for this study, with instrument counts up to 30 shown in Table 3.3, with 23 time periods T. Roodman (2009) considers this does not compromise consistency because any choice of a scalar A will give a consistent estimator, but may 'dramatize' the distance of the fixed effect GMM from the asymptotic ideal. I check the robustness of the results by reducing the number of instruments used. However, under GMM estimation it is not possible to include fewer instruments than the number of explanatory variables. An example of this is provided in the regression example in Appendix B.5.A, with 8 explanatory variables and 8 instrument variables.

I estimate regressions using robust standard errors to adjust for heteroskedasticity effects. The chosen models are based on the highest number of observations, the Arellano-Bond zero auto-correlation test results, together with the smallest standard errors.

3.3.3 Further Tests for Robustness

I undertake a number of measures to improve the robustness of the results. Structural break tests and modelling evaluate any coefficient bias that may be present - particularly for the 2008 to 2010 period of the global financial crisis (GFC). The structural break tests provide evidence for breakpoints, but that these vary within the years of the GFC. Accordingly, I include time dummy interactions with variables of significance in regression equations for differing time periods of possible breakpoints. These are the 2010 to 2020, 2011 to 2020, and 2013 to 2020 periods. The base periods for each are the corresponding earlier periods. The results of statistical significance are for the 2012 to 2020 period, with the base period being 1996 to 2011. The results for these regression equations are presented in Appendix B.7. in Tables 3.12 and 3.13 for this chapter. The results are not economically different from results without interactions for the global financial crisis. I have judged to present the results without GFC time dummies but to include the latter findings as reference in Appendix B.7.

I perform model variation tests to evaluate any change in the significance of different combinations of variables of interest and control variables. These include using different industries as the base group and using different industry skill groupings/categories as the base group. Results are found to be consistent across the variations. I include three different measures of earnings in regressions to assess the consistency of results for alternative labour cost measures. Some consistency is found, although, as discussed earlier, the labour earnings measures contain differing labour cost components resulting in differing effects on the dependent variable and on other explanatory variables. The results presented are of a specific-to-general methodology. I also develop regressions using a general-to-specific approach which show similar results. The former method is presented to include effects from the further variables of interest when incorporated in the models.

3.4 Empirical Results Analysis

3.4.1 The Effects of Average Industry Skill and Other Factors on Average Labour Productivity

In Table 3.3, I present estimation results evaluating factors affecting labour productivity at the aggregate level for the New Zealand economy. The base growth model is presented in Column 1. The explanatory variables are capital relative to labour and total factor productivity (TFP). In Columns 2 and 3, I expand the model to include further variables of interest. Real wage rates are included in Column 2 as a narrow measure of labour cost. In Column 3, I use instead a wider measure in total annual employee cost/compensation. This latter measure includes further remuneration including holiday pay, fringe benefits, and employer pension contributions. The differing labour cost measures also serve as a robustness test.

For the base growth model in Column 1, and in the expanded models in Column 2 and 3, I find a significant positive relationship between both capital relative to labour (capital intensity) and labour productivity, and between total factor productivity (TFP) and labour productivity at the aggregate level. An increase in capital intensity is estimated to increase average labour productivity by up to 16 per cent per annum, at the 5 per cent significance level. I observe an almost unitary effect from increased total factor productivity. These findings highlight the importance of both physical capital, and technology and efficiency for lifting average labour productivity.

For the further variables of interest, only total employee compensation is statistically significant in Column 3, with a negative effect observed. This result is at the 10 per cent significance level. This is evidence against hypothesis three of an efficiency wage effect occurring in the New Zealand labour market. This result is consistent with the mixed results found in the literature. Peach and Stanley (2009) are among those finding a strong efficiency wage effect on productivity. Huselid (1995) and Shaw et al. (1998) find less conclusive evidence for such a relationship. It may be difficult to propose an argument for improved labour productivity arising from wage increases. Any labour efficiency gains may prove to be transitory as worker motivation resulting from higher income begins to wear off. While an increase in fulltime equivalent employment is negative for labour productivity, the result is not statistically significant. I find no statistically or economically significant effect from a change in the producer price index on average labour productivity. This finding does not support the view of Freeman and Yerger (2000) for a loss of productivity due to rising price effects on competitiveness in the New Zealand economy. While it was hoped to see results for the further explanatory variables of interest of trade openness, total labour supply, and the real trade-weighted index, these are omitted due to collinearity in regression estimation. While utilising data for total factor productivity calculated by Statistics New Zealand in their national productivity data series, I also estimate the regressions using the residual as the TFP variable. The results obtained are inconsistent. The use of the Statistics NZ data provides more consistent results as my study makes use of associated productivity series data for other variables. This supports a more reliable estimate of TFP.

3.4.2 Capital Intensity Effects on Average Labour Productivity by Industry

Having established the significant positive relationship between capital intensity and labour productivity for the overall New Zealand economy, I next assess impacts on productivity from greater use of physical capital in individual sectors, and the part that

Table 3.3. Factors Affecting Average Labour Productivity in the New Zealand Economy.

	(1)	(2)	(3)
log labour productivity $_{t-1}$	-0.395	-0.443	-0.505
	(0.349)	(0.424)	(0.454)
capital relative to labour	0.163**	0.162**	0.161**
	(0.065)	(0.064)	(0.064)
log total factor productivity	0.967***	0.972***	0.983***
	(0.035)	(0.032)	(0.034)
log wage rate/total employee compensation	-	0.173	-0.093*
		(0.197)	(0.054)
log fulltime-equivalent employment	-	-0.065	-0.048
		(0.067)	(0.060)
producer price index	-	0.000	0.000
		(0.000)	(0.00)
year dummies	Yes	Yes	Yes
constant	2.97	3.16	-0.002
	(2.53)	(3.06)	(0.007)
observations	336	336	336
no. of instruments	27	30	30
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.41	0.87	0.87

Notes: The dependent variable is log labour productivity. Column 1 is the base production function with explanatory variables of capital relative to labour and total factor productivity. Column 2 includes further variables of interest. These are the real wage rate as a labour compensation measure, fulltime-equivalent employment and the producer price index. Column 3 substitutes total employee compensation as a robustness measure. Explanatory variables for trade openness, total labour supply, and the real trade-weighted index are omitted from regression estimations due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors are shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

average industry skill level may play in this. The work of Rao, Tang, and Wang (2003) finds a positive relationship between physical capital and labour productivity for the United States and Canada. They examine differences by industry, but do not consider skill level in the causes. Similarly, Razzak (2007) observes higher capital intensity and endogenous technology shocks (TFP) as key explanatory drivers for Australia's higher labour productivity relative to New Zealand's for the 1989 to 2003 period, without labour skill consideration. My results will contribute to the literature through evaluating hypothesis one, that average labour productivity will rise with industry skill and physical capital complementarities in the New Zealand economy. I present the results in Tables 3.4 and 3.5.

Table 3.4 shows capital relative to labour, or capital intensity, effects on labour productivity for each industry, relative to the lower-skilled retail sector as the base group. I present regression equations with two measures of labour compensation: real wage rates in Column 1, and total annual employee compensation in Column 2. The two measures represent a broadening out of labour income and serve as a robustness measure. The results show partial support for hypothesis one across the regressions. I find a positive and significant relationship between capital intensity and labour productivity for the majority of industries. The largest economically significant effects are observed for the lower to medium-skilled industries, relative to the retail sector, as the base group. These industries, including utilities, wholesale trade, rental, and transport and storage will already possess relatively high levels of capital by their nature. Their productivity may reasonably be expected to benefit through increased capital investment, supporting capital-labour complementarities. I also present these results graphically in Figure 3.2, which shows the economically significant results for lower-to-medium skilled industries. The results for hospitality, manufacturing, and education, while positive, are not statistically significant and are omitted from the graphical presentation. While a reduced effect, I find gains for the higher-skilled industries including information communication and the professional sector. However, their greater reliance on skilled labour may limit any further capital-skill complementarities available. For the relatively labour-intensive, lower-skilled industries, productivity increases by 12 per cent for construction. The overall results appear as large economic effects but point to the potential for improvement in productivity through capital-skill complementarities from greater physical capital adoption in production. This is seen particularly for the lower to medium-skilled sectors.

In Table 3.5, I show the effects of greater industry capital intensity on labour productivity for industries grouped by average skill level, relative to the lower-skilled as the base group. The results also support hypothesis one, with a positive relationship between capital intensity and labour productivity for the lower-to-medium and the medium-to-higher skilled industries. The highest productivity performance gains are estimated for the lower to medium-skilled industries, with a 38 per cent annual gain across Columns 1 and 2. This is followed by a 13 per cent increase for the medium-to-higher skilled grouping. The results indicate lower capital-skill complementarities for the lower-skilled and higher-skilled sectors. This is likely due to a higher gearing of labour in these industries. However, there may be potential for improvement to productivity for many sectors from greater physical capital use in production.

3.4.3 Input Cost and Return Effects on Capital Intensity

My findings of a strong link between capital intensity and average labour productivity for New Zealand industry leads next to investigation of the causes of change for capital intensity. The two main inputs to production are of course, labour and physical capital. For producers, the use of each will be affected by their cost and the return they generate. Changes in input costs and returns can result in substitution effects, leading to change in the capital intensity of production. This may have impacts for productivity in the New Zealand economy, which is considered to exhibit relatively more labour-intensive production than peer economies (Mason and Osborne, 2007). I evaluate input substitution effects through hypothesis two, that skill level-related input substitution drives capital intensity change in New Zealand industry.

I present results examining the effects for labour cost on capital intensity (capital relative to labour) by industry in Table 3.6, and for physical capital returns in Table 3.7. For labour cost in Table 3.6, I use three separate labour cost measures for each industry. These are: real wage rate in column 1; real weekly earnings in Column 2; and total

Table 3.4. Capital Intensity Effects on Average Labour Productivity by Industry.

	(1)	(2)
log labour productivity $_{t-1}$	-0.173	-0.170
	(0.121)	(0.117)
capital relative to labour x	0.163***	0.162***
	(0.024)	(0.023)
construction	0.118***	0.120***
	(0.016)	(0.013)
hospitality	0.180	0.177
	(0.031)	(0.032)
manufacturing	0.146	0.147
	(0.015)	(0.015)
utilities	0.366***	0.368***
	(0.012)	(0.010)
wholesale	0.308***	0.306***
	(0.010)	(0.008)
rental	0.774***	0.771***
	(0.007)	(0.008)
transport and storage	0.277***	0.278***
	(0.029)	(0.028)
information communication	0.104***	0.103***
	(0.013)	(0.013)
financial and insurance	0.133*	0.133*
	(0.016)	(0.015)
healthcare and social assistance	0.087**	0.087***
	(0.028)	(0.028)
professional, scientific and technical	0.162**	0.161
services	(0.031)	(0.031)
education	0.177	0.179
	(0.045)	(0.042)
arts and recreation	0.326**	0.326**
	(0.076)	(0.075)
log wage rate/total compensation)	0.028	- 0.001
	(0.043)	(0.007)
log total factor productivity	0.994***	0.995***
	(0.016)	(0.015)
log fulltime-equivalent employment	-0.004	-0.003
	(0.017)	(0.017)
producer price index	0.000	0.000
	(0.000)	(0.000)
year dummies	Yes	Yes
constant	-0.418	-0.163
	(0.521)	(0.480)
observations	336	336
no. of instruments	43	43
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.71	0.69

Notes: The dependent variable is log labour productivity. Industries are interacted with their respective capital relative to labour. The base industry is the retail sector. Column 1 includes the real wage rate as the labour income measure. Column 2 substitutes total employee compensation as a robustness measure. Explanatory variables for total labour supply, trade openness, and the real trade-weighted index are omitted from regression estimates due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors are shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Figure 3.2 New Zealand Industry Capital Intensity Effects on Average Labour Productivity.

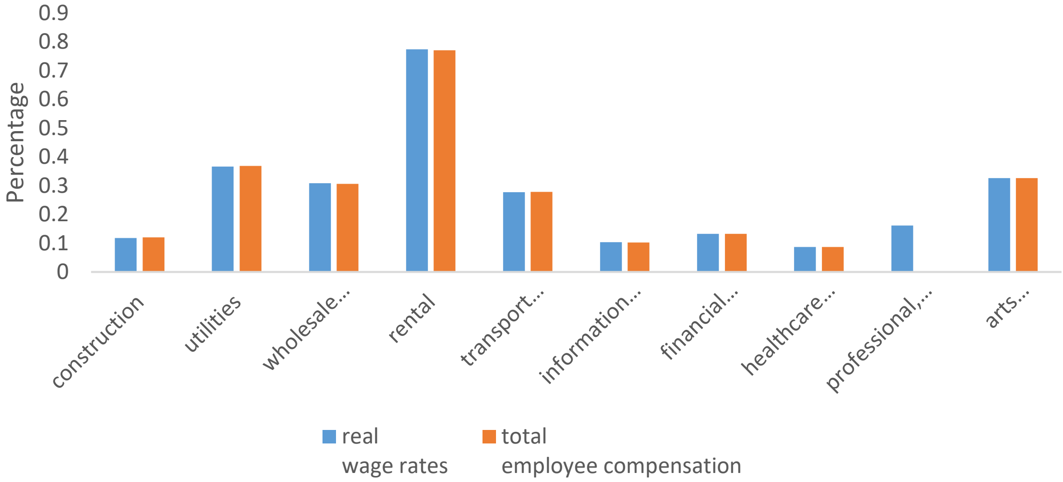

Table 3.5. Capital Intensity Effects on Average Labour Productivity. Industries Grouped by Average Skill Level.

	(1)	(2)
log labour productivity $_{t-1}$	-0.339	-0.346
	(0.357)	(0.361)
capital relative to labour x	0.186***	0.186***
	(0.040)	(0.040)
lower-to-medium-skilled industries	0.377***	0.378***
	(0.051)	(0.050)
medium-to-higher-skilled	0.128***	0.128***
industries	(0.022)	(0.022)
higher-skilled industries	0.184	0.183
	(0.095)	(0.097)
log wage rate/total compensation	0.041	-0.012
	(0.076)	(0.016)
log total factor productivity	0.992***	0.993***
	(0.026)	(0.016)
log labour supply	0.114	0.122
	(0.191)	(0.202)
log fulltime-equivalent	0.023	0.026
employment	(0.031)	(0.202)
producer price index	0.000	0.000
	(0.000)	(0.000)
year dummies	Yes	Yes
constant	0.223	0.352
	(1.04)	(1.11)
observations	336	336
no. of instruments	33	33
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.72	0.79

Notes: The dependent variable is log labour productivity. Industries are grouped by average skill level and interacted with their respective capital relative to labour. The base group is lower-skilled industries. Column 1 includes the real wage rate as the labour income measure. Column 2 substitutes total employee compensation as a robustness measure. Explanatory variables for total labour supply, trade openness, and the real trade-weighted index are omitted from regression estimates due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

employee compensation in Column 3. While the statistical significance isn't consistently strong across labour measures, I find a negative relationship between higher labour cost and capital intensity for the majority of New Zealand industries. This does not appear to change by average skill level. Broadly, the results suggests that firms do not substitute physical capital for labour when their labour costs rise. Capital investment may instead fall as firms seek to reduce their costs. The utilities and financial and insurance sectors are industries showing a positive relationship, but with a small economic effect. A 10 per cent increase in labour cost increases capital intensity by an annual 0.1 per cent for both sectors. The results do not support hypothesis two for skill level-related input substitution to drive capital intensity change in New Zealand industry.

Considering further variables of interest, I find significant results for other factors that may impact on capital intensity in the economy. An increase in industry-level gross fixed capital formation results in a small increase in capital intensity. A 10 per cent increase results in a 0.02 per cent increase per annum. This may perhaps indicate the need for targeted fixed capital formation to improve overall capital intensity. A 10 per cent increase to full-time equivalent employment reduces the capital-to-labour ratio by 0.1 per cent. This result indicates a tendency for labour to be favoured in production, with increased labour demand reducing demand for physical capital in the overall economy. No statistically or economically significant effect is observed for capital intensity from changes to overall producer input prices (producer price index).

Turning next to an examination of the relationship between the return on physical capital and capital intensity, the results presented in Table 3.7 show partial support for hypothesis two. There is a positive relationship with statistically significant results for many sectors. However, the economic effects are again small. A 10 per cent increase in the return to physical capital for the utilities sector in Column 1 results in only a 0.01 per cent increase in capital intensity per year. There is an overall low sensitivity for capital intensity change from increasing capital returns[27].

3.5 Summary and Policy Implications

The results of my analysis provide evidence of the importance of capital intensity for lifting labour productivity in the New Zealand economy, particularly as a relatively labour-intensive economy. Higher total factor productivity is also needed, with the technology and efficiency gains this will bring. In evaluating capital intensity effects on labour productivity by industry, I find statistically significant results and a positive relationship for the majority of industries studied. By average skill level, the largest economic gains are for industries with lower-to-medium average labour skill. These include the utilities, wholesale trade, rental, and transport and storage sectors. These industries use relatively high levels of physical capital, demonstrating their potential for skills-capital complementarities gains. Increased capital intensity may further improve labour productivity for these industries. For industries with lower and higher-skilled workers which tend to be more labour-intensive, there may also potentially be productivity gains from greater capital use.

I also examine the effects of change in input cost and returns on capital intensity by industry, through labour cost, and the returns to physical capital. Such changes may drive input substitution decisions, altering capital intensity and in turn, labour productivity. I observe a negative relationship between labour cost and capital intensity,

[27]The annual 10-year NZ Government bond rate was also included as a variable for the effects of interest rate change for capital intensity but was omitted due to confounding variable effects.

Table 3.6. Labour Cost Effects on Capital Intensity by New Zealand Industry.

	(1)	(2)	(3)
capital relative to labour $_{t-1}$	0.686***	0.667***	0.632***
	(0.126)	(0.103)	(0.094)
log wage rate/weekly earnings/total	-0.310	-0.146	-0.306
compensation) x	(1.01)	(0.396)	(0.214)
construction	-0.140	-0.225***	0.145***
	(0.586)	(0.284)	(0.090)
hospitality	-1.54***	-0.747**	-0.441**
	(0.342)	(0.284)	(0.066)
manufacturing	-1.23***	-1.22	-0.504
	(0.303)	(0.845)	(0.242)
utilities	0.563*	0.300**	0.787***
	(0.463)	(0.20)	(0.053)
wholesale	0.020	-0.922**	-0.368
	(0.595)	(0.316)	(0.079)
rental	0.449	0.142	-0.441*
	(1.19)	(0.488)	(0.079)
transport and storage	- 0.781	-0.163	-0.598***
	(0.398)	(0.148)	(0.102)
information communication media	-0.741	0.536	0.077**
	(0.539)	(0.555)	(0.166)
financial and insurance	1.03***	0.558***	-0.275
	(0.327)	(0.266)	(0.118)
healthcare and social assistance	-1.01**	-0.801***	-0.722**
	(0.309)	(0.152)	(0.076)
professional, scientific and technical services	-0.198	-0.382	-0.278
	(0.428)	(0.201)	(0.088)
education	-0.110	-0.450	-0.834***
	(0.857)	(0.245)	(0.151)
arts and recreation	-0.327	-0.376	-0.762***
	(0.787)	(0.119)	(0.059)
log return to physical capital	0.000	0.003	0.009
	(0.025)	(0.025)	(0.025)
log gross fixed capital formation	0.184**	0.183***	0.181***
	(0.072)	(0.069)	(0.066)
log full-time equivalent employment	-0.745***	-0.743***	-0.675***
	(0.241)	(0.229)	(0.233)
producer price index	-0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)
year dummies	Yes	Yes	Yes
constant	-11.08**	-13.52**	-23.40***
	(5.11)	(5.43)	(8.85)
observations	336	336	336
no. of instruments	43	43	43
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.61	0.59	0.66

Notes: The dependent variable is capital relative to labour. Industries are interacted with labour cost variables. The base industry is the retail sector. Column 1 interacts industries with the real wage rate as the labour income measure, Columns 2 and 3 substitute weekly earnings and total employee compensation in industry interactions, as robustness measures. Explanatory variables for total labour supply, trade openness, and the real trade-weighted index are omitted from regression estimates due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Table 3.7. Capital Return Effects on Capital Intensity by New Zealand Industry.

	(1)	(2)
capital relative to labour $_{t-1}$	1.070***	0.998***
	(0.034)	(0.047)
log return to physical capital x	-0.027	-0.032
	(0.024)	(0.021)
construction	0.015***	- 0.009***
	(0.004)	(0.008)
hospitality	-0.045**	-0.048**
	(0.007)	(0.008)
manufacturing	0.033***	0.031***
	(0.008)	(0.008)
utilities	0.112***	0.096***
	(0.016)	(0.013)
wholesale	0.109**	0.112***
	(0.031)	(0.046)
rental and real estate	0.034***	0.063***
	(0.016)	(0.020)
transport and storage	0.052***	0.052***
	(0.011)	(0.010)
information communication	0.106***	0.104***
	(0.009)	(0.010)
financial and insurance	0.029***	0.035***
	(0.013)	(0.014)
healthcare and social assistance	-0.012	-0.009***
	(0.010)	(0.012)
professional, scientific and technical services	0.030**	0.021**
	(0.026)	(0.020)
education	-0.026	0.003
	(0.028)	(0.025)
arts and recreation	-0.018	-0.007**
	(0.010)	(0.007)
log wage rate /total compensation)	-0.295	-0.516**
	(0.593)	(0.218)
log gross fixed capital formation	0.249***	0.249***
	(0.079)	(0.078)
producer price index	-0.000	-0.000
	(0.00)	(0.00)
year dummies	Yes	Yes
constant	-1.15	2.92
	(1.60)	(2.03)
observations	336	336
no. of instruments	42	42
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.21	0.24

Notes: The dependent variable is capital relative to labour. Industries are interacted with the return to physical capital. The base industry is the retail sector. Column 1 includes the real wage rate as a labour income measure. Column 2 substitutes total employee compensation as robustness measures. Explanatory variables for total labour supply, trade openness, and the real trade-weighted index are omitted from regression estimates due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

for the majority of New Zealand industries. Average industry skill level does not appear to play a part in this. The result indicates that firms do not substitute physical capital for labour when labour costs rise. Investment spending may instead reduce as costs are rising. This is of concern in a labour-intensive economy and will not support greater capital intensity and labour productivity. For physical capital returns, I find a positive relationship with capital intensity, but with economically small effects. This indicates an overall low sensitivity for capital intensity from changes to physical returns.

The results reflect the importance of policy designed to encourage greater physical capital adoption in New Zealand production. Shallow existing capital markets highlight the need for growth in funding pools to support capital investment. This may include through the continued encouragement of household savings into the Kiwisaver superannuation funds. Well-functioning markets with attractive returns and a low interest-rate/price environment through effective monetary policy will support capital formation. The positive effects for labour productivity from increases in total factor productivity supports policy to encourage greater use of technology in industry (through greater physical capital use). Existing Government initiatives include support for research and development (R&D) activity[28]. Statistics New Zealand's 2020 Research and Development survey shows that spending on research and development increased by 16% since the previous survey in 2018. The survey results indicate that a healthy 60 per cent of the business sector's research spending came from own funds[29]. These findings are positive for technology and productivity improvements.

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[28]Callaghan Innovation is New Zealand's innovation agency, set up to support innovation and to partner with Government agencies and partner organisations to provide a range of assistance in digital technology to firms to increase their growth potential. https://www.callaghaninnovation.govt.nz/scaleup-nz [29]The business sector was the largest contributor to R&D spending, accounting for 60 per cent in 2020. Higher education contributed 24 per cent and Government sectors a further 17 per cent. The computer services industry accounted for 34 per cent of total R&D expenditure, followed by manufacturing at 30 per cent. https://www.stats.govt.nz/information-releases/research-and-development-survey-2020

The findings in Chapter 3 highlight the importance of labour skill, physical capital, and technology in New Zealand industry for growing productivity. Further examination of the relationship between human capital and worker earnings is required, which will form the focus of my study in Chapter 4.

Appendix B

Appendix B.1. Summary Statistics and Correlation Coefficients.

Table 3.8. Summary Statistics for Key Variables.

Variables	Observations	Mean	Median	St.Dev	Min.	Max.
log labour productivity	350	7.30	7.18	0.5500	6.46	9.25
log real wage rate	350	3.32	3.33	0.2282	2.83	3.83
capital relative to labour	345	2.1723	1.55	1.6299	0.89	10.53
log TFP	350	7.05	7.01	0.3550	6.42	8.00
unemployment rate	325	5.37	5.4	1.1053	3.6	7.70
log labour supply	350	14.61	14.62	0.1284	14.41	14.85
log gross fixed capital formation	350	7.37	7.39	0.7030	5.50	9.11
log real capital return rate	350	3.68	3.65	1.0460	0.91	5.99
log fulltime-equivalent employment	350	11.16	11.29	0.8219	9.24	12.47
log real TWI	350	4.24	4.260	0.1021	3.98	4.38
trade openness	350	0.20	0.19	0.0247	0.15	0.24
producer price index	350	2.17	1.92	3.8026	-22.90	34.95

Table 3.9. Pearson Correlation Coefficients for Key Variables.

	labprod	wagerate	empcomp	caplab	TFP	unemprate	labsupply	ftemp	gfcf
labprod	1.0000								
wagerate	0.4840	1.0000							
empcomp	-0.0756	0.1059	1.0000						
caplab	0.7947	0.4372	0.0030	1.0000					
TFP	0.8818	0.3414	-0.0010	0.4903	1.0000				
unemprate	-0.0836	-0.1584	-0.1572	-0.0927	-0.0566	1.0000			
labsupply	0.1379	0.3340	0.2981	-0.0034	0.0686	-0.5041	1.0000		
ftemp	-0.4505	-0.2773	0.8371	-0.2900	-0.3039	-0.0874	0.1605	1.0000	
gfcf	0.4261	0.4252	0.0846	0.1700	0.4598	-0.2132	0.2559	-0.2381	1.0000

Notes: labprod is log labour productivity; wagerate is log real wage rate; empcomp is log total annual employee compensation; caplab is capital relative to labour input (capital intensity); TFP is log total factor productivity; unemprate is unemployment rate; labsupply is log total labour supply; ftemp is log total fulltime-equivalent employment; gfcf is log total gross fixed capital formation. Many general sources provide guidance to correlation strength. Those adopted here are: coefficient values between ± 0.50 and ± 1 - strong correlation; between ± 0.30 and ± 0.49 – moderate/medium correlation; below ± 0.29 – Weak/small correlation.

Appendix B.2. Labour Productivity – Real Wage Rate Relationships.

Figure 3.3. Labour Productivity - Real Wage Rate Relationships

Industry average annual growth rates. Labour productivity: 0.9 per cent. Real wage rates: 0.5 per cent.

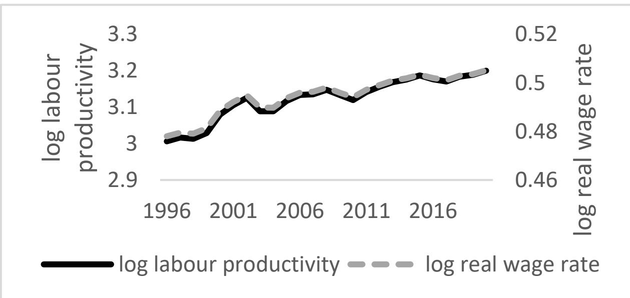
Retail trade average annual growth rates. Labour productivity: 1.07 per cent. Real wage rates: 0.5 per cent.

Hospitality average annual growth rates. Labour productivity: 0.03 per cent. Real wage rates: 0.4 per cent.

Construction average annual growth rates. Labour productivity: 0.4 per cent. Real wage rates: 0.05 per cent.

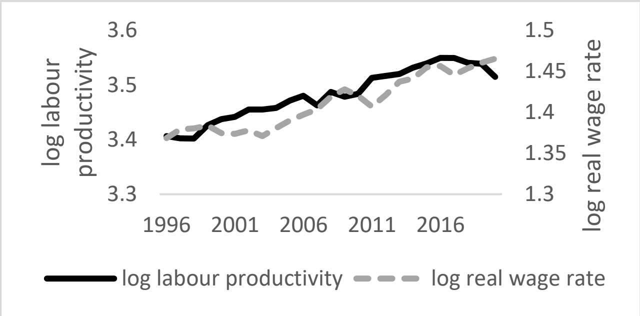
Manufacturing average annual growth rates. Labour productivity and real wage rates: 0.5 per cent.

Rental and real estate average annual growth rates. Labour productivity: 0.6 per cent. Real wage rates: 0.5



Wholesale trade average annual growth rates. Labour productivity: 0.8 per cent. Real wage rates: 0.11 per cent.

Utilities average annual growth rates. Labour productivity -0.4 per cent. Real wage rates: 0.72 per cent.



Transport and Storage average annual growth rates. Labour productivity and real wage rates: 0.4 per cent.

Information Media and Communications average annua growth rates. Labour productivity: 2.2 per cent. Real wage rates: 0.4 per cent.

Financial and Insurance average annual growth rates. Labour productivity: 1.1 per cent. Real wage rates: 0.14 per cent.

Health and Social Services average annual growth rates. Labour productivity: 0.3 per cent. Real wage rates: 0.51 per cent.

Professional and Scientific average annual growth rates. Labour productivity: 0.22 per cent. Real wage rates: 0.43 per cent.

Education average annual growth rates. Labour productivity: -0.56 per cent. Real wage rates: 0.53 per cent.

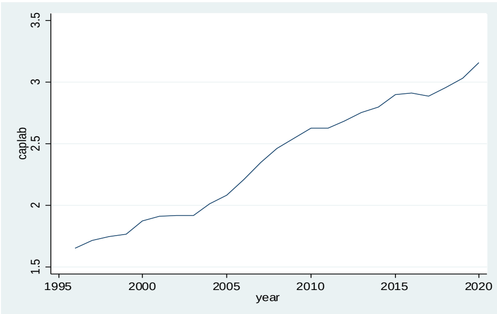
Arts and Recreation average annual growth rates. Labour productivity: -0.20 per cent. Real wage rates: 0.42 per cent.

Appendix B.3.

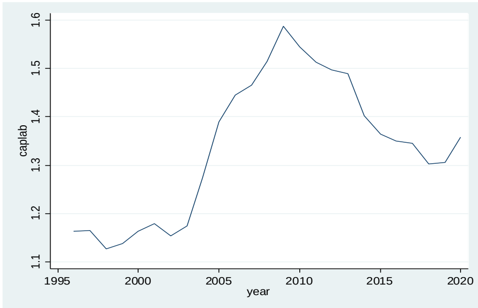
Figure 3.4. Capital-to-Labour Trends by New Zealand Industry

The trends show an overall significant increase in capital intensity amongst industry over the 1995 to 2020 time period. Industries showing a rising trend are the retail, wholesale trade, transport and warehousing, information and communications, financial and insurance, professional and scientific, and the education sectors. Other sectors experience an increase, followed by a plateauing in capital intensity. These are the construction, manufacturing, rental and real estate, utilities, health and social services, and the arts and recreation sectors. The hospitality sector has seen an increase in capital-to-labour from the 2004 to 2010 period, followed by a fall in capital intensity.

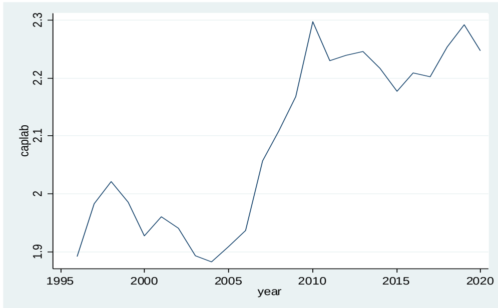
Retail



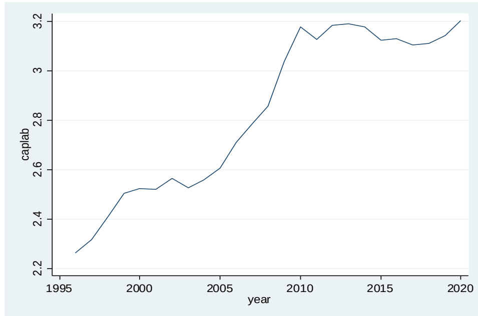
Hospitality



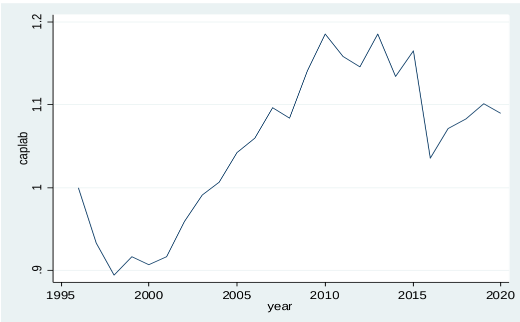
Construction



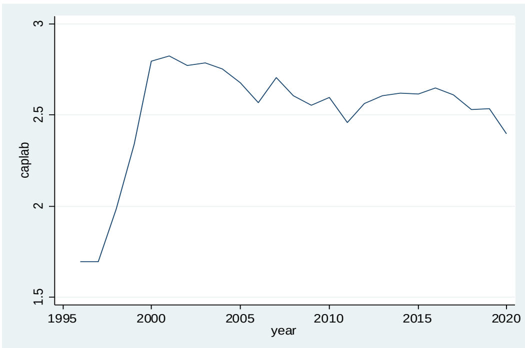
Manufacturing



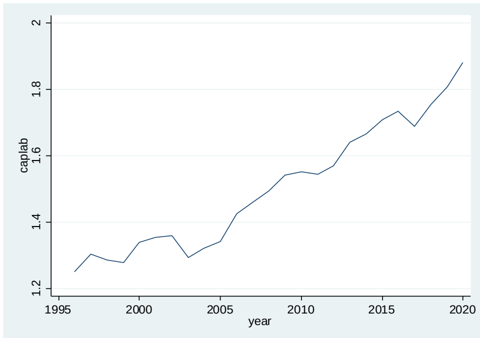
Rental and Real Estate



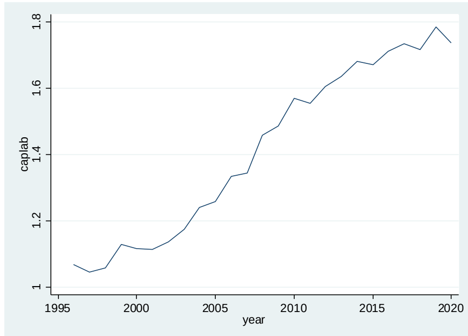
Utilities



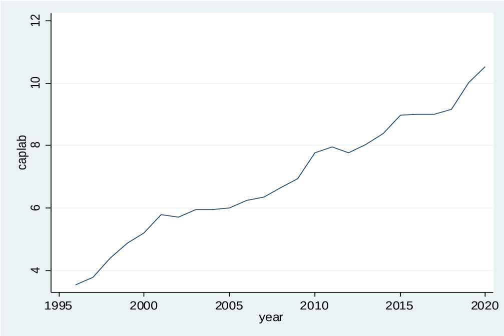
Wholesale Trade



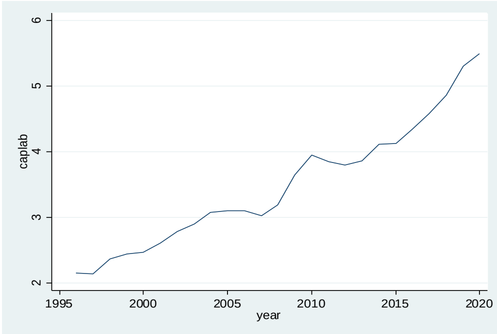
Transport and Warehousing



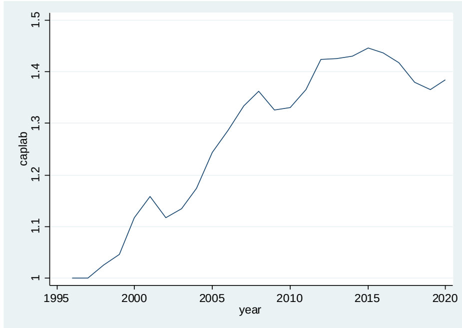
Information Media and Telecommunication



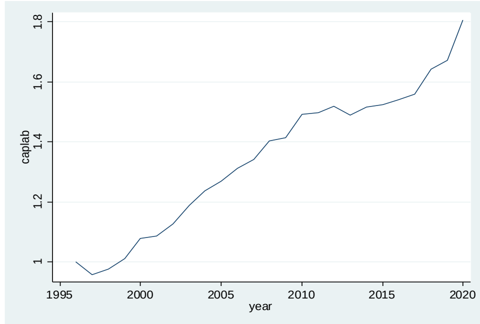
Financial and Insurance



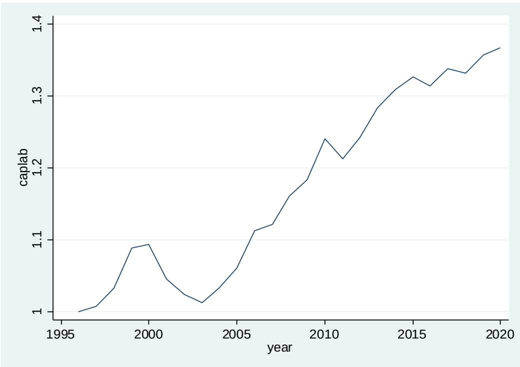
Health and Social Services



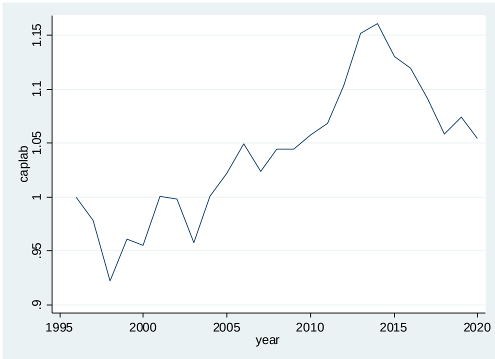
Professional/Scientific



Education



Arts and Recreation



Appendix B.4.

Table 3.10 shows annual growth rates for the three labour earnings/cost variables used in this study for New Zealand industry sectors. The growth rates are provided for the full 1990 to 2020 period, and also split into three 10-year periods. The aim is to compare industry labour income growth performance between the three earnings measures. Greater overall growth rates are seen for total employee compensation compared with the narrower income measures of hourly wage rates and Weekly earnings. There is not a clear difference in trend by average industry skill level.

Table 3.10. New Zealand Annual Average Labour Income/Cost Growth Rates.

	Hourly wage rates				Weekly earnings				Total employee compensation			
	1990-2020	1990-1999	2000-2008	2011-2020	1990-2020	1990-1999	2000-2008	2011-2020	1990-2020	1990-1999	2000-2008	2011-2020
Construction	1.05	0.82	1.24	1.25	1.12	1.38	0.90	1.43	4.23	0.77	8.86	4.85
Hospitality	0.57	-0.10	0.10	1.55	1.01	0.26	0.33	1.92	3.60	3.12	4.35	3.83
Retail	0.93	0.39	0.66	1.93	1.18	0.42	1.04	2.17	2.83	2.21	4.85	2.61
Manufacturing	1.05	0.92	0.86	1.35	1.19	1.10	0.94	1.45	0.64	0.06	1.66	0.94
Utilities	1.49	1.53	1.17	1.87	1.5	1.56	1.30	2.04	1.50	-3.6	3.87	3.65
Transport and Storage	0.79	0.51	0.91	1.07	0.78	-0.56	1.46	1.39	1.39	-0.61	2.24	3.14
Wholesale Trade	0.96	1.26	0.64	1.32	0.90	1.42	0.27	1.20	2.33	2.51	3.13	2.10
Rental	1.02	0.95	0.51	1.61	0.97	0.54	0.72	1.77	3.98	2.21	5.86	5.79
Information and Communication Media	0.85	0.74	0.81	1.25	1.06	0.54	0.78	2.07	-0.36	-1.23	-0.02	-0.23
Financial and Insurance Services	1.87	2.63	1.50	1.67	1.92	2.52	1.21	2.11	1.92	0.64	3.68	1.97
Health and Social Assistance	0.97	0.60	1.44	1.07	1.18	-0.24	2.20	1.68	3.66	2.75	5.32	2.40
Professional, Scientific and Technical Services	0.88	0.99	0.67	1.01	0.98	0.58	0.86	1.32	4.80	5.51	5.33	4.01
Education	0.76	0.39	1.78	0.42	0.88	-0.44	2.40	0.97	2.66	2.45	3.75	1.53
Art and Recreation	0.78	0.46	0.611	1.59	0.61	-0.07	0.62	1.77	4.00	5.10	5.01	2.18
All Industries	0.98	0.79	1.01	1.24	1.02	0.43	1.12	1.58	2.47	1.47	3.96	2.45

Source data: Statistics New Zealand. Income measures are in real values, deflated using the CPI.

Appendix B.5.Stata Commands/Codes.

Appendix B.5.A. Difference GMM Command Regressions Using Level Equations.

The results for the Stata command regressions (for the Table 3.3 results) using Difference GMM estimator are presented here. Both the equation variables and the instruments are in levels and are estimated in Differences. The Difference estimation does not make available Sargan and Hansen tests for overidentifying instruments.

xtabond2 L(0/1).llabprod caplab lmfp lwagerate llabsupply lftemp trdeopen lrealtwi piprate yr1997-yr2020, gmm(llabprod, lag(3 3) collapse eq(diff)) iv(caplab lmfp lwagerate llabsupply lftemp trdeopen lrealtwi piprate yr1997-yr2020, eq(diff)) robust

```
Favoring space over speed. To switch, type or click on mata: mata set matafavor speed, perm.

trdeopen dropped due to collinearity

lrealtwi dropped due to collinearity

yr1998 dropped due to collinearity

yr2018 dropped due to collinearity

Warning: Number of instruments may be large relative to number of observations.

Warning: Two-step estimated covariance matrix of moments is singular.

  Using a generalized inverse to calculate robust weighting matrix for Hansen test.

  Difference-in-Sargan/Hansen statistics may be negative.

Dynamic panel-data estimation, one-step system GMM

------------------------------------------------------------------------------

Group variable: sector                    Number of obs      =      336

Time variable : year                    Number of groups   =       14

Number of instruments = 30                 Obs per group: min =       24

Wald chi2(29) =   4989.32                              avg =     24.00

Prob > chi2   =     0.000                              max =       24

------------------------------------------------------------------------------

           |             Robust

   llabprod | Coefficient  std. err.      z    P>|z|     [95% conf. interval]

-------------+----------------------------------------------------------------

   llabprod |

       L1. |  -.4425033   .4244528    -1.04   0.297    -1.274415    .3894089
```

caplab	.1615016	.0642199	2.51	0.012	.0356328	.2873703
lmfp	.9717584	.0321435	30.23	0.000	.9087582	1.034758
lwagerate	.1725694	.1965843	0.88	0.380	-.2127287	.5578675
llabsupply	.2810893	.1757213	1.60	0.110	-.0633181	.6254967
lftemp	-.0645255	.0666022	-0.97	0.333	-.1950633	.0660124
piprate	.0001877	.0002894	0.65	0.517	-.0003796	.000755
yr1997	.0070842	.0125963	0.56	0.574	-.0176042	.0317726
yr1999	.0138468	.0089644	1.54	0.122	-.0037232	.0314167
yr2000	.0315864	.0250171	1.26	0.207	-.0174461	.0806189
yr2001	.0537385	.0449573	1.20	0.232	-.0343762	.1418531
yr2002	.0567278	.0481715	1.18	0.239	-.0376867	.1511422
yr2003	.0517965	.0436329	1.19	0.235	-.0337223	.1373153
yr2004	.055164	.0455348	1.21	0.226	-.0340826	.1444106
yr2005	.0520207	.0411512	1.26	0.206	-.0286341	.1326755
yr2006	.0494885	.0351883	1.41	0.160	-.0194792	.1184563
yr2007	.0462428	.0309163	1.50	0.135	-.014352	.1068376
yr2008	.0438856	.0285796	1.54	0.125	-.0121293	.0999006
yr2009	.0374156	.0211604	1.77	0.077	-.004058	.0788892
yr2010	.0272445	.0148623	1.83	0.067	-.0018851	.056374
yr2011	.0376693	.0218776	1.72	0.085	-.00521	.0805486
yr2012	.0345696	.0181784	1.90	0.057	-.0010594	.0701985
yr2013	.0386957	.0208514	1.86	0.063	-.0021723	.0795638
yr2014	.0355714	.0199558	1.78	0.075	-.0035413	.0746842
yr2015	.0236521	.0145747	1.62	0.105	-.0049137	.052218
yr2016	.0191076	.0121008	1.58	0.114	-.0046096	.0428248
yr2017	.010975	.0081439	1.35	0.178	-.0049867	.0269367
yr2019	-.0079371	.0083101	-0.96	0.340	-.0242247	.0083504
yr2020	-.0184803	.0117956	-1.57	0.117	-.0415992	.0046386
_cons	-.6638401	1.938563	-0.34	0.732	-4.463354	3.135674

```
------------------------------------------------------------------------------
Instruments for first differences equation
  Standard
    D.(caplab lmfp lwagerate llabsupply lftemp trdeopen lrealtwi piprate
    yr1997 yr1998 yr1999 yr2000 yr2001 yr2002 yr2003 yr2004 yr2005 yr2006
    yr2007 yr2008 yr2009 yr2010 yr2011 yr2012 yr2013 yr2014 yr2015 yr2016
    yr2017 yr2018 yr2019 yr2020)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L3.llabprod collapsed
Instruments for levels equation
  Standard
    _cons
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =   0.82  Pr > z =  0.415
Arellano-Bond test for AR(2) in first differences: z =   0.17  Pr > z =  0.865
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(0)    =   0.00  Prob > chi2 =      .
  (Robust, but weakened by many instruments.)
```

Appendix B.5.B. OLS Panel Data Regression – Differenced variables, fixed effects.

For comparative purposes, regression results for the Stata command from OLS panel data estimation with fixed effects are presented here. The results are similar to those obtained from dynamic panel data modelling applying difference GMM estimation, supporting the consistency of the two approaches.

```
xtreg dllabprod dcaplab dlrealwagerate dlmfp dllabsupply dlftemp dtrdeopen dlrealtwi dpiprate yr1997-yr2020, fe robust

note: yr2018 omitted because of collinearity.

note: yr2019 omitted because of collinearity.
```

```
note: yr2020 omitted because of collinearity.

Fixed-effects (within) regression            Number of obs     =       345
Group variable: sector                     Number of groups  =        14

R-squared:                               Obs per group:
     Within  = 0.8939                                  min =        24
     Between = 0.9752                                     avg =       24.6
     Overall = 0.8999                                  max =        25

                                       F(13,13)          =          .
corr(u_i, Xb) = -0.4385                        Prob > F          =          .

                              (Std. err. adjusted for 14 clusters in sector)
------------------------------------------------------------------------------
             |               Robust
    dllabprod | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
---------------+----------------------------------------------------------------
      dcaplab |   .1540104   .0414933     3.71   0.003     .0643695    .2436513
dlrealwagerate |   .0775474   .0809178     0.96   0.355    -.0972649    .2523597
        dlmfp |   .9589824    .034352    27.92   0.000     .8847693    1.033195
   dllabsupply |   .3657137   .3625812     1.01   0.332    -.4175953    1.149023
      dlftemp |  -.0310468   .0493129    -0.63   0.540    -.1375809    .0754873
    dtrdeopen |    .640191   .4026071     1.59   0.136    -.2295888    1.509971
    dlrealtwi |   .0449114   .0358938     1.25   0.233    -.0326326    .1224553
     dpiprate |   .0000203   .0000661     0.31   0.764    -.0001226    .0001632
       yr1997 |  -.0035962   .0033473    -1.07   0.302    -.0108277    .0036353
       yr1998 |   .0217353    .015347     1.42   0.180     -.01142    .0548905
       yr1999 |    .014892   .0109421     1.36   0.197    -.0087471     .038531
       yr2000 |   .0207369   .0146311     1.42   0.180    -.0108716    .0523453
```

```
      yr2001 |   .0107798   .0061837     1.74   0.105    -.0025793     .024139
      yr2002 |  -.0004248   .0040963    -0.10   0.919    -.0092742    .0084247
      yr2003 |  -.0059467   .0057929    -1.03   0.323    -.0184615    .0065682
      yr2004 |    .004374   .0019859     2.20   0.046     .0000838    .0086642
      yr2005 |   .0024324   .0035516     0.68   0.505    -.0052404    .0101052
      yr2006 |    .009004   .0029541     3.05   0.009      .002622     .015386
      yr2007 |   .0039055   .0026367     1.48   0.162    -.0017908    .0096018
      yr2008 |   .0116179   .0082521     1.41   0.183    -.0062098    .0294455
      yr2009 |   .0061775   .0062867     0.98   0.344    -.0074042    .0197592
      yr2010 |   .0044951   .0059275     0.76   0.462    -.0083105    .0173006
      yr2011 |   .0036506   .0046212     0.79   0.444     -.006333    .0136341
      yr2012 |   .0043349   .0055862     0.78   0.452    -.0077334    .0164032
      yr2013 |   .0130021   .0078044     1.67   0.120    -.0038584    .0298625
      yr2014 |  -.0061991   .0040883    -1.52   0.153    -.0150314    .0026331
      yr2015 |   .0001746    .003791     0.05   0.964    -.0080153    .0083646
      yr2016 |  -.0014318   .0060812    -0.24   0.818    -.0145694    .0117058
      yr2017 |    -.00373   .0090275    -0.41   0.686    -.0232326    .0157727
      yr2018 |          0  (omitted)
      yr2019 |          0  (omitted)
      yr2020 |          0  (omitted)
       _cons |  -.0095121   .0081141    -1.17   0.262    -.0270416    .0080174
-------------+----------------------------------------------------------------
     sigma_u |  .00505635
     sigma_e |  .01249984
         rho |  .14062081   (fraction of variance due to u_i)
------------------------------------------------------------------------------

.
```

Appendix B.6.

Table 3.11 presents results for factors impacting labour earnings by New Zealand industry. No significant results are observed for factors impacting earnings.

Table 3.11. Factors Affecting Labour Earnings by New Zealand Industry.

	log wage rate (1)	log weekly earnings (2)	log total compensation (3)
log wage rate $_{t-1}$ / log weekly earnings $_{t-1}$ / log total compensation $_{t-1}$	0.937***	0.518	1.26**
	(0.132)	(0.360)	(0.622)
unemployment rate	0.002	-0.021	0.045
	(0.002)	(0.022)	(0.092)
log fulltime-equivalent employment	-0.003	-0.028	0.041
	(0.046)	(0.055)	(0.156)
log labour productivity	-0.015	-0.048	-0.138
	(0.076)	(0.117)	(0.179)
log total factor productivity	0.051	0.149	0.351***
	(0.104)	(0.161)	(0.128)
year dummies	Yes	Yes	Yes
constant	-	2.98	-4.23
		(2.59)	(5.13)
observations	312	312	312
no. of instruments	28	28	28
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.78	0.74	0.16

Notes: The dependent variables are Column 1: log real wage rate; Column 2: log real weekly earnings; Column 3: log real annual total compensation. The base industry is the retail sector. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Appendix B.7 GFC Structural Break Modelling

Tables 3.12 and 3.13 show the results of testing for structural breakpoints arising from the global financial crisis (GFC). Structural break tests provide evidence for breakpoints but these vary within the years of the GFC. Time dummy variable interactions with variables of statistical significance are tested in regression equations for different time periods of possible breakpoints. These are 2010 to 2020, 2011 to 2020, 2012 to 2020, and 2013 to 2020. The results with some economic significance are for the 2012 to 2020 period. The base period is the 1996 to 2011 time period.

Table 3.12. GFC Structural Break Dummy Variable Interactions for the period 2012 to 2020. Base Group 1996 to 2011.

	log real wage rate (1)	log total employee compensation (2)
log labour productivity $_{t-1}$	-0.569	-0.731
	(0.555)	(0.706)
capital relative to labour	0.173**	0.182**
	(0.074)	(0.085)
capital relative to labour/year 2012 to 2020	0.003	0.002
	(0.006)	(0.005)
log wage rate/total employee compensation	0.214	-0.115
	(0.275)	(0.079)
log wage rate/total employee	-0.036	-0.012
compensation/year 2012 to 2020	(0.045)	(0.021)
log total factor productivity	0.961***	0.973***
	(0.044)	(0.053)
log total factor productivity/year 2012 to	0.036**	0.057
2020	(0.039)	(0.058)
log labour supply	-0.227	-
	(0.612)	
log fulltime-equivalent employment	-0.063	-0.044
	(0.066)	(0.062)
log fulltime-equivalent employment)/year	0.005	015**
2012 to 2020	(0.011)	(0.026)
producer price index	0.000	0.000
	(0.000)	(0.000)
producer price index/year 2012 to 2020	-0.001	-0.001
	(0.001)	(0.001)
year dummies	Yes	Yes
constant	7.48	6.85
	(12.57)	(6.38)
observations	336	336
no. of instruments	35	35
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.88	0.65

Notes: The dependent variable is log labour productivity. Year dummies are included for the period 1997 to 2020. Column 1 includes the real wage rate as a labour income measure, Columns 2 substitutes total employee compensation as a robust measure. Explanatory variables for total labour supply, trade openness, and the real trade-weighted index are omitted from regression estimates due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Table 3.13. GFC Structural Breakpoint Dummy Variable Industry Interactions for the period 2012 to 2020. Base Group 1996 to 2011.

	log real wage rate (1)	log total employee compensation (2)
log labour productivity $_{t-1}$	-0.503	-0.606
	(0.468)	(0.544)

construction/year 2012 to 2020	0.045	0.022
	(0.045)	0.057)
hospitality/year 2012 to 2020	-0.045	0.018
	(0.035)	(0.112)
manufacturing/year 2012 to 2020	-0.013	-0.062
	(0.073)	(0.070)
utilities/year 2012 to 2020	0.426**	0.483***
	(0.181)	(0.151)
wholesale/year 2012 to 2020	0.089	0.069
	(0.079)	(0.085)
rental/year 2012 to 2020	0.273	0.333***
	(0.172)	(0.118)
transport and storage/year 2012 to 2020	0.257	0.222
	(0.194)	(0.202)
information communication/year 2012 to 2020	0.677**	0.675**
	(0.320)	(0.275)
financial and insurance/year 2012 to 2020	0.289*	0.262**
	(0.152)	(0.107)
healthcare and social assistance/year 2012 to 2020	-0.071	-0.126
	(0.062)	(0.129)
professional, scientific, and technical services/year 2012 to 2020	-0.107	-0.140**
	(0.70)	(0.159)
education/year 2012 to 2020	-0.132	-0.166*
	(0.089)	(0.091)
arts and recreation/year 2012 to 2020	-0.016	0.041
	(0.061)	(0.140)
capital relative to labour	0.191**	0.197**
	(0.082)	(0.087)
capital relative to labour/year 2012 to 2020	-0.045	-0.047
	(0.045)	(0.043)
log wage rate/total employee compensation	0.214	-0.103
	(0.283)	(0.076)
log wage rate/total employee compensation/year 2012 to 2020	-0.044	0.046
	(0.152)	(0.136)
log total factor productivity	1.04***	1.03***
	(0.062)	(0.078)
log total factor productivity/year 2012 to 2020	-0.148	-0.102
	(0.144)	(0.150)
log fulltime-equivalent employment	-0.123**	-0.106**
	(0.058)	(0.053)
log fulltime-equivalent employment)/year 2012 to 2020	0.176**	0.178*
	(0.073)	(0.106)
producer price index	0.000	0.000
	(0.000)	(0.000)
producer price index/year 2012 to 2020	-0.000	-0.001
	(0.001)	(0.001)
year dummies	Yes	Yes
constant	3.15	4.45
	(3.08)	(4.19)
observations	336	336
no. of instruments	48	48
Arrelano-Bond test for AR(2) in first-differences: Pr>z	0.82	0.61

Notes: The dependent variable is log labour productivity. Industries are interacted with a year dummy for the period 2012 to 2020. The base industry is the retail sector. Year dummies are included for the period 1997 to 2020. Column 1 includes the real wage rate as a labour income measure, Columns 2 substitutes total employee compensation as a robust measure. Explanatory variables for total labour supply, trade openness, and the real trade-weighted index are omitted from regression estimates due to collinearity. Unit of analysis: Industry. Year dummies are included for the period 1997 to 2020. Robust standard errors shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Chapter 4

Cognitive Skill Effects on Earnings in the New Zealand Labour Market

4.1. Introduction

The importance of human capital in the pursuit of sustainable growth in productivity and income, and for improving social equality and cohesion, is a forefront consideration for policymakers (OECD, 2021). The earnings-skills empirical framework is established in the seminal work of Mincer (1974), using years of schooling, and qualifications as principle measures of human capital. These measures capture the quantity of foundation human capital accumulated by individuals and are important gauges of worker skill to firms in their employment and renumeration decisions. Barro and Lee (1976, 2001, 2013) have developed a prominent educational dataset covering attainment from 1950 to 2010, from which they and others have drawn in applied research work. However, concerns for the usefulness of these measures include their broadness, changes in the perceived value of qualifications arising from changing education programmes over time, and that they do not consider the value of skills obtained beyond the foundation years. For the latter point, Card (1999) notes that base education tends to be a 'one-time' thing, essentially unchanging after a worker reaches twenty-five years of age.

Recent concern over educational proficiency and skills gaps in industry has seen a focus on the core cognitive skills of literacy and numeracy. The importance of the core skills for improving economic performance has been highlighted by various international and country institutions, together with industry (IMF, 2021). Cognitive skills are those connected with the ability to think, read, learn, remember, reason, and pay attention (Mind Matters, 2018). These are skills that underlie the broader attainment measures. Important international programmes have undertaken to better measure population proficiency in the cognitive and other important skills. These are the

International Adult Literacy Survey (IALS); the Literacy and Life Skills Survey (ALLS)[30] and the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), on which this study will draw. The IALS programme was undertaken between 1994 and 1998, assessing adult literacy skills in 22 participating countries; the ALL programme was conducted between 2003 and 2008, assessing adult literacy and numeracy skills in participating 11 countries; the first cycle of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) was undertaken during the 2011 to 2017-year period for 36 participating countries.

The PIAAC dataset measures population literacy, numeracy, and ICT problem-solving cognitive skills, together with a broad range of skills and demographic variables. The cognitive skill domains, described more completely in the Programme's framework (OECD, 2013) refer to key information-processing competencies defined as: literacy - the ability to understand, evaluate, use, and engage with written texts to participate in society to achieve one's goals, and to develop one's knowledge and potential; numeracy - the ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life; problem-solving in technology-rich environments - the ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others, and perform practical tasks.

My study in Chapter 4 will draw on the skill measures provided in the PIAAC dataset to evaluate the importance of the core cognitive skills for lifting New Zealand worker income levels and standards of living. In pursuit of this research objective, I will

[30] For the source information for these skills data - IALS: https://nces.ed.gov/surveys/ials/
ALL: https://nces.ed.gov/surveys/all/

assess not only the relationship between skill proficiency and earnings, but also, as a main contribution to the literature, the impacts from greater use of the cognitive skills. Key findings and contributions from my study are that, while the larger impacts for worker earnings occur from years of schooling, as established in the literature, increases in literacy and numeracy proficiency provide additional benefits for worker income. Numeracy skill, in particular, has a consistently strong positive impact. In evaluating effects of frequency of use of the core cognitive skills in workplace tasks on earnings, I find a significant positive relationship between use of writing and ICT problem-solving skills in workplace tasks and worker income. Greater use of tasks involving reading and numeracy skills in the workplace are also positive when considering monthly compensation. Additionally, skilled workers see the most benefit from higher cognitive skill use. The results indicate industry demand for these skills and the potential for improving productivity and income growth through greater integration of the core skills and technology in the New Zealand workplace.

The rest of this Chapter is organized as follows: In section 4.2 I develop the hypotheses to evaluate. Section 3 describes the data, variables, and methodology. In section 4.3 I present the empirical results. Section 4.5 examines causality as further robustness measures. In section 4.6, I present conclusions and policy implications.

4.2. Literature Review and Hypotheses Rationale

The PIAAC skills programme dataset provides extensive skills and demographic data, together with worker income information. Studies making use of this dataset include Pellizzari and Fichen (2013) in focusing on skills mismatch effects. Pellizzari and Fichen (2013) contend that a better match of workers' ability in the core skills to the requirements of their jobs can improve labour market efficiency. They find further that overlap between the skill domains of literacy and numeracy is substantial: 94 per cent of workers who are well-matched in literacy are also well-matched in numeracy. Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) use the PIAAC data to assess labour market returns to proficiency in cognitive skills for 23 countries - not including New Zealand - establishing a positive relationship between numeracy skills, in particular, and labour returns. For the labour market returns from use of the cognitive skills, De la Rica, Gortazar, and Lewandoswski (2020) address the empirical relationship between abstract, routine, and manual tasks and wages. They find a wage premium from an increase in abstract task usage. For gender effects, a key variable to control for in my study, Christl and Koppl-Turyna (2020) use the PIAAC data to explore impacts of task skill and usage on wage differences in the Austrian labour market. They find that skill factors explain a sizeable proportion of the difference in gender returns.

In addition to the literacy and numeracy measures collected and processed in the IALS and ALLS programmes, the PIAAC data allows for measurement of a third important skill proficiency variable, that of ICT problem-solving. This latter variable captures the effects of demand for technology skills in the modern workplace. In this study I will draw on the work of Hanushek et al. (2015) and others to contribute to the literature in examining the impacts on labour market returns from cognitive skill proficiency and usage in workplace tasks in the New Zealand labour market, together with other relevant skills-earnings effects. Adopting the human capital framework developed by Mincer (1974), and controlling for workplace experience and other skill and demographic explanatory variables of interest, I will examine the impacts from core cognitive skills on earnings in evaluating the main hypothesis for this chapter:

Hypothesis One*: Increases in proficiency and frequency of use of the core cognitive skills of literacy, numeracy, and ICT problem-solving will increase average worker income in the New Zealand labour market.*

Occupational skills are an important determinant of worker earnings. Carbonaro (2006) finds in study of the United States (U.S.) labour market that occupational sorting accounts for over half of the difference in worker income. Autor and Dorn (2013) and Guo (2022) are amongst those to find a 'hollowing out' effect for those in middle-skilled occupations as tasks traditionally performed by white-collar workers are replaced by automation. This reduces demand for their skills, and in turn, employment and income. These findings support the need to evaluate the impacts of occupational skill for worker earnings in the New Zealand labour market to identify if similar trends are occurring and to allow for further analysis. I will then extend these findings to contribute further to the literature in assessing whether greater use of the core cognitive skills in workplace tasks will improve earnings by occupational skill group. These relationships will be evaluated through hypothesis two and three:

Hypothesis Two: *Average hourly earnings will rise with increases in occupational skill in the New Zealand labour market.*

Hypothesis Three: *An increase in occupational skill group use of the core cognitive skills will increase average hourly earnings for that skill group.*

The literature shows that the demographic factors of age and gender have impacts on worker earnings. For age effects, the work of Mincer (1974), and Thornton, Rodgers, and Brookshire (1997) show a typical concave age-earnings profile with peak earnings occurring for workers aged 45-years and above. Murphy and Welch (1990) contend that the earnings profile may not be as clearly defined as often depicted. Differences in human capital, reflected in the current market value of qualifications attained, including differences in the perceived quality of schooling between generational groups, may also affect the age-earnings profile. Age may also necessarily be connected with worker experience in influencing earnings. The impacts of these variables on earnings should be separated out as much as possible. It may be expected that improvements in cognitive skill will increase worker income, regardless of age, as workers add to their stock of human capital and increase their value to employers. I evaluate this relationship through age interactions with numeracy proficiency skill, assessed in the empirical work undertaken as the most stable of the core skill measures. These impacts on earnings will be examined through hypothesis four:

Hypothesis Four: *Increases in numeracy skill proficiency will raise average worker earnings for each age group in the New Zealand labour market.*

For gender earnings effects, the negative earnings gap that exists for female workers relative to males is widely reported in government labour force data and examined in the literature. In their study of gender lifetime earnings for the German workforce, Boll, Jahn, and Lagemann (2017) find that for individuals born in the period 1950 to 1964, at the end of their employment career, women accumulate average earnings that are 49.8 per cent lower than for men. This gender lifetime income gap is more than twice as high as the recorded German labour market gender pay gap at the time of the study in 2017. As discussed, Christl and Koppl-Turyna (2020) find that cognitive skill and use can reduce the gender wage gap for the Austrian labour market. I will evaluate the ability of cognitive skills to offset any negative effects of gender by age group in the New Zealand labour market, after controlling for schooling, work experience, and natural ability. These relationships will be assessed through change in numeracy proficiency skill, in the fifth hypothesis:

Hypothesis Five: *Greater numeracy skill proficiency will increase earnings for each age group by gender in the New Zealand labour market.*

4.3. Data and Methodology

4.3.1 Data and Variables

The data used for this study is the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) skill survey dataset for the New Zealand labour market. New Zealand was included in the second round of country surveys, in the first, and current, cycle of the programme. New Zealand's survey data was collected during the 2014 to 2015-year period[31]. The Programme involves a comprehensive survey completed by a representative sample of each participating country's population, aged 16 to 65-years. Each participant is asked a wide range of questions on subjects including their qualifications, their ability in and use of core cognitive skills, further skills and occupation-related questions, and demographic information. The programme is designed to collect and measure key cognitive and workplace skills needed for individuals to function in the workplace, to advance in their jobs, and for their participation in society. Cognitive skills are assessed in three domains: literacy, numeracy, and problem-solving in technology-rich environments. The tasks respondents were given to solve are often framed as real-world problems, such as maintaining a driver's logbook (numeracy domain), or reserving a meeting room on a

[31]The first cycle of this international survey was undertaken for 36 participating countries, over three rounds, during the period 2011 to 2017. The second cycle is scheduled for the 2022 to 2023 period. www.oecd.org/skills/piaac

particular date using a reservation system (problem-solving domain).

The PIAAC survey methodology uses a self-weighting design with a minimum required sample size of 5,000 completes. 6,176 New Zealanders were surveyed. A four-stage stratified probability-proportionate-to-size sampling design is utilised. For Stage 1 the sample is drawn from Statistics New Zealand's Household Survey Frame (2013), the 2013 Census meshblocks for Stage 2, and from field enumeration for Stages 3 and 4. For sample collection, each person, or household, has an equal probability of selection. Within primary sampling units (PSUs) the household base weight is determined as:

$$W_k = \frac{1}{P_{hi}\, CP_{hik}}$$

where P_{hi} is the probability of selecting PSU i in stratum h, and CP_{hik} is the conditional probability of selecting household k within PSU i of stratum h. Screening also took place, as for a number of countries, for sample suitability. Additional samples of 16-to-25-year-olds, and persons of Maori and Pacific ethnicities were undertaken to support obtaining reliable estimates for groups of special interest. The sample groups were weighted separately up to, and including, the non-response adjustment stages. Composite weighting was then used to combine samples using population control totals corresponding to the target screener subgroups. The weight trimming and final calibration were carried out on the combined New Zealand sample. Calculations for the methodology are presented as Appendix C.3.

For variables, in evaluating the main hypothesis that greater core skill proficiency and use will raise worker income, I utilise hourly wage rates as the main income measure and dependent variable. As a robustness check, and to evaluate additional earnings effects not captured by hourly earnings, I include two further income measures: monthly earnings and monthly earnings comprising all worker compensation paid. The latter includes earnings of the self-employed. Each earnings measure is in logarithmic form. These measures represent a widening-out of income from the narrow hourly wage rate to a fuller monthly compensation measure. Outliers for the income measures are removed from the data[32]. The core explanatory skill variables are continuous scale measures for proficiency in literacy, numeracy, and problem-solving using ICT. Each scale measures the skills and abilities required to perform a variety of tasks as a 500-point scale, from the least to the most advanced skills. The tasks themselves range from easy to very challenging[33]. I take the median value of the ten skill samples provided for each of the proficiency measures. The scale data are transformed into logarithmic form as literacy proficiency, numeracy proficiency, and problem-solving using ICT proficiency.

In addition to cognitive skill proficiency measures, I utilise variables for frequency of use of the core skills in workplace tasks. These are PIAAC skill data measures used in a limited number of income studies in the literature. These include Christl and Koppl-Turyna's (2020) work examining impacts of task skill and usage on gender wage differences in the Austrian labour market. Variables are available from the PIAAC dataset for both work and home use. I include only variables for skill use in tasks in the workplace in regressions. The following rationale is provided for the omittance of the skill use at home measures: While Wald tests indicate joint significance, Pearson tests indicate weak correlation for the home use measures compared with workplace skill use,

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[32]Investigation of outliers suggest that these largely represent data entry or coding errors.[33]To develop the proficiency scales, expert groups including psychometricians and test developers were utilised to assess how the tasks were distributed along the 500-point scales and articulate how the required skills and knowledge to complete those tasks progressively increased along the scale. OECD's Survey of Adult Skills Technical Report (2nd Edition) 2016, Chapter 21.
https://www.oecd.org/skills/piaac/PIAAC_Technical_Report_2nd_Edition_Full_Report.pdf

regressions produce statistically insignificant results for the use at home variables, and, additionally, no direct link between home use and worker income may reasonably be expected. The frequency of skill use variables are the following, with general descriptions of tasks undertaken: reading at work: reading letters and emails, reading professional journals, reading financial statements; writing at work: writing articles, writing reports, filling in forms; use of numeracy at work: calculating costs, developing budgets, preparing charts or tables, using advanced mathematics or statistics; use of ICT at work: using the Internet, using Microsoft Word or spreadsheets, programming[34].

Each frequency of skill use measure comprises a 7-digit continuous scale, transformed into logarithmic form. The variables are also available as Likert categorical variables with results presented in this form for the statistically significant use of writing at work and use of ICT at work variables as robustness checks presented in Table 4.3. For other skill measures, I use occupational skill categorical variables to identify and analyse differences in worker earnings by broad occupational skill level. From the literature, differing occupational classification systems are available. Esposto and Abbott (2011) make use of the United States' O*NET system in their comparative study on knowledge intensity in the Australian and New Zealand labour markets. The PIAAC methodology uses the ISCO-08 International Standard Classification of Occupations[35]. This system establishes four broad skill categories as follows: elementary occupations,

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[34]Greater detail on tasks is provided in the OECD's Survey of Adult Skills Technical Report (2nd Edition) 2016, Chapter 19.
https://www.oecd.org/skills/piaac/PIAAC_Technical_Report_2nd_Edition_Full_Report.pdf

[35]The ISCO-08 is the International Standard Classification of Occupations. This system was adopted by the International Labour Organisation (ILO) through a resolution of a tripartite meeting of experts on labour statistics held in December 2007. This resolution was subsequently endorsed by the Governing Body of the ILO in March 2008. https://www.ilo.org/public/english/bureau/stat/isco/isco08/

semi-skilled blue-collar occupations, semi-skilled white-collar occupations, and skilled occupations.

I include further skill measures as control variables and explanatory variables of interest. Control variables are: qualifications imputed into years of schooling as a broad measure of human capital, and years of work experience. Both variables are established in the foundation work of Mincer (1974), together with a quadratic for experience (years of work experience^2) to capture non-linear effects (Wooldridge, 2013). The measure of experience refers to actual work experience and is collected as the number of years where at least 6 months per year were spent in paid work. To control for innate, or natural ability (Altonji and Zhong, 2021), the highest parental qualifications obtained are included as proxy dummy variables. These are: at least one parent has attained secondary and post-secondary, but not tertiary qualifications and, at least one parent has attained tertiary qualification, with a base variable of neither parent attaining upper-secondary qualifications. For other skill variables of interest, I add a dummy variable for whether individuals have participated in formal and informal adult education and training in the last twelve months that is job-related (further education). Rees (2010) and the European Commission (2021), amongst others, emphasise the importance of adult education and training beyond foundation study for improving an individual's skills to support employment and income opportunities. Also included is a variable for the quantity of training at work employees have received, log learn at work. A positive relationship between workplace training and worker income is observed in the studies of Loewenstein and Spletzer, (1994), and Bartel, (1995).

I add dummy variables to capture language effects. These are intended to evaluate whether there are communication barriers affecting worker earnings in the New Zealand labour market. The variables are: English as the individual's native language, bilingual including English, and English as the language most commonly spoken in the home. I employ a dummy variable to capture and control for gender effects (female) on earnings, using males as the base group. The negative earnings gap for female workers is widely recognised empirically in the literature (Boll, Jahn and Lagemann, 2017, Christl and Koppl-Turyna, 2020). This variable will determine the size of the gender income difference in the New Zealand labour market. I present summary statistics for the key variables in Table 4.1.

Table 4.1. Summary Statistics for Key Skill Variables.

Variables	Observations	Mean	Median	St.Dev	Min.	Max
hourly wage rate	3,542	24.60	21.00	12.45	5.00	136.36
literacy proficiency	6,020	279.03	283.01	44.26	91.18	408.88
numeracy proficiency	6,020	267.90	271.52	51.16	64.31	429.17
ICT problem-solving proficiency	5,460	286.02	289.97	42.82	115.75	409.44
read at work	4,775	2.26	2.22	0.96	0.30	7.02
write at work	4,479	2.06	2.01	1.06	0.06	5.80
numeracy at work	4,146	2.15	2.08	0.97	0.07	6.05
ICT problem-solving at work	3,465	2.14	2.01	1.06	0.01	5.46
workplace training	3,988	2.24	2.17	0.962	0.069	4.16
years of schooling	6,000	13.57	13	2.50	6	21
years of work experience	5,777	18.67	17	13.36	0	55
male	1,578	26.15	22.22	13.55	5.17	115
female	1,964	23.36	20.00	11.34	5.0	136.36

Notes: Table 4.1. provides summary statistics for key variables used in regressions, without logarithmic transformations.

I present Pearson correlation scores for the core skill variables in Table 4.2. These tests are undertaken as preliminary analysis of the strength of relationship between the skill proficiency variables, the use of skill variables, and years of schooling and work experience variables. I observe strong positive correlations between the skill proficiency variables, ranging from 0.8854 for numeracy and literacy skill proficiency, and 0.7644 for ICT problem-solving and numeracy skills. These scores point to an expected dependent relationship, where literacy skill supports numeracy skill, literacy and numeracy skill support ability in ICT problem-solving. I find moderate positive correlations between the use of skill variables: a 0.5237 correlation between writing at work and reading at work; a 0.30 correlation between numeracy at work and use of reading and writing skills; and a 0.3914 to 0.4859 correlation range between use of ICT skills in the workplace and use of reading, writing, and numeracy skills. These scores point to the core skills reinforcing each other in their use in the work environment. There are weak positive correlations between the skill proficiency measures and use of the cognitive skills in workplace tasks. A 0.20 to 0.23 correlation range is observed between the three skill measures and use of ICT problem-solving in tasks. A similar score of 0.19 occurs for numeracy proficiency and use of numeracy at work. Positive but still weaker relationships exist between the skill proficiency measures and the use of reading and writing skills in the workplace. These relationships indicate that while cognitive skill proficiency is important, and that use of skills reinforce each other, proficiency is important up to a certain level, after which use of the skills becomes the dominate factor for income. For the relationship between the cognitive skills and years of schooling, I find a moderate positive correlation in the range of 0.31 to 0.44. The relationship between work experience and use of the cognitive skills is strongest for reading skills.

Table 4.2. Pearson Correlation Coefficients for Core Skill Variables.

	literacy proficiency	numeracy proficiency	ICT problem-solving proficiency	reading - work	writing - work	numeracy - work	ICT - work
literacy proficiency	1.0000						
numeracy proficiency	0.8854	1.0000					
ICT problem-solving proficiency	0.8297	0.7644	1.0000				
reading -work	0.0107	0.0297	-0.0494	1.0000			
writing -work	0.0933	0.0545	0.0616	0.5237	1.0000		
numeracy - work	0.0810	0.1911	0.0979	0.3157	0.3032	1.0000	
ICT - work	0.2029	0.2139	0.2251	0.4859	0.5246	0.3914	1.0000
years of schooling	0.4403	0.4389	0.3120	0.3487	0.3242	0.1502	0.2959
years of work experience	-0.0107	0.0192	-0.1935	0.2299	0.1258	0.0440	0.0973

Notes: Variables are for skill proficiency, use of skills in workplace tasks, years of schooling, and years of work experience. Variables are in in logarithmic form, except years of schooling and years of work experience. Many general sources provide guidance to correlation strength. Those adopted here are: coefficient values between $\pm$ 0.50 and $\pm$ 1 - strong correlation; between $\pm$ 0.30 and $\pm$ 0.49 – moderate/medium correlation; below $\pm$ 0.29 – weak/small correlation.

4.3.2 Models and Methodology

I develop a series of regression equations to test the proposed hypotheses in this study. The basic equation takes the following form:

$$\ln(w)_i = \alpha + \beta 1 CS_i + \delta X_i + \beta Z_i + \mu_i \qquad (1)$$

where:

i is observations for individuals,

$\ln(w)_i$ is the logarithm of hourly wage rate (and other income measures),

CS_i is a vector of variables for proficiency in, and frequency of use of the core cognitive skills of literacy, numeracy, and ICT problem-solving,

X_i is a vector of further variables of interest,

Z_i is a vector of control variables,

μ_i is the error term.

The modelling methodology employed is cross-sectional regression. Cross-sectional modelling is used as the survey provides data for one time-period only. A second cycle of the skills programme is planned for the 2022–2023 period, for which New Zealand is a participating country[36]. This will allow for further research of core cognitive skill-income effects. Stata is used as the modelling software.

4.3.3 Tests for Robustness

I undertake a variety of tests as checks on the robustness of the results. These include regressions with three alternative earnings measures as dependent variables, presented in Table 4.3. This has allowed examination of the consistency of results as well as an evaluation of the impacts of skills as income is widened from the hourly wage rate to all monthly compensation paid. Ramsay tests show evidence of omitted variables, however the model specification improves with more variables added in Column 3, with a p-value of 0.0590. This further improves when all monthly compensation is the dependent variable, with a p-value of 0.3677 in Column 5. I employ model variation tests with regressions incorporating differing combinations of variables of interest and control variables. This allows examination of the consistency of results. Different categorical variables are trialled as base variables with similar results obtained. I examine the effects of the core skill frequency of use variables on income using both continuous and Likert-type scales. The results for both measures are shown to be similar. These findings are presented in Tables 4.3, 4.4, and 4.5. Wald tests for joint significance are undertaken for the skill proficiency variables, the frequency of skill use variables, and both sets of skill measures combined. For each set of tests, the null hypothesis of no difference between the variables is strongly rejected. Breusch-Pagan/Cook-Weisberg and Cameron and Trivedi's decomposition tests are undertaken, indicating the presence

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[36]Due to the Covid-19 pandemic, the data collection for the 2nd cycle of the survey will take place in the 2022-2023 period with the results to be published in 2024.
https://www.oecd.org/skills/piaac/about/piaac2ndcycle/

of heteroskedasticity in some of the modelling work. Models presented use robust standard errors to correct for this, with overall lower standard errors. I undertake variance inflation factor (VIF) tests for collinearity between variables. The results for most equations record mean VIF scores of less than 2.0. Standard statistical practice for VIF test scores (see Green, Hand, and Zhang, 2017) consider a score of 1 indicates no correlation, between 1 and 4 indicates weak to moderate correlation. Green et al. (2017) reject models with variable VIF scores higher than 5. In this study, Hanushek I examine reverse causality between earnings and skills in Section 4.5 and Appendix C.4 which further support robustness of results.

4.4 Empirical Results

I now present the empirical results. These show the impacts of the core cognitive skills, and their interactions with occupational skills, gender, and age, on labour income for the representative sample of New Zealanders surveyed.

4.4.1 Proficiency and Frequency of Skill Use Effects on Earnings in the New Zealand Labour Market

In this section I evaluate hypothesis one: that an increase in proficiency and use of the core cognitive skills of literacy, numeracy, and ICT problem-solving will increase average worker income in the New Zealand labour market. The results are presented in Table 4.3. and provide support for the hypothesis, particularly for the skill use effects. In Columns 1, 2, and 3, I show the results for increased skill proficiency on the main dependent variable of hourly wage rates. In Column 1, only years of work experience is controlled for. Columns 2 and 3 show the impacts from adding successive explanatory variables. In Columns 4 and 5, I evaluate skill impacts on the broader worker income measures of monthly earnings and all monthly earnings including income of the self-employed. Combining the three skill proficiency measures in Column 1, I find positive income effects from increased literacy and numeracy proficiency. A 10 per cent increase in literacy skill increases average hourly earnings by 5.8 per cent, and by 6.2 per cent for numeracy skills. For ICT problem-solving skill, while significant, the sign is negative in each of the regressions. This is counter-intuitive to the expected result and may indicate collinearity with the other core cognitive skills. It would reasonably be expected that a degree of literacy and numeracy proficiency would be required to support problem-solving[37]. For work experience in Columns 1 and 2, there is a positive relationship between experience and earnings, as expected, with a 3 per cent gain to labour income. Adding years of schooling to the regression in Column 2, I find an additional year improves hourly earnings by 5 per cent on average. Income effects for the cognitive skills fall, with a decrease from 6.2 to 5.5 per cent for numeracy, and from 5.8 to 2.1 per cent for literacy skill. These results show controlling for schooling helps to separate out the contribution to income of the differing skills. I add further explanatory variables in Column 3. Increasing frequency of use of the core skills in workplace tasks provides modest gains to income. The strongest effect is from greater use of ICT problem-solving in tasks. Here a 10 per cent increase results in a 1.4 per cent increase in earnings. Greater use of writing skills in workplace tasks raises average hourly earnings by 1.2 per cent. The gains to income do not mean that workers will automatically obtain higher compensation if they increase their use of the core skills,

[37] I apply alternate methodologies to correct for the negative sign on log ICT problem-solving. These are: (1) ICT proficiency regressed on the other two skill proficiency variables together with the frequency of skill use variables. The residual from this regression then replaced the ICT problem-solving variable in the original regression. Similar results to those for the original ICT problem-solving variable were obtained. (2) Standardising the skills proficiency variables was trialled. This approach yielded similar results to the non-standardised regressions.

but rather reflects demand for these skills in the New Zealand labour market, and the potential benefit to productivity and household income from continuing integration of the cognitive skills into workplace tasks. For further education beyond the foundation years, receiving job-related formal and informal adult education and training within the last 12-month period (further education) raises worker income by 4 per cent. This shows the importance of adult education, and of policy to support its provision.

The aim of the inclusion of the broader income measures of monthly earnings and all monthly earnings including income of the self-employed as dependent variables in Columns 4 and 5 is to provide a consistency and robustness check. They will also identify if certain skill effects are captured by the fuller income measures, where they are not using the narrower hourly wage rate. Including earnings of the self-employed also recognises their share of income, but without including a weighting for it. For the skill proficiency measures, only numeracy skill is positive and statistically significant across the regressions. Using monthly compensation, I now observe gains to worker income for each of the four variables for use of cognitive skills in workplace tasks. These include significant results for greater use of reading and for use of numeracy at work. In Columns 4 and 5, workplace training (log learn at work) is positive for earnings where it was not for hourly wage rates. Training may not be a factor when setting wage rates (when it may not yet have occurred), with the value it adds to employees and firms being accounted for instead in the fuller monthly compensation measures. This result supports the findings of Bartel (1995) and others. For variables measuring the effects on income from use of the English language in the workplace, I now observe a positive relationship for English as the native language in the fuller income measures in Columns 4 and 5. There is a 9 and 12 per cent gain to average worker income respectively, at the 5 per cent significance level. There is no significant effect on hourly wage rates. These results indicate some value for English-speaking skills in the New Zealand labour market, but the effect is not strong enough to warrant being a factor when setting wage rates. The value may instead be recognised in the full monthly compensation paid to employees. I find no significant impacts on income from bilingual skill or for when English is the main language spoken in the home environment.

For gender effects, average female earnings are less than for males in the range of 12 to 36 per cent across regressions in Columns 3, 4, and 5. This result highlights the significant negative earnings gap for female workers in the New Zealand workforce, similar to international markets (Boll, Jahn and Lagemann, 2017). The returns to cognitive skills may be biased by unobserved innate factors hidden in the error term. These may include the genetic influence of parental education. I control for the effects of natural ability on income using dummy variables for the highest parental education achieved as proxies. These are: at least one parent attaining secondary or post-secondary qualifications (parent-non-tertiary), or at least one parent having obtained a tertiary qualification (parent-tertiary), against a base variable of no parent having attained secondary level qualifications. In Column 3 in Table 4.3, I show there are no statistically significant effects evident for genetic skill attributes on income arising from parental education.

While the skill frequency of use variables utilised in my study are continuous scales, with natural logarithms taken, the PIAAC data also allows for Likert categorical measures. For the continuous scales, I find the most consistently significant results across worker earnings measures are for use of ICT problem-solving skills and for use of witing at work skills in the workplace. I next present regressions in Table 4.4. using Likert categorical variables for these two use-of-skill measures for comparison of results and as a robustness check. Results for writing at work are presented in Panel A, and use of ICT problem-solving skills in Panel B. I control for years of schooling, work experience, highest parental qualification, and gender in each regression. As for Table 4.3, I present regressions using three alternative income measures. These are: hourly wage rate; monthly earnings, and all monthly earnings, each in logarithmic form. Each skill category measures frequency of use in tasks in 20 per cent bands, with workers using the skill in 0 to 20 per cent of tasks as the base group.

For use of writing skills in workplace tasks in Panel A, I do not observe an increasing income effect for use in 61 to 80% of tasks and for 81% and higher use in Column 1, for average hourly earnings. However, a more even spread between the skill use categories is evident in the alternative income measures in Columns 2 and 3. The results for ICT use show a more even spread as frequency increases, for the three income measures. Regressions for the frequency of use at work skill variables of reading and numeracy produce similar earnings category distribution results. These are not produced here but are available on request. Overall, the Likert frequency of skill use results support those obtained for the continuous scale measures presented in Table 4.3.

With the unexpected negative coefficient of ICT skill proficiency, I next examine the individual effects on average hourly labour return of the three skill proficiency measures. These are presented in Table 4.5. in separate, pairwise, and combined regressions. When modelled separately in Columns 1, 2, and 3, each skill measure has a significant positive relationship with hourly earnings. For the combinations, both literacy and numeracy skill show positive and statistically significant results. However, variance inflation scores for collinearity for literacy are above 8. ICT problem-solving skill has a positive economic return in the separate regression in Column 3, but insignificant and negative returns in regressions with combinations of variables. This indicates a positive stand-alone effect for earnings which may be ‘obscured’ when combined with literacy and numeracy skill, on which ICT skill depends. In addition to high VIF scores for literacy, and the significant results for numeracy presented in Table 4.5, numeracy proficiency is also consistent against the hourly wage rate and monthly income measures in Table 4.2. From these findings, the further sections I present will examine numeracy cognitive skill interactive effects on variables including occupation and age. Literacy proficiency interactions may still, however, be a candidate for further study.

4.4.2 Occupational Skill and Frequency of Use Effects on Average Hourly Earnings

I next examine the relationship between occupational skill and frequency of use of the cognitive skills on worker earnings. Occupational skill effects will be evaluated through hypothesis two, that average hourly earnings will rise with increases in occupational skill in the New Zealand labour market. Cognitive skill effects are evaluated through hypothesis three, that an increase in occupational skill group use of the core cognitive skills will increase average hourly earnings for that skill group. Previous studies find support for a positive relationship between average occupational skill and worker income. Carbonaro (2006) finds, using data from the U.S. National Adult Literacy Study, that occupational skill sorting accounts for just under half of human capital impacts on earnings, after controlling for education and other skill factors. De la Rica, Gortazar, and Lewandoswski (2020) use PIAAC data to consider the empirical relationship between abstract, routine, and manual tasks and wages for a set of 19 countries, including New Zealand. They find a wage premium from an increase in abstract task usage. Usage of the task types will tend to differ between occupational skill groups. It will be expected that workers in higher- skilled occupations will make greater use of cognitive skills in their workplace tasks, enhancing their employment value and

Table 4.3. Proficiency and Frequency of Skill Use Earnings Effects in the New Zealand Labour Market.

	log hourly wage rate (1)	(2)	(3)	log monthly earnings (4)	log all monthly earnings including bonuses (5)
log literacy proficiency	0.577***	0.209**	0.292**	0.240	0.209
	(0.110)	(0.107)	(0.149)	(0.234)	(0.292)
log numeracy proficiency	0.624***	0.549***	0.569***	0.765***	1.052***
	(0.084)	(0.079)	(0.120)	(0.180)	(0.226)
log ICT proficiency	-0.372***	-0.211**	-0.324***	-0.563***	-0.847***
	(0.086)	(0.083)	(0.108)	(0.168)	(0.196)
log reading at work	-	-	0.033	0.183***	0.183**
			(0.045)	(0.066)	(0.081)
log writing at work	-	-	0.118***	0.273***	0.342***
			(0.031)	(0.053)	(0.070)
log numeracy at work	-	-	-0.003	0.112***	0.125***
			(0.026)	(0.041)	(0.044)
log ICT use at work	-	-	0.141***	0.279***	0.269***
			(0.027)	(0.040)	(0.055)
further education	-	-	0.036**	0.095***	0.050
			(0.018)	(0.029)	(0.038)
log learn at work	-	-	0.015	0.146***	0.142**
			(0.029)	(0.049)	(0.071)
years of schooling	-	0.048***	0.042***	0.034***	0.031***
		(0.003)	(0.004)	(0.006)	(0.007)
years of work experience	0.029***	0.026***	0.020***	0.021***	0.020***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
years of work experience^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
English native language	-		0.021	0.093**	0.122**
			(0.029)	(0.042)	(0.048)
bilingual with English	-	-	-0.054	0.039	-0.009
			(0.034)	(0.046)	(0.063)
home language English	-	-	0.025	0.035	0.040
			(0.034)	(0.053)	(0.069)
parent-non-tertiary education	-	-	-0.011	-0.025	-0.004
			(0.020)	(0.029)	(0.035)
parent-tertiary education	-	-	0.005	-0.015	-0.011
			(0.019)	(0.028)	(0.037)
female			-0.116***	-0.343***	-0.364***
			(0.016)	(0.023)	(0.030)
cons	-1.85***	-0.909***	-1.004**	3.89***	4.08***
	(0.250)	(0.245)	(0.401)	(0.592)	(0.765)
observations	3,311	3,304	1,907	1,907	2,107
R-squared	0.35	0.35	0.36	0.38	0.29
Ramsay test	0.000	0.000	0.059	0.057	0.368

Notes: Dependent variables: log hourly wage rate for wage and salary earners in Columns 1,2, and 3; log monthly earnings in Column 4; log all monthly earnings including bonuses for wage and salary earners and self-employed in Column 5. Column 1 is the baseline model for skill proficiency measures. Column 2 includes years of schooling. Column 3 includes variables for frequency of task use and further skill variables of interest. For the highest parental education variables, parent-non-tertiary is at least one parent attaining secondary or post-secondary qualifications; parent-tertiary is at least one parent having obtained a tertiary qualification, the base group is neither parent upper secondary. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Table 4.4. Writing at Work and ICT Problem-Solving Frequency of Skill Use Earnings Effects - Likert Scales.

	log hourly wage rate (1)	log monthly earnings (2)	log all monthly earnings including bonuses (3)
Panel A: Write at Work			
write at work 21% to 40%	0.071*** (0.021)	0.193*** (0.045)	0.166*** (0.048)
write at work 41% to 60%	0.180*** (0.020)	0.469*** (0.040)	0.486*** (0.046)
write at work 61% to 80%	0.252*** (0.019)	0.606*** (0.037)	0.613*** (0.043)
write at work 81% and higher	0.250*** (0.019)	0.663*** (0.035)	0.714*** (0.041)
Number of obs.	2,864	2,863	3,384
R-squared	0.37	0.42	0.31
Panel B: ICT Problem-solving at Work			
ICT at work 21% to 40%	0.085*** (0.023)	0.290*** (0.045)	0.240*** (0.054)
ICT at work 41% to 60%	0.153*** (0.022)	0.376*** (0.045)	0.373*** (0.051)
ICT at work 61% to 80%	0.194*** (0.023)	0.528*** (0.042)	0.541*** (0.048)
ICT at work 81% and higher	0.224*** (0.023)	0.627*** (0.040)	0.627*** (0.048)
observations	2,256	2,256	2,732
R-squared	0.35	0.38	0.26

Notes: The base group is use of skill in 0 to 20% of workplace tasks. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Table 4.5. Returns to Skills for Alternative Skill Measures: Literacy, Numeracy, and ICT Problem-Solving.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
literacy proficiency	0.572*** (0.047)			0.273*** (0.091)	0.695*** (0.091)		0.420*** (0.116)
numeracy proficiency		0.494*** (0.041)		0.287*** (0.081)		0.533*** (0.071)	0.314*** (0.090)
ICT Problem-solving proficiency			0.493*** (0.047)		-0.086 (0.087)	0.013 (0.077)	-0.140 (0.090)
observations	3,114	3,114	2,934	3,114	2,934	2,934	2,934
R^2	0.36	0.36	0.36	0.36	0.37	0.37	0.37

Notes: Dependent variable: Log hourly wage rate. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, *10% level.

compensation. Little research is evident on impacts from greater use of the core cognitive skills for improving earnings in an occupational skill group setting. My study will seek to contribute to the literature in examining this relationship for the New Zealand labour market. I first report baseline results for hypothesis two for occupational skill level effects on hourly earnings. This is then followed by a consideration of occupational income effects from greater use of each cognitive skill, in evaluating hypothesis three. The results are presented in Table 4.6.

For the baseline model presented in Column 1, I utilise four occupational skill categories as explanatory variables: elementary-skilled occupations, semi-skilled blue-collar occupations, semi-skilled white-collar occupations, and skilled occupations. I evaluate differences in earnings relative to the highest skilled workers as the base group. I have also tested the elementary-skilled occupations category as the base group with similar results obtained. I control for years of schooling, years of work experience, highest parental qualifications as a measure of innate ability, and gender. Log hourly earnings is the dependent variable. In Column 1, as expected, workers in the three skill categories of elementary, blue-collar, and white-collar occupations earn average hourly wage rates that are less than those of the base group of skilled workers, in the New Zealand labour market. The results are statistically significant at the 1 per cent level. The largest earnings difference, as expected, occurs for elementary-skilled occupations where average wage rates are 35 per cent lower than those in the skilled category. A result of interest is that there is a similar earnings gap for blue-collar and white-collar workers, relative to the base group. White-collar workers earn an average 28 per cent less than skilled occupations and blue-collar workers earn 27 per cent less. A further point of interest is that the difference in average earnings between blue- and white-collar workers is found to be larger in modelling work when not controlling for gender (with white-collar workers earning less, on average). This latter finding shows the significant effect that gender has on occupational differences.

The results may point to the possibility of a ‘hollowing out’ effect occurring in the New Zealand labour market. This is the trend observed by Levy and Murnane (1992), Dao, Das, Koczan and Lian (2017), and Guo (2022) of the loss of substitutable and ‘middle-range’ tasks typically found in white-collar positions to automation. These tasks include clerical work and data-processing. The results suggest a decline in the value of white-collar workers’ contribution to the economy, which, in turn, is constraining or reducing their income. Other factors contributing to this may include the existence of conditions payments for blue-collar workers, whose occupations are typically in industries with higher workplace environmental considerations. These include in the manufacturing, construction, and transport and storage sectors. I next examine the potential of greater use of the cognitive skills to raise income for workers across the occupational skill levels, strengthening the economic value of tasks undertaken. This will be undertaken through an evaluation of hypothesis three.

I present the results for assessing the occupational skill impacts of greater use of the cognitive skills in Columns 2, 3, 4, and 5 in Table 4.6. For these regressions I have selected elementary occupations as the base group to assess earnings impacts as occupational skill level rises. Controlling for occupational skill, I find partial evidence in support of hypothesis three with modest gains, particularly for greater use of numeracy skills in workplace tasks, as presented in Column 4. Here, average earnings increase by 0.8 to 1.1 per cent from a 10 per cent increase in numeracy skill use, relative to elementary-skilled workers (who also experience gains). Greater use of reading skills in workplace task is also expected to raise worker earnings, by 1.7 per cent for white-collar workers, and 2.1 per cent for skilled workers, in Column 2. Skilled workers experience earnings gains for three of the cognitive skills use measures: reading at work, writing at work, and numeracy at work. I do not find statistically significant results for ICT problem-solving use, using elementary-skilled occupations. However, when using skilled workers as the base group there are statistically significant gains to blue- and white-collar worker earnings. Blue-collar workers experience earnings gains from greater use of each of the cognitive skills. Although not comprehensive evidence statistically, my results support the value of policy to further integrate cognitive skill use in tasks across occupational skill level groupings, for improving worker income.

4.4.3 Returns by Age and Gender in the New Zealand Labour Market and Numeracy Proficiency Effects.

Many studies including Davey (2003) for the New Zealand workforce find that age impacts on labour returns. Studies including those by Thornton, Rodgers, and Brookshire (1997) show a typical concave age-earnings profile with the highest average earnings for workers in their prime years. These workers have typically accumulated significant experience in their occupation, and often hold senior positions. New entrant workers are not perceived as having the experience and other workplace skills required to command higher wage rates. Older workers, while experienced, may also not be considered to possess the skills required in the ‘modern’ workplace. My research will contribute to the literature in identifying the age group representing peak earnings, and the age group by gender, in the New Zealand labour market. This will allow analysis for why this particular age and age/gender bracket may experience the highest average earnings.

Improvements in core cognitive skill proficiency may play a part in reducing age-earnings trends through upskilling the workforce. For cognitive skills, Hanushek et al. (2015) use PIAAC data to examine the impacts of improved numeracy skill on wage

Table 4.6. Returns to Occupational Skill and from Greater Use of Cognitive Skills.

	Returns to Occupational Skills	Returns to Occupational Skill from Greater Use of Cognitive Skills			
	(1)	(2)	(3)	(4)	(5)
log read at work		0.059			
		(0.067)			
log write at work)			0.070		
			(0.065)		
log numeracy at work				0.448***	
				(0.045)	
log ICT problem-solving					0.332***
					(0.059)
elementary occupations	-0.351***				
	(0.025)				
blue collar occupations	-0.268***				
	(0.018)				
white collar occupations	-0.278***				
	(0.015)				
blue collar - reading at work		0.164			
		(0.080)			
white collar reading at work		0.172*			
		(0.071)			
skilled occupations – reading at work		0.208**			
		(0.175)			
blue collar – writing at work			0.123		
			(0.069)		
white collar -writing at work			0.110		
			(0.068)		
skilled occupations – writing at work			0.153*		
			(0.072)		
blue collar - numeracy at work				0.082**	
				(0.102)	
white collar - numeracy at work				0.104**	
				(0.100)	
skilled occupations – numeracy at work				0.109**	
				(0.098)	
blue collar - ICT at work					0.216
					(0.136)
white collar - ICT at work					0.128
					(0.120)
skilled occupations – ICT at work					0.189
					(0.121)
cons	2.54***	2.19***	2.19***	2.25***	0.218***
	(0.048)	(0.069)	(0.062)	(0.103)	(0.101)
observations	3,102	3,019	2,852	2,643	2,244
R-squared	0.41	0.42	0.41	0.41	0.32

Notes: Dependent variable is log hourly wage rate. For returns to occupational skill in Column 1 the base group is skilled occupations. Occupational skill variables are interacted with use of each cognitive skill in workplace tasks in Columns 2 to 5. Elementary skilled occupation/interactions are the base group for each. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. Robust standard errors are shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

rates for prime age and exit age workers, relative to new entry workers for 23 countries. They find a positive relationship between increased cognitive skill and earnings for prime age workers, with no significant earnings effect for exit age workers. I will contribute to the literature through evaluating the impacts of increased numeracy skill, as the most consistently significant cognitive skill-earnings relationship measure in this study, on wage rates by age group in the New Zealand labour market. I will also examine cognitive skill impacts in gender-age interactions. These relationships will be evaluated through hypothesis four, that increases in numeracy skill proficiency will raise average worker earnings for each age group, and hypothesis five, that greater numeracy skill proficiency will increase earnings for each age group by gender in the New Zealand labour market.

I first present descriptive statistics for hourly earnings by age and gender for the New Zealand workforce, in Table 4.7. This will allow an examination and establishment of peak earnings by age group, age-earnings ranges, and mean gender wage differences. Workers are grouped into five categories: aged 24-years or less; aged 25 to 34-years; aged 35 to 44-years; aged 45 to 54-years; and aged 55-years and over. As a robustness check, I compare the sample age group proportions relative to total workers employed with actual proportions from Statistics New Zealand data. The proportions are for total workers employed in each age group, and for male and female workers in each age group. The findings for both data sources are similar overall although the sample proportion for workers aged 24-years or less overstate the actual proportion by 3 to 4 per cent. For workers aged 55-years and over the sample proportion understates the actual proportion by 1 to 2 per cent. The descriptive statistics show that worker earnings follow the typical concave age-earnings profile found in the literature, with peak earnings for the 35 to 44-year age group. This is seen for average hourly wage rates in

Column 3, and for median wage rates in Column 4, rows 2 to 6. Average wage rates are $27.40 for workers in the 35 to 44-year age bracket, and a median rate of $24.04, with a decrease in earnings as age increases further for both measures. From the literature it may be expected that the highest earnings would occur for those in the 45-year and older age brackets, where experience and seniority support earnings. Possible reasons for a lower peak earnings age grouping may include less importance being placed on experience, a greater value for the qualifications and skills of younger workers, or possibly age discrimination.

Gender effects may play some part in the pulling downward towards a younger peak earnings age group. In rows 11 to 20 in Table 4.7, I present wage rate information by age and gender. In Column 3, although there is some increase in average hourly earnings as age increases for male workers, a peak rate of $29 is effectively reached for those aged 35 to 44-years. Small increases up to age 55-years and over occur up to an average of $29.77 per hour. In contrast, for female workers, the highest average wage rate occurs in the 35 to 44-year age bracket at $25.97. Average rates then fall to $24.71 for those aged 55-years and over. I find a similar trend for median wage rates presented in Column 4. The highest rate for female workers is $22.50 in the 35 to 44-year age bracket. The highest median rate for males is $26.04 in the 45 to 54-year age group. Male wage rates follow more closely the pattern of higher wages for more senior staff, and for females, the traditional concave age-earnings profile (with an arguably lower peak age-wage rate). On average, female workers are paid $2.79 per hour less than males, as shown in Column 3, rows 8 and 9. The difference for the median wage is slightly less at $2.22 per hour, Column 4. Males earn more than females in each age group for both the average and median hourly rate, and this difference grows by age category. In Column 4, there is a $0.97 median wage difference between males and females aged 24-years or less. This grows to a $4.37 difference in the median rate for female and male workers aged 55-years and over.

There is also a growing variance in the range of earnings available as age increases. I provide this information through the interquartile range in Column 5 which shows the spread of hourly earnings in each age group and for gender/age interactions. The aim is to evaluate how equally income is distributed within each grouping. In row 2, Column 5, the earnings range between the 25th to the 75th percentile for those workers sampled aged 24-years or less is $4.25. This increases to $14.55 for workers aged 45 to 54-years in row 5. The variance in wage rates falls slightly to $13.23 for those aged 55-years and over. By gender, in rows 11 to 20, the variance in wage rates grows for males from $5.50 for the youngest cohort to $15.92 per hour for those aged 45 to 54-years, falling slightly to $13.89 for male workers aged 55 and over. This is a difference in interquartile range from the youngest to the oldest male age group of $8.39. Female workers experience a similar increase in age-related earnings variance with an interquartile range of $3.70 for those in the 24-years or less age category, rising to $14.38 for those aged 45 to 54-years. As for male workers, the variance in wage rates again falls slightly for those aged 55-years and over, to $12.91. These results indicate growing inequality in the rewards available from the New Zealand labour market as workers move through the age brackets. While this arguably reflects the working of a flexible labour market, the results indicate the need for continued policy promoting greater equality in earnings, both by gender and age, to support improvements to overall income levels.

I next present my results for the effects of increased numeracy proficiency on income by age and gender in Table 4.8. In the baseline age results in Column 1, workers are again grouped into five categories: aged 24-years or less; aged 25 to 34-years; aged

35 to 44-years; aged 45 to 54-years; and aged 55-years and over. Workers aged 24-years or less are the base group, with similar results obtained when trialling alternative age base categories. The results show support for hypotheses four with increasing average earnings from greater numeracy skill proficiency for each age group in the New Zealand labour market. I find the greatest gain for workers in the peak earnings age bracket of those aged 35 to 44-years. A 10 per cent increase in numeracy proficiency improves average worker income by 7.6 per cent, relative to the base group. Workers aged 24-years or less also experience a small gain of 1 per cent. Those in the 55-years and over group experience a wage gain of 6.3 per cent from higher numeracy skill. These positive results are after controlling for schooling, experience, and highest parental qualification. Age is also part of the regression controls.

In Column 2, I present average labour returns when numeracy skill is interacted with age group and gender. The base group is males aged 24-years or less. The results support hypothesis five, although while earnings increase for each age group by gender, the gains are marginally higher for male workers than female. Male workers experience an average gain in earnings of 6 per cent from a 10 percent increase in numeracy proficiency. For females the gain is 5.4 per cent. I find the greatest earnings improvements are again for workers aged 35 to 44-years, for both genders. Males in this peak earnings age group experience a 7.7 per cent increase from improved numeracy skills, and females only slightly less at 7.5 per cent higher. Workers aged 55-years and over also benefit, with a 6.3 per cent increase for males, and a 6.1 per cent gain for females. While the greater income gains are found for workers in the peak earnings 35 to 44-year age group, aligning with their higher earning capacity, there are gains for those in other age brackets and by gender from increases in numeracy skill proficiency.

The results are after controlling for schooling, experience, and highest parental qualifications. Age and gender are also included in regression controls.

Table 4.7. The Mean and Range of Hourly Earnings by Age and Gender for the New Zealand Labour Market.

Age	No. of observations	Average hourly wage rates ($)	Median hourly wage rates ($)	Interquartile Range 25%	75%
(1)	(2)	(3)	(4)	(5)	
aged 24-years or less	703	17.26	15.50	14.25	18.50
aged 25 to 34- years	713	24.15	21.63	17.14	28.00
aged 35 to 44-years	809	27.40	24.04	18.00	31.92
aged 45 to 54-years	725	27.24	23.81	17.50	32.05
aged 55-years and over	592	26.83	23.40	18.00	31.23
By Gender					
Males	1,578	26.15	22.22	17.31	30.00
Females	1,964	23.36	20.00	15.64	27.28
Age and Gender Interactions					
males aged 24-years or less	343	17.81	16.00	14.40	19.00
males aged 25 to 34-years	333	25.77	23.00	18.18	30.77
males aged 35 to 44-years	361	29.18	25.18	20.00	33.65
males aged 45 to 54-years	293	29.57	26.04	19.79	35.71
males aged 55-years and over	248	29.77	26.00	20.00	33.89
females aged 24-years or less	360	16.75	15.03	14.25	17.95
females aged 25 to 34-years	380	22.72	20.14	16.34	26.00
females aged 35 to 44-years	448	25.97	22.50	16.81	30.00
females aged 45 to 54-years	432	25.65	22.50	16.62	31.00
females aged 55-years and over	344	24.71	21.63	17.00	29.91

Notes: Source: PIAAC Survey Descriptive Data. Comparable data for earnings by age and gender is not available from Statistics New Zealand's official data series.

4.5 Further Robustness Tests - Causality Measures

While my study evaluates the causal impacts of skills on labour returns, there is also the possibility of reverse causation from income to skills, whereby workers' cognitive

Table 4.8. Numeracy Proficiency Returns by Age and Gender in the New Zealand Labour Market.

	Age Group (1)	Age Group Interacted with Gender (2)
numeracy x workers:	0.099	0.115
	(0.082)	(0.082)
aged 25 to 34-years	0.412***	
	(0.119)	
aged 35 to 44-years	0.762***	
	(0.110)	
aged 45 to 54-years	0.551***	
	(0.121)	
aged 55-years and over	0.628***	
	(0.118)	
males aged 25 to 34-years		0.418**
		(0.119)
males aged 35 to 44-years		0.771***
		(0.109)
males aged 45 to 54-years		0.561***
		(0.120)
males aged 55-years and over		0.632***
		(0.116)
females aged 24-years or less		0.106**
		(0.004)
females aged 25 to 34-years		0.398**
		(0.120)
females aged 35 to 44-years		0.752***
		(0.109)
females aged 45 to 54-years		0.542***
		(0.120)
females aged 55-years and over		0.607***
		(0.117)
cons	1.65***	1.53***
	(0.458)	(0.451)
observations	3,114	3,114
R-squared	0.38	0.38

Notes: The dependent variable is log hourly wage rate. The coefficient numeracy reflects returns to numeracy skills for the baseline categories: workers aged 24-years or less in Column 1, and males aged 24-years or less in Column 2. Other categories were trialled as the base group for both regressions with similar results obtained. For Column 1, Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. For Column 2, regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, and highest parental education. Robust standard errors are shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

skills may improve in part because they have higher paying jobs. Higher employment income in jobs requiring advanced skills may better allow individuals the opportunity to develop and maintain their human capital. This can occur through the regular practicing of skills or by providing the necessary income for additional training and further education. I test for reverse causation through two-stage least squares regression, using instrumental variables (IV) for numeracy skill proficiency. The instrumental variables are: school attainment through years of schooling, and parental education. These are instrument measures that are related to an individual's cognitive skills but observed before the start of their labour market career. Parental education is separated into two measures: at least one parent has attained secondary qualifications, and at least one parent has attained a tertiary qualification. I present the results in Table 4.9. Years of schooling, in Column 1, and at least one parent having a tertiary qualification, in Column 3, show a statistically significant, positive relationship with earnings as instrumental variables for numeracy skill. Non-tertiary qualifications result in an economically small, statistically insignificant effect on earnings for numeracy (Column 2). I also run manual two-stage least squares regressions, with both schooling and parental qualification being strongly related to numeracy skills in the first stage.

It may not be possible to interpret these IV estimates as fully eliminating the possibility of reverse causality. The reasons for this are conveyed in the returns-to-schooling literature. These include that schooling is a choice variable, family background may exert direct effects on earnings, and ability may show intergenerational persistence (Card, 1999). However, my results suggest that reverse causation, as addressed through these IV estimates, may not provide evidence of a first-order upward bias in OLS estimates of returns to skills. I also test for reverse causation for use of the cognitive skills and income using the same instrumental variables. Similar results are obtained and are presented in Table 4.12, Appendix C.4.

Table 4.9. Reverse Causality Analysis – Numeracy Skill Instruments.

Instrument:	Years of Schooling	Parent-Non-Tertiary	Parent-Tertiary
	(1)	(2)	(3)
numeracy proficiency IV	2.04***	0.392	1.14***
	(0.101)	(2.06)	(0.152)
experience	0.024***	0.033***	0.029***
	(0.002)	(0.012)	(0.002)
experience^2	-0.000	-0.001*	-0.000***
	(0.000)	(0.000	(0.000)
female	-0.046***	-0.099	-0.071***
	(0.015)	(0.077)	(0.014)
constant	-8.59***	0.629	-3.57***
	(0.570)	(11.56)	(0.850)
instrument F statistic	217.98	216.98	205.97
observations	3,532	3,122	3,122

Notes: Dependent variable: log hourly wage rate. Three instrumental variables are utilised for numeracy skill: Column 1: Years of schooling; Column 2: At least one parent has attained secondary or non-secondary qualifications, non-tertiary parent-non-tertiary; Column 3: At least one parent has attained tertiary qualification, parent-tertiary. Regressions control for years of work experience, a quadratic for non-linear years of work experience, and gender. Robust standard errors are shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level. Methodology: 2SLS. Data source: PIAAC.

4.6 Conclusions and Policy Implications

Previous studies (Mincer, 1974, Barro and Lee, 1996, 2001, 2013) have utilised years of schooling, or qualifications, as the dominant measures of human capital. In this study I apply the OECD’s Programme for the International Assessment of Adult Competencies (PIAAC) skills survey data to drill down further in examining the effects of the core underlying cognitive skills in literacy, numeracy, and ICT problem-solving on earnings in the New Zealand labour market and economy. For skill proficiency, the larger positive impacts for worker earnings are found from years of schooling, however the results obtained support the main hypothesis whereby an increase in literacy and numeracy skill proficiency will improve worker earnings. I find that numeracy skill, in particular, has a consistently strong positive effect on worker income. I contribute further to the literature in evaluating the impact of frequency of use of the core cognitive skills in workplace tasks on earnings. An increase in the use of writing and ICT problem-solving skills in workplace tasks have a significant positive relationship with worker income. Greater use of tasks involving reading and numeracy skills in the workplace are also positive when considering monthly compensation, rather than hourly wage rates. The results indicate industry demand for these skills and the potential for improving productivity and income growth through greater integration of the core skills and technology in the New Zealand workplace.

In evaluating the effects of occupational skill on earnings in the New Zealand labour market, expected skill-earnings differences are observed relative to a base group of skilled workers. The largest difference occurs between elementary skilled and skilled occupations. A point of interest is that a uniform gradient earnings relationship is not observed between the occupational groups. There is a smaller earnings gap for blue-collar workers than for white-collar workers, relative to the base group. Possible contributing factors for this deviation in the skill-earnings relationship may include differences in compensation for working conditions and a 'hollowing out' effect that may be occurring in the New Zealand work force. This is in line with Levy and Murnane's (2004) observation of the replacement by automation of substitutable and 'middle-range' tasks typically found in white-collar positions such as clerical work and data-processing. I make a further contribution to the literature in examining the impacts for occupational skill level on labour earnings from greater use of the cognitive skills in workplace tasks. I find gains to income for each occupational skill level from greater use of numeracy skills in the workplace and for all but use of ICT skills at work for skilled workers. The latter result is unexpected, with greater use of ICT problem-solving having significant effects on income overall.

In evaluating overall differences in earnings by age, I find that peak earnings occur for those in the 35 to 44-year age group, with some influence from gender effects. For males, a tapering effect occurs with the strongest average hourly earnings increases for the 35 to 44-year group, followed by smaller increases through to the 55-year and over age bracket. For female workers, the more traditional concave age profile occurs, with peak earnings in the 35 to 44-year age bracket. These findings indicate a pulling down of overall peak earnings by female wage rates. As the maximum earnings level occurs at a relatively young age in working life, particularly for female workers, it indicates a loss of potential earnings for the New Zealand economy in undervaluing a significant proportion of the workforce. The results may also point to discrimination against older workers and for female workers in particular. It will be important that policy seeks to counteract these trends.

For reducing demographic/labour market effects on earnings, I find that improved numeracy skill proficiency raises worker income by age group and gender. For workers in the prime working age grouping of 25 to 54-year-olds, I find a consistent positive effect on earnings relative to a base group of workers aged 24-years or less. Workers aged 55-years and older see less benefit for earnings. The highest wage gains are for workers in the peak earnings group of those aged 35 to 44-years old, however greater cognitive skill is also beneficial for those in other age brackets. Greater numeracy proficiency also improves income by gender, but with a smaller effect for female workers. The results show that improved numeracy skill is positive for raising female worker earnings in the prime working age years of 25 to 54 but that higher skills are not sufficient to completely offset lower average earnings by gender. This indicates the influence of other factors other than skills impacting on gender earnings.

Additionally, I find the gains expected to worker income from foundation schooling and work experience. Further education that is job-related is important for improving worker income. This result is consistent with the findings of Loewenstein and Spletzer (1994) and Rees (2010) and supports policy for the continued development of programmes aimed at increasing the educational opportunities for New Zealand workers over and above foundation studies. There is also a positive effect on earnings from increased learning at work, or training opportunities. This finding supports the importance of these programmes within New Zealand industry for lifting the productivity and earnings potential of both firms and their workers.

Appendix C.

Appendix C.1.

Table 4.10. presents the results for 15-year-old student achievement in reading, mathematics, and collaborative problem-solving for the OECD's Programme for International Student Assessment (PISA), for the period 2012 to 2018. Countries are ranked from the top to the fifteenth highest attainment. New Zealand students rank in the top 15 countries for 2015 and 2018 for literacy achievement and for the 2015-year top fifteen rankings for collaborative problem-solving. New Zealand ranks 20th for numeracy skills in 2015, 26th in 2018.

Table 4.10. Pisa Score Rankings: 2012 to 2018.

Reading			Numeracy			Collaborative Problem-Solving
Top Fifteen Countries 2012	2015	2018	Top Fifteen Countries 2012	2015	2018	Top Fifteen Countries 2015*
China	Singapore	China	China	Singapore	China	Singapore
Hong Kong	Canada	Singapore	Singapore	Hong Kong	Singapore	Japan
Singapore	Hong Kong	Macao	Hong Kong	Macao	Macao	Hong Kong
Japan	Finland	Hong Kong	Taiwan	Japan	Hong Kong	Korea
Korea	Ireland	Estonia	Korea	China	Taiwan	Canada
Finland	Estonia	Canada	Macao	Korea	Japan	Estonia
Canada	Korea	Finland	Japan	Switzerland	Korea	Finland
Ireland	Japan	Ireland	Liechtenstein	Estonia	Estonia	Macao
Taiwan	Norway	Korea	Switzerland	Taiwan	Netherlands	New Zealand
Poland	Germany	Poland	Netherlands	Canada	Poland	Australia
Estonia	New Zealand	New Zealand	Estonia	Netherlands	Switzerland	Taiwan
Liechtenstein	Macao	Sweden	Finland	Finland	Canada	Germany
New Zealand	Poland	United States	Canada	Denmark	Slovenia	Denmark
Australia	Slovenia	Japan	Poland	Slovenia	Denmark	United States
Netherlands	Australia	United Kingdom	Belgium	Belgium	Belgium	United Kingdom

Notes: *Only the 2015-year results are included for collaborative problem-solving as a number of countries were omitted in 2012. Problem-solving tests were not undertaken in 2018.
Source: 2012: https://www.oecd.org/pisa/keyfindings/pisa-2012-results-overview.pdf
2015: https://www.oecd.org/pisa/pisa-2015-results-in-focus.pdf 2018: https://www.oecd-ilibrary.org/

Appendix C.2.

Table 4.11. shows the timeline and participating countries for the first cycle of the PIAAC Adult Skills Survey. A total of 39 countries participated in the first cycle of the survey, conducted between 2011-2018. The survey focuses on skills in three domains: literacy, numeracy, and problem-solving in technology-rich environments. There were three rounds of survey data collection. New Zealand was included in the second round. The second cycle is scheduled to take place during the 2022 to 2023 period.

Table 4.11. Timeline and Participating Countries in the PIAAC First Round Surveys.

PIAAC 1st Cycle	**Round 1 (2011-2012)**	Australia, Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), United States
	Round 2 (2014-15)	Chile, Greece, Indonesia, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey
	Round 3 (2017)	Ecuador, Hungary, Kazakhstan, Mexico, Peru, United States

Notes: Source: https://www.oecd.org/skills/piaac/about/piaac1stcycle/

Appendix C.3. PIAAC Sample Selection Methodology – New Zealand.

From the sample selection methodology set out in the PIAAC design (Technical Report, 2nd edition, Chapter 14-14), the New Zealand survey used a four-stage stratified sample design. Primary sampling units (PSUs) and secondary selection units (SSUs) are selected with a probability proportionate to a measure of size (MOS) design set out as:

m_h = number of PSUs to be sampled in stratum h; and

MOS_{hi} = measure of size for PSU i in stratum h.

The probability of selecting PSU i in stratum h is

$$P_{hi} = \frac{m_h \times MOS_{hi}}{\sum i \in h\ MOS_{hi}}$$

For SSU selection, let

q = total number of SSUs to be sampled;

MOS_{hij} = measure of size for SSU j of PSU i in stratum h; and

I_{SSU} = sampling interval for the selection of SSUs.

The *conditional* probability of selecting SSU j from PSU i in stratum h is

$$CP_{hij} = \frac{q \times \left(\frac{MOS_{hij}}{P_{hi}}\right)}{\sum hij \left(\frac{MOS_{hij}}{P_{hi}}\right)} = \frac{MOS_{hij}\ /\ P_{hi}}{I_{SSU}}$$

For the selection of dwelling units (DU), let

d = total number of housing units to be sampled;

D = total number of housing units in the sampling frame;

D_{hij} = number of housing units to be sampled in SSU j of PSU i of stratum h; and

D_{hij} = number of housing units in SSU j of PSU i of stratum h.

Let $r = d/D$, then the conditional probability of selecting housing unit k from SSU j of PSU i in stratum h is

$$CP_{hijk} = \frac{r}{P_{hi} \times CP_{hij}} = \frac{r \times I_{SSU}}{MOS_{hij}}$$

The overall probability of selecting housing unit k from SSU j of PSU i in stratum h is

$$P_{hijk} = P_{hi} \times CP_{hij} \times CP_{hijk} = r$$

The DU sample size in a SSU is

$$d_{hij} = CP_{hijk} \times D_{hij} = r \times I_{SSU} \times \frac{D_{hij}}{MOS_{hij}}$$

For person selection, let

n_{hijk} = number of persons to be sampled from housing unit *k* of SSU *j* in PSU *i* within stratum *h*; and

N_{hijk} = total number of eligible persons in housing unit *k* of SSU *j* in PSU *i* within stratum *h*.

The *conditional* probability of selecting person *i* from housing unit k of SSU *j* in PSU *i* within stratum *h* is

$$CP_{hijkl} = \frac{n_{hijk}}{N_{hijk}}$$

The *overall* probability of selecting person *i* from housing unit k of SSU *j* in PSU *i* within stratum *h* is

$$P_{hijkl} = P_{hi} \times CP_{hij} \times CP_{hijk} \times CP_{hijkl} = r \times \frac{n_{hijk}}{N_{hijk}}$$

Appendix C.4.

In testing for reverse causality from income to use of cognitive skills in workplace tasks, the results presented in Table 4.12 show a statistically significant, positive relationship with earnings using schooling and highest parental education as tertiary as instrumental variables for use of the cognitive skills in workplace tasks. This indicates that reverse causation, as addressed by the IV estimates, may not give rise to a first-order upward bias in OLS estimates of returns to skills.

Table 4.12. Reverse Causality Analysis – Frequency of Earnings-Skill Use Measures.

Instrument:	Years of Schooling (1)	Parent-Non-Tertiary (2)	Parent-Tertiary (3)
reading at work	1.62***	0.005	1.44***
	(0.087)	(2.16)	(0.245)
years of work experience	0.002	0.035	0.006
	(0.003)	(0.044)	(0.005)
years of work experience^2	0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.000)
female	-0.113***	-0.115***	-0.115***
	(0.017)	(0.014)	(0.017)
constant	1.29***	2.83	1.46***
	(0.087)	(2.06)	(0.236)
instrument F statistic	178.06	189.04	108.69
observations	3,429	3,037	3,037
writing at work	1.40***	0.668	1.51***
	(0.080)	(1.09)	(0.311)
years of work experience	-0.001	0.018	-0.004
	(0.003)	(0.029)	(0.008)
years of work experience^2	0.000	-0.000	0.000
	(0.000)	(0.001)	(0.000)
female	-0.162***	-0.136***	-0.156***
	(0.019)	(0.031)	(0.022)
constant	1.69***	2.29**	1.59***
	(0.074)	(0.922)	(0.266)
instrument F statistic	147.37	159.81	66.98
observations	3,236	2,869	2,869
numeracy use at work	3.44***	0.782	2.32***
	(0.462)	(1.21)	(0.735)
years of work experience	-0.001	0.027*	0.009
	(0.008)	(0.014)	(0.009)
years of work experience^2	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
female	0.188***	-0.043***	0.092
	(0.057)	(0.107)	(0.072)
constant	-0.830*	2.02	0.387
	(0.496)	(1.28)	(0.783)
instrument F statistic	29.67	127.51	32.64
observations	2,968	2,659	2,659
ICT problem-solving use at work	1.63***	1.11	1.37***
	(0.124)	(2.01)	(0.334)
years of work experience	-0.000	0.011	0.005
	(0.004)	(0.045)	(0.008)
years of work experience^2	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
female	-0.130***	-0.125***	-0.122***
	(0.117)	(0.029)	(0.022)
constant	1.39***	1.90	1.67***
	(0.117)	(1.83)	(0.306)
instrument F statistic	94.71	91.66	73.42
observations	2,481	2,261	2,261

Notes: Dependent variable: log hourly wage rate. Three instrumental variables are utilised. Column 1: Years of Schooling; Column 2: At least one parent attained secondary or non-secondary qualifications, non-tertiary parent-non-tertiary; Column 3: At least one parent attained tertiary qualification, parent-tertiary. Regressions control for work experience and gender. Robust standard errors are shown in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level. Methodology: 2SLS.

Chapter 5

Cognitive Skill Effects on Earnings in International Labour Markets

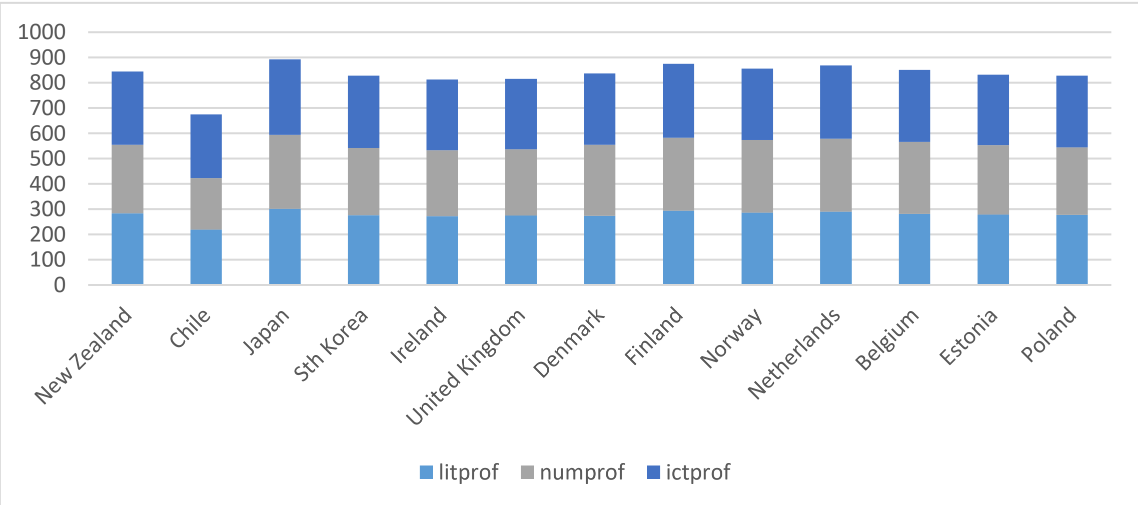
5.1 Introduction

In Chapter 5, I extend the work undertaken in Chapter 4 for the New Zealand labour market to investigate the potential of greater proficiency in and use of the core cognitive skills of literacy, numeracy, and ICT problem-solving to lift worker earnings in international labour markets. This will again be possible through the availability of the Organisation for Economic Cooperation and Development (OECD)'s Programme for the International Assessment of Adult Competencies (PIAAC's) skills datasets. The literature using the PIAAC data shows an emphasis on skills mismatch research. This includes Pellizzari and Fichen's (2013) under and over-utilisation probability study, Allen, Levels and van der Velden's (2013) work on job satisfaction and income effects, and McGowan and Andrews's (2015) research into skills mismatch and productivity. For cognitive skills proficiency relationships with labour market earnings, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) conduct a study for 23 OECD member countries surveyed in the first round of the first PIAAC cycle. This study does not include New Zealand or other countries surveyed in the second round of the first cycle, which my research will include. There is a growing literature utilising this rich skills dataset in single and multi-country studies. My study in Chapter 5 will seek to contribute to this research body in undertaking an analysis of the effects of cognitive skills on earnings, encompassing 13 OECD countries with both similar and diverse labour market characteristics.

A comparative study will allow me to identify similarities and differences in country performance, and to evaluate international trends. Identifying those countries or groups of countries that show higher relative income performance resulting from the differing skill measures will allow for analysis of the underlying causes. This, in turn, will support appropriate policy recommendations aimed at improving international human capital performance. This study also supports the robustness of the results obtained in Chapter 4. A single-country study such as that for New Zealand allows a detailed analysis, however, it is also important to assess the consistency or otherwise of the findings. The approach I use in this chapter allows an evaluation of the impacts of the various human capital variables on worker earnings for a range of countries.

As an overview of country performance in the key cognitive skills, Figure 5.1 shows median literacy, numeracy, and ICT problem-solving skill proficiency levels for the 13 countries included in this study. The majority of countries have similar cumulative scores, with Japan recording the highest scores for each individual skill. New Zealand's overall ranking is supported by a literacy score of 272. Chile, as a developing country, has lower relative scores in each cognitive skill. The country comparative skill performance data is supported with further descriptive information in Appendix D.1, Table 5.7.

Figure 5.1. Country Comparison of Median Cognitive Skill Proficiency.



Notes. Source: Processed median cognitive skill proficiency data from the OECD's PIAAC skills dataset. https://www.oecd.org/skills/piaac/

For the key findings in this chapter, of the three core cognitive skills of literacy, numeracy, and ICT problem-solving, improvements to numeracy proficiency has the most significant impact on raising worker earnings internationally. This is found for eleven of the thirteen countries studied, with the greatest potential benefit for the Japanese labour market. For frequency of use of the cognitive skills, greater use of ICT problem-solving skills in workplace tasks is significant in raising average hourly wage rates in eleven countries. Greater use of reading skills also has a positive effect. The traditional measures of human capital also perform strongly for lifting earnings, as expected. Here, I find a positive relationship between years of schooling and worker earnings across countries. This result is consistent with the literature (Mincer, 1974, Barro and Lee, 1996, 2001). My international study contributes to the literature in identifying income growth potential for countries with currently less developed further education infrastructure. This result points to the need for continued policy to increase the provision of these programs internationally.

Worker earnings increase as broad occupational skill levels rise, as expected. However, on average, white-collar workers earn less than blue-collar workers across countries. This provides evidence in support of a ‘hollowing out’ effect for the value placed on white-collar roles in international labour markets. I find that differences in income by occupational skill are reduced through greater worker protection. This is evidenced by smaller earnings gaps for Nordic countries compared with those characterised by more flexible labour markets, including the United Kingdom and South Korea. Increased numeracy skill proficiency reduces differences in occupational skill level earnings, and in contrast, the gains are higher for countries with more flexible labour markets. I further find that greater cognitive skill has positive impacts for workers by age group internationally, with income gains for those in the lower age bands from higher numeracy and ICT skill proficiency. Again, those countries with more flexible labour markets experience the higher income gains from numeracy skill improvement, by age group. These findings indicate that worker protection is not always the most effective way to deliver labour income growth.

5.2. Literature Review and Hypotheses Rationale

In international studies, Kollo (2006) examines the importance of cognitive skills for employment in the Central and East European (CEEs) countries of the Czech Republic, Hungary, Poland, and Slovenia, and two groups of West-European countries, including the United Kingdom, Ireland, and Finland. A negative employment bias is found against workers in CEE countries who hold primary and apprentice-based vocational qualifications. This is considered due to perceived skill deficiencies in the core skills of literacy and numeracy compared with these skills for workers in the more mature European market economies. Similarly, Nikoloski, and Ajwad (2014) find a strong link between cognitive skill development and employability in the Tajikistan and Uzbekistan labour markets. They also observe important positive correlations between cognitive skills, occupational skill and worker earnings. Such country-comparative studies highlight the importance of cognitive skills for employment and income and provide a key motivation for this chapter's contribution to the literature in examining the effects on earnings from greater proficiency and use of the core human capital skills for a diverse, selected range of countries.

For foundation skills, Barro and Lee (1996) have developed prominent international data sets using the key measures of years of schooling and qualifications gained. Barro and Lee concede there are limitations with years of schooling as a measure of human capital as it makes no allowance for the quality of education across countries or skills and experience acquired after formal schooling. Such limitations have encouraged the development of further datasets to examine the impacts of skills that underlie these broad measures and allow for country-comparative studies. These include the International Adult Literacy Survey (IALS) (1996)[38] and the Adult Literacy and Life Skills Survey (ALL) (2006)[39]. The IALS was seen as a first attempt to assess the literacy skills of entire adult populations in a framework that provides comparable data across cultures and languages. Denny, Harmon, and O'Sullivan (2003) find, using the IALS dataset, that the inclusion of the core skill of literacy in cross-country studies reduces downward bias in earnings results. The ALL survey further expanded this data to include the impacts of numeracy skills on economic and social measures across a broad range of countries. The availability of these data sets has allowed for further international comparison of human capital effects on worker earnings and productivity. However, the importance of technological skills has not been captured until the development of the OECD's PIAAC's skills dataset. The first cycle of this programme is for the period 2011 to 2017, on which this study draws. The inclusion of survey data on proficiency and use of ICT in problem-solving captures interactive effects of technology for human capital on earnings.

For international studies using the PIAAC survey data, Hanushek, Schwerdt,

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[38]The International Adult Literacy Survey (IALS) was a collaborative effort by twenty governments and three intergovernmental organizations. The IALS is considered the world's first international comparative survey of adult skills, undertaken in three rounds of data collection between 1994 and 1998. https://www150.statcan.gc.ca/n1/en/catalogue/89M0014X [39]The Adult Literacy and Life Skills Survey (ALL) is a large-scale co-operative effort undertaken in 2003, 2006 and 2008 by governments, national statistics agencies, research institutions and multi-lateral agencies. The ALL study builds on the International Adult Literacy Survey (IALS), collecting numeracy skill and further skills data. The development and management of the study was co-ordinated by Statistics Canada and the Educational Testing Service (ETS) based in the United States.
https://www.ets.org). https://www150.statcan.gc.ca/n1/en/catalogue/89M0016X

Wiederhold, and Woessmann (2015) assess labour market returns to proficiency in the cognitive skills for 23 countries using PIAAC data from the first round of the Programme. They establish a positive relationship between numeracy skill and labour returns. For some countries reported, wage information is provided in deciles rather than as a continuous measure. This requires Hanushek et al. (2015) to assign decile medians to several countries. My international study in this chapter makes use of continuous wage measures available for all countries included. Additionally, my study includes countries from the second round of surveys conducted in the 2014 to 2015 period, which were not available at the time of Hanushek et al's. (2015) research. These are New Zealand and Chile. For use the core cognitive skills, De la Rica, Gortazar, and Lewandoswski (2020) address the empirical relationship between abstract, routine, and manual tasks and wages for 19 countries, including New Zealand. They find a wage premium from an increase in abstract task usage. My study will further 'narrow down' cognitive skill usage effects in examining the relationship between income and increased literacy, numeracy, and ICT-problem-solving usage. Christl and Koppl-Turyna (2020) use the PIAAC data to examine impacts of task skill and usage on wages by gender in the Austrian labour market. I will extend their findings in examining cognitive skill labour return differences internationally, and gender relationships in further hypotheses. These relationships will be assessed through an evaluation of hypothesis one, that *increases in proficiency and in the frequency of use of the core cognitive skills of literacy, numeracy, and ICT problem-solving will increase earnings in labour markets in developed and developing countries.*

The evaluation of hypothesis one will be supported by controlling for and examining the effects on income of other important human capital variables including years of qualification, experience, and further education. Worker earnings are also impacted by broad occupational skill. The skills of workers are typically grouped into elementary, blue-collar, white-collar, and skilled occupations. Workers in higher-skilled occupations are expected to earn more than elementary-skilled workers. My study will evaluate whether earnings differences are uniform across the skill groupings and consider reasons for any differences found between countries.

Similar to Hanushek et al. (2015), my study will assess effects for worker earnings from increases in cognitive skills. However, in an extension, I will examine impacts from increased skill proficiency on the returns to occupational skill. Like Hanushek et al's. overall study, this will focus on numeracy skill proficiency. Workers in higher skilled occupations involved in more abstract, task-intensive roles (Autor and Dorn, 2013) may be expected to see the greatest benefit from increased use of cognitive skills. My study will determine if there are earnings improvements available also for the lower skilled occupations internationally, through the evaluation of hypothesis two, that *an increase in numeracy skill proficiency will increase average earnings by occupational skill level in developed and developing country labour markets.*

While not a skill factor, age also impacts on worker income across the working life cycle. Age is expected to increase a worker's earnings with its shared attribute of experience. It will be expected that earnings will follow the familiar inverted U-shaped age-earnings profile observed by Thornton, Rodgers and Brookshire (1997) and others. Younger workers do not possess the experience and job-specific skills needed to attract higher compensation. Older workers may not, on average, possess the skills required of workers within the contemporary technology setting. Davey (2003) notes this for the latter in the New Zealand labour market, where skill demand may affect older workers negatively, as their skills and qualifications become outdated - an issue particularly in an ageing population. Hanushek et al. (2015) test for age-varying returns to skill using cognitive skill interactions with entry-age, prime-age, and exit-age workers. In my study, I will extend this to examine cognitive skill effects for a greater range of worker age categories in evaluating hypothesis three, that *increases in cognitive skill proficiency will increase earnings across the working age life cycle in developed and developing country labour markets.*

In section 5.3, I set out the data sources and methodology to be applied. The empirical results are reported and analysed in Section 5.4, with conclusions reached and policy implications set out in Section 5.5.

5.3 Models and Methodology

5.3.1 Data and Variables

For this chapter's analysis, I utilise a comprehensive range of census-type data from the 1st Cycle of the OECD's PIAAC survey of adult skills for individuals in 13 countries. The data comprises variables for earnings, skills, and demographic information developed from the survey results. This data was collected between 2011 and 2017 and has been collected in three rounds. The countries studied in Chapter 5 were surveyed in the first two rounds. These are Round 1 (2011-2012): Belgium, Denmark, Estonia, Finland, Ireland, Japan, Netherlands, Norway, Poland, South Korea, and the United Kingdom; and Round 2 (2014-2015): Chile and New Zealand.

The data is part of the officially recognised information for the Statistics departments for each of the countries included. It was endeavoured to include a range of countries within the OECD grouping for which PIAAC data is available. Several further countries were not available due to earnings data restriction. These are Australia, the United States and Canada. For the variables employed, for each country, the dependent variable is hourly wage rate, in logarithmic form. Together with many of the explanatory variables included, a logarithmic scaling for the dependent variable allows for a percentage change interpretation of earnings effects (Wooldridge, 2013). To adjust for price level effects for the earnings for the later Round 2 countries of New Zealand and Chile relative to those in Round 1, their hourly wage rate data is rebased using their respective 2012 consumer price index values to provide real hourly earnings comparative to those for the 2011 to 2012 Round 1 group of countries. This study uses similar explanatory variables to those in the individual in-depth study for the New Zealand labour market in Chapter 4. However, in an international study, some differences will necessarily occur. These include the omission of variables for language effects in this chapter. These were of interest in Chapter 4, but their significance is reduced in an international multiple-language setting. For each country, I trim the bottom and top one per cent of the wage distribution to limit the influence of income outliers[40].

5.3.2 Methodology

For a country-comparative analysis, I run identical individual country regressions. The results are then tabulated and compared.

The basic regression equation takes the following form:

$$\ln(w)_i = \alpha + \beta 1CS_i + \delta X_i + \beta Z_i + \mu_i \qquad (1)$$

where

$\ln(w)_i$ is hourly wage rate, in logarithmic form,

[40]Investigation of outliers suggests that these largely represent data entry or coding errors.

CS_i is a vector for proficiency in, and frequency of use of the core skills of literacy, numeracy, and ICT problem-solving variables,

Z_i is a vector of control variables,

X_i is a vector of further variables of interest,

μ_i is the error term.

The modelling methodology I employ in this study is a cross-sectional regression for each country. Cross-sectional modelling is used as each country's survey provides data for one time period. This provides a snapshot of comparative earnings effects for the separate populations and economies. Stata is used as the modelling software.

5.3.3 Tests for Robustness

The consistency (with variation) of results for the separate but identical regressions for the 13 countries under study in this chapter supports confidence in the robustness of the results. This consistency also supports the robustness of the results obtained for the single country study of the New Zealand economy in Chapter 4, although rebasing wage rates to 2012 price levels does change some earnings results for New Zealand. I employ model variation tests through the uniform inclusion and omission of variables in regressions to identify significance and consistencies in variable coefficient results and for assessment of their standard errors to aid in determining the most representative results.

To test for heteroskedasticity I undertake the Breusch-Pagan / Cook-Weisberg and Cameron & Trivedi's decomposition tests for each of the country regressions. The tests indicate a presence of heteroskedasticity for some of the modelling work performed. To correct for this, models presented use robust standard errors which produce lower overall standard errors. Variance inflation factor (VIF) tests are undertaken to test for multi-collinearity between variables. For most of the regressions, the test results record VIF scores less than 2.0. These results were subjected to the standard VIF acceptance guidelines where a score of 1 indicates no correlation and between 1 and 4 indicates some to moderate correlation. VIF scores of 5 and higher indicate high correlation, and accordingly, regressions with average scores of 5 and higher are rejected (Green, Hand and Zhang, 2017).

5.4 Empirical Results

5.4.1 The Effects of Core Cognitive Skill Proficiency and Usage on Average Hourly Earnings in International Labour Markets

The central hypothesis I evaluate in Chapter 5 is that an increase in proficiency and in the frequency of use of the core skills of literacy, numeracy, and ICT problem-solving will increase average hourly earnings in international labour markets. I present the results for each of the 13 countries examined, together with a pooled regression in Table 5.1. For core cognitive skill proficiency, only numeracy skill is included in country regressions. When including the three skill proficiency measures, collinearity levels rise together with negative signs for the literacy and ICT problem-solving measures. The results support hypothesis one. I find a strong positive relationship between numeracy skill proficiency and average hourly earnings for 11 of the 13 countries studied. The largest earnings increase is observed for Japan, where a 10 per cent increase in numeracy skill increases average hourly earnings by 5.4 per cent. New Zealand and Chile are the only two countries that do not show statistically significant results. For the single country study of New Zealand in Chapter 4, I find that numeracy skills are significant for raising earnings when combined with literacy and ICT problem-solving proficiency, together with other explanatory variables.

For the relationship between use of the cognitive skills and hourly earnings, I find the most consistent statistically significant result is for greater use of ICT problem-solving skills in workplace tasks, although the effect is economically modest. This relationship is positive for all but Ireland and Belgium. The result for Ireland may be of interest as this country has been considered a leading economy for economic growth from ICT-related industry activity. The median earnings increase from a 10 per cent rise in ICT problem-solving use is 1 per cent. Estonia records the strongest economic effect for earnings, with a 1.4 per cent increase, followed by the United Kingdom at 1.2 per cent. These results highlight the value not only of use of ICT problem-solving skills, but also of investment in technology infrastructure for improving the productivity and earnings of workers. I find positive earnings results for a number of countries from greater use of literacy skills in workplace task. 10 countries show economic gains from greater use of reading skills, and 6 countries for writing skills. Only for Denmark, is there evidence of a benefit to earnings from greater numeracy use.

When considering the control variables, I find an increase in years of schooling has a positive and significant effect on worker income for all 13 countries studied. The median earnings increase from one further year of schooling is 3.6 per cent, with 7 countries achieving earnings gains above this. New Zealand workers gain an average of 4.5 per cent. Chilean workers are expected to enjoy the highest gain to income from an additional year of schooling at 10.3 per cent. Improvements in human capital through foundation study continues to play an important role for lifting earnings internationally. I find that work experience is also important for earnings growth for all countries studied. An additional year of work experience adds 2.4 per cent to median earnings. Work experience adds less to worker income for Chile, with a 1.1 per cent gain at the 10 per cent significance level.

For other variables of interest, there is a positive relationship between further education that is job-related and average worker earnings for 12 of the countries studied, with a median gain of 5.2 per cent. The Nordic countries of Denmark, Finland, Norway, the Netherlands, and Belgium see a smaller gain, at 3.3 per cent. These latter European countries are considered to have well-developed further education systems[41]. The results indicate potential income gains from further development of adult education programmes for a number of countries. Little evidence is observed of income gains from greater workplace training. Only for Poland are there positive effects, with a 0.4 per cent earnings increase at the 10 per cent significance level. To control for genetic factors affecting the relationship between education and income, I include dummy variables for highest parental education attained. The measures are: at least one parent obtaining upper secondary, but not a tertiary qualification (parent-no tertiary), and at least one parent attaining a tertiary qualification (parent-tertiary). For 2 countries there is a significant effect on worker income from parental attainment of secondary qualification: Japan and South Korea. There are 4 countries for tertiary attainment: Japan, Belgium, Estonia, and Poland. The results show that genetic factors do affect education-labour market returns for workers in some countries.

Although not a skill effect, a significant and negative earnings difference is observed between female and male workers across countries. Only Ireland shows a positive female earnings gap, but this is not statistically significant at conventional

[41]The European Union Commission considers that adult education systems are well developed in many member countries including Norway, Denmark, and Finland, with a long tradition of folk high schools, study associations, and distance learning. Equity is considered a fundamental principle in the Norwegian education system. Finland's rate of participation in adult education by persons aged 25-64 years was 29 per cent in 2019 compared with 10.8 per cent in the EU-27 in the same year. https://eacea.ec.europa.eu/national-policies/eurydice/content/adult-education-and-training-54_en

levels. The largest difference is for female workers in Estonia, where females earn 29 per cent less than males on average. Belgium shows the smallest gender earnings difference at 3.5 per cent lower for females. The median difference in average hourly earnings by gender is 11.3 per cent, with a similar 12 per cent difference for the New Zealand workforce. This result continues to highlight the significant gender pay gap that exists across countries and the loss of potential earnings for individuals and households. I also present the findings evaluating hypothesis one as a pooled regression in Table 5.1. These results show similar impacts of skills on earnings as for the country-comparative regressions, supporting the robustness of the results obtained.

Table 5.1. The Effects of Core Cognitive Skill Proficiency and Frequency of Use on Average Hourly Earnings. Country Comparisons.

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
log numeracy proficiency	0.226**	0.014	-0.081	0.544***	0.370**	0.481***	0.459***	0.264***	0.296***	0.295***	0.386***	0.385**	0.492***	0.333***
	(0.080)	(0.030)	(0.058)	(0.082)	(0.113)	(0.066)	(0.051)	(0.034)	(0.044)	(0.033)	(0.058)	(0.058)	(0.082)	(0.072)
log read at work	0.074**	0.035	0.174***	0.086***	0.113***	0.234***	0.070**	0.000	0.076***	0.010	0.094	0.053**	0.133***	0.097***
	(0.025)	(0.026)	(0.062)	(0.028)	(0.039)	(0.032)	(0.028)	(0.019)	(0.021)	(0.022)	(0.031)	(0.023)	(0.036)	(0.030)
log write at work	0.020	0.042***	-0.003	0.036	-0.037	0.063	0.096***	0.003	0.037***	0.046***	0.037**	0.037**	-0.012	-0.022
	(0.015)	(0.015)	(0.038)	(0.024)	(0.028)	(0.021)	(0.017)	(0.010)	(0.012)	(0.011)	(0.018)	(0.015)	(0.020)	(0.020)
log numeracy at work	0.008	0.012	0.004	-0.024	-0.021	-0.009	0.011	0.017***	-0.001	0.008	-0.007	-0.015	-0.020	0.012
	(0.005)	(0.011)	(0.030)	(0.018)	(0.025)	(0.014)	(0.011)	(0.006)	(0.009)	(0.007)	(0.009)	(0.009)	(0.016)	(0.017)
log ICT problem-solving at work	0.083***	0.085***	0.075**	0.098***	0.112***	0.012	0.122***	0.104***	0.089***	0.084***	0.105***	0.015	0.137***	0.049**
	(0.015)	(0.013)	(0.039)	(0.018)	(0.027)	(0.018)	(0.015)	(0.011)	(0.013)	(0.011)	(0.018)	(0.016)	(0.023)	(0.026)
further education	0.045***	0.050**	0.073**	0.098***	0.046*	0.083***	0.093***	0.032***	0.040**	0.031**	0.037	0.034***	0.053***	0.081***
	(0.011)	(0.015)	(0.038)	(0.017)	(0.025)	(0.019)	(0.014)	(0.010)	(0.012)	(0.010)	(0.014)	(0.012)	(0.019)	(0.020)
log workplace training	-0.015	-0.020	-0.090***	-0.022	-0.027	-0.012	0.005	-0.014	-0.037***	0.005	-0.037	-0.019	-0.051**	0.038**
	(0.010)	(0.015)	(0.035)	(0.015)	(0.018)	(0.018)	(0.012)	(0.011)	(0.013)	(0.013)	(0.014)	(0.013)	(0.021)	(0.020)
years of schooling	0.040***	0.045***	0.103***	0.024***	0.049***	0.036***	0.039***	0.031***	0.036***	0.031***	0.042***	0.033***	0.032***	0.048***
	(0.005)	(0.003)	(0.007)	(0.004)	(0.006)	(0.004)	(0.003)	(0.002)	0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
years work experience	0.022***	0.024***	0.011*	0.035***	0.031***	0.025***	0.025***	0.016***	0.019***	0.018***	0.027***	0.023***	0.015***	0.031***
	(0.004)	(0.002)	(0.006)	(0.003)	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
years work experience^2	-0.000***	-0.000***	-0.000	-0.001***	-0.000	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
parent-no tertiary	-0.006	-0.003	0.026	0.096***	0.068**	-0.022	-0.019	-0.001	0.000	-0.005	-0.014	-0.005	0.008	0.034
	(0.007)	(0.016)	(0.038)	(0.024)	(0.026)	(0.020)	(0.016)	(0.009)	(0.011)	(0.011)	(0.014)	(0.015)	(0.025)	(0.036)
parent-tertiary	0.026***	0.013	0.051	0.084***	0.044	0.004	0.020	0.001	0.018	-0.003	0.022	0.034**	0.069**	0.106**
	(0.008)	(0.015)	(0.050)	(0.026)	(0.031)	(0.023)	(0.019)	(0.010)	(0.014)	(0.012)	(0.015)	(0.021)	(0.027)	(0.041)
female	-0.109***	-0.118***	-0.124***	-0.201***	-0.123***	0.023	-0.073***	-0.045***	-0.136***	-0.103***	-0.062***	-0.035***	-0.288***	-0.129***
	(0.019)	(0.013)	(0.038)	(0.018)	(0.025)	(0.017)	(0.013)	(0.008)	(0.010)	(0.009)	(0.013)	(0.015)	(0.019)	(0.019)
constant	1.92***	2.113***	6.70***	3.33***	6.18***	-0.998***	-1.21***	3.02***	0.363	2.95***	-1.09	-0.196	-1.78***	-0.229
	(0.494)	(0.169)	(0.322)	(0.446)	(0.616)	(0.355)	(0.278)	(0.183)	(0.243)	(0.180)	(0.670)	(0.319)	(0.458)	(0.397)
observations	25,149	1,844	868	1,903	1,615	1,607	2,602	3,026	2,433	2,430	1,899	1,568	2,016	1,325
R-squared	0.16	0.35	0.29	0.41	0.28	0.29	0.33	0.34	0.42	0.37	0.39	0.37	0.29	0.36

Notes: The dependent variable is log hourly wage rate. Explanatory variables are log numeracy proficiency; frequency of use of cognitive skills in workplace tasks variables in logarithms: reading at work; writing at work; numeracy at work; ICT problem-solving use. Further variables of interest are: further education - a dummy variable for having received job-related formal and informal adult education and training in the last 12 months; log workplace training is a scale measure for quantity of workplace training received. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. The pooled regression controls for country fixed effects. R^2 refers to within-country R-squared. Robust standard errors are in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

5.5.2 Numeracy Proficiency Effects on Occupational Skill Returns in International Labour Markets

I next evaluate hypothesis two: that an increase in numeracy proficiency will increase occupational skill level earnings in developed and developing country labour markets. I set out my findings in Table 5.3. Before assessing the impacts of numeracy skill, it will first be important to evaluate relative earnings differences by occupational skill group for each country. These results are set out in Table 5.2. I utilise four categorical variables for occupational skill: skilled, white-collar, blue-collar, and elementary-skilled occupations. I select skilled occupations as the base group. This allows an assessment of comparisons to the highest attainable skill level and is also based on variance inflation factor (VIF) test scores for multicollinearity for the four skill measures. While VIF test results were moderate using the differing skill categories as the base group, I find the lowest score is for skilled occupations. I include control variables and further variables of interest in the regression equations. These are: years of schooling, years of work experience, a quadratic for experience, a dummy variable for whether an individual has engaged in further education, a continuous scale variable for the quantity of workplace training receiving, proxies for natural ability as the highest qualifications for at least one parent is upper secondary or tertiary, and a dummy variable for gender as female.

I find as expected that elementary-skilled workers experience the largest median earnings difference, relative to skilled workers. These are 33 per cent lower, with the elementary-skilled generally having the lowest skill requirements. Median earnings for white-collar workers are marginally less than for blue-collar, relative to skilled workers. These are 24 per cent and 22 per cent less respectively. While this is not a significant difference, the fact that white-collar workers earn mean wages that are similar to blue-collar workers internationally points to the 'hollowing out' observed by Levy and

Murnane (2004) and others. The pooled results also presented in Table 5.2. show similar average values at 19 per cent less for blue-collar workers, and 23 per cent less for white-collar, relative to skilled workers. Reasons for this difference may include that blue-collar jobs are typically found in heavier industry and vocational employment, and workers in these sectors can expect increased compensation for the more difficult employment conditions they face. Additionally, empirical research does not conclude, but commentary indicates a growing shortage of blue-collar workers, which supports higher wage rates. The results point to earnings differences arising not just from the lower skill levels of elementary occupations but also possibly by the value placed on skills in white-collar roles across countries.

I consider next whether the degree of flexibility in labour markets has an impact on differences in occupational skill level earnings. The Nordic countries possess a greater degree of worker protection compared with the more flexible labour markets of New Zealand, Ireland, the United Kingdom, and South Korea. I find that differences in average earnings are smaller for the Nordic countries than for those with more flexible markets[42] (Kahn, 2012). Elementary-skilled workers in Denmark earn 18 per cent less than skilled workers, and 23 per cent less in Norway. This compares with 41 per cent less in the United Kingdom, 35 per cent less in South Korea, and 34 per cent less in New Zealand. The earnings gap for white-collar workers relative to blue-collar is evident regardless of the labour market regime existing. Overall, Chile and Estonia have

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[42]Belgium is considered to have a lower level of job security but lower job strain than most OECD countries. Denmark employs a ‘flexicurity’ labour market model with sizeable unemployment insurance benefits and comprehensive active labour market policies. Norway is ranked as a top performer for labour market security with the lowest job strain among OECD countries. For countries with the largest occupational skill earnings differentials, in broad terms, the United Kingdom provides an example of a labour market that is relatively more flexible. While the Japanese labour market has the feature of lifetime employment, there is also wage flexibility within firms. https://www.oecd.org/denmark/jobs-strategy-DENMARK-EN.pdf

the largest occupational skill earnings differences. Elementary-skilled workers in Chile earn 54 per cent less than skilled workers on average, white-collar workers earn 50 per cent less[43]. Estonian elementary-skilled workers earn 45 per cent less than skilled workers.

For the control variables, I find a positive relationship between further education and worker income for all countries studied, with a 5 per cent gain to earnings in the pooled regression. I find the highest effects for Japan at 12 per cent, and 11 per cent for Ireland. Foundation schooling is important for improving income for all countries. Having at least one parent attaining tertiary level education is important for average income in the overall pooled result and for seven of the countries examined. The strongest result is observed for Poland, with a 15 per cent increase to income.

My findings in Chapter 4 show that policy to increase the use of literacy, numeracy, and ICT problem-solving skills support income gains by occupational skill grouping in the New Zealand labour market. In Chapter 5, I evaluate the ability of increasing numeracy skill to raise occupational earnings. These results are presented in Table 5.3. For these regressions, elementary-skilled occupations are utilised as the base group. The results support hypothesis two, that an increase in numeracy skill will increase average earnings by occupational skill group for many countries. From a 10 per cent increase in numeracy skill, blue-collar workers experience a 2.5 per cent

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[43]Chile has one of the lowest rankings for earnings quality among OECD countries with relatively low average earnings and high levels of inequality. Despite significant improvements over the last decade, the level of earnings is currently a third of the OECD average. This partly reflects relatively lower skill levels and a high incidence of precarious jobs. Labour market insecurity is high relative to the OECD average. Unemployment risk is similar to other OECD countries, however, the level of unemployment insurance (coverage and replacement rates of public unemployment benefits) is much lower than the OECD average. Given the reduced level of social protection, many workers need to accept very low-quality jobs when better jobs are not available because they cannot afford to be unemployed for longer periods. https://www.oecd.org/chile/jobs-strategy-CHILE-EN.pdf

median increase in income relative to elementary-skilled workers, but with only 4 countries with statistically significant results; white-collar workers see a median gain of 3.6 per cent, for 9 countries; skilled occupations see an increase of 4.7 per cent. The latter group has statistically significant results for 11 of the 13 countries. White-collar workers see greater gains than blue-collar, demonstrating the importance of policy aimed at increasing numeracy skill for raising the value and income of occupational skill groupings.

In contrast to my occupational skill level-income findings presented in Table 5.2, I observe the greater gains from increases to numeracy skill proficiency by occupational skill is for countries with relatively more flexible labour markets. Blue-collar workers in the United Kingdom see a 5.5 per cent increase in income. For white-collar workers, Japan and the United Kingdom are top performers, with a 5.5 and 4.2 per cent income gain, respectively. For skilled occupations, Ireland, Korea, and the United Kingdom see strong income gains from greater numeracy skill, although the Netherlands also performs strongly. Estonia sees income gains for each of the occupational skill categories. For the more protected labour market economies, white-collar workers in Denmark experience a 2.2 per cent income gain from a 10 per cent increase in numeracy proficiency. Finland’s result is insignificant, and Norway has a 2.1 per cent gain. For numeracy proficiency, flexible labour markets appear to strengthen the benefits from cognitive skill improvement. The results for the pooled regression support the individual country findings with significant and rising income gains for each occupation category.

Table 5.2. Occupational Skill Effects on Average Hourly Earnings. Country Comparisons

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
elementary skill	-0.274***	-0.340***	-0.542***	-0.358***	-0.353***	-0.325***	-0.410***	-0.177***	-0.304***	-0.233***	-0.307***	-0.258***	-0.454***	-0.241***
	(0.036)	(0.021)	(0.054)	(0.034)	(0.041)	(0.030)	(0.027)	(0.016)	(0.021)	(0.022)	(0.026)	(0.018)	(0.030)	(0.032)
blue collar	-0.192***	-0.216***	-0.435***	-0.257***	-0.265***	-0.217***	-0.277***	-0.132***	-0.183***	-0.137***	-0.272***	-0.157***	-0.153***	-0.171***
	(0.026)	(0.016)	(0.047)	(0.023)	(0.032)	(0.024)	(0.022)	(0.012)	(0.015)	(0.015)	(0.020)	(0.016)	(0.021)	(0.023)
white collar	-0.226***	-0.239***	-0.500***	-0.275***	-0.206***	-0.242***	-0.314***	-0.135***	-0.220***	-0.190***	-0.178***	-0.114***	-0.339***	-0.264***
	(0.026)	(0.014)	(0.038)	(0.018)	(0.024)	(0.018)	(0.014)	(0.010)	(0.012)	(0.011)	(0.014)	(0.013)	(0.021)	(0.020)
further education	0.051***	0.042***	0.065**	0.124***	0.104***	0.113***	0.080***	0.036***	0.039***	0.035***	0.039***	0.055***	0.067***	0.099***
	(0.015)	(0.012)	(0.026)	(0.015)	(0.021)	(0.015)	(0.012)	(0.008)	(0.009)	(0.009)	(0.012)	(0.010)	(0.015)	(0.014)
log workplace training	0.006	-0.008	-0.038**	-0.013	-0.027*	0.015	0.011	-0.000	-0.011	0.016	-0.005	0.005	-0.009	0.028***
	(0.006)	(0.010)	(0.019)	(0.011)	(0.015)	(0.012)	(0.009)	(0.008)	(0.010)	(0.011)	(0.010)	(0.007)	(0.013)	(0.011)
years of schooling	0.032***	0.034***	0.050***	0.029***	0.047***	0.041***	0.038***	0.031***	0.030***	0.025***	0.043***	0.032***	0.031***	0.040***
	(0.005)	(0.002)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
years work experience	0.020***	0.021***	0.004	0.030***	0.026***	0.028***	0.025***	0.018***	0.017***	0.020***	0.027***	0.021***	0.009***	0.022***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
years work experience^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
parent-no tertiary	0.008	0.007	-0.005	0.078***	0.034***	-0.015	0.005	0.015*	0.004	0.008	-0.005	0.011	0.063***	0.078***
	(0.009)	(0.013)	(0.028)	(0.019)	(0.023)	(0.017)	(0.013)	(0.008)	(0.010)	(0.010)	(0.012)	(0.011)	(0.019)	(0.021)
parent-tertiary	0.035***	0.011	-0.018	0.086***	0.059**	0.009	0.061***	0.015	0.015	0.016	0.032**	0.043***	0.121***	0.152***
	(0.011)	(0.012)	(0.033)	(0.021)	(0.028)	(0.019)	(0.016)	(0.009)	(0.013)	(0.012)	(0.014)	(0.013)	(0.021)	(0.028)
female	-0.115***	-0.119***	-0.118***	-0.241***	-0.201***	-0.043***	-0.098***	-0.083***	-0.140***	-0.123***	-0.083***	-0.055***	-0.316***	-0.146***
	(0.020)	(0.011)	(0.028)	(0.015)	(0.022)	(0.015)	(0.012)	(0.007)	(0.009)	(0.009)	(0.011)	(0.010)	(0.015)	(0.015)
constant	3.53***	2.56***	7.46***	6.68***	8.57***	1.93***	1.75***	4.59***	2.37***	4.85***	1.95***	2.13***	1.26***	1.96***
	(0.099)	(0.042)	(0.097)	(0.060)	(0.078)	(0.057)	(0.049)	(0.030)	(0.036)	(0.037)	(0.046)	(0.039)	(0.056)	(0.060)
observations	36,963	2,650	1,907	2,788	2,490	2,429	3,417	4,148	3,036	2,765	2,707	2,424	3,437	2,765
R-squared	0.19	0.41	0.33	0.44	0.29	0.37	0.41	0.36	0.46	0.42	0.44	0.42	0.35	0.36

Notes: The dependent variable is log hourly wage rate. Occupational skill groups are: elementary; blue collar; white collar; skilled occupations is the base group. Further variables of interest are: further education as job-related formal and informal adult education and training in the last 12 months; log workplace training is a scale measure for quantity of workplace training received. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. The pooled specification controls for country fixed effects. R^2 refers to within-country R^2. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Table 5.3. Numeracy Proficiency Effects on Occupational Skill Returns in International Labour Markets. Country Comparisons.

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
numeracy	-0.041	0.039	-0.129	0.167	-0.198	0.083	0.089	0.052	0.044	0.075	0.033	-0.009	-0.139	0.079
	(0.049)	(0.080)	(0.100)	(0.151)	(0.152)	(0.153)	(0.090)	(0.050)	(0.105)	(0.055)	(0.106)	(0.074)	(0.147)	(0.106)
x blue collar	0.104***	-0.024	-0.052	0.380	0.073	0.283	0.552***	0.163*	0.136	0.233**	0.244	0.074	0.258**	0.185
	(0.034)	(0.092)	(0.127)	(0.181)	(0.192)	(0.173)	(0.135)	(0.067)	(0.120)	(0.074)	(0.131)	(0.101)	(0.174)	(0.128)
x white collar	0.238***	0.024	-0.028	0.553**	0.362***	0.316	0.421***	0.220**	0.193	0.207*	0.275**	0.299***	0.507***	0.366**
	(0.037)	(0.093)	(0.114)	(0.167)	(0.185)	(0.165)	(0.105)	(0.066)	(0.118)	(0.070)	(0.125)	(0.091)	(0.189)	(0.131)
x skilled occupations	0.331***	0.018	-0.098	0.510**	0.591***	0.623***	0.472***	0.356***	0.437***	0.337***	0.553***	0.279***	0.622***	0.337**
	(0.060)	(0.087)	(0.122)	(0.214)	(0.204)	(0.165)	(0.106)	(0.062)	(0.116)	(0.070)	(0.120)	(0.095)	(0.163)	(0.128)
further education	0.049***	0.041***	0.067***	0.115***	0.098***	0.104***	0.078***	0.032***	0.040***	0.035***	0.036***	0.053***	0.071***	0.104***
	(0.015)	(0.012)	(0.025)	(0.014)	(0.020)	(0.014)	(0.012)	(0.008)	(0.009)	(0.009)	(0.011)	(0.010)	(0.014)	(0.013)
years of schooling	0.027***	0.032***	0.047***	0.018***	0.036***	0.028***	0.031***	0.025***	0.024***	0.020***	0.033***	0.027***	0.022***	0.032***
	(0.005)	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
years work experience	0.018***	0.021***	0.002	0.028***	0.025***	0.026***	0.023***	0.016***	0.017***	0.018***	0.025***	0.020***	0.009***	0.020***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
years work experience^2	-0.000***	-0.000***	0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
parent-no tertiary	-0.002	0.009	0.002	0.074***	0.041*	-0.026	-0.017	0.008	0.001	0.074	-0.005	0.011	0.061***	0.083***
	(0.010)	(0.013)	(0.028)	(0.018)	(0.022)	(0.016)	(0.013)	(0.008)	(0.010)	(0.018)	(0.012)	(0.011)	(0.018)	(0.020)
parent-tertiary	0.014	0.009	0.006	0.078***	0.043	-0.010	0.024	0.001	0.003	0.002	0.021	0.035***	0.105***	0.143***
	(0.010)	(0.012)	(0.035)	(0.020)	(0.028)	(0.019)	(0.016)	(0.009)	(0.013)	(0.011)	(0.014)	(0.013)	(0.020)	(0.026)
female	-0.101***	-0.111***	-0.122***	-0.234***	-0.198***	-0.018	-0.073***	-0.066***	-0.122***	-0.104***	-0.057***	-0.041***	-0.288***	-0.131***
	(0.020)	(0.011)	(0.027)	(0.015)	(0.021)	(0.015)	(0.012)	(0.007)	(0.009)	(0.009)	(0.011)	(0.010)	(0.015)	(0.015)
constant	3.59***	2.03***	7.60***	5.52***	9.49***	1.35	0.940*	4.22***	1.86***	4.28***	1.58***	1.99***	1.65***	1.38***
	(0.33)	(0.443)	(0.526)	(0.831)	(0.821)	(0.833)	(0.494)	(0.277)	(0.588)	(0.294)	(0.589)	(0.402)	(0.808)	(0.572)
observations	38,917	2,719	2,048	2,958	2,949	2,593	3,581	4,247	3,078	2,796	2,815	2,528	3,578	3,027
R-squared	0.19	0.40	0.33	0.45	0.28	0.39	0.44	0.38	0.47	0.44	0.45	0.43	0.37	0.36

Notes: The dependent variable is log hourly wage rate. Numeracy proficiency interacted with occupational skill groups. Elementary skilled occupations is the base group. Occupational skill groups are: elementary; blue collar; white collar; skilled occupations is the base group. Further variables of interest are: further education as job-related formal and informal adult education and training in the last 12 months. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. The pooled specification controls for country fixed effects. R^2 refers to within-country R^2. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

5.5.3 Cognitive Skill Effects for Increasing Earnings Across the Working Age Life Cycle in International Labour Markets.

In this section I examine age-earnings profiles to assess if the familiar concave earnings profile (Thornton et al. 1997) is evident for the subset of countries evaluated using PIAAC data. Further, I will analyse the ability of increased cognitive skill proficiency to improve average earnings by age group internationally. The two skills I will assess are numeracy and ICT problem-solving. These relationships will be evaluated through hypothesis three, that increases in cognitive skill proficiency will increase earnings across the working age life cycle in developed and developing country labour markets. I first present results by age category alone in Table 5.4, to assess baseline age-earnings profiles by country. In Table 5.5 I set out results for each age group interacted with cognitive skill proficiency. Expanding the broader age categories evaluated by Hanushek et al. (2015), I utilise five categories: workers aged 24-years or less, workers aged 25 to 34-years, workers aged 35 to 44-years, workers aged 45 to 54-years, and workers aged 55-years and over. The base age category is workers aged 35 to 44-years. From the Table 5.4 results, I find this age group represents peak earnings internationally, making it a suitable comparison group. Other age categories were trialled as the base group, with similar results obtained.

For the results by age category in Table 5.4, while there are country differences, workers aged 35 to 44-years have the highest median earnings relative to other age groups. As expected, those aged 24-years or less see the largest difference with median earnings that are 8.2 per cent less than the 35 to 44-year base group. Workers aged 55-years and over have the second-largest earnings gap at 6.2 per cent less than the base age category. While the results do follow the expected concave, or inverted U-shaped age-earnings profile, peak earnings may have been expected for a later age bracket, perhaps for those aged 45 to 54-years. Workers in this age category will generally hold more senior positions within organisations. However, controlling for experience, the results point to an international trend for mid-career stage workers to be considered of higher value to firms. Possible reasons for this include a significant relative value being placed on the mix of skills and up-to-date qualifications that younger cohorts may possess. Additionally, I observe little difference in median age-earnings differentials between countries with greater worker protection, principally in the Nordic region, and countries with more flexible labour markets, including New Zealand, Ireland, and the United Kingdom. Relative to the base group, median labour earnings are 4.1 per cent less for workers aged 25 to 34-years in more protected markets, and 3.5 per cent less in more flexible markets. For workers aged 45 to 54-years, the results are 2.5 per cent less, and 2.8 per cent less, respectively. Workers aged 24-years or less in countries with flexible markets experience median wage rates that are 15 per cent less compared with 11 per cent for protected markets, and compared with the total median of 8.2 per cent. Overall, greater labour market protection is not protecting worker income by age.

Having assessed earnings differences by age category internationally, I now turn to the evaluation of hypothesis three, whether increases in cognitive skill proficiency will increase average earnings for each age group in developed and developing country labour markets. An analysis of whether cognitive skills reduce age-earnings differences would have been preferred but may prove more difficult to quantify. For this hypothesis, I interact numeracy and ICT problem-solving skill with each age group, controlling for age. The base group is again workers aged 35 to 44-years, representing the peak earnings age category. I present the results in Table 5.5, finding support in favour of the hypothesis. For both cognitive skills, the majority of statistically significant results are for the youngest three age groups. Workers in the 35 to 44-year age group experience the largest income gains. For numeracy skill, in Panel A, a 10 percent improvement increases median income by 4.9 per cent, and 3.1 per cent for workers aged 25 to 34-years, relative to the base group. Those aged 24-years or less see very modest income gains, at 0.5 per cent. For ICT proficiency, in Panel B, workers aged 35 to 44-years experience a 5.7 per cent improvement in median earnings. For workers aged 25 to 34-years in countries with statistically significant results, the median gain is 3.1 per cent. There is a negative median return for workers aged 24-years or less.

As for the findings for occupational skill level-numeracy interactions, I find those countries with more flexible labour markets see the largest age-related income gains from greater numeracy skill proficiency. In Panel A, workers aged 35 to 44-years see a median increase of 6.8 per cent. In countries with more protected markets, the median gain is 4.8 per cent. For workers aged 25 to 34-years, the gains are 4.8 per cent and 3.2 per cent respectively. In contrast, the gains are similar by market type for improvements in ICT skills. In Panel B, workers aged 35 to 44-years see a similar 4.7 per cent gain to in income, and by 3.2 per cent for those aged 25 to 34-years. Perhaps ICT proficiency skills are valued equally, regardless of labour market type.

Table 5.4. Age Effects on Average Hourly Earnings. Country Comparisons.

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
workers aged 24 or less	-0.147***	-0.082**	-0.054	0.040	-0.120***	-0.197***	-0.178***	-0.161***	-0.072***	-0.108***	-0.278***	-0.007	0.028	0.032
	(0.036)	(0.021)	(0.053)	(0.031)	(0.044)	(0.032)	(0.027)	(0.018)	(0.026)	(0.019)	(0.028)	(0.026)	(0.041)	(0.032)
workers aged 25 to 34-years	-0.031*	0.011	-0.034	0.017	-0.035	-0.063	-0.034**	-0.058***	0.037**	-0.041***	-0.099***	0.018	0.103***	0.063**
	(0.015)	(0.016)	(0.035)	(0.021)	(0.027)	(0.020)	(0.017)	(0.013)	(0.016)	(0.014)	(0.019)	(0.016)	(0.026)	(0.026)
workers aged 45 to 54-years	-0.033*	-0.034**	-0.017	-0.063***	-0.022	-0.002	-0.055***	-0.037***	-0.025	-0.026**	-0.025	-0.007	-0.187***	-0.090***
	(0.018)	(0.017)	(0.036)	(0.020)	(0.028)	(0.023)	(0.017)	(0.012)	(0.015)	(0.012)	(0.017)	(0.016)	(0.024)	(0.027)
workers aged 55-years and over	-0.068**	-0.084***	-0.049	-0.176***	-0.006	0.026	-0.097***	-0.062***	-0.065***	-0.049***	-0.056**	-0.003	-0.224***	-0.094**
	(0.030)	(0.024)	(0.047)	(0.029)	(0.047)	(0.033)	(0.027)	(0.016)	(0.024)	(0.019)	(0.025)	(0.029)	(0.040)	(0.046)
years of schooling	0.055***	0.055***	0.091***	0.065***	0.071***	0.062***	0.076***	0.045***	0.053***	0.045***	0.061***	0.054***	0.066***	0.063***
	(0.007)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
years work experience	0.016***	0.021***	-0.001	0.034***	0.022***	0.023***	0.023***	0.014***	0.015***	0.016***	0.013***	0.022***	0.022***	0.027***
	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
years work experience^2	-0.000***	-0.000***	0.000	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
female	-0.120***	-0.099***	-0.118***	-0.267***	-0.178**	-0.056***	-0.114***	-0.074***	-0.159***	-0.120***	-0.080***	-0.063***	-0.342***	-0.157***
	(0.020)	(0.009)	(0.025)	(0.014)	(0.020)	(0.014)	(0.011)	(0.007)	(0.009)	(0.007)	(0.010)	(0.009)	(0.014)	(0.012)
constant	3.20***	2.15***	6.67***	6.09***	8.21***	1.61***	1.19***	4.44***	2.01***	4.57***	1.83***	1.80***	0.648***	1.59***
	(0.136)	(0.037)	(0.065)	(0.055)	(0.061)	(0.050)	(0.045)	(0.028)	(0.036)	(0.062)	(0.045)	(0.037)	(0.058)	(0.051)
observations	45,595	3,619	2,453	3,310	3,160	2,846	4,546	4,696	3,337	3,625	3,223	2,793	4,044	3,943
R-squared	0.17	0.35	0.21	0.36	0.23	0.30	0.33	0.42	0.39	0.40	0.45	0.37	0.26	0.24

Notes: The dependent variable is log hourly wage rate. The base age category is workers aged 35 to 44-years. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. The pooled specification controls for country fixed effects. R^2 refers to within-country R^2. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Table 5.5. Numeracy and ICT Problem-Solving Proficiency Effects on Average Hourly Earnings by Age. Country Comparisons.

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
Panel A														
numeracy x	0.418***	0.101*	-0.139*	0.800***	0.585***	0.677***	0.780***	0.360***	0.493***	0.403***	0.654***	0.367***	0.563***	0.393***
	(0.088)	(0.056)	(0.081)	(0.106)	(0.130)	(0.071)	(0.059)	(0.050)	(0.056)	(0.044)	(0.071)	(0.055)	(0.108)	(0.119)
aged 24-years or	-0.010**	-0.041**	-0.379*	0.177***	0.106*	0.193***	0.027***	0.007***	-0.054***	0.049***	0.070***	-0.052***	0.229**	0.193
less	(0.142)	(0.066)	(0.144)	(0.148)	(0.257)	(0.166)	(0.108)	(0.067)	(0.106)	(0.059)	(0.108)	(0.083)	(0.171)	(0.148)
aged 25 to 34-	0.187***	-0.029*	-0.050	0.498**	0.354**	0.480**	0.559***	0.259	0.168***	0.310	0.368**	0.209**	0.499	0.373
years	(0.062)	(0.078)	(0.109)	(0.147)	(0.173)	(0.092)	(0.083)	(0.062)	(0.084)	(0.058)	(0.117)	(0.080)	(0.139)	(0.132)
aged 45 to 54-	0.374	-0.016	-0.041	0.721	0.457	0.500	0.586**	0.359	0.523	0.447	0.787	0.447	0.579	0.489
years	(0.054)	(0.079)	(0.111)	(0.145)	(0.163)	(0.113)	(0.089)	(0.064)	(0.075)	(0.063)	(0.095)	(0.078)	(0.138)	(0.142)
aged 55-years	0.286**	0.045	-0.095	0.552*	-0.022***	0.280**	0.749	0.294	0.368	0.289	0.536	0.375	0.309	0.192
and over	(0.052)	(0.083)	(0.126)	(0.139)	(0.209)	(0.155)	(0.102)	(0.061)	(0.083)	(0.075)	(0.101)	(0.107)	(0.156)	(0.190)
observations	43,267	3,096	2,232	3,124	3,134	2,755	3,896	4,653	3,278	3,580	3,176	2,679	3,811	3,853
R-squared	0.18	0.35	0.22	0.39	0.24	0.34	0.38	0.45	0.42	0.44	0.48	0.40	0.29	0.27
Panel B														
ICT Problem-	0.370***	0.204***	0.696***	0.466***	0.397**	0.576***	0.938***	0.447***	0.476***	0.607***	0.780***	0.429***	0.571***	0.597***
solving x	(0.116)	(0.076)	(0.169)	(0.116)	(0.157)	(0.101)	(0.081)	(0.069)	(0.086)	(0.062)	(0.091)	(0.076)	(0.114)	(0.107)
aged 24-years or	0.063	-0.026**	0.526	0.159*	0.213	0.184**	0.233***	0.001***	-0.107***	-0.010***	0.075 ***	-0.073***	0.380	0.257***
less	(0.186)	(0.093)	(0.279)	(0.175)	(0.352)	(0.168)	(0.155)	(0.099)	(0.164)	(0.089)	(0.152)	(0.115)	(0.199)	(0.128)
aged 25 to 34-	0.132**	-0.029***	0.879	0.329	0.042	0.401	0.708**	0.322	0.105***	0.415**	0.538***	0.202**	0.456	0.468
years	(0.107)	(0.103)	(0.239)	(0.171)	(0.237)	(0.137)	(0.118)	(0.091)	(0.117)	(0.093)	(0.124)	(0.102)	(0.158)	(0.129)
aged 45 to 54-	0.299	-0.016**	0.367	0.670	0.355	0.600	0.728*	0.459	0.562	0.526	0.735	0.471	0.696	0.470
years	(0.055)	(0.106)	(0.244)	(0.156)	(0.249)	(0.175)	(0.115)	(0.086)	(0.108)	(0.091)	(0.123)	(0.102)	(0.160)	(0.206)
aged 55-years	0.056	0.045	0.682	0.400	0.510	0.530	1.01	0.312	0.322	0.308***	0.739	0.304	0.486	0.324
and over	(0.089)	(0.116)	(0.269)	(0.181)	(0.454)	(0.237)	(0.140)	(0.084)	(0.119)	(0.102)	(0.124)	(0.125)	(0.200)	(0.375)
observations	34,869	2,846	1,399	2,152	2,317	2,130	3,601	4,116	2,920	3,271	2,965	2,395	2,863	2,610
R-squared	0.20	0.35	0.10	0.42	0.27	0.35	0.37	0.45	0.42	0.45	0.50	0.41	0.27	0.29

Notes: For both Panels A and B, the dependent variable is log hourly wage rate. Panel A: log numeracy skill proficiency is interacted with workers aged 24 or less, workers aged 25 to 34-years, workers aged 45 to 54-year, workers aged 55-years and over. In Panel B, ICT problem-solving proficiency is interacted with the same age categories. The base group is workers aged 35 to 44 years in both panels. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. The pooled specification controls for country fixed effects. R^2 refers to within-country R^2. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

5.5 Further Robustness Tests - Causality Measures

In this section I investigate the possibility of reverse causation from income to skills, whereby workers may have better skills in part because they have higher paying jobs. This may lead to the regular workplace practicing of higher skills or to providing the necessary income for additional training and further education. As for the Chapter Four study for New Zealand, I test for reverse causation through two-stage least squares regression using instrumental variables (IV) for numeracy proficiency. This is applied to the pooled country data. The instrumental variables are school attainment through years of schooling, and parental education. Both measures are related to an individual's cognitive skills but observed before the start of their labour-market career. Parental education is separated into two measures: At least one parent has attained secondary qualifications, and at least one parent has attained a tertiary qualification. I present the results in Table 5.6. Years of schooling, in Column 1, and at least one parent having a tertiary qualification, in Column 3, show a statistically significant, positive relationship with earnings as instrumental variables for numeracy skill. The result for non-tertiary qualifications (Column 2) is statistically insignificant, with an unexpected negative sign.

The results for the IV estimates are not complete evidence against reverse causality. The reasons for this include the same as for using these variables as instrumental variables: that schooling can be a choice variable, family background may exert direct effects on earnings, and ability may show intergenerational persistence (Card, 1999). However, my results suggest that reverse causation, as addressed by these IV estimates, may not give rise to a first-order upward bias in OLS estimates of returns to skills.

Table 5.6. Reverse Causality Analysis – Numeracy Skill Instruments.

Instrument	Years of Schooling (1)	Parent-Non-Tertiary (2)	Parent-Tertiary (3)
numeracy proficiency IV	3.19***	-0.431	1.59***
	(0.054)	(0.759)	(0.076)
experience	0.027***	0.039***	0.033***
	(0.001)	(0.003)	(0.001)
experience^2	-0.000	-0.001*	-0.001***
	(0.000)	(0.000	(0.000)
female	-0.057***	-0.174***	-0.0108***
	(0.007)	(0.025)	(0.006)
Constant	-14.05***	6.28	-5.10***
	(0.306)	(4.27)	(0.429)
instrument F statistic	34,768	45,508	48,473
observations	45,385	43,449	43,449

Notes: Dependent variable: log hourly wage rate. Three instrumental variables are utilised for numeracy skill: Column 1: Years of schooling; Column 2: At least one parent attained secondary or non-secondary qualifications, non-tertiary parent-non-tertiary; Column 3: At least one parent attained tertiary qualification parent-tertiary. Regressions control for years of work experience and gender. Statistical significance: *** at the 1% level, ** 5% level, * 10% level. Methodology: 2SLS, fixed effects.

5.6 Summary and Policy Implications

In Chapter 5, I examine the potential of proficiency in and the use of the three core cognitive skills of literacy, numeracy, and ICT problem-solving for lifting average worker earnings in international labour markets. Using a country-comparative approach in this chapter, I contribute to the literature in finding significant demand, as reflected through higher average hourly wage rates, from greater use of ICT problem-solving skills in the workplace. This finding points to the potential to lift productivity and income levels internationally through policy to improve ICT infrastructure and for greater integration of these skills into workplace tasks. For usage effects for the other core skills, I find that literacy skills improve worker earnings, reflecting demand for tasks involving reading skills in particular. For proficiency effects, it is improvements to numeracy skills that are the most consistently important across countries for raising income.

While the results indicate the importance of the core cognitive skills, years of schooling as a measure of human capital accumulation remains a bedrock. A consistently significant and positive relationship is found between foundation learning and labour income for all 13 countries examined. Work experience is also positive for average earnings for most countries; however, the effects are more modest than for educational attainment. My research also contributes in finding significant gains for worker income from further job-related adult education and training. Gains occur for workers in Japan, the United Kingdom, and Ireland, compared with countries with arguably more developed adult education networks. These are particularly the northern European nations.

For occupational skill effects, white-collar workers internationally generally see lower earnings than blue-collar workers, relative to a base group of skilled workers. To some degree, this may indicate the effects of working conditions and labour demand considerations. The observation may also be indicative of the 'hollowing out' effect found in the literature for the earnings and employment of white-collar workers. In evaluating the impact of increased cognitive skill proficiency for raising occupational skill level income, I find a positive relationship from greater numeracy skill. This likely reflects skill complimentary effects internationally. While worker protection measures help to smooth out occupational earnings differences for some countries, greater labour market flexibility in others supports higher earnings from increased cognitive skill. Greater cognitive skill also has positive impacts for workers by age group internationally, with income gains for those in the lower three age bands from higher numeracy skill proficiency in particular. Again, countries with more flexible labour markets experience the higher gains for numeracy skill, indicating that worker protection is not always the most effective way to deliver higher income growth. In contrast, while positive, increased ICT skill improves labour earnings by similar rates in both market types. ICT skills are valued highly, regardless of labour market type.

Appendix D

Appendix D.1. Table 5.7. provides summary statistics for the baseline sample. Respondents in Japan achieve the highest average score for each of numeracy, literacy, and ICT problem-solving. Chile records the lowest proficiency score for each cognitive skill. Chile, as a developing county, also records the highest wage inequality, as measured as the log wage differential between the 90th and 10th percentile of the wage distribution. Norway records the lowest wage inequality, with similar results for other Nordic countries. Average years of schooling is similar across countries, with Ireland recording the highest at 15 years. The majority of the countries how average work experience of 18 years and higher.

Table 5.7. Descriptive Statistics - Key Variables. Country Comparison.

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
gross hourly wage (national currency)	419.38 (803.71)	22.5 (8.2)	2738.9 (1946.2)	1520.0 (742.8)	12460.1 (7553.8)	18.0 (7.9)	11.3 (4.9)	181.4 (53.2)	17.0 (5.4)	210.6 (60.8)	16.4 (6.2)	16.4 (5.0)	4.8 (2.4)	14.0 (6.3)
wage inequality	5.99	1.02	2.02	1.38	1.80	1.30	1.24	0.96	0.97	0.91	1.23	0.94	1.56	1.35
literacy	273.37 (0.162)	279.2 (44.3)	218.9 (49.4)	297.1 (36.5)	271.8 (39.4)	268.6 (44.0)	271.7 (44.7)	267.4 (47.3)	289.9 (46.0)	281.2 (43.5)	285.4 (44.1)	275.4 (44.9)	275.6 (41.2)	273.8 (43.0)
numeracy	267.49 (0.180)	268.2 (51.3))	202.4 (56.4)	289.3 (40.4)	262.3 (43.3)	257.7 (50.3)	260.5 (50.5)	276.2 (50.1)	284.9 (47.0)	281.7 (50.1)	282.0 (46.2)	279.8 (47.9)	272.2 (42.2)	264.8 (45.7)
ICT problem-solving	281.07 (0.162)	286.1 (42.9)	251.7 (44.2)	294.9 (40.5)	283.1 (34.4)	277.0 (37.2)	277.3 (38.70	279.2 (39.9)	290.0 (39.3)	288.4 (37.2)	286.4 (38.1)	281.5 (40.6)	276.8 (40.0)	280.4 (42.6)
years of schooling	12.89 (0.010)	13.6 (2.5)	11.3 (3.3)	13.1 (2.4)	12.6 (3.3)	14.9 (3.2)	13.2 (2.3)	12.8 (2.8)	12.4 (3.0)	14.1 (2.6)	13.1 (2.7)	12.3 (2.9)	12.1 (2.70	12.5 (2.7)
work experience (years)	17.89 (0.048)	18.7 (13.4)	12.4 (11.8)	18.8 (12.6)	13.4 (10.9)	17.9 (11.8)	19.8 (12.6)	23.3 (14.3)	19.4 (13.7)	18.6 (12.8)	19.8 (12.8)	19.9 (12.6)	19.7 (13.2)	10.7 (2.7)
observations	46,182	6,177	5,212	5,278	6,667	5,983	4,904	4,700	3,337	3,628	3,228	2,803	4,051	3,989

Notes: Means, standard deviations (in parentheses), and numbers of observations for selected variables by countries. Full country sample. Gross hourly wage and wage inequality only for those reporting income data, on trimmed data. Wage inequality: log wage differential between 90th and 10th percentile of the wage distribution. Data source: PIAAC.

Appendix D.2. Table 5.8. shows the 2017-year ICT Development Index ranking of countries by the United Nation's specialised agency for Information Communication Technology (ICT), the International Telecommunication Union (ITU). Countries are ranked according to their level of development of ICT infrastructure, access and use of ICT in society, and the impact of ICT as measured by the results and outcomes of more efficient and effective ICT use. A comparison is provided with the 2016-year rankings. Countries such as the United Kingdom show a high ranking and more established ICT infrastructure. Countries including New Zealand, Australia, and the United States have lower rankings for the criteria.

Table 5.8. The 2017 ICT Development Index (IDI) Country Rankings with Comparison to the 2016 Rankings.

IDI 2017 Rank	Economy	IDI 2017 Value	IDI 2016 Rank	IDI 2016 Value
1	Iceland	8.98	2	8.78
2	South Korea	8.85	1	8.80
3	Switzerland	8.74	4	8.66
4	Denmark	8.71	3	8.68
5	United Kingdom	8.65	5	8.53
6	Hong Kong, China	8.61	6	8.47
7	Netherlands	8.49	10	8.40
8	Norway	8.47	7	8.45
9	Luxembourg	8.47	9	8.40
10	Japan	8.43	11	8.32
11	Sweden	8.41	8	8.41
12	Germany	8.39	13	8.20
13	New Zealand	8.33	12	8.23
14	Australia	8.24	16	8.08
15	France	8.24	17	8.05
16	United States	8.18	15	8.13
17	Estonia	8.14	14	8.16
18	Singapore	8.05	20	7.85
19	Monaco	8.05	18	8.03
20	Ireland	8.02	19	7.90

Source: https://www.itu.int/net4/ITU-D/idi/2017/index.html

Appendix D.3. Table 5.9. shows the results for age effects on average hourly earnings using differing age categories as the base group. The results are consistent with those presented in Table 5.4, which shows peak earnings occurring for workers aged 35 to 44 years of age.

Table 5.9. Age Effects on Average Hourly Earnings. Country Comparison. Alternative Base Groups.

	Pooled	New Zealand	Chile	Japan	South Korea	Ireland	United Kingdom	Denmark	Finland	Norway	Netherlands	Belgium	Estonia	Poland
Panel A														
workers aged 24	-0.113**	-0.048*	-0.037	0.103***	-0.099**	-0.195***	-0.124***	-0.124***	-0.047	-0.082***	-0.253***	-0.000	0.215***	0.122***
or less	(0.049)	(0.025)	(0.059)	(0.036)	(0.047)	(0.037)	(0.032)	(0.022)	(0.032)	(0.023)	(0.033)	(0.030)	(0.051)	(0.039)
workers aged 25	0.003	0.045**	-0.017	0.080***	-0.013	-0.061**	0.021	-0.021	-0.013	-0.015	-0.074***	0.025	0.290***	0.153***
to 34-years	(0.031)	(0.020)	(0.042)	(0.026)	(0.033)	(0.027)	(0.022)	(0.016)	(0.023)	(0.017)	(0.024)	(0.022)	(0.036)	(0.034)
workers aged 35	0.033*	0.034**	0.017	0.063***	0.022	0.002	0.055***	0.037***	0.025	0.026**	0.025	0.007	0.187***	0.090***
to 44-years	(0.018)	(0.017)	(0.036)	(0.020)	(0.028)	(0.023)	(0.017)	(0.012)	(0.015)	(0.012)	(0.017)	(0.016)	(0.024)	(0.027)
workers aged 55-	-0.035**	-0.050**	-0.031	-0.113*	0.016	-0.024	-0.042	-0.0258*	-0.041**	-0.023	-0.031	0.005	-0.037	-0.003
years and over	(0.015)	(0.020)	(0.044)	(0.026)	(0.042)	(0.029)	(0.023)	(0.012)	(0.018)	(0.015)	(0.019)	(0.022)	(0.030)	(0.037)
Panel B														
workers aged 24	-0.078	0.002	-0.005	0.215***	-0.114**	-0.171***	-0.082**	-0.099***	-0.007	-0.059**	-0.222***	-0.005	0.252***	0.126**
or less	(0.059)	(0.030)	(0.065)	(0.041)	(0.057)	(0.041)	(0.037)	(0.025)	(0.037)	(0.026)	(0.037)	(0.037)	(0.060)	(0.053)
workers aged 25	0.038	0.094***	0.014	0.192***	-0.029	-0.037	0.063**	0.004	0.028	0.008	-0.043	0.021	0.327***	0.156***
to 34-years	(0.043)	(0.026)	(0.051)	(0.034)	(0.050)	(0.035)	(0.031)	(0.020)	(0.030)	(0.022)	(0.030)	(0.032)	(0.049)	(0.051)
workers aged 35	0.068**	0.084***	0.049	0.176***	0.006	0.026	0.097***	0.062***	0.065***	0.049***	0.056**	0.003	0.224***	0.094**
to 44-years	(0.030)	(0.024)	(0.047)	(0.029)	(0.047)	(0.033)	(0.027)	(0.016)	(0.024)	(0.019)	(0.025)	(0.029)	(0.040)	(0.046)
workers aged 45	0.035**	0.050**	0.031	0.113***	-0.016	0.024	0.042*	0.025**	0.041**	0.023	0.031	-0.005	0.037	0.003
to 54-years	(0.015)	(0.020)	(0.044)	(0.026)	(0.042)	(0.029)	(0.023)	(0.012)	(0.018)	(0.015)	(0.019)	(0.022)	(0.030)	(0.037)
observations	45,595	0.35	2,453	3,310	3,160	2,846	4,546	4,696	3,337	3,625	3,223	2,793	4,044	3,943
R-squared	0.17	3,619	0.21	0.36	0.23	0.30	0.33	0.42	0.39	0.40	0.45	0.37	0.26	0.24

Notes: The dependent variable is log hourly wage rate. Panel A: Base group is workers aged 45 to 54 years. Panel B: Base group is workers aged 55-years and over. Regressions control for years of schooling, years of work experience, a quadratic polynomial in years of work experience, highest parental education, and gender. Pooled specification controls for country fixed effects. Robust standard errors in parenthesis. Statistical significance: *** at the 1% level, ** 5% level, * 10% level.

Chapter 6

Conclusions and Future Research

6.1 Summary of Contributions

The performance of the New Zealand economy has lagged behind that of comparative economies in key metrics, including productivity and income growth over time. Production in New Zealand is considered relatively labour-intensive, making human capital a factor of interest in an evaluation of contributing factors for performance. The work of Kidd (2008) and others identifies skills as a key driver of New Zealand labour productivity. It is well established that human capital provides the skills, knowledge, and creativity organisations need to drive innovation, productivity, and economic growth. Further, investment in human capital provides employment opportunities, lifting income levels and standards of living, as well as improving social cohesion and equity. As for physical capital, human capital depreciates, making on-going investment necessary. Theoretically and in empirical studies, human capital is embedded within the neoclassical growth framework including the exogenous models of Mankiw, Romer, and Weil (1992) and endogenous models of Romer (1990). Human capital is also an essential element in Mincer's (1974) education-labour return model. These frameworks set the foundation for my human capital-growth-labour market study for the New Zealand economy. The literature is scarce on the impacts of this key metric on the performance of the New Zealand economy. In addition, there are limitations in the ability of traditional measures of human capital, notably years of schooling, and qualifications (Barro and Lee, 1996, 2001) to fully capture the effects of skills on performance metrics. These considerations motivate my study to identify and more fully evaluate relationships between existing and expanded human capital measures and income and productivity. These findings will, in turn, allow for policy suggestions aimed at further improving standards of living for New Zealanders, and internationally.

A comprehensive analysis requires an understanding of human capital interactions both at the macro- and the micro-economic level. Accordingly, I examine the impacts of skill factors on productivity and earnings at the economy-wide level and then at the individual industry level, within a neoclassical growth framework. I then drill down beyond the traditional measures of schooling and qualifications using a Mincer (1974) earnings model to examine the effects of the core cognitive skills of literacy, numeracy, and ICT problem-solving on worker income. I also evaluate expanded measures including the effects of further education beyond the foundation years, as considered by Rees (2010), to assess the importance of lifelong learning for income.

In Chapter 3, in first evaluating factors affecting labour productivity for the aggregate New Zealand economy, I find positive relationships between capital intensity and labour productivity, and between total factor productivity and labour productivity at the aggregate level. These results support the literature including Rao, Tang, and Wang's (2003) findings of stronger productivity growth for the United States compared to Canada from greater physical capital utilisation, and Razzak's (2007) observation of higher capital intensity and endogenous technology (TFP) shocks as key explanatory drivers for Australia's higher labour productivity relative to New Zealand's for the 1989 to 2003 period. For total factor productivity, the results are indicative of the potential to lift New Zealand's economic performance through greater use of technology in production (Sorbe, Gal, Nicoletti, and Timiliotis, 2019). I find no significant results from average industry skill or productivity on labour earnings. This result does not support the literature in finding a link from productivity gains to worker income (Krugman, 1997).

I also observe a positive relationship between capital intensity and labour productivity at the micro-level, for most industries studied. When considering average industry skill level, those industries with lower-to-medium average labour skill see the largest productivity gains from increased capital intensity, relative to the lower skilled sectors as the base group. These industries include the utilities, wholesale trade, rental, and transport and storage sectors. They make relatively high use of physical capital in production, pointing to skills-capital complementary effects. Industries with lower and higher average skilled workers, which tend to be more labour-intensive, may also potentially see productivity gains from greater capital use.

In examining the effects of input cost and returns on capital intensity by industry, I observe a negative relationship between labour cost and capital intensity for most New Zealand industries studied. Average industry skill level does not appear to play a part in this. The result indicates that firms do not substitute physical capital for labour when labour costs rise but may instead reduce investment spending as part of cost management. This will not support greater capital intensity and labour productivity, particularly in a labour-intensive economy. For physical capital returns, I find a positive relationship with capital intensity, but with economically small effects. This indicates an overall low sensitivity for capital intensity change arising from higher physical capital returns. Greater industry fixed capital formation modestly increases capital intensity, and an increase in full-time equivalent employment by industry will lower capital intensity. The latter result indicates a further substitution effect of labour for capital, which may serve to lower overall productivity. Compounding these results, I find an increase in the total supply of labour lowers average labour productivity, suggesting decreasing efficiency effects from greater labour use in production. This may point to falling labour quality. My results contribute to the literature in finding no evidence of efficiency wage effects in the New Zealand economy, with no significant results from wage rates to labour productivity. The findings point to the importance of labour skill, technology, and physical capital for productivity and income growth in the New Zealand economy.

Where previous education-earnings studies have principally applied years of schooling, or qualifications, as the dominant measures of human capital in Mincer models, in my Chapter 4 study, I seek to drill down to evaluate the impact of the underlying core cognitive skills of literacy, numeracy, and ICT problem-solving on worker income. More recent data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) has made this study possible. While each skill proficiency measure individually is positive for income, I find a consistently significant and positive relationship for numeracy skill proficiency. As a more novel element, I evaluate the relationship between frequency of use of the core skills and earnings. Here I find an increase in the frequency of use of ICT problem-solving skills in work tasks has a significant and positive effect on worker income. Greater use of reading and numeracy skills in the workplace are also positive when considering monthly compensation, rather than hourly wage rates. These results reflect demand for these skills in the New Zealand workplace and highlights the importance of technology and its continued adoption in workplace tasks for improving labour earnings, together with greater numeracy skill proficiency.

Although not the main variables of interest in this study, though controlled for, I find consistently significant positive effects for the traditional human capital variable of years of schooling, and for experience on income, as expected from the literature A further important result obtained is that further job-related adult education and training in New Zealand is positive for worker earnings (Rees, 2010). This highlights the policy need for ongoing development of programmes aimed at supporting adult education both in the workplace and beyond to improve the earnings potential of individuals.

My study also considers the impact of average occupational skill level on New Zealand worker earnings. The findings of this thesis support the literature with a positive relationship between average occupational skill and income. A result against this trend is that white-collar workers experience lower earnings than blue-collar workers, relative to the base group of skilled workers. This result aligns with the finding of Levy and Murnane (2004), among other authors, of a 'hollowing out' effect where 'middle-range' tasks typically found in white-collar skill positions are lost or substituted to automation. I contribute further to the literature in examining the impacts for occupational skill level labour earnings from greater use of the cognitive skills in workplace tasks. There are gains to income for each occupational skill grouping from greater use of numeracy skills in the workplace and for all skills except use of ICT at work for skilled workers. These results reinforce the benefits of cognitive skill use for improving earnings.

I also evaluate the important effects that age may have for earnings, separate from and controlling for work experience. This is undertaken through age and age/gender interactions. The literature (Murphy and Welch, 1990, Thornton, Rodgers and Brookshire, 1997) provides evidence of a concave age/earnings profile with earnings rising with age and experience. At a certain point, the importance of these variables, and particularly experience, diminishes. A contribution of this study is that whilst there is indication of the typical concave profile, I find peak earnings overall for workers in the

35 to 44-year age group, rather than the 45 to 54-year or older age groups suggested through the literature. By gender, a concave age-earnings profile is observed for females, with males showing a tapering profile in contrast. I find that improved numeracy skill proficiency raises worker income both by age group and gender. For workers in the prime working age grouping of 25 to 54-year-olds, there is a consistent positive effect on earnings relative to a base group of workers aged 24-years or less. Workers aged 55-years and older see less benefit for earnings. Males see greater income benefit from an increase in numeracy proficiency than female workers. For age effects on income inequality, the interquartile range increases with age. This suggests that higher wages are distributed to a diminishing number of workers as age increases. These results indicate a loss of earnings potential for the New Zealand economy in undervaluing a significant proportion of the workforce, and particularly the contribution of female workers. It may also point to possible discrimination for older workers.

In Chapter 5, I examine the impacts on average worker earnings growth from increases to cognitive skill proficiency and usage for 13 countries. A key objective is to identify and evaluate common trends and differences between individual countries and country groupings for further analysis. Similar to the results for my New Zealand study, I find the largest gains to average earnings from skills usage across the 13 countries is from greater use of ICT problem-solving skills in workplace tasks. This indicates international demand for this technology skillset. For skill proficiency effects, improvements to numeracy skill provides the most consistent benefit for worker earnings in labour markets. The results also support the robustness of my findings in the New Zealand economy study in Chapter 4.

Building on the significance of years of schooling for earnings, further adult education and job-related training beyond foundation learning is important for improving worker income internationally. Countries with the highest income potential from greater investment in further education programs include Japan, the United Kingdom, and Ireland. Countries with the least income potential are those with well-established programmes, principally Northern European countries. In examining the relationship between occupational skill and earnings internationally, I find that white-collar workers generally see lower earnings than blue-collar workers. However, increased numeracy skill proficiency helps to reduce these earnings differences. This is particularly so for countries with more flexible labour markets. Greater cognitive skill also has positive impacts for worker income by age group internationally, with income gains for those in the lower three age bands from higher numeracy skill and for workers in the 25 to 44-year age band from greater ICT skill proficiency. Countries with more flexible labour markets experience the largest gains from numeracy skill improvements. ICT skills benefit workers regardless of labour market type. Overall, these results indicate that regulation is not always the most effective way to deliver income growth. Addressing labour skill demand in flexible markets may provide the most effective outcomes.

6.2 Policy Recommendations

My study identifies a number of policy measures to support improvements to income and productivity in the New Zealand economy. From Chapter 3, I identify greater capital intensity as a key driver for gains in labour productivity, with a positive, although economically modest, relationship also found between overall gross fixed capital formation and the capital-to-labour ratio in production. From this, labour productivity gains may occur from further government financial support or subsidy to encourage increased capital formation. This should be targeted particularly at lower and medium-skill industries. The strong relationship I find between total factor productivity and labour productivity also highlights the importance of technology and the need for policy to further encourage technology adoption in industry. This will be particularly beneficial in lower-skilled industries including the retail and hospitality sectors but also to enhance the value of elementary and white-collar workers, to reduce the 'hollowing out' effect seen for the latter occupational skill group. It is essential that this occurs in a way that is not job-depleting. Such policy may include the further use of subsidy and attractive financing for new technology embedded in physical capital. This in turn may raise labour productivity, income levels and growth rates in the medium to longer term.

I also observe the benefit from greater adoption and integration of technology for lifting New Zealand's economic performance in Chapter 4 through the gains to worker income from greater use of ICT problem-solving skills in the workplace. Policy for the continuing development of information and communication infrastructure will also support this. For skill proficiency, demand for higher proficiency in numeracy skills is reflected through a positive earnings relationship. This is found in both the New Zealand study in Chapter 4 and the international study in Chapter 5. These results highlight the need for continuing policy to strengthen numeracy skills through education systems. These gains are also evident for reducing gender and age earnings imbalances. Additionally, while worker protection reduces occupational skill earnings differences, as evident for northern European countries, more flexible labour markets may provide higher income gains from improvements in cognitive skill proficiency. These findings support the need for balance in labour markets to promote income equality and income gains from skills. The results also support policy to encourage the development of and engagement in further adult education and training to improve worker earnings in the New Zealand labour market.

A finding of great concern, well recognised in the literature, is the earnings gap for female workers. In addition, when measuring age and gender effects, this study shows that female workers have the lowest average earnings for every age category relative to a base group of males aged 35 to 44 years. In addition to the benefits identified from greater cognitive skill proficiency and use for reducing income disparities, these findings suggest a strong need for action to lift female earnings as a significant way to raise household income, both for the New Zealand economy and internationally. Peak earnings occur for workers overall in the 35 to 44-year age group, with a more pronounced fall in earnings for female workers after this age range. Such age-related earnings trends may discourage involvement in the workplace and lower productivity for workers still in their prime working years. Policy to encourage non-age-driven employment and promotion practices are needed for improving productivity and household income. Hence, each of these policy initiatives are critical for supporting growth in earnings and productivity in the New Zealand labour market and internationally, to improve future economic growth and support higher levels of household standards of living.

6.3 Limitations of the Study

For the research and analysis in Chapter 3 for the New Zealand economy, a limitation has been a lack of available data for skill measurement by industry. Inconsistency in data availability has also limited the number of industries included in my study to 14 industries. The omitted sectors include agriculture and ICT-specific industries. The agriculture sector is vital as a key contributor to New Zealand’s export earnings, and

ICT-specific industries are of significance as a future-facing sector. The lack of data for these industries limited analysis of the wider New Zealand economy. Further, the annual frequency for some of the economic data series prevented time-series evaluation. For Chapters 4 and 5, the analysis of labour earnings relies on cross-sectional methods. This has prevented panel data comparisons and greater robustness checks for the results. PIAAC earnings data was also not available for some of the developed countries of relevance to this study. These included the Australian and United States economies.

6.4 Further Research

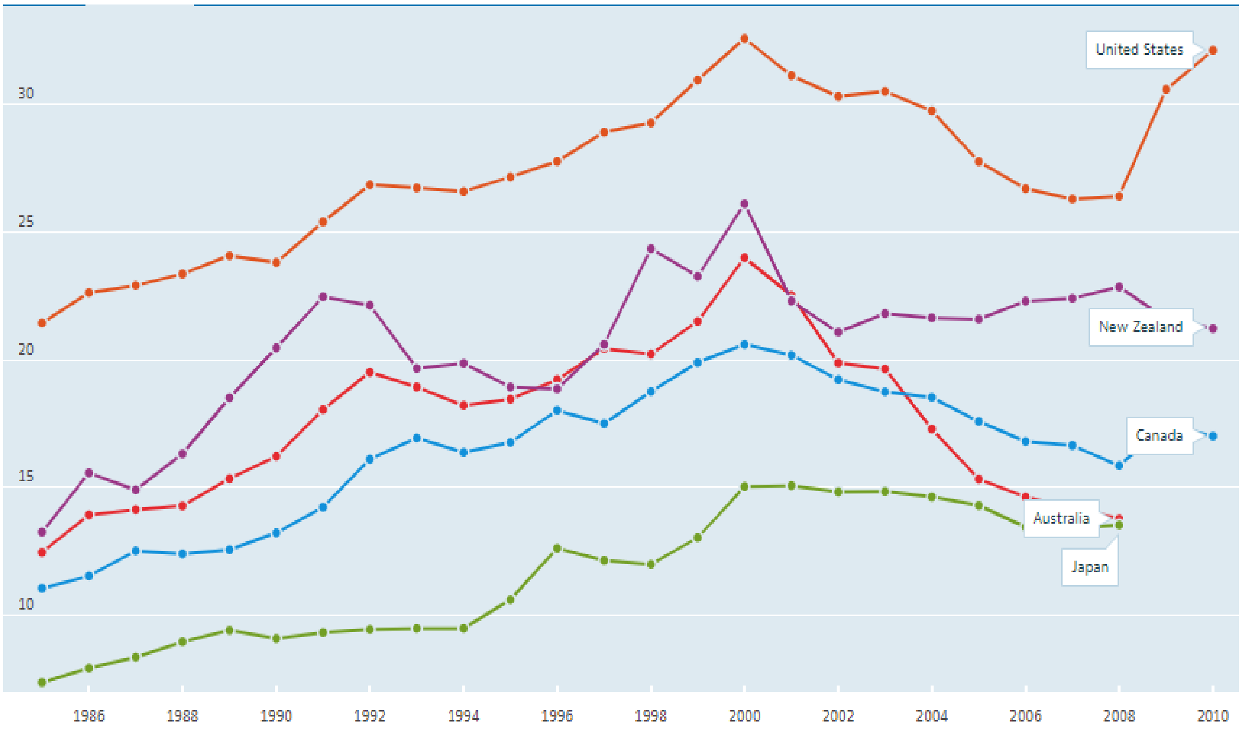
The findings from my study support additional avenues for research into the potential impacts of human capital on productivity and earnings for the New Zealand labour market and economy. Importantly, further research using the second survey cycle of the Programme for the International Assessment of Adult Competencies (PIAAC), taking place from 2022 to 2023, will allow the continued evaluation of human capital effects for earnings over time. It will also allow for panel data analysis to further strengthen the robustness of the results obtained here. For the New Zealand economy as the focus of this study, data for a longer time period will allow for time series studies and for the inclusion of additional important industries. A targeted comparative analysis with an economy similar to New Zealand's will offer additional insights. Long-run growth modelling incorporating human capital and technology will provide another dimension to this research, allowing for the evaluation of convergence effects for the New Zealand economy. These further research avenues will support ongoing progress in understanding human capital's impact on productivity and income. This will allow for further policy guidance supporting improvements in economic growth and overall standards of living aimed at closing New Zealand’s income gap with comparative economies.

Appendix E.

Appendix E.1.

Figure 6.1 shows the share of ICT investment used in production as a share of total non-residential gross fixed capital formation for New Zealand and comparative countries. The time period is for the full period of data collection: 1985 to 2010. Growth in investment occurred until 2000, after which the next decade experienced a flattening or decline in investment, with some increase for the United States from 2008.

Figure 6.1 Share of ICT Investment Used in Production as a Share of Total Non-Residential Gross Fixed Capital Formation



Notes: ICT investment is defined as the acquisition of equipment and computer software that is used in production for more than one year. ICT has three components: information technology equipment (computers and related hardware); communications equipment; and software. Software includes the acquisition of pre-packaged software, customised software and software developed in-house. This indicator is measured as a percentage of total non-residential gross fixed capital formation (The data is only available to 2010). Source: OECD Data: https://data.oecd.org/ict/ict-investment.htm

Appendix E.2.

Table 6.1. presents the rankings for the United Nation's education index, the Human Development Index (HDI). The index is calculated from mean years of schooling and expected years of schooling. The HDI is presented for the period 1980 to 2013 for multiple countries, with rankings calculated over the full period. New Zealand's human capital ranks in 7th place, with an incremental increase in performance over the time period, similar to many countries.

Table 6.1. United Nation's Education Index – Human Development Index (HDI), 1980 to 2013.

HDI Rank	Country	1980	1985	1990	1995	2000	2005	2006	2007	2008	2009	2010	2011	2012	2013
1	Norway	0.666	0.699	0.75	0.805	0.87	0.91	0.912	0.909	0.903	0.902	0.907	0.91	0.91	0.91
2	Australia	0.87	0.87	0.874	0.894	0.895	0.902	0.905	0.907	0.913	0.916	0.919	0.922	0.927	0.927
3	Switzerland	0.678	0.675	0.695	0.726	0.804	0.822	0.827	0.828	0.83	0.834	0.841	0.844	0.844	0.844
4	Netherlands	0.667	0.686	0.744	0.811	0.824	0.844	0.85	0.86	0.86	0.859	0.866	0.892	0.894	0.894
5	United States	0.79	0.805	0.834	0.861	0.85	0.867	0.87	0.876	0.88	0.884	0.887	0.89	0.89	0.89
6	Germany	0.59	0.6	0.646	0.739	0.787	0.858	0.872	0.875	0.877	0.879	0.879	0.884	0.884	0.884
7	New Zealand	0.76	0.772	0.794	0.864	0.885	0.908	0.91	0.911	0.913	0.915	0.917	0.917	0.917	0.917
8	Canada	0.749	0.763	0.809	0.826	0.808	0.853	0.853	0.852	0.851	0.851	0.85	0.85	0.85	0.85
9	Singapore	..	..	0.545	0.58	0.606	0.667	0.684	0.698	0.714	0.715	0.759	0.759	0.759	0.768
10	Denmark	0.672	0.704	0.711	0.751	0.804	0.864	0.863	0.865	0.867	0.868	0.873	0.873	0.873	0.873
11	Ireland	0.633	0.666	0.697	0.743	0.837	0.866	0.867	0.88	0.884	0.886	0.887	0.887	0.887	0.887
12	Sweden	0.659	0.665	0.692	0.792	0.866	0.83	0.827	0.824	0.824	0.823	0.833	0.83	0.83	0.83
13	Iceland	0.598	0.639	0.673	0.732	0.786	0.829	0.833	0.836	0.84	0.843	0.847	0.847	0.847	0.847
14	United Kingdom	0.608	0.622	0.642	0.791	0.836	0.866	0.854	0.852	0.859	0.865	0.878	0.86	0.86	0.86
15	Hong Kong, China (SAR)	0.53	0.589	0.626	0.639	0.648	0.683	0.69	0.713	0.748	0.758	0.759	0.762	0.767	0.767
15	Korea (Republic of)	0.565	0.638	0.679	0.743	0.797	0.837	0.843	0.848	0.854	0.856	0.862	0.865	0.865	0.865
17	Japan	0.663	0.681	0.699	0.74	0.767	0.785	0.79	0.792	0.795	0.8	0.802	0.808	0.808	0.808
18	Liechtenstein	..	..	..	..	..	..	..	..	..	..	0.75	0.762	0.762	0.762
19	Israel	0.675	0.706	0.714	0.764	0.82	0.848	0.846	0.849	0.844	0.847	0.848	0.851	0.854	0.854
20	France	0.543	0.571	0.633	0.728	0.761	0.79	0.792	0.796	0.8	0.803	0.807	0.813	0.816	0.816
21	Austria	0.592	0.614	0.661	0.699	0.73	0.747	0.756	0.759	0.771	0.78	0.794	0.794	0.794	0.794
21	Belgium	0.626	0.655	0.705	0.804	0.835	0.792	0.794	0.796	0.797	0.802	0.807	0.812	0.812	0.812
21	Luxembourg	0.551	0.584	0.598	0.641	0.734	0.743	0.744	0.746	0.748	0.755	0.762	0.762	0.762	0.762
24	Finland	0.645	0.665	0.691	0.758	0.765	0.812	0.816	0.814	0.815	0.808	0.812	0.815	0.815	0.815
25	Slovenia	..	0.653	0.697	0.724	0.794	0.842	0.849	0.85	0.854	0.858	0.864	0.862	0.863	0.863
26	Italy	0.542	0.556	0.592	0.65	0.695	0.762	0.768	0.775	0.779	0.78	0.784	0.79	0.79	0.79
27	Spain	0.516	0.551	0.596	0.694	0.721	0.742	0.747	0.753	0.763	0.768	0.783	0.792	0.794	0.794
28	Czech Republic	..	0.689	0.693	0.726	0.783	0.85	0.848	0.854	0.851	0.86	0.863	0.866	0.866	0.866
29	Greece	0.543	0.595	0.596	0.637	0.68	0.794	0.803	0.792	0.794	0.795	0.797	0.797	0.797	0.797
30	Brunei Darussalam	0.519	0.541	0.589	0.626	0.646	0.672	0.682	0.681	0.677	0.682	0.678	0.681	0.692	0.692
31	Qatar	0.479	0.513	0.508	0.562	0.612	0.673	0.686	0.699	0.703	0.689	0.68	0.671	0.686	0.686
32	Cyprus	0.465	0.513	0.546	0.655	0.676	0.731	0.74	0.751	0.765	0.778	0.765	0.771	0.776	0.776
33	Estonia	..	..	0.674	0.705	0.808	0.855	0.853	0.854	0.852	0.852	0.859	0.859	0.859	0.859
34	Saudi Arabia	0.304	0.363	0.427	0.482	0.565	0.617	0.624	0.63	0.641	0.66	0.688	0.707	0.721	0.723

35	Lithuania	..	..	0.662	0.668	0.767	0.85	0.856	0.864	0.872	0.882	0.883	0.877	0.877	0.877
35	Poland	0.591	0.628	0.667	0.72	0.78	0.795	0.797	0.799	0.801	0.808	0.817	0.823	0.825	0.825
37	Andorra	..	..	..	..	..	..	..	..	..	..	0.67	0.67	0.67	0.67
37	Slovakia	..	..	0.68	0.708	0.743	0.784	0.789	0.797	0.8	0.802	0.805	0.802	0.802	0.802
39	Malta	0.58	0.584	0.585	0.587	0.616	0.684	0.682	0.679	0.688	0.705	0.722	0.722	0.733	0.733
40	United Arab Emirates	0.358	0.416	0.471	0.543	0.604	0.649	0.654	0.659	0.664	0.669	0.673	0.673	0.673	0.673
41	Chile	0.528	0.576	0.625	0.615	0.65	0.707	0.705	0.717	0.74	0.737	0.74	0.746	0.746	0.746
41	Portugal	0.451	0.502	0.535	0.631	0.656	0.661	0.667	0.677	0.69	0.701	0.713	0.72	0.728	0.728
43	Hungary	0.604	0.625	0.597	0.7	0.755	0.793	0.797	0.798	0.799	0.801	0.808	0.805	0.805	0.805
44	Bahrain	0.425	0.535	0.574	0.619	0.656	0.711	0.703	0.706	0.708	0.711	0.714	0.714	0.714	0.714
44	Cuba	0.553	0.586	0.625	0.62	0.66	0.735	0.771	0.803	0.819	0.819	0.79	0.768	0.743	0.743
46	Kuwait	0.454	0.514	0.471	0.524	0.637	0.609	0.61	0.612	0.619	0.626	0.633	0.639	0.646	0.646
47	Croatia	..	..	0.497	0.553	0.656	0.708	0.719	0.729	0.737	0.744	0.76	0.77	0.77	0.77
48	Latvia	0.58	0.605	0.601	0.622	0.709	0.796	0.804	0.814	0.824	0.823	0.822	0.813	0.813	0.813
49	Argentina	0.538	0.598	0.627	0.648	0.711	0.726	0.73	0.729	0.732	0.756	0.783	0.783	0.783	0.783
50	Uruguay	0.545	0.567	0.597	0.609	0.66	0.691	0.693	0.708	0.709	0.709	0.707	0.71	0.712	0.712

Notes: Calculated using mean years of schooling and expected years of schooling. Data in the table are those available to the Human Development Report Office as of 15 November, 2013. Source: http://hdr.undp.org/en/content/education-index

Appendix E.3.

Table 6.2. presents the results for 15-year-old student achievement in reading, mathematics, and collaborative problem-solving for the OECD's Programme for International Student Assessment (PISA) for the period 2012 to 2018. Countries are ranked from the top to the fifteenth highest attainment. New Zealand students are included in the rankings for the top 15 countries for 2015 and 2018 for literacy achievement and for the 2015-year top fifteen rankings for collaborative problem-solving. New Zealand ranks 29th for numeracy skills.

Table 6.2. Pisa Score Rankings, 2012 to 2018

Reading			Numeracy			Collaborative Problem-Solving
Top Fifteen Countries 2012	2015	2018	Top Fifteen Countries 2012	2015	2018	Top Fifteen Countries 2015*
China	Singapore	China	China	Singapore	China	Singapore
Hong Kong	Canada	Singapore	Singapore	Hong Kong	Singapore	Japan
Singapore	Hong Kong	Macao	Hong Kong	Macao	Macao	Hong Kong
Japan	Finland	Hong Kong	Taiwan	Japan	Hong Kong	Korea
Korea	Ireland	Estonia	Korea	China	Taiwan	Canada
Finland	Estonia	Canada	Macao	Korea	Japan	Estonia
Canada	Korea	Finland	Japan	Switzerland	Korea	Finland
Ireland	Japan	Ireland	Liechtenstein	Estonia	Estonia	Macao
Taiwan	Norway	Korea	Switzerland	Taiwan	Netherlands	New Zealand
Poland	Germany	Poland	Netherlands	Canada	Poland	Australia
Estonia	New Zealand	New Zealand	Estonia	Netherlands	Switzerland	Taiwan
Liechtenstein	Macao	Sweden	Finland	Finland	Canada	Germany
New Zealand	Poland	United States	Canada	Denmark	Slovenia	Denmark
Australia	Slovenia	Japan	Poland	Slovenia	Denmark	United States
Netherlands	Australia	United Kingdom	Belgium	Belgium	Belgium	United Kingdom

Notes: Only the 2015-year results are included for collaborative problem-solving as a number of countries Were omitted in 2012. Problem-solving tests Were not undertaken in 2018.
Source: 2012: https://www.oecd.org/pisa/keyfindings/pisa-2012-results-overview.pdf
2015: https://www.oecd.org/pisa/pisa-2015-results-in-focus.pdf 2018: https://www.oecd-ilibrary.org/

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