Investigating drivers for macroeconomic soft skill demand

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To my parents, Bernhard and Marion

Statement of originality

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Acknowledgement of Authorship

I hereby certify that the work embodied in this thesis contains published paper/s/scholarly work of which I am a joint author. I have included as part of the thesis a written declaration endorsed in writing by my supervisor, attesting to my contribution to the joint publication/s/scholarly work. By signing below I confirm that Aaron Semtner contributed significantly to the following: conceptualisation, literature review, selecting and accessing data, methodological design, empirical analysis, writing for publication, and submission to the journal for the papers/publications entitled:

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List of abbreviations and acronyms

ABS	Australian Bureau of Statistics
AI	Artificial intelligence
AIC	Akaike Information Criterion
ANZSIC	Australian and New Zealand Standard Industry Classification
ANZSCO	Australian and New Zealand Standard Classification of Occupations
ASC	Australian Skills Classification
ATSI	Aboriginal and Torres Strait Islander
CFA	Confirmatory factor analysis
CFI	Comparative fit index
CLMM	Cumulative link mixed model
CPS	Current Population Survey
ESB	English-speaking background
GAI	Generative artificial intelligence
GFC	Global Financial Crisis
GLMM	Generalised linear mixed method
GMM	Generalised method of moments
HILDA	Household, Income and Labour Dynamics Australia
ICT	Information communication technology
IMF	International Monetary Fund
IPS	Im, Pesaran, & Shin (2003)
KLEMS	Capital, labour, energy, materials, and services
LLM	Large language model
MFP	Multifactor productivity
NESB	Non-English-speaking background
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
PIAAC	Progress for the International Assessment of Adult Competencies
PISA	Programme for International Student Assessment
PMM	Predictive mean matching
R&D	Research and development
RBA	Reserve Bank of Australia

RBTC	Routine-biased technological change
RMSEA	Root mean square error of approximation
SNA	System of National Accounts
SBTC	Skill-biased technological change
TFP	Total factor productivity
TLI	Tucker-Lewis Index
USA	United States of America
VAR	Vector Autoregressive
VIF	Variance inflation factor

Abstract

From the implementation of new and emerging technologies including artificial intelligence (AI) through to occupational shifts with reduced employment in traditional manufacturing and even some service jobs, Australian workers risk facing displacement from a range of sources. These risks can reduce the wages and job mobility of Australian workers, increase the risk of unemployment particularly among those in traditional routine task jobs, and potentially slow productivity and output growth. One possible avenue for supporting workers during this instability while improving their productivity is to improve their human capital; however, there has been limited research on how specific forms of human capital benefit Australian workers and production in modern technological environments. This thesis investigates soft skills as a form of human capital relevant in modern economies, due to how these skills simultaneously enable workers to better work in offices affected by these transitions and as these skills are difficult to automate. However, there is a knowledge gap on the strength of the benefit of soft skills, particularly for the Australian economy. As such, this thesis investigates whether these soft skills have previously benefited Australian workers and the broader economy via analyses from multiple perspectives on the Australian labour market and economy.

The first empirical chapter in this thesis investigates whether worker job mobility is associated with higher soft skills, as these skills are utilised across a range of occupations and thus should enable workers to reallocate to where they are most valued. This chapter utilises the Household, Income and Labour Dynamics of Australia (HILDA) data to investigate worker job mobility and how this is associated with a selection of soft skill proxies including time management, social capital, and low task repetitiveness in the job. A Cox survival analysis is chosen to test if soft skills are associated with a reduced duration between job-to-job transitions. This modelling finds none of the soft skill measures have a significant association with the duration between job transitions. By comparison, endowments of overall skills have a mixed relationship: education is primarily relevant through the positive relationship between vocational education and duration, although some specifications suggest school education is also positively associated; meanwhile, having a job with a higher ability to decide what to do in it is positively associated with lower mobility. When further testing how this job mobility correlates with wages in a linear random effects model with Mundlak corrections and

interactions between job mobility and skills, this research finds job mobility has no significant association with wages, excluding one interaction term with university education that has a negative association with wages. These results find soft skills have no broader relationship with wages, with only low task repetitiveness having a significant and positive association with wages.

The second empirical chapter in this thesis investigates how soft skills are associated with unemployment risk, also using the HILDA data and replacing communication skills with social capital as a form of soft skill development. This chapter focuses on the Global Financial Crisis (GFC) as being associated with further reducing the risk of unemployment for workers with higher soft skills, based on skill-biased technological change (SBTC) or routine-biased technological change (RBTC). As businesses may use alternative methods to control costs or fill necessary employment gaps during a negative economic shock, additional specifications are tested that include underemployment and overskilling as intermediate levels of labour match between well employed and unemployed. This chapter also utilises the HILDA data to determine the risk of unemployment in nonlinear random effects logit regression models with Mundlak corrections and year effect interactions to test for year-by-year changes in these skills. The results find social capital has a significant association with reducing all negative outcomes, while the remaining soft skill proxies demonstrate insignificant results for all specifications bar overskilling. In this overskilling model, low task repetitiveness is associated with a lower risk of overskilling; however, this appears to stem from job attributes instead of underlying skills. Similarly, time management has a significant and positive association with unemployment risk, appearing to stem from the underlying construct rather than time management itself. Further, the overskilling specification has significant year interactions for all skill measures from 2009 to 2015, potentially suggesting SBTC and RBTC occurred and had lingering effects. Of these interactions, both time management and social capital have negative associations with overskilling risk, reinforcing the potential effects of the GFC on skill usage for Australian workers. Overall, this is some evidence in favour of soft skills having an effect on workers, albeit constrained by the significance primarily within the overskilling model and the overall positive association between time management and overskilling.

The third empirical chapter investigates the industry perspective to determine whether soft skills are associated with increased productivity and output. To investigate SBTC and

RBTC in particular, this chapter includes information communication technology (ICT) as both an individual variable and with a moderating interaction with overall soft skill level in some specifications. Seven skills formed the basis for the soft skill component: initiative and innovation, learning ability, oral communication, planning and organising, problem solving, teamwork, and writing as a measure of written communication. Models were tested using two specifications of soft skills: an overall soft skill measure generated using confirmatory factor analysis (CFA) for investigating the overall relationship and for the moderating relationship with ICT, and the individual measures for more detailed investigation of individual skill relationships. These specifications were tested for three measures of industry capability: multifactor productivity (MFP), overall value-added output, and per worker value-added output. Based on the Australian Skills Classification (ASC) and Australian Bureau of Statistics (ABS) data utilised, a short-run fixed effects model estimated using ordinary least squares (OLS) was used to test these specifications. This research finds overall soft skills and their moderating interaction with ICT are insignificant. When broken down into individual soft skills, oral communication is associated with higher industry value added and written communication is associated with lower industry value added, with no other soft skills of significance. This suggests soft skills are of limited value in the short-run. Further, oral and written communication are also only significant in the overall value added model, suggesting potential industry-wide effects of deep labour pools are more relevant than the aggregate skill level of the workers.

These results suggest the effect of soft skills on the Australian economy varies depending on the type of skill measure and the economic outcome governments to be improved, with the conclusion detailing policy recommendations and theoretical contributions. For the practical applications, soft skills have limited effect at the macroeconomic level beyond overskilling and to a lesser degree unemployment risk, thus training should depend on what is required for the job or education program. However, broader communication skills and social capital did demonstrate significance across multiple specifications, reinforcing the relevance of these particular skills. The significance of social capital highlights the importance of developing soft skills beyond traditional education and workplace environments. Further, while soft skills do not affect employment duration, overall skills that synergise with soft skills can be associated with longer employment durations. This suggests businesses should develop these skills via internal training or recruitment out of university for the whole set of skills relevant.

For research contributions, these results suggest businesses seeking to acquire skills should not expect to easily find workers changing jobs who have a broader array of skills. However, there are potential benefits to having deeper pools of workers groups of businesses can draw from based on the significance of certain skills at the industry level even in the short-run. For governments, these results suggest limited widespread effects of SBTC and RBTC on workers or skill categories outside of overskilling risk to a limited degree, suggesting skills development needs to be tailored for specific uses rather than anticipating broader applications to worker security. However, as these data were all before the advent of widely utilised artificial intelligence (AI), there is the need to consider changes among these associations as applications of this emerging technology develop.

Chapter 1. Introduction

1.1. Introduction

This chapter introduces soft skills, the Australian economy, and how the former can assist the latter's performance. Section 1.2 provides background on the overall linkage between the Australian economy and these particular skills in the modern day. Section 1.3 describes the theory behind the value of how soft skills can contribute to the Australian economy, while Section 1.4 describes characteristics that distinguish the Australian economy from other countries where more research on soft skills and associated theories has been conducted. Section 1.5 describes this gap in detail, with Section 1.6 describing the research questions and Section 1.7 the research objectives of this thesis. Section 1.8 describes the methods applied to answer these questions and resolve the overall gap. Section 1.9 provides additional information on the particular significance of this thesis. Finally, Section 1.10 outlines the rest of the thesis.

1.2. Background

Modern developed economies, including Australia, have been facing multiple forces affecting their labour utilisation since the turn of the century. New technologies and uses for technology have been introduced, including Big Data, chatbots, and potentially artificial intelligence (AI). Education requirements for jobs, particularly entry-level jobs, have also been increasing over this time period (Jobs and Skills Australia, 2023), along with the demand for additional skills to utilise modern technologies and applications (Jobs and Skills Australia, 2023). Further, occupations have been transitioning from historic manufacturing and agricultural jobs to service sector jobs (Mackey et al., 2022), with the loss of the local car manufacturing industry since 2017 a particularly notable example (Irving et al., 2022). Even among blue-collar work, it is skilled trades or other similar forms of skilled work that are in demand, as demonstrated by growth in the nonroutine manual occupation employment share (Mackey et al., 2022). Further, the mining sector that supported the Australian economy through the Global Financial Crisis (GFC) (Foo & Salim, 2022) also relies on skilled fly-in fly-out workers as a key component of its labour supply (Cameron et al., 2014). Modern workers also face less stable careers, changing employers more regularly (Foster & Guttmann, 2018), and thus need to be able to transfer skills between employers to maintain their position in the labour force. This all comes at a time when Baby Boomers globally are retiring from the labour force (Agarwal & Bishop, 2022), reinforcing the importance of retaining labour force employment to maintain macroeconomic conditions. And although the aforementioned mining sector was valuable during the GFC, it has experienced relatively minimal growth in productivity (Australian Bureau of Statistics, 2024b), while the Australian economy as a whole has yet to return to pre-GFC levels of productivity growth (Bruno et al., 2023). As such, the Australian economy can particularly benefit from improvements in productivity.

These effects appear disparate; however, one common link is the shift in skill requirements. In particular, international evidence suggests a key set of skills to support these modern transitions is soft skills (Robles, 2012; Whiting, 2020), a subset of skills that focuses on intrapersonal skills for self-management (Andreas, 2018; Marin-Zapata et al., 2021; National Careers Service, n.d.; Shakir, 2009) and interpersonal skills to work with others or communicate information (Andreas, 2018; Balcar, 2016; Marin-Zapata et al., 2021; National Careers Service, n.d.; Shakir, 2009; Ubalde & Alarcón, 2020). While these skills are harder to measure than traditional skill proxies such as education, understanding the types of skills required in modern jobs enables education and training to be directed to where it is most valuable. However, much of the research on soft skills and similar skills sets is from other nations, including the United States, with their own economic differences to Australia. Consequently, this thesis investigates whether soft skills have an effect on the modern Australian economy and labour force via multiple metrics.

1.3. Theorised value of soft skills

Following the above discussion of soft skills, this thesis draws upon two subsets of soft skills from the literature. The first group of skills is interpersonal skills to enhance productivity when working with a group or to better convey ideas (Andreas, 2018; Deng et al., 2014; National Careers Service, n.d.; Pang et al., 2019), which particularly includes communication (Andreas, 2018; Bacolod et al., 2009; National Careers Service, n.d.; Shakir, 2009; Ubalde & Alarcón, 2020) and teamwork (Andreas, 2018; Deng et al., 2014; Shakir, 2009). The second group considered is intrapersonal or self-management skills to improve one's own efficiency (Andreas, 2018; Marin-Zapata et al., 2021; National Careers Service, n.d.; Shakir, 2009), which includes time management (Andreas, 2018;

Deng et al., 2014; National Careers Service, n.d.; Pang et al., 2019) and problem solving (Andreas, 2018; National Careers Service, n.d.; Shakir, 2009). One further element is that these skills can be actively developed by workers (Andreas, 2018; National Careers Service, n.d.; Shakir, 2009). While some research considers personality traits and other individual-specific capabilities as soft skills or the similar category of noncognitive skills (Cinque et al., 2021; Cobb-Clark & Schurer, 2013), these traits are very stable, particularly among adults (Cobb-Clark & Schurer, 2013), and thus difficult to actively develop to meet demand.

This initial definition demonstrates soft skills contribute to productivity by enhancing the ability of workers to perform their role as a whole (Cimatti, 2016), rather than improving the efficiency of individual tasks. Beyond this, soft skills also contribute to overall human capital as skills form part of human capital (Becker, 1994). However, neither of these explain the particular relevance of soft skills in modern economies. As discussed later in Section 2.3.4, two further reasons stem from skill-biased technological change (SBTC) and routine-biased technological change (RBTC), where technology is biased in favour of high-skilled workers and jobs with nonroutine tasks respectively (Autor et al., 2003). Soft skills' relationship with SBTC stems from these skills contributing to the overall level of skills a worker has; however, RBTC is beneficial for soft skills specifically as these skills assist workers in performing nonroutine jobs (Robles, 2012; Tamm, 2018). As nonroutine occupations are a large and growing share of Australian employment (Mackey et al., 2022), this provides further evidence in favour of soft skill utilisation. A further relevant aspect of soft skills in the modern day is their transferability between different jobs and employers (Cimatti, 2016; Leighton & Speer, 2020; Snell et al., 2016), which is valuable with the previously raised increased change in employers in recent years.

1.4. Australia's economic background

The above discussions show the potential value of soft skills in modern economies, in particular developed economies. However, the Australian economy has its own characteristics that need to be considered. This section discusses some of these characteristics.

1.4.1. Economic structure

Australia's labour market has a high level of education, with the 9th highest level of tertiary education in the OECD (Mackey et al., 2022). Nonroutine employment, particularly for cognitive occupations, has been a growing proportion of employment even prior to the 21st Century (Borland & Coelli, 2024). These two factors combined suggest Australia is relatively skilled. The high skill level translates to improved wages for skilled Australian workers, with Strauss and de la Maisonneuve (2009) finding both Australian men and, to a lesser degree, women have a beneficial increase in log wages from tertiary education. While this premium is beneficial, there is also a risk of workers being overeducated or overskilled for their work if job matching systems are inefficient or there is an excess of education. Mavromaras et al. (2013) investigated the effects of overskilling and overeducation on the wages of Australian workers, with the panel data estimations finding workers who are simultaneously overskilled and overeducated have a significant wage penalty, while workers who are only overskilled or overeducated but not both have no significant penalty. However, Australian wages have grown at a slower pace in the 21st century, with the 15th highest wage growth in the OECD for 2000-2017 while average real wages have not changed since 2011 (Brell & Dustmann, 2019).

Australian labour market regulations are determined by the Federal Government, with the *Fair Work Act 2009* being a key piece of legislation (Rafi, 2017). A key and unique element of Australian workplace agreements is awards to specify minimum workplace requirements, with 122 award standards as of 2017; however, casual workers are less protected under these regulations. Overall, labour market regulation is moderate in relation to the OECD as a whole (Rafi, 2017).

The largest Australian industry since the mid-90s by value added has been the Mining sector, accounting for 9–10% of GDP. However, from 2010 to 2016 this share grew from 10% to 13% of GDP, highlighting the relevance of this sector in the post-GFC period (Australian Bureau of Statistics, 2024a). Further, Mining was only the largest contribution to MFP for two years from 1991 to 2024 (Australian Bureau of Statistics, 2024b), suggesting much of Mining's growth in value added was due to increased inputs and a large base rather than due to productivity improvements.

Australia's capital investment is skewed towards private businesses compared with the global average. Government investment was 3–4% of GDP from 2010 to 2019 (International Monetary Fund, 2022), which is close to the bottom quartile of the G20. In comparison, business investment was 20–25% of GDP for the same period excluding 2010 (International Monetary Fund, 2022), which is only consistently lower than Turkey and South Korea. This emphasises the importance of the market sector when analysing capital investment and technological applications.

1.4.2. Business cycle

Prior to the GFC, the Australian economy was enjoying relatively stable and good economic growth (Australian Bureau of Statistics, 2024a). When the GFC occurred, most developed economies went into recession; however, the Australian economy only experienced one quarter of real economic decline and thus avoided a technical recession (Debelle, 2018). Government support was a key component of this, with the Reserve Bank of Australia (RBA) having sufficient room to drop interest rates 375 basis points and fiscal policy providing three stimulus packages totalling over A$30 billion in October–December 2008 (McDonald & Morling, 2012). The overall fiscal package was also the third largest as a proportion of GDP for developed nations (Waring & Lewer, 2013). The surrounding conditions further benefited Australia's economy: China was implementing its own stimulus package, generating high demand for Australian exports that boosted economic growth (McDonald & Morling, 2012; Perlich, 2009; Waring & Lewer, 2013), while international migration to Australia was relatively strong during this period (McDonald & Morling, 2012; Waring & Lewer, 2013).

Between the GFC and COVID-19 pandemic shocks, Australia experienced some weakness in its growth. While exports, particularly mining, supported the economy during the GFC, the rest of the economy did not experience the same level of growth and thus created a two-speed economy (Perlich, 2009). Further, there was an increase in both overall unemployment (Mackey et al., 2022) and youth unemployment (Ballantyne et al., 2024; Junankar, 2015) after the GFC. And while there was no decline in real GDP during this time, the aforementioned migration masked a per capita recession in 2018-19 (Lorkin, 2019).

At the start of the pandemic, Australia initially implemented strict lockdowns on both domestic and international travel to curb the spread of COVID-19. Due to the economic effect of these restrictions, the Federal Government implemented three packages totalling A$150 billion in March 2020 alone to subsidise both businesses and households (Reserve Bank of Australia, n.d.-a). Despite this, the initial shock of the pandemic and lockdowns was sufficient to declare a recession (Janda & Lasker, 2020). Lockdowns were initially lifted internally in mid-May 2020, although additional state-level lockdowns continued to be implemented later and international travel only began to open up in November 2021 (Reserve Bank of Australia, n.d.-a).

By mid-2022 Australian production had nearly finished recovering to pre-COVID trends (Australian Bureau of Statistics, 2022). Unemployment and underemployment were low shortly after the pandemic and shutdowns, although they did begin to climb again by 2022 (Ballantyne et al., 2024). A key challenge for the Australian economy has been to manage inflation after the GFC as well, resulting in interest rate increases beginning in June 2022 (Reserve Bank of Australia, n.d.-b). Finally, Australia faces an additional economic challenge from Chinese manufacturing slowing down since COVID, potentially restricting Australian manufacturing export revenue (Leahy & Lockett, 2024).

1.5. Research gap

There are two research gaps addressed in this thesis. The first is the limited investigation of specific forms of human capital in the Australian economy. Despite the previously discussed benefits of soft skills, the usage of particular forms of human capital beyond key occupations or qualification match means there is a question of whether current qualifications and workers provide the correct type of skills even if their total skill endowments are appropriate. Soft skills are also applicable across a range of occupations and synergise with modern technologies, suggesting they can be applied more widely than other traditional skills and potentially benefit macroeconomic production as well. Further, while Australia has some similarities to other developed economies, the above discussions suggest some key differences in sectors, labour regulation, and the business cycle that may affect the types of skills required and technological implementation, affecting the overall use of soft skills. The second research gap to be addressed is expanding on the investigation of soft skills as a specific type of human capital and its association with economic shocks; Australia’s lack of technical recession provides a point of comparison with other developed nations to further investigate how the GFC affected skill usage. This is specifically considering technological change as a key driver for changes in skill relevance from this shock; however, this thesis does not investigate specific technologies, instead focusing on the economic shock associated with technological shocks in other research.

1.6. Research questions and conceptual model

For this thesis, the primary research question is whether soft skills have become more relevant for Australia's economic state since 2005. To investigate this primary research question, the following specific questions are utilised to investigate different measures of soft skill usage and relevance:

RQ1: Are soft skills positively associated with Australian worker job mobility, as measured via job changes and wage gains from job changes, between the years 2011 and 2019?

RQ2: Are soft skills negatively associated with Australian worker unemployment risk and the risk of associated negative employment states during and after economic downturns, between the years 2005 and 2016?

RQ3: Are soft skills positively associated with Australian multifactor productivity (MFP) growth and value-added output at the industry level between the years 2006 and 2021?

The conceptual model in Figure 1-1 displays these elements in relation to their associated theories and the Australian economy, and which chapters investigate each element.

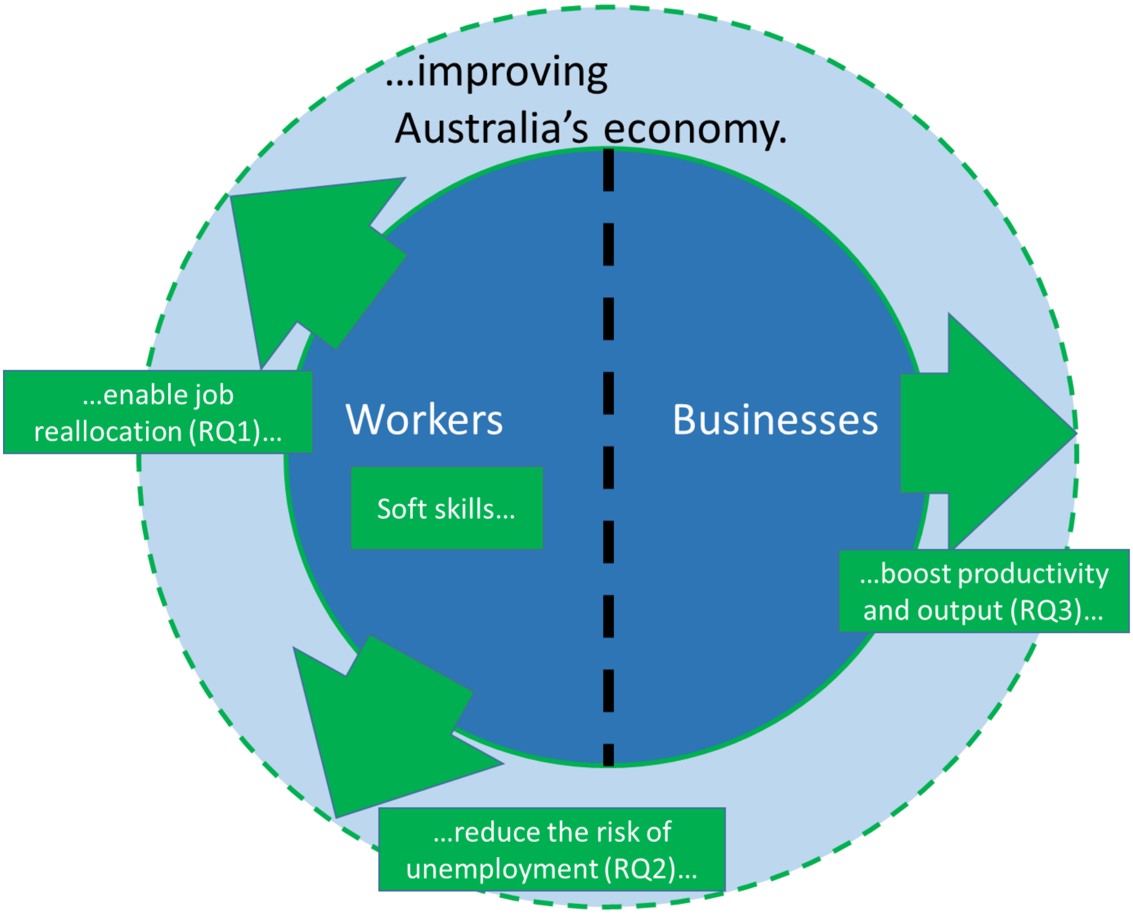

Figure 1-1: Thesis conceptual model
Source: thesis author.

1.7. Research objectives

The research objectives to be achieved are:

RO1: To investigate the relationship between soft skills and worker job mobility, as measured via job changes and wage gains from job changes in Australian.

RO2: To investigate the relationship between soft skills and worker unemployment risk or the risk of other negative employment states during and after economic downturns in Australia.

RO3: To investigate the relationship between soft skills, multifactor productivity (MFP) growth, and value-added output at the industry level in Australia.

1.8. Research methods

To achieve these research objectives, each empirical chapter utilises relevant methods and techniques to focus on a specific research question from Figure 1-1. To address RO1, the first empirical method utilises the Household, Income and Labour Dynamics in Australia (HILDA) dataset to investigate job mobility from a worker perspective using longitudinal data. Three proxies are used to capture different elements of soft skills: time management, social capital, and low task repetitiveness. Three further measures of overall skills are utilised for comparison against soft skills to determine if they have any additional benefit: education level, the ability to decide what to do in a job, and the ability to decide how to do the job, with the latter two capturing task intensity. Job mobility itself is directly analysed using job-to-job transitions in a survival analysis model to determine whether soft skill endowments reduce the time to job change. As some of this job mobility may include unstable casualisation (McGann et al., 2016) or overskilled and overeducated workers who are more likely to change jobs (Mavromaras et al., 2013), a linear random effects model with Mundlak corrections is utilised to test how soft skills, and particularly the interactions between soft skills and job mobility, affect worker wages as one major job requirement prospective workers consider when searching for a new job (PwC, 2021).

To address RO2, the same HILDA dataset is applied to an analysis of unemployment risk. All soft and other skill measures are retained from the prior analysis to improve consistency. As businesses may avoid layoffs via alternative means that would limit unemployment, some specifications also include overskilling and underemployment as a third level to capture imperfect matches (McGuinness & Wooden, 2009; Rones, 1981). All models utilise a logit link for a random effects model with Mundlak corrections, enabling an understanding of how soft skills assist in the reduction of unemployment risk. A further element of this analysis is to understand how the relevance of skills changed during the GFC. This negative shock is chosen for its relatively recent occurrence while still having sufficient years of data following the shock to investigate perpetual changes to the association between soft skills and unemployment risk. Further, prior research internationally has found associated SBTC and RBTC during this period (Hershbein & Kahn, 2018; Jaimovich & Siu, 2020), providing a further theoretical link to soft skills specifically. These perpetual elements were investigated by including interactions between the year categories and the soft skill terms, providing data on whether there was a significant change in the effect of any of the soft skills from prior to the GFC to after.

To address RO3, the industry-level Australian Skills Classification (ASC) data are utilised to build a single measure of soft skills to test against industry-level measures of productivity and value-added output. This soft skill measure applies a confirmatory factor analysis (CFA) to combine seven soft skill measures into a single overall soft skill term: initiative and innovation (Cimatti, 2016), learning ability (Buayai et al., 2025), oral communication (Andreas, 2018; Balcar, 2016; National Careers Service, n.d.; Shakir, 2009; Ubalde & Alarcón, 2020), planning and organising (Cimatti, 2016), problem solving (Shakir, 2009), teamwork (Andreas, 2018; Deng et al., 2014; Shakir, 2009), and writing as a measure of written communication (Andreas, 2018; Balcar, 2016; National Careers Service, n.d.; Shakir, 2009; Ubalde & Alarcón, 2020). Productivity and value-added production have different method formats investigated, choosing a short-run fixed effects model using ordinary least squares (OLS) estimators as the best suited method. The value-added production method also utilises a per worker format to further investigate this aspect.

1.9. Significance of research

This thesis makes three contributions to the literature. First, this research applies the HILDA dataset with its unique combination of large sample size, long duration, and high retention of participants. This enables a large-scale analysis of soft skills and the relevant theories at the worker level that has not been applied in the prior research reviewed for this thesis, enabling contributions to be drawn for the broader Australian labour market. The methodologies applied to these data further support this novelty. The analysis of job mobility uses a survival analysis to test job-to-job mobility, incorporating not only the mobility aspect but also the duration to better account for the frequency of job mobility, combined forming a method that has not been applied in the prior research reviewed. This is further supported via the use of interaction terms in the wage analysis and the longitudinal nature of the data to understand not just how job mobility or different skills affect wages, but the effect of both combined. These two methods and the data utilised contribute towards human capital theory by understanding how different components of soft skills associate with the worker's career mobility and how these skills compare to overall skills. Research on this human capital use for soft skills is limited internationally, and it has not been studied in-depth in Australia specifically to the author's knowledge.

Second, this research applies the same HILDA dataset to unemployment analysis. This is further supported by the use of intermediate imperfect match outcomes to better measure negative worker outcomes while the worker is technically still employed. The use of a categorical dependent variable to measure these varied match qualities from unemployed to well employed has not been previously utilised to the author's knowledge. These results also contribute to the previously discussed understanding of how soft skills are associated with employment. Further, the shared or similar skill terms between the two analyses contribute to comparing the effects of these skills between the different models and worker outcomes. These match quality results also have macroeconomic applications as poor quality employment and unemployment reduce productivity, and thus negatively affect economic growth. The use of the GFC period also provides further information on the relationship between these skills and this shock, providing guidance on the broader potential prevalence of SBTC and RBTC in Australian workplaces. Australian literature includes limited research on SBTC and RBTC in the modern labour market to the author's knowledge, making this an additional novel contribution.

Third, this research continues the investigation of soft skills overall by researching how soft skills are associated with production and productivity at the industry level as additional macroeconomic indicators. To the author's knowledge similar research has not been conducted in Australia, nor have longitudinal analyses been applied internationally to measure how changes in skill endowments within these industries affect productivity. This further deepens the understanding of soft skills as a form of human capital for production and the potential for SBTC or RBTC by including technology investments and interactions between these investments and soft skills.

There are also practical applications of the research in this thesis for both governments and businesses. For governments, this research provides information on whether soft skills are relevant to train for government outcomes. This is particularly seen in the second and third empirical chapters, as the former provides guidance for mitigating the cost of economic downturns and the latter provides information on factors associated with improved Australian productivity and output for overall growth. Further, the use of social capital in the second empirical chapter can provide information on whether this development mechanism is relevant for employment outcomes, thus suggesting whether government resources should be spent on developing and maintaining these capabilities.

Businesses also benefit from these analyses. The first analysis enables them to have a better understanding of recruiting and retaining talent with the relevant skills based on wages and job mobility. The third analysis is also of some relevance as it provides an understanding of how effective certain investments and factors of production are, thus providing further information on where investments are most beneficial. Regarding AI, data are only newly emerging following the release of ChatGPT that brought generative artificial intelligence (GAI) into the spotlight; further, as this technology is at the peak of the hype cycle (Gartner, 2024) and how many data series take multiple years for release, AI's direct impact cannot be readily assessed at this time. Thus, I choose to exclude this period from analysis and do not specifically consider the impact of AI itself. Instead, this research focuses on understanding how the biased technological changes that affected employment other developing countries including the United States (Gartner, 2024) affected Australian employment and production outcomes more traditionally. What is currently known of AI's application in the workplace and how this is theorised to link to the results generated is discussed in Section 7.6.1.

1.10. Thesis structure

The rest of this thesis progresses as follows. Chapter 2 delves further into defining skills, in particular soft skills, and the relevant theories applied in this research. Chapter 3 describes the methodologies used across all three empirical chapters. Chapter 4 is the first empirical chapter, analysing the association between soft skills for job mobility and thereby answering the first research question. Chapter 5 is the second empirical chapter, approaching this labour value question from a different perspective by analysing how soft skills are associated with unemployment, overskilling, and underemployment risk to answer the second research question. Chapter 6 is the third empirical chapter, focusing on the industry perspective by analysing the association between soft skills and productivity and production outcomes, thus answering the third research question. Chapter 7 summarises the results of these empirical chapters in relation to the overall research question alongside their contributions and applications.

Chapter 2. Literature review

2.1. Introduction

While the general characteristics of soft skills and their value have been outlined, this chapter provides the specific definitions and theories relevant to this thesis. Section 2.2 begins with a definition of overall skills, with specific subsections for how skills are affected by the business cycle and defining soft skills. Section 2.3 follows by going through each of the four theories this thesis utilises as the bases for the empirical chapters. Section 2.4 concludes the chapter.

2.2. Definition of skills

To understand skills in the workplace, and particularly soft skills, skills overall must be defined. Jobs and Skills Australia (n.d.) defines skills based on two key elements: they are utilised to perform tasks in the workplace and are broadly transferrable between or applicable across occupations. Becker (1994) was an early contributor to human capital more broadly, where this human capital can be either general, and thus applied across a wide range of businesses and roles, or specific to the business or role. Marin-Zapata et al. (2021) focus on soft skills specifically; however, they also define overall skills as a subset of overall competencies. This separates skills from other competencies, including knowledge and motivation, and from base personalities and abilities that affect competencies as a whole. Further, skills can be divided into soft and hard skills, with the latter focusing on technical and practical abilities (Marin-Zapata et al., 2021). Brunello and Wruuck (2021) note that skills encompass cognitive and noncongitive abilities, along with specific technical skills. Cognitive skills include literacy, numeracy, and abstract problem-solving abilities, while non-cognitive abilities incorporate further components including behavioural and physical characteristics, with technical skills combining these to achieve specific tasks (Brunello & Wruuck, 2021). They further note that skills can be difficult to measure.

2.2.1. Cyclical element of skills

One element to consider for the second empirical chapter in particular is how skill demand and usage change during the business cycle. There are two relevant components: the cyclical, primarily related to skills as a whole, and the perpetual, primarily for soft skills.

The cyclical element involves the current state of the business cycle affecting skill demand and usage, forming the initial shock that can cause the perpetual effect. During downturns, businesses tend to lay off staff who are either underskilled low performers (Balleer & van Rens, 2013; Brunello & Wruuck, 2021) or overall poorly matched workers (Brunello & Wruuck, 2021; Liu et al., 2016). The former case aligns with prior research suggesting high-skilled workers find temporary employment at a lower skill level, displacing those workers and resulting in a bumping down of workers overall (Mavromaras et al., 2015), further increasing aggregate overskilling or skill underutilisation (McGuinness & Wooden, 2009). New recruitment also typically has increased skill requirements during economic downturns (Hershbein & Kahn, 2018), further affecting the skills mix of employment preferences. Some businesses avoid layoffs via alternative means including reducing employment hours or wage rates (Rones, 1981) rather than full layoffs, potentially muting this cyclical effect on unemployment. In contrast, the perpetual element instead involves skill demand and usage changes persisting beyond the initial business cycle state. This forms the primary element of interest for the second empirical chapter due to the slow rebound in employment seen internationally after recessions, particularly for certain types of employees (Graetz & Michaels, 2017; Hershbein & Kahn, 2018; Jaimovich & Siu, 2020) and the resulting risks of higher structural unemployment. Further sources of these changes are considered via creative destruction and technological bias theories discussed later in this chapter.

2.2.2. Soft skills

Soft skills are a subset of overall skills, with a varied range of characteristics and types of skills included among the definitions in the literature (Cimatti, 2016; Marin-Zapata et al., 2021; Robles, 2012; Wats & Wats, 2009; Whiting, 2020). As such, this section investigates a range of definitions to determine relevant elements for this thesis while also retaining the characteristics of skills as a whole discussed above.

Soft skills themselves originated from Whitmore and Fry (1974), who discussed these skills in relation to US military usage as a set of further skills beyond traditional skills. Marin-Zapata et al. (2021) provide a detailed meta-analysis of how soft skills are utilised, synthesising this into a conceptual model in which soft skills incorporate intrapersonal and interpersonal skills, where the former include self-management and the latter include communication and teamwork. Further, as discussed above, they specify that soft skills are distinct from hard skills, personality, and other abilities unrelated to skills (Marin-Zapata et al., 2021). Cimatti (2016) does not consider soft skills as part of specific tasks; instead, soft skills enhance the hard skills of workers.

Similarly, Shakir (2009) discusses soft skills in Malaysian higher education, defining soft skills as a set of interpersonal and intrapersonal skills. Further, she considers soft skills to be developed in a range of learning environments, from formal academic courses through to general campus experience. Wats and Wats (2009) discuss soft skills for Indian students by investigating student and teacher perceptions, noting that communication, problem solving skills, leadership skills, and teamwork skills are considered important by over 75% of respondents. They further note that experiential learning has the highest response rate as a preferred method for soft skill development, aligning with Shakir (2009). Tamm (2018) investigates how different training is associated with routine and nonroutine tasks in German firms, finding that occupations with more nonroutine tasks are more likely to receive training for soft and communication skills.

The National Careers Service (n.d.) presents a government perspective on soft skills and developing these skills, focusing on communication, decision making, organisation, and adaptability. Robles (2012) notes that communication, integrity, and courtesy are highly valued soft skills among surveyed business leaders, with over three quarters of respondents considering these skills very or extremely important. She further defines soft skills as traits that are not specific to the job or even the overall occupation, and that enhance the person’s performance overall, which does differ from some definitions of overall skills.

Stewart et al. (2020) go beyond the definitional focus of the above research by empirically investigating soft skills at the regional level, utilising detailed occupation data from the USA. These data were used to select a subset of knowledge, skills, and abilities to act as measures of soft skills and science, technology, engineering, and mathematics (STEM) skills. They categorise occupations into one of nine groups based on the levels of each of the two skill categories before creating regional weightings of these categories. These were used as regressors for two regressions: one on regional wages and another on total factor productivity (TFP). They found these skill categories did a better job of explaining both wages and TFP compared to traditional education measures, and higher ratios of workers high in at least one skill typically made a positive contribution to both dependent variables. In comparison, other categories of workers had insignificant or negative effects on wages and TFP (Stewart et al., 2020).

Based on this literature and the prior definitions of skills, this thesis considers the following elements for defining soft skills. First, soft skills include interpersonal skills (Andreas, 2018; Marin-Zapata et al., 2021; National Careers Service, n.d.; Shakir, 2009) and intrapersonal skills (Andreas, 2018; Deng et al., 2014; National Careers Service, n.d.; Pang et al., 2019), providing two types of skills that augment the productivity of the other skills a worker brings (Cimatti, 2016). Second, soft skills can be developed by workers via a range of development approaches (Andreas, 2018; National Careers Service, n.d.; Shakir, 2009), and thus it is possible to actively fill shortages of these skills as required. This excludes personality and emotional traits; while some literature includes these elements, they are not considered skills (Marin-Zapata et al., 2021) and are inflexible among adults (Cobb-Clark & Schurer, 2013), thus making it difficult to proactively change these components.

2.3. Applied theories

2.3.1. Human capital

Human capital theory focuses on the productive capabilities of individuals themselves (Becker, 1994), with soft skills forming part of total human capital. Research varies on the level of detail, with some studies focusing on broader skill categories (Quintini, 2011) while others delve deeper into specific skill categories (Stewart et al., 2020; Ubalde & Alarcón, 2020).

Becker (1994) was one of the earliest authors on this subject, utilising this theory to explain multiple economic facets: the increase of wages in the workforce and the association between wages and age, how unemployment rates are negatively correlated with skill, why young individuals tend to change employers more regularly than older workers, and why employers are more cautious of investing in their staff compared to physical capital. He further explained that human capital can take the form of either general or specific capital, with the former applicable to a range of organisations and jobs while the latter is specific to the organisation or role. Specific capital, in particular, is also likely to result in a reduced wage explicitly given to the employee, as their marginal productivity should equal training costs plus their wage (Becker, 1994). The funding of training by the organisation will also vary based on the type of employer, with workers in monopsonistic markets having to pay for more of their training. Further, any additional income earned should be equivalent to the opportunity cost of education, so the options of education or not receiving education are equivalent.

Schultz (1961) was another early researcher into human capital, including considering the potential implications of associating emotionally cold concepts of capital ownership and investment with the concept of humanity. His research into human capital stemmed from the mobility of young workers, a decline in physical capital relative to income, and increases in real earnings by workers (Schultz, 1961). While Becker considered human capital development driven by businesses and workers, Schultz instead focused on human capital as a form of consumption by workers with the aim of improving their own productivity. This investment consistent of five groups: health activities, on-the-job training, formal education, additional training programs, and migration. Similarly to Becker, Schultz also considered the opportunity cost of education, including wages forgone.

Quintini (2011) provides a more recent perspective on human capital, among other related theories. She describes human capital as having varied levels of transferability depending on whether it is specific to a firm, occupation, or industry. She further applies this to skill mismatch, noting that education mismatch is more likely than skill mismatch. She finds job latitude, or freedom to perform tasks in the job, is associated with an increase in overskilling likelihood while having minimal to no effect on other measures, including underskilling. In comparison, job complexity has no impact on overskilling likelihood and instead is associated with an increase in underskilling likelihood. These results are somewhat contrary considering that both variables are measures of worker human capital in other literature (Fraser, 2008). Higher levels of education are also positively associated with overskilling and are not related to underskilling.

Ubalde and Alarcón (2020) also study human capital, particularly in the context of specific communication skills that are also part of soft skills. They presume an occupation that requires additional skills would come with a wage premium for these skills. They further note that historic research suggests specific skills, such as cognitive skills, are rewarded while social skills are less likely to be rewarded due to the types of occupations that utilise these skills, limiting the practical wage benefit of these skills. Their results showed that while most skills were associated with higher logged wages, some skills, including nurturing, science and engineering, and foreign languages, were only slightly significant or insignificant, while verbal reasoning had a negative effect on logged wages (Ubalde & Alarcón, 2020).

Stewart et al. (2020) focus on soft skills and STEM skills in the human capital context, utilising US data to investigate whether these skills affect regional median wage and TFP. They analyse these two skills by classifying occupations into categories dependent on the level of each skill and analysing the proportion of jobs in each category at the geographic region level. Their analysis finds that a majority of the skill categories have a significant effect on wages and TFP, with positive contributions from jobs with high levels of at least one skill while other categories have lower or insignificant contributions. Further, these models have a better model fit compared to the education models also tested in this research. This significance of overall soft skills differs from Ubalde and Alarcón's (2020) finding that only select skills have a significant effect on wages.

Carroll and Poehl (2007) utilise the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey to investigate job-to-job mobility, with a particular focus on firm-specific human capital measured using firm tenure as a proxy. Their findings support this, as workers with more years of experience with their current employers have lower separation rates.

2.3.2. Signalling and search frictions

Compared to human capital, which applies for all labour market participants, signalling theory or job search theory focuses on the job search (Quintini, 2011), in particular the imperfections during the search (Pissarides, 2011). Due to the previously raised difficulties of measuring skills (Brunello & Wruuck, 2021), there is the potential for workers to end up poorly matched if they cannot sufficiently demonstrate these skills. This is one of the potential benefits of having prior work experience or visible education qualifications on a résumé (Burdett, 1978; Kalb & Meekes, 2021).

Pissarides (2011) details the search frictions in labour markets where job search focuses on finding a good match rather than being dependent on an equilibrium wage. However, he says relatively little on the actual causes of the match, instead treating this as a black box. Quintini (2011) utilises signalling theory along with the aforementioned human capital theory to analyse job search, primarily focused on prior unemployment history. In this case, education itself is also considered an imperfect signal.

Weiss (1995) is an older study that discusses the potential for higher education to signal higher skills, instead of fully being human capital. As people with higher education qualifications have different characteristics to those without, and as education is relatively easy to see and check, this suggests qualifications may support signalling. Pericles Rospigliosi et al. (2014) delve further into this concept, while also noting the risk of this signal losing its value due to the increase in higher education graduates. Further, they also that note both signalling and human capital would show similar empirical results; thus, both can be acknowledged.

2.3.3. Creative destruction

Creative destruction is the oldest theory utilised in this thesis, stemming back to Schumpeter's published works in the 1940s (Andrews & Saia, 2017). This theory proposes that businesses ending and labour market churn are ways for newer businesses and technologies to be implemented, improving overall productivity. Unlike the first two theories, which focus on individuals in the labour market and their potential wages or job search, this theory focuses on the forces that change the demand for particular skills. While the analyses utilised in this thesis do not look at specific technologies or changes brought about by creative destruction, this theory still provides value as a driver of perpetual effects of the business cycle on skills that are investigated.

Andrews and Saia (2017) focus on how creative destruction affects worker displacement and potential government policies to assist in reintegration, utilising European life history data prior to the GFC. The three main findings from their analysis are the importance of active labour market programs for displaced workers to find a new job in a timely manner; the importance of stimulating labour demand to support these policies; and the relevance of regional mobility for reintegration. Dachs et al. (2017) also utilise European data to analyse the similar concept of reallocation of labour, albeit instead focusing on how firms can counter the negative effects of worker displacement. Their analysis finds that creative destruction is unevenly distributed between different sectors based on whether they are technical or nontechnical manufacturing and whether they are knowledge intensive. Dachs et al further find limited evidence for a dichotomy between manufacturing and services sectors, suggesting there is a better way to categorise industries and businesses.

Lin and Huang (2012) investigate creative destruction and the cleansing effect of recessions on resource reallocation, particularly employment, between businesses using a stochastic frontier model. Their analysis finds job creation and destruction both occur in organisations pushing the technological frontier, with created jobs typically having a higher skill than the initial jobs. Further, organisations with higher technological efficiency tend to perform relatively better with job creation during recessions, while less productive organisations do better during periods of growth. Schubert (2013) discusses how creative destruction affects the welfare decisions of governments from an evolutionary economics perspective. He notes the difficulty of adapting to these changes reactively due to the speed of technological change, which is relevant for this research as proactive skills development for flexibility and working with technology can protect workers against technological disruption and further improve productivity. Jaimovich et al. (2024) investigate the routine task share and age of businesses that enter and exit markets, with older businesses having lower routine task shares and exiting businesses typically having a higher routine task share.

2.3.4. Tech biases

While creative destruction explains one of the underlying reasons for employment and skill changes in occupations and industries, it says relatively little on which occupations and industries are impacted or how they are affected. Three related theories detail expectations of which workers are affected by this technological change in modern economies: skill-biased technological change (SBTC), routine-biased technological change (RBTC), and the newer task-biased technological change (TBTC). Use of these theories forms the other approach to investigate perpetual effects of the business cycle on skills. As above, the analyses in this thesis focus on either driving shocks or broad technology investment as a mechanism for SBTC and RBTC, rather than which technologies were implemented or how they specifically link to skills.

SBTC presumes technology is biased in favour of the skill level of the worker, with higher-skilled workers experiencing greater wage and employment opportunities than lower-skilled workers (Violante, 2008). Modern research into this area in developed nations is somewhat limited, although there are a couple of relevant papers. Mellacher and Scheuer (2021) utilise an agent-based model with endogenous growth and presumed skill-biased technological change. They find that firms with market power will drive skill-biased technological change, while firms can counteract this with training policies. Balleer and van Rens (2013) apply a constant elasticities of substitution (CES) production model as a basis to investigate SBTC in the USA via productivity changes and the skill premium in a structural vector autoregressive (VAR) model. Their results suggest capital investment in the USA has benefited workers of lower skill levels, thus substituting skilled workers. Bowlus et al. (2023) account for some of the limitations of prior SBTC research by applying approaches to measure unobserved skills. They also investigate whether SBTC tends to occur during recessions. Applying USA Current Population Survey (CPS) data, they find evidence supporting SBTC when accounting for these skills and a relatively consistent trend for SBTC change outside of a period between the Dot-Com bubble collapse in 2000–2001 and the GFC.

One notable limitation of SBTC is evidence of employment hollowing out the middle by skill, with high- and low-skill jobs retained while jobs with moderate levels of skills have reduced employment (Autor et al., 2003; Frey & Osborne, 2017). RBTC was developed to address this contradiction by instead analysing the task content of jobs, and particularly whether these tasks are routine. This provides an approach to determine if a job was susceptible to automation due to a high proportion of routine tasks, while nonroutine tasks are seen as harder to automate (Autor et al., 2003; Frey & Osborne, 2017). Soft skills are valuable for RBTC as these skills are particularly relevant in nonroutine jobs, as previously discussed.

Autor et al. (2003) is an early paper investigating RBTC utilising US occupational data, finding support for this routine task bias when accounting for various labour supply-side factors. Frey and Osborne (2017) employ this theory to investigate automation risk for US occupations. Their results find an upper estimate of 47% of employment is at high risk of automation. Hershbein and Kahn (2018) investigate how RBTC occurred in US jobs during the GFC based on geographic region and job data on skill requirements. They find jobs tended to upskill in areas affected by the GFC to a greater degree: this particularly occurred within occupations, rather than between them, and continued through to 2015, suggesting there were relatively long-lasting perpetual elements to skill demand and use. This upskilling was typically in cognitive routine jobs, while routine manufacturing jobs resulted in employment cuts without upskilling nor a recovery. Jaimovich and Siu (2020) further investigate employment trends in US jobs based on skill and routine level. They show routine jobs consistently declined after the 1991, 2001, and 2009 recessions, while both low-skilled nonroutine and high-skilled nonroutine jobs experienced either a shorter decline or even no decline after these recessions. This has contributed to the growth in employment percentage of both types of nonroutine employment.

The third area of TBTC is a variant of RBTC where automation affects specific tasks without a strict relationship with skill or job routineness. This provides some additional flexibility for what types of skills are affected by emerging technologies including AI and modern robotisation (Damelang & Otto, 2023). While it has use as an explanation for directly linking the implementation of technology with task change, the lack of further linkage to the capabilities of the worker or the characteristics of the job limits the ability to understand why certain tasks are likely to be automated. As such, this theory is not considered an effective lens of analysis for this research.

2.4. Conclusion

This section has incorporated prior literature to build both the definition of the skills investigating in this thesis and the theoretical frameworks used to interpret the models. Soft skills are narrowed to focus on the key aspects of being intrapersonal or interpersonal skills that augment other productive skills. Further, soft skills should be developable to address potential skill gaps. The theories of human capital, signalling and job search, creative destruction, SBTC, and RBTC are each seen as relevant for econometric analysis of soft skills to understand how soft skills contribute to production and employment, how they are limited, and how the value of these skills change over time. While the relevance of soft skills can be connected to each of these in order to deepen understandings and connect differing theoretical perspectives together, research into how soft skills integrate into these approaches is lacking, particularly for Australia's economy. As this thesis is focused on soft skills to support workers in changing times, three theories are explored in the following empirical analyses: human capital for explicit measurement of soft skills, and both SBTC and RBTC for changes in demand for and use of soft skills. The remaining theories are drawn upon for comparison or support: signalling and job search for specific value for additional skills, and creative destruction for when SBTC and RBTC may be strongest and a relevant source of these changes.

Chapter 3. Methodology and data

3.1. Introduction

Following the research questions and objectives outlined in Chapter 1 and the literature review in Chapter 2, this chapter now details the methodologies and data applied for each empirical chapter. Each section details the approach used for each empirical chapter, with subsections discussing the data tested and the methods applied to answer the questions.

3.2. Soft skills and job mobility[1]

3.2.1. Data

The primary data source for this study is the Household, Income and Labour Dynamics in Australia (HILDA) Survey, with additional data drawn from the Australian Bureau of Statistics (ABS) as required. This longitudinal survey began in 2001 with approximately 7,000 households, before expanding to 9,600 households since 2011. Household members are surveyed annually on topics relating to their socioeconomic status and employment. This survey is useful for this study due to its longitudinal nature and the low attrition rate of participants. One potential weakness is the lack of direct measures of soft skills and limits to measuring skills as a whole; despite this, these data are still relevant due to including relevant proxies to address this restriction along with limits to other known datasets of potential relevance, particularly for Australia.

This analysis measures soft skills using three variables. The first soft skill variable is time management (Andreas, 2018; Deng et al., 2014; National Careers Service, n.d.; Pang et al., 2019) using the measure for time pressure "How often do you feel rushed or pressed for time?" The second soft skill variable captures a general endowment of soft skills via low task repetitiveness (Robles, 2012; Tamm, 2018) using the measure "My job requires me to do the same things over and over again". The third soft skill variable measures interpersonal skills. One limitation of the HILDA dataset is the lack of a variable that captures workplace usage of interpersonal skills; as such, overall social capital is drawn on instead. While the direction of the relationship between social capital and specific soft

[1] This section was originally published in Semtner, A., Dzator, J., & Nadolny, A. (2025). Is no (soft) skill left behind? Do soft skills enable job mobility. *Applied Economics, 57*(33), 4897-4915. https://doi.org/10.1080/00036846.2024.2364103. Further edits to the methodology applied in this thesis were made based on reviewer feedback.

skills is beyond the scope of this thesis, prior research suggests that the social interactions utilised to measure social capital for this research are also applied for managing and developing soft skills (Andreas, 2018; Jackson, 2020; Rungo et al., 2024), along with these interpersonal skills further enabling the development of social capital (Baron & Markman, 2000). Together, these suggest a synergistic relationship between social capital and communication skills and thus the use of social capital as a proxy. Six base measures are utilised: satisfaction with "felling part of your local community" (losatlc); satisfaction with "the neighbourhood in which you live" (losatnl); "When I need someone to help me out, I can usually find someone" (lssupsh); "I seem to have a lot of friends" (lssuplf); "I enjoy the time I spend with the people who are important to me" (lssuppi); and "When something's on my mind, just talking with the people I know can make me feel better" (lssuptp). Cronbach's alpha is used to test whether these are measuring the same underlying item. The result of 0.72 is above the common threshold of 0.7 (Lance et al., 2006) and removal of any components negatively affects the alpha: thus, this is considered a relevant measure of underlying social capital. To combine these together in a consistent manner over the two samples, each component is adjusted to a standardised 0-10 scale, then all components are averaged together. While individually these components are only partial metrics of underlying soft skills and thus a single significant result would likely stem from the underlying measure instead of soft skills, significant results across multiple factors would suggest underlying soft skills have a relevant relationship.

As previously discussed, soft skills alone are insufficient for production (Cimatti, 2016); thus, this analysis includes measures for overall skills. Further, as none of the above capabilities are readily measurable by employers, these should also include at least one easily measured skill term to account for both human capital and signalling theory perspectives (Lam et al., 2012; Quintini, 2011). Both are achieved using three further skill variables for overall skills. The first variable is the level of education (HILDA variable name: hgage) as a readily observable measure of skill endowments from formal education systems. Three combined levels are applied: school level, vocational level, and university level. Even if education is of limited use as a single measure of skills (Cord & Clements, 2010), their use as one skill measure among many alleviates this concern. The last two variables are the ability to decide how to do the job and the ability to decide what to do in the job, measuring the skill intensity of the job as utilised by Fraser (2008).

One notable question with these proxies is their treatment: the base measures for the freedom to determine how to do a job and what do on the job, task repetitiveness, and time management are Likert terms, a balance needs to be struck between treating these as interval data, categorical for each level, or a smaller range of categories down to binary treatment. Treatment as interval and categorical data in the independent model are compared in Appendix A, with the categorical model reversing the order for task repetitiveness to convert it to low task repetitiveness to better align with soft skill expectations. With very similar adjusted R^2 terms, the categorical variable approach is unsuitable due to the notable reduction in degrees of freedom, along with the relevance of moderating relationships with these variables. Further, the coefficients for the Mundlak corrections to measure average capabilities of individuals over the time period have the highest significance of the skill terms across both models and demonstrate relatively consistent trends over the categorical coefficients, suggesting these four skill measures can be treated as interval variables.

An additional element with these proxies is their broader scope than innate skill: in particular, time management encompasses broader life pressures, while the ability to decide how to do a job, the ability to decide what to do in a job, and the task repetitiveness of a job each measure workplace components. To control for these in particular, two variables are utilised. The first variable controls for all of these using the measure "My job is more stressful than I had ever imagined" (jomms), where a more stressful job would negatively impact the ability for a worker to manage their time and would suggest they are less capable for a particular job. The second variable further controls for time management by measuring the total hours spend on activities per week considered in section B19 of the survey, which includes time spent on work, transit, care duties, and volunteering among other activities. This variable scales up to 168; for comparison, this is in a model where component Likert scale variables reach a maximum of between 7 and 10, thus potentially distorting eigenvalues in the methods applied in Chapter 5. To resolve this, this variable is converted to day equivalents with a maximum of 7, bringing it in line with the interval Likert scale variables in particular. Observations with outcomes greater than 7 are dropped due to unfeasibility of the results.

This analysis uses two different dependent variables to capture different aspects of the job mobility decision. The first is whether the worker changed employers in the last year (lejob) as a mix of horizontal and vertical movement (Shah, 2009), capturing the direct mobility outcome. This measure is applied for four reasons. First, it captures the modern labour markets workers are expected to navigate with the increase in number of different jobs and even occupations workers are expected to navigate in modern labour markets that include horizontal movement along with traditional vertical (Lyons et al., 2015). Second, a key focus of this research is the transferability and flexibility of soft skills; the analysis of job-to-job mobility helps to filter out organisation or job-specific human capital that is important within the business but cannot be transferred elsewhere (Becker, 1994; Nawakitphaitoon, 2014). Third, job-to-job movement accounts for two thirds of worker separations among Australian workers (Carroll & Poehl, 2007). Fourth, while the HILDA data also tracks promotions, it lacks a measure of time between promotion; without this information, a survival analysis as applied in Section 3.2.2 is unfeasible. The second dependent variable is the hourly wage, as this is commonly utilised in the literature (Kalb & Meekes, 2021; Wen & Maani, 2019) and captures a key aspect of remuneration, with workers emphasising this aspect in their job search (PwC, 2021). The hourly wage is estimated using the weekly wage divided by the usual number of hours the worker spends at their primary job each week, removing any workers with the combination of positive weekly wage and zero hours worked. As this does not account for mobility by itself, an additional set of coefficients is generated using the interactions between the job mobility decision above and each skill term. These are interpreted as the benefit of soft skills when changing jobs and are of primary interest to RQ1; the base skill coefficients still provide useful information on the base wage benefit of these skills.

As this survey does not specifically track people from workforce entry nor to their exit, censoring is utilised for the survival analysis. For time prior to their measurement in the sample, including changing employers in an unobserved year, this analysis uses initial years employed at their current employer as a baseline. The duration at exit or at changing employers is set to initial years employed plus years in the sample to that point. Individuals who do not change jobs within the sample or are unmeasured during the change are right censored. As the HILDA data is taken annually while the initial years employed measure may be in months or years employed, any individuals with less than one year of experience are rounded up to one year. This overall variable is called years since last job change to distinguish it from the underlying year variables.

This analysis also includes additional personal and workplace controls. These include: gender, age, disability, whether in a long-term relationship including marriage, children, whether the person is from an English-speaking background (ESB) or not (NESB), whether the person is of Aboriginal or Torres Strait Islander (ATSI) heritage, overall life quality, whether the person lives in an urban geographic region, whether the person feels they are underemployed or overemployed by hours worked, whether the person is employed full-time, job satisfaction, the natural log of their weekly wage, years employed at the business, whether the employer is a medium or large business with at least 20 employees, the regional unemployment rate, the percent gap between the state-level GDP growth rate and the state-level industry value-added growth rate (sector-GDP gap), and the occupation and industry classifications at the first and second level. This analysis also includes the interaction between gender and relationship due to different expectations of married women compared to unmarried women in the workplace (Treasury, 2023), potentially affecting their mobility decisions and wages. All controls excluding years employed are used for the survival regression, while the random effects regression excludes weekly wage and overall life quality. Further, weekly wage is included in the survival regression instead of the hourly wage as this accounts for whether the person has a higher wage but few hours and thus practically has low earnings and a desire to move for higher wages.

Observations are selected for the years 2011 through 2019 to provide a buffer from the GFC and to conclude prior to the COVID-19 pandemic, where observations are currently limited and may be skewed by the COVID shock. This analysis excludes observations with missing values for variables used, and the independent variables and controls used are lagged by one period (one year) unless otherwise stated to take advantage of the longitudinal nature of these data. This results in an unbalanced set of panel data.

There are two further aspects regarding the industry and regional controls. First, percentage gap in growth rates is not captured in the HILDA dataset, with chain volume percentage change measures drawn from the ABS Australian National Accounts: State Accounts dataset Tables 2-9. This variable is also not lagged, as this measure captures the economic environment within which the movement decision was made. Second, the occupation and industry controls are applied individually to provide comparisons while minimising loss of parsimony.

Table 3-1 includes the descriptive statistics for both the survival analysis on job change and the panel data regression on hourly wage. Due to the structure of the survival results, there are fewer observations for each individual as observations are only included when there is right censoring or the person changes jobs; in comparison, additional people are removed from the wage regression due to reporting zero hours worked and thus an infinite hourly wage.

Table 3-1: Descriptive statistics – empirical chapter 1

	Job change	Wage		Job change	Wage
Employment duration			**Controls**		
Less than 5 years	0.459		Job stress	3.203	3.197
				(1.668)	(1.651)
5-9 years	0.275		Total hours busy	2.573	2.631
				(1.029)	(1.004)
At least 10 years	0.266		Gender (female)	0.508	0.501
ln hourly wage		3.429	Age		
		(0.49)			
Soft skills			Under 30	0.35	0.308
Social capital	7.451	7.475	30-39	0.208	0.212
	(1.345)	(1.326)			
Time management	2.604	2.603	40-49	0.192	0.217
	(0.888)	(0.88)			
Low task repetitiveness	3.207	3.303	50-59	0.173	0.195
	(1.631)	(1.644)			
Overall skills			60 and over	0.077	0.069
Highest education			Disabled	0.161	0.153
School	0.337	0.32	Relationship	0.613	0.636
Vocational	0.332	0.327	Children	0.335	0.351
University	0.332	0.353	Aboriginal and Torres Strait Islanders (ATSI)	0.021	0.018
Decide what do in job	4.118	4.199	Migrant (ESB)	0.1	0.101
	(1.756)	(1.74)			
Decide how do job	4.489	4.567	Migrant (NESB)	0.086	0.084
	(1.737)	(1.725)			
Change jobs	0.331	0.121	Overall life quality	0.002	
Year			Urban	0.895	0.899
2012		0.12	Years employed	6.18	7.028
				(7.733)	(8.046)
2013		0.118	Hour preference		
2014		0.117	Underemployed	0.235	0.245
2015		0.118	Well-employed	0.597	0.611
2016		0.125	Overemployed	0.168	0.145
2017		0.133	Full time	0.665	0.69
2018		0.132	Job satisfaction	0.008	
2019		0.137	ln weekly wage	6.785	
				(0.85)	
			Medium-large business	0.601	0.637
			Regional unemployment	5.25	5.392
				(0.865)	(0.86)
			Sector-GDP gap	0.32	0.221
				(4.206)	(4.161)
Individuals	11195	11213	Observations	16386	39745

For binary variables, measure is the proportion of the sample that is true for the variables. For categorical variables, measure is the proportion of the sample that is of the relevant level. For numerical variables, measure takes the form of mean (standard deviation). Occupation and industry breakdowns are not reported due to space limitations.

3.2.2. Method

The first analysis on employment transitions utilises a Cox proportional hazards survival model to determine whether soft skills have a negative association with employment duration. As per Amorim and Cai (2014), the Andersen and Gill counting process is used as this can handle repeat occurrences of the event of interest for each individual. This is represented using Equation 1 below:

$$\lambda_i(t) = \lambda_o(t)\exp\left(\beta_1^1 SS_i(t-1) + \beta_2^1 OS_i(t-1) + \gamma_1^1 X_{1i}(t-1) + \gamma_2^1 X_{2i}\right)(1)$$

where $\lambda_i(t)$ is the hazard for years since last job change t for person i, $\lambda_o(t)$ is the nonnegative baseline hazard, SS_i is the vector of soft skill variables, OS_i is the vector of other skill terms, X_{1i} is the vector of time-variant controls, X_{2i} is the vector of time-invariant controls, and all β and γ terms are the relevant vectors of coefficients. The 1 superscripts for coefficients denote survival analysis estimates, while exp is the natural exponent. Independent terms are lagged and specified using $(t-1)$ or time-invariant, thus no future or immediate present results explain current or near-past results. As stated previously, an exception is made for percentage gap in growth rates for time relevance as this measures macroeconomic conditions over the year of the decision. The Efron estimation approach is used to balance the discrete nature of years employed and the number of ties in the data (Therneau, 1997). Standard errors are clustered by individuals to account for the nature of repeat events of job mobility. Results interpretation uses the hazard ratio to investigate whether a variable results in increased or decreased likelihood of changing employers.

A key assumption of the Cox model is proportional hazards, where the hazard risk of a variable does not depend on the survival duration of the person (Therneau, 1997). Table 3-2 column 1 below tests for this using the chi-square results for their Pearson product-movement correlation of the Schoenfeld residuals of the variables (Therneau, 1997), finding ten variables with significant results: time management, highest education level, job stress, age, disability, job satisfaction, weekly wage, whether the business is a small or medium-large employer, regional unemployment, and whether the person lives in an urban region. Visual investigation of graphs of the Schoenfeld residuals, as displayed in Figure 3-1 below, suggest all of these excluding job stress reflect underlying trends of concern and thus need correction. Job stress instead appears to stem from overly tight confidence intervals resulting in a false positive without distinct trends of concern, thus does not require correction. Stratification of the time variable is utilised (Therneau, 1997) based on inflection points of the graphs, stratifying these results for year = 5 (highest education level, urban, time management, job satisfaction, business employees, regional unemployment) and year =10 (disability, weekly wage, age). The updated results with this stratification are displayed in Table 3-2 column 2 below, with most variables including job stress no longer violating the proportional hazards assumption, while the corrections for job satisfaction, regional unemployment, and age remain significant. Visual inspection of these graphs in Figure 3-2 below suggests that there is no practical effect of these remaining violations on the results, with the significant results stemming from the tight confidence intervals. As such, these terms do not require further adjustments.

Table 3-2: Pearson product-movement correlation chi-squared statistics of the Schoenfeld residuals for variables prior to and after the correction.

	Initial	With year strata interactions
Soft skills		
Social capital	0.323 (0.57)	0.488 (0.485)
Time management	5.524* (0.019)	
Time management * 5 year strata		1.355 (0.508)
Low task repetitiveness	0.633 (0.426)	1.319 (0.251)
Overall skills		
Highest education	21.813*** (0)	
Highest education * 5 year strata		15.018** (0.005)
Decide what do in job	0.178 (0.673)	0.028 (0.868)
Decide how to do job	0.116 (0.733)	0.596 (0.44)
Control variables		
Job stress	4.892* (0.027)	0.055 (0.815)
Total hours busy	0.26 (0.61)	0.382 (0.537)
Gender (female)	0.897 (0.344)	0.437 (0.508)
Gender (female) * Relationship	0.182 (0.67)	0 (1)
Age	91.073*** (0)	
Age * 10 year strata		48.101*** (0)
Disabled	10.887*** (0.001)	
Disabled * 10 year strata		2.428 (0.297)
Relationship	0.021 (0.884)	0.156 (0.693)
Children	2.077 (0.15)	0.911 (0.34)
Aboriginal and Torres Strait Islanders (ATSI)	0.553 (0.457)	0.052 (0.82)

	Initial	With year strata interactions
Migrant (ESB)	0.001 (0.972)	0.991 (0.319)
Migrant (NESB)	0.106 (0.744)	0.064 (0.8)
Overall life quality	0.039 (0.844)	0.945 (0.331)
Urban	10.991*** (0.001)	
Urban * 5 year strata		3.946 (0.139)
Hour preference	3.317 (0.19)	1.341 (0.512)
Full time	1.933 (0.164)	0.383 (0.536)
Job satisfaction	39.76*** (0)	
Job satisfaction * 5 year strata		24.043*** (0)
ln weekly wage	8.467** (0.004)	
ln weekly wage * 10 year strata		3.848 (0.146)
Medium-large business	4.099* (0.043)	
Medium-large business * 5 year strata		2.606 (0.272)
Regional unemployment	9.411** (0.002)	
Regional unemployment * 5 year strata		6.606* (0.037)
Sector-GDP gap	2.111 (0.146)	2.566 (0.109)
Overall	227.725*** (0)	126.465*** (0)

*, **, *** Significant at 5%, 1%, and 0.1% levels respectively.

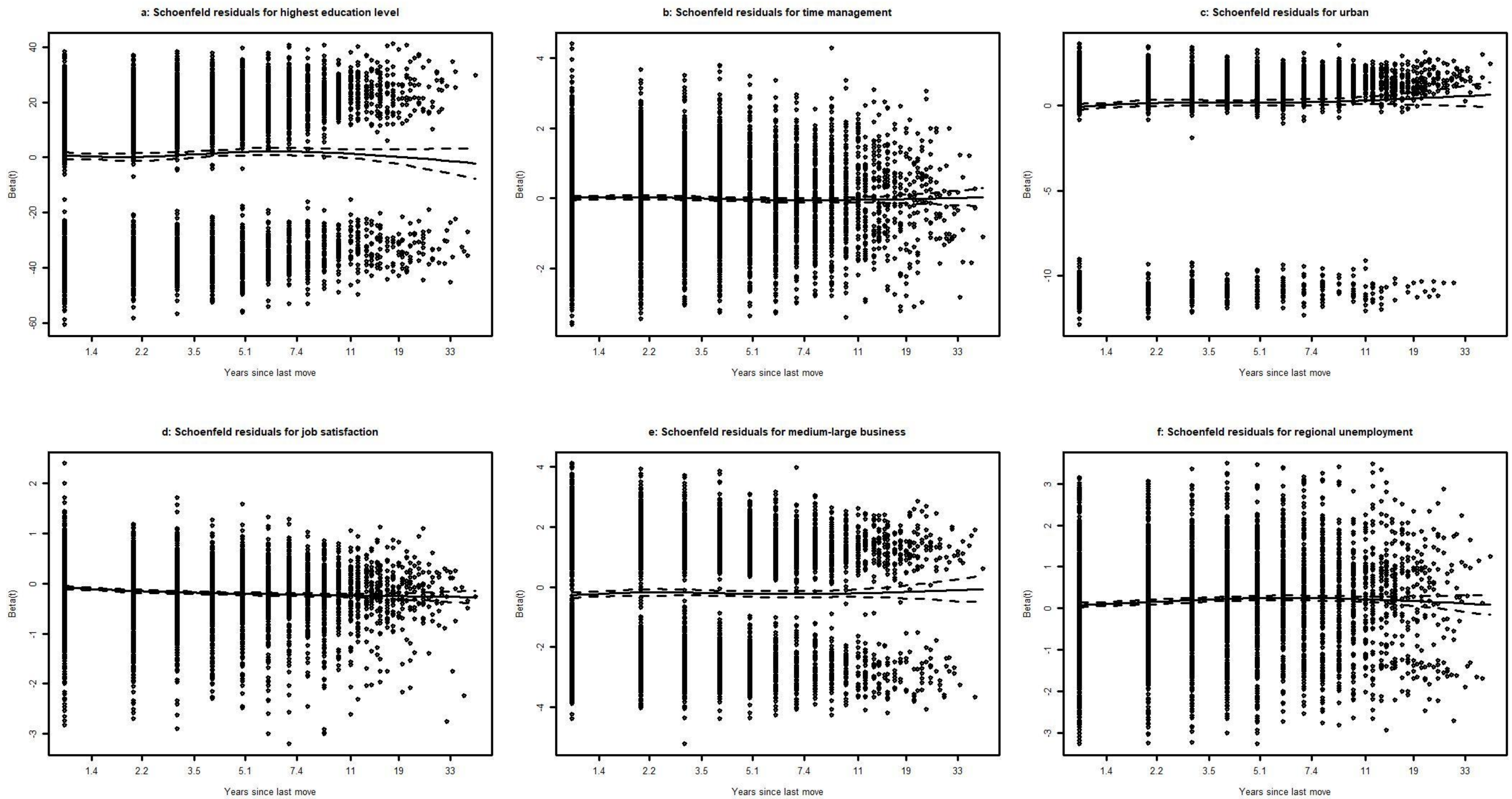

Figure 3-1: Schoenfeld residuals prior to correction
All variables here have significant Pearson correlation. These residuals are based on the specification with all skill terms and no industry nor occupation categorical variables. The dotted lines represent the 95% confidence interval.

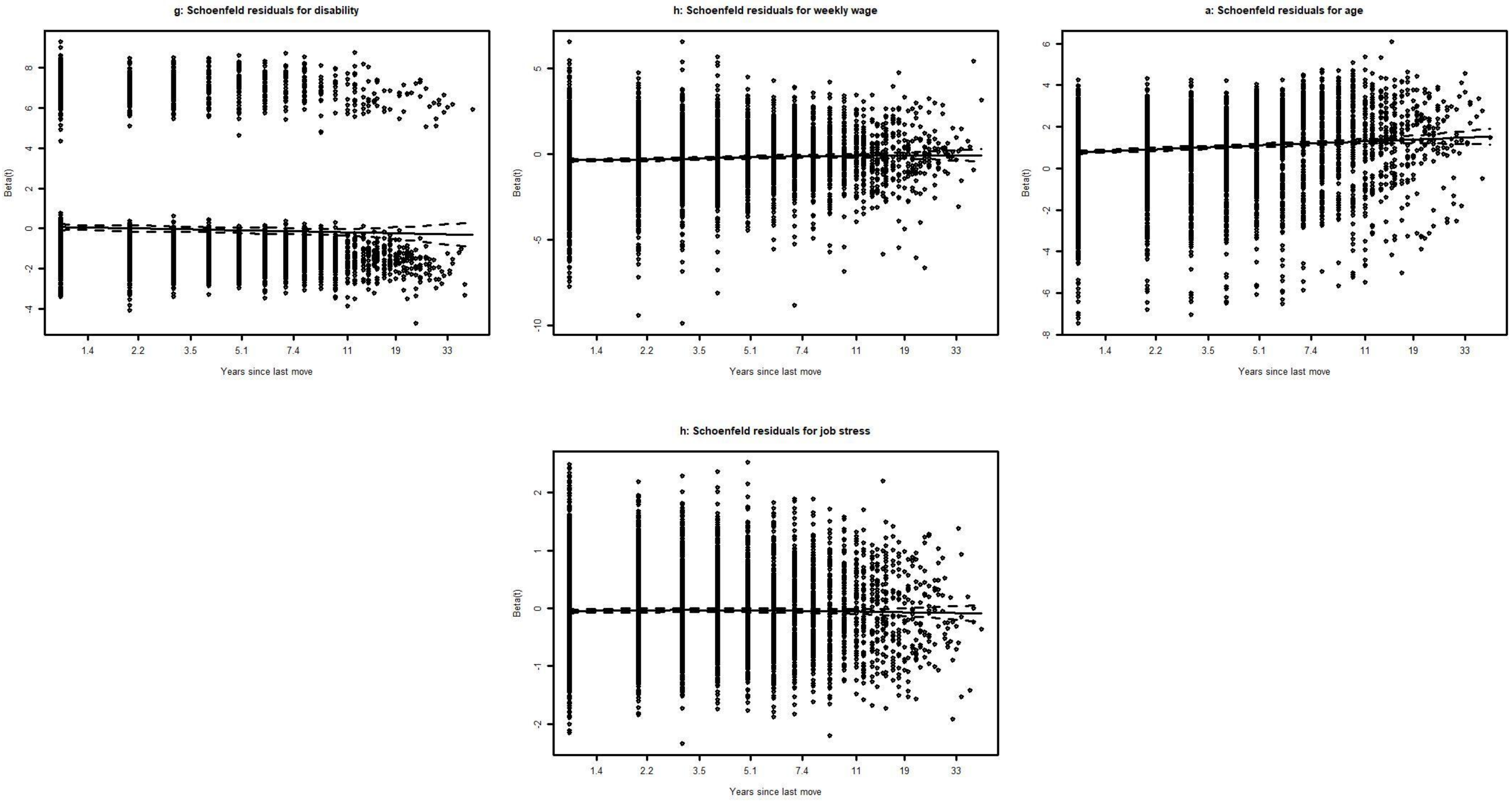

Figure 3-1 (cont.)

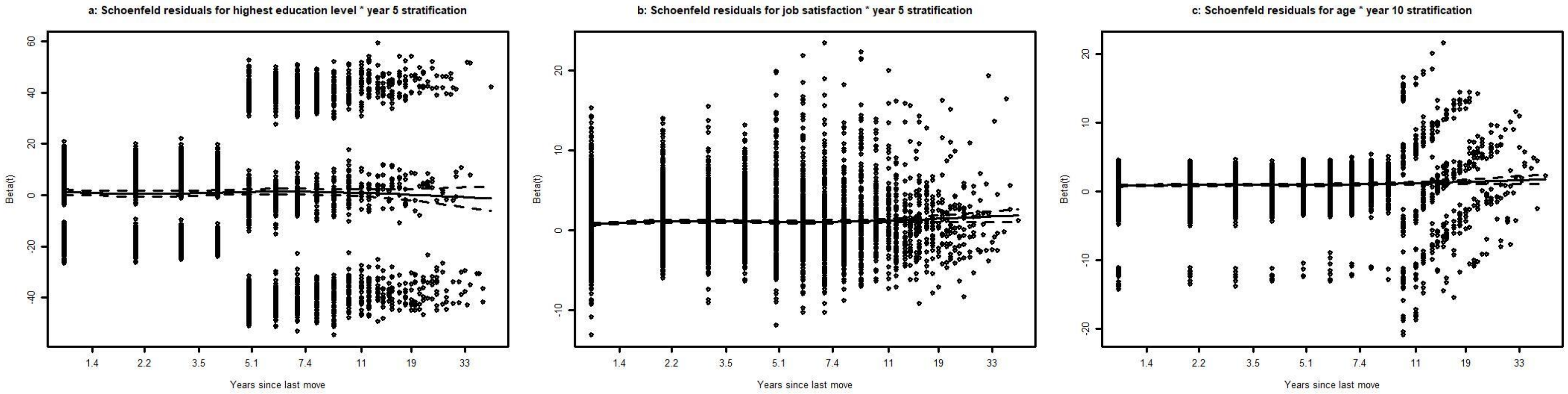

Figure 3-2: Schoenfeld residuals after correction through year stratification

All variables here have significant Pearson correlation. These residuals are based on the specification with all skill terms and no industry nor occupation categorical variables. The dotted lines represent the 95% confidence interval.

The second analysis on hourly wage uses a panel data regression. Two key model formats for this are random effects and fixed effects, where the former accounts for the individual variation in the error term while the latter uses separate fixed intercepts for all individuals. As explanatory variables, including education level, are time-invariant terms inseparable from individual intercepts, fixed effects are not well suited to answering the research question. As such, the random effects model is tested for endogeneity using a Durbin-Wu-Hausman test for endogeneity. The test on the model with all key explanatory terms and moderations and excluding any industry or occupational categories has a chi-squared of 124.42 with a p-value of ~0, signalling the random effects model by itself has problematic endogeneity. This is corrected by applying Mundlak corrections to all time variant terms (Bell & Jones, 2015), also known as correlated random effects (Wooldridge, 2019), to account for individual heterogeneity. The application of these corrections beings with the initial fixed effects model in Equation 2:

$$y_{it} = \beta_1^2 SS_{it-1} + \beta_2^2 OS_{it-1} + \beta_3^2 job_{it-1} + \beta_4^2 job_{it-1} * SS_{it-1} + \beta_5^2 job_{it-1} * OS_{it-1} + \gamma_1^2 X_{1it-1} + \alpha_{2i} + u_{it} \quad (2)$$

where y is the hourly wage for individual i at year t, job_{it-1} is whether the worker changes job, $job_{it-1} * SS_{it-1}$ is the moderated interaction between changing jobs and the vector of soft skills, $job_{it-1} * OS_{it-1}$ is the moderated interaction between changing jobs and other skills, α_1 is the overall intercept, α_{2i} is the individual intercept, and u_{it} is the fixed effects error term. All other terms follow from the prior equation. The 2 superscripts for coefficients denote panel data regression result estimates. Mundlak corrections are estimated using Equation 3 (Bell & Jones, 2015) along with the time-invariant individual variables otherwise contained in the individual intercepts, and substitute them into Equation 4:

$$\alpha_{2i} = \gamma_2^2 X_{2i} + \delta_1 \overline{SS}_{it-1} + \delta_2 \overline{OS}_{it-1} + \delta_3 \bar{X}_{1it-1} + \alpha_1 + \varepsilon_i \quad (3)$$

$$y_{it} = \beta_1^2 SS_{it-1} + \beta_2^2 OS_{it-1} + \beta_3^2 job_{it-1} + \beta_4^2 job_{it-1} * SS_{it-1} + \beta_5^2 job_{it-1} * OS_{it-1} + \gamma_1^2 X_{1it-1}^1 + \gamma_2^2 X_{2i}^2 + \delta_1 \overline{SS}_{it-1} + \delta_2 \overline{OS}_{it-1} + \delta_3 \bar{X}_{1it-1} + \alpha_1 + (u_{it} + \varepsilon_i) \quad (4)$$

The Mundlak correction for age is removed due to extreme multicollinearity with the baseline term, affecting the model estimation. Models with fewer parameters exclude the relevant parameters from Equation 4. When interpreting the model, the main coefficients measure changes within individuals over time while the Mundlak corrections measure differences between individuals over the whole period.

3.3. Soft skills, unemployment risk, and Australian economic downturns[2]

3.3.1. Data

This study also uses the HILDA Survey data. This analysis uses observations for the years 2005 through to 2016 as this provides not only a comparison point from prior to and during the GFC, but also enables observation of perpetual effects well after the crisis. In particular, extending the sample to 2016 includes the peak of the mining boom in 2012 and the subsequent slowdown (Foo & Salim, 2022). Only labour market participants are retained, regardless of current employment status, along with marginally attached workers who may reenter the labour market under certain circumstances. One potential issue is the introduction of new individuals in the sample in 2011: as this analysis includes measuring persistent effects of the GFC primarily observed after 2011, potential biases in these participants risk conflating a persistent shift after the GFC with a shift in the sample. As such, the model is filtered to those observed at least once prior to or during the GFC, consisting of 34,545 observations of 6,890 people. All soft and overall skill terms are utilised as previously described in Section 3.2.1, along with the job stress and time usage controls.

Unemployed is based on the detailed employment state variable (esdtl). Employed individuals are full-time or part-time employed, and unemployed individuals are unemployed or marginally attached. However, this may be insufficient to capture negative labour market outcomes from the GFC as discussed in Section 2.2.1; thus, two categorical variables are developed that utilise a third imperfect match state between unemployment and good quality employment. The first intermediate category is underemployment due to fewer hours of employment than desired (Rones, 1981). This uses the "If you could choose the number of hours you work each week… would you prefer to work" measure (jbhrcpr), with the answer "more hours than you do now" treated as underemployment, and answers for fewer or same hours treated as well-matched. The

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[2] This section was originally published in Semtner, A., & Dzator, J. (2024) Soft skills, unemployment risk, and Australian economic downturns. The Economic and Labour Relations Review. https://doi.org/10.1017/elr.2025.10039. Further edits to the methodology applied in this thesis were made based on reviewer feedback.

second intermediate category measure is whether the person feels overskilled for or underutilised in their job in alignment with bumping down (McGuinness & Wooden, 2009). This uses the Likert scale question “I use many of my skills and abilities in my current job” (jomus), with a score of 5–7 treated as overskilling and 1–4 considered well-matched (Mavromaras et al., 2015). The binary conversion is applied to ensure a consistent categorical scaling without excessive individual levels for the dependent variable. While there is potential endogeneity between these intermediate categories and employment-dependent skill terms, the highest education measures, time management measure, and all social capital components are measured outside of employment and thus provide a comparison of whether skills overall shift, while the use of the job stress control in particular provides a further means of comparison. Further, all skill terms are all lagged as discussed in the next session to prevent endogeneity with unemployment outcomes. Each model also includes an autoregressive measure of the dependent variable to incorporate prior employment states. To further distinguish cyclical or frictional unemployment from structural unemployment, a subset of specifications includes an independent variable for structurally unemployed participants who are marginally attached or unemployed for at least two consecutive years.

Some measures for the independent variables are only collected in the workplace and thus unmeasured for the unemployed or marginally attached. Specifically, the underlying measures for both job intensity variables and the task repetitiveness variable are only measured within the workplace. Years of unemployment immediately following or prior to a year of employment can be approximated using that year of employment, with preference for the former case. All other structurally unemployed workers are considered lacking these skills due to decay (Becker, 1994).

This analysis also includes two business cycle variables: the regional unemployment rate and year categorical terms. The latter enables detailed tracking of how unemployment progresses annually prior to and after the crisis, enabling investigation of persistent effects to recovery overall. The year categorical terms also enable specific investigation of both SBTC and RBTC from the GFC by including moderating interactions between all skill terms and the year categories, enabling measurement of how the effect of skills on unemployment changes from prior to the recession through subsequent years.

Finally, this analysis includes personal and workplace control variables. These include: gender, age, disability, whether the person is in a long-term relationship including marriage, children, whether the person is of Aboriginal or Torres Strait Islander (ATSI) heritage, whether the person is an immigrant from an English speaking background (ESB) or not (NESB), whether the person lives in an urban geographic region, the regional unemployment rate, and the occupation and industry classifications at the first level. The occupation and industry classifications provide further information on specific sectors affected by the crisis and potential unmeasured components of workers. As in the first study, each set of classifications are applied individually to minimising loss of parsimony. Structural unemployment is used as a type of classification in both groups, while frictionally or cyclically unemployed workers use their prior occupation or industry. Summary statistics are provided in Table 3-3 below.

Table 3-3: descriptive statistics - empirical chapter 2

	Summary statistics		Summary statistics
Current employment state		**Year**	
Unemployed	0.032	2006	0.084
Well-skilled or overskilled		2007	0.079
Well-skilled	0.772	2008	0.107
Overskilled	0.196	2009	0.104
Well-employed or underemployed		2010	0.108
Well employed	0.863	2011	0.097
Underemployed	0.105	2012	0.091
Soft skills		2013	0.087
Social capital	7.522 (1.304)	2014	0.083
Time management	2.592 (0.869)	2015	0.08
Low task repetitiveness	3.42 (1.673)	2016	0.079
Overall skills		**Controls**	
Highest education		Job stress	3.139 (1.639)
School	0.348	Total hours busy	2.688 (0.979)
Vocational	0.32	Gender (female)	0.479
University	0.333	Age	
Decide what do in job	4.403 (1.758)	Under 30	0.253
Decide how do job	4.757 (1.702)	30-39	0.209
Prior employment state		40-49	0.256
Unemployed	0.003	50-59	0.212
Well-skilled or overskilled		60 and over	0.07
Well-skilled	0.79	Disabled	0.158
Overskilled	0.207	Relationship	0.651
Well-employed or underemployed		Children	0.353
Well employed	0.878	Aboriginal and Torres Strait Islanders (ATSI)	0.014
Underemployed	0.12	Migrant (ESB)	0.107
Regional unemployment	4.982 (1.062)	Migrant (NESB)	0.071
		Urban	0.886
Individuals	6890	Observations	34545

For binary variables, measure is the proportion of the sample that is true for the variables. For categorical variables, measure is the proportion of the sample that is of the particular level. For numerical variables, measure takes the form of mean (standard deviation).

3.3.2. Method

The unemployment analysis uses panel data with a binary dependent variable. This method is based off Mavromaras et al. (2015): a generalised linear mixed method (GLMM) model with a logit link and random marginal effects. To account for potential endogeneity within individuals, Mundlak corrections are applied to all time-variant terms (Bell & Jones, 2015; Mavromaras et al., 2015). This process is similar to the process for the wage analysis in Section 3.2.2, beginning with a fixed effect model as specified in Equation 5 below:

$$y_{it}^{*} = \beta_1 SS_{it-1} + \beta_2 OS_{it-1} + \beta_3 y_{it-1} + \beta_4 t + \beta_5 SS_{it-1} * (t-1) + \beta_6 OS_{it-1} * (t-1) + \beta_7 y_{it-1} + \gamma_1 X_{1it-1} + \gamma_1 X_{2i} + \alpha_{2i} + u_{it} \quad (5)$$

where y_{it}^{*} is the continuous latent form of the underlying y_{it} dependent variable for unemployment, SS_i is the vector of soft skill measures, OS_i is the vector of other skill measures, t is the time measured as the year, X_{1i} is the vector of time-variant controls, X_{2i} is the vector of time-invariant controls, all β and γ terms are the relevant vectors of estimated coefficients, α_1 is the overall constant, α_{2i} is the individual intercept, and u_{it} is the fixed effects error term. These are measured for individual i, with all time-variant independent terms lagged to enable the model to better track how a worker's capabilities affect their future performance in the labour market.

This model form has two issues: the time-invariant variables, particularly education, cannot be separated from the individual intercepts, and the standard fixed effects model cannot be readily applied to a logit link function due to the incidental parameter problem (Lancaster, 2000). The Mundlak corrections applied as per Equation 6 enable minimisation of the incidental parameter problem and account for individual heterogeneity:

$$\alpha_{2i} = \delta_1 \overline{SS}_{it-1} + \delta_2 \overline{OS}_{it-1} + \delta_3 \bar{X}_{1it-1} + \alpha_1 + \varepsilon_i \quad (6)$$

This equation is then substituted into Equation 5, resulting in Equation 7:

$$y_{it}^{*} = \beta_1 SS_{it-1} + \beta_2 OS_{it-1} + \beta_3 job_{it-1} + \beta_4 t + \beta_5 SS_{it-1} * t + \beta_6 OS_{it-1} * t + \gamma_1 X_{1it-1} + \gamma_1 X_{2i} + \alpha_1 + \delta_1 \overline{SS}_{it-1} + \delta_2 \overline{OS}_{it-1} + \delta_3 \overline{X}_{1it-1} + (\varepsilon_i + u_{it}) \quad (7)$$

Models with fewer parameters exclude the relevant parameters from Equation 7.

This format removes the need for the individual intercepts, resolving the concerns of the standard fixed effects model with a logit link. When interpreting the model, the main coefficients measure changes within individuals over time while the Mundlak corrections measure differences between individuals over the whole period. The Mundlak correction for age is excluded as the age categories have minimal change within individuals over the period.

Two adjustments to this method are required for the overskilled and underemployed analyses. First, the functional format for Equation 7 is adjusted so the link variable y_{it}^{*} has multiple thresholds to determine whether a worker is well-matched, unemployed, or the intermediate category; these effectively replace the intercept term. Second, a cumulative link mixed model (CLMM) is used instead of GLMM for estimation, while retaining the logit link.

An initial comparison of different specifications for this model is provided in Table 3-4 to determine the base suitability of the model for the hypotheses discussed in Chapter 5. To summarise these hypotheses for the purpose of model selection, H2.1 is the expectation that soft skills are negatively associated with the risk of negative labour outcomes, particularly unemployment, while H2.2 is the expectation that year interactions with soft skills after the GFC increase the magnitude of this negative association. This comparison begins with three model forms: one with the base controls, one with the skill variables to determine if H2.1 is relevant, and one with the year interactions to determine if H2.2 is relevant. These results demonstrate that the inclusion of skills are relevant to the model, as seen with the significance of a range of soft and other skill terms and the reduced Akaike Information Criterion (AIC) when the skill variables are included compared to the base model. However, this AIC increases above the skill term model when the year interactions are added. This stems from an only modest reduction in log likelihood compared with the reduction when the skill variables are added, while a notably large number of interaction variables are added and require approximation.

Despite this, some interactions are significant and school education exhibits some trend in the year interactions, suggesting this is still theoretically relevant.

Table 3-4: Empirical chapter 2, unemployment random effects results

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
Intercept	-4.273***	-0.538	-1.034	-1.069	-1.383	-1.295
	(0.001)	(0.689)	(1.051)	(1.036)	(1.06)	(1.03)
Soft skills						
Social capital		-0.073	-0.065	-0.045	-0.064	-0.058
		(0.047)	(0.098)	(0.098)	(0.098)	(0.097)
Social capital (Mundlak)		-0.175**	-0.179**	-0.188**	-0.154*	-0.159*
		(0.067)	(0.068)	(0.068)	(0.068)	(0.068)
Time management		0.122	0.027	0.059	0.03	0.036
		(0.07)	(0.158)	(0.157)	(0.157)	(0.156)
Time management (Mundlak)		-0.002	0.027	0.039	0.029	-0.011
		(0.108)	(0.11)	(0.11)	(0.109)	(0.108)
Low task repetitiveness		-0.108**	-0.078	-0.07	-0.056	-0.055
		(0.034)	(0.083)	(0.083)	(0.083)	(0.082)
Low task repetitiveness (Mundlak)		0.049 (0.054)	0.074 (0.055)	0.07 (0.055)	0.096 (0.054)	0.082 (0.054)
Overall skills						
Highest education						
School		0.343**	1.088**	0.973**	0.805*	0.723
		(0.128)	(0.379)	(0.368)	(0.372)	(0.372)
Vocational		0.015	0.579	0.474	0.394	0.373
		(0.132)	(0.414)	(0.405)	(0.406)	(0.404)
Decide what do in job		-0.032	-0.142	-0.174	-0.184	-0.155
		(0.039)	(0.103)	(0.103)	(0.102)	(0.102)
Decide what do in job (Mundlak)		-0.176* (0.074)	-0.189* (0.076)	-0.191* (0.076)	-0.227** (0.076)	-0.193* (0.075)
Decide how do job		-0.051	-0.011	-0.02	0.014	-0.005
		(0.038)	(0.102)	(0.101)	(0.101)	(0.101)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
Decide how do job (Mundlak)		0.098	0.105	0.121	0.135	0.126
		(0.075)	(0.077)	(0.077)	(0.076)	(0.076)
Prior unemployment						
Unemployed	-0.754***	-0.008	0.072	-0.424	-0.346	-0.336
	(0.001)	(0.466)	(0.47)	(0.648)	(0.627)	(0.626)
Structurally unemployed				1.275	1.399	1.58
				(0.981)	(0.975)	(0.972)
Regional unemployment	0.207***	0.23***	0.242***	0.236***	0.236***	0.239***
	(0.001)	(0.065)	(0.066)	(0.066)	(0.066)	(0.066)
Regional unemployment (Mundlak)	-0.532***	-0.44***	-0.473***	-0.458***	-0.484***	-0.473***
	(0.001)	(0.087)	(0.088)	(0.089)	(0.088)	(0.087)
Year						
2007	-0.001	0.096	0.21	0.159	0.094	-0.12
	(0.001)	(0.17)	(1.165)	(1.153)	(1.163)	(1.151)
2008	-0.403***	-0.084	1.508	1.66	1.422	1.55
	(0.001)	(0.165)	(1.113)	(1.099)	(1.113)	(1.093)
2009	0.015***	0.2	0.347	0.249	0.358	0.223
	(0.001)	(0.162)	(1.104)	(1.089)	(1.104)	(1.087)
2010	-0.194***	-0.15	-0.523	-0.574	-0.513	-0.48
	(0.001)	(0.175)	(1.191)	(1.173)	(1.189)	(1.168)
2011	-0.26***	-0.128	1.411	1.212	1.156	1.033
	(0.001)	(0.176)	(1.208)	(1.198)	(1.219)	(1.195)
2012	-0.157***	-0.058	-1.41	-1.606	-1.759	-1.54
	(0.001)	(0.177)	(1.245)	(1.232)	(1.249)	(1.229)
2013	0.115***	0.151	-0.386	-0.248	-0.215	-0.264
	(0.001)	(0.176)	(1.239)	(1.217)	(1.235)	(1.215)
2014	-0.142***	-0.107	-1.158	-1.178	-1.201	-1.193
	(0.001)	(0.19)	(1.224)	(1.209)	(1.227)	(1.205)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
2015	-0.621***	-0.494*	0.807	0.899	1.144	1.067
	(0.001)	(0.216)	(1.317)	(1.293)	(1.303)	(1.287)
2016	-0.073***	0.027	1.382	1.434	1.229	1.262
	(0.001)	(0.195)	(1.2)	(1.182)	(1.201)	(1.18)
Year interactions						
2007 * Social capital			-0.112	-0.127	-0.119	-0.115
			(0.126)	(0.126)	(0.126)	(0.125)
2008 * Social capital			-0.113	-0.151	-0.134	-0.145
			(0.118)	(0.117)	(0.118)	(0.116)
2009 * Social capital			0.094	0.093	0.073	0.097
			(0.119)	(0.118)	(0.119)	(0.117)
2010 * Social capital			0.136	0.105	0.108	0.112
			(0.131)	(0.13)	(0.131)	(0.129)
2011 * Social capital			0.002	0.001	0.011	0.006
			(0.129)	(0.129)	(0.131)	(0.129)
2012 * Social capital			0.114	0.09	0.122	0.079
			(0.135)	(0.134)	(0.135)	(0.133)
2013 * Social capital			0.101	0.078	0.087	0.092
			(0.132)	(0.131)	(0.131)	(0.13)
2014 * Social capital			0.039	0.018	0.049	0.027
			(0.135)	(0.135)	(0.135)	(0.134)
2015 * Social capital			-0.246	-0.305*	-0.295*	-0.303*
			(0.15)	(0.15)	(0.15)	(0.149)
2016 * Social capital			-0.159	-0.185	-0.168	-0.183
			(0.136)	(0.135)	(0.136)	(0.134)
2007 * Time management			0.149	0.115	0.153	0.195
			(0.201)	(0.2)	(0.199)	(0.199)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
2008 * Time management			0.041	0.01	0.05	0.049
			(0.194)	(0.194)	(0.193)	(0.193)
2009 * Time management			-0.025	-0.082	-0.036	-0.041
			(0.189)	(0.188)	(0.188)	(0.187)
2010 * Time management			0.076	0.064	0.11	0.106
			(0.202)	(0.202)	(0.202)	(0.201)
2011 * Time management			-0.131	-0.132	-0.089	-0.076
			(0.212)	(0.213)	(0.212)	(0.211)
2012 * Time management			0.15	0.181	0.198	0.236
			(0.217)	(0.218)	(0.217)	(0.217)
2013 * Time management			0.206	0.139	0.163	0.163
			(0.208)	(0.207)	(0.207)	(0.206)
2014 * Time management			0.234	0.221	0.265	0.239
			(0.213)	(0.213)	(0.212)	(0.211)
2015 * Time management			0.069	0.056	0.024	0.056
			(0.231)	(0.23)	(0.229)	(0.229)
2016 * Time management			0.082	0.058	0.091	0.107
			(0.216)	(0.216)	(0.216)	(0.215)
2007 * Low task repetitiveness			0.028	0.039	0.024	0.028
			(0.112)	(0.111)	(0.111)	(0.11)
2008 * Low task repetitiveness			-0.135	-0.149	-0.145	-0.144
			(0.109)	(0.11)	(0.109)	(0.108)
2009 * Low task repetitiveness			-0.111	-0.14	-0.116	-0.134
			(0.105)	(0.106)	(0.105)	(0.104)
2010 * Low task repetitiveness			0.035	0.043	0.031	0.017
			(0.11)	(0.11)	(0.11)	(0.109)
2011 * Low task repetitiveness			-0.115	-0.136	-0.128	-0.108
			(0.118)	(0.118)	(0.118)	(0.116)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
2012 * Low task repetitiveness			0.04	0.038	0.031	0.025
			(0.115)	(0.115)	(0.114)	(0.114)
2013 * Low task repetitiveness			-0.121	-0.128	-0.127	-0.135
			(0.114)	(0.114)	(0.113)	(0.113)
2014 * Low task repetitiveness			0.003	-0.022	-0.038	-0.013
			(0.117)	(0.117)	(0.117)	(0.115)
2015 * Low task repetitiveness			-0.07	-0.049	-0.06	-0.067
			(0.13)	(0.13)	(0.129)	(0.129)
2016 * Low task repetitiveness			0.033	0.025	0.043	0.035
			(0.118)	(0.118)	(0.117)	(0.116)
2007 * Highest education -			-0.333	-0.17	-0.18	-0.133
School			(0.497)	(0.489)	(0.49)	(0.489)
2008 * Highest education -			-0.651	-0.485	-0.496	-0.441
School			(0.476)	(0.469)	(0.469)	(0.468)
2009 * Highest education -			-0.643	-0.507	-0.54	-0.485
School			(0.457)	(0.449)	(0.449)	(0.447)
2010 * Highest education -			-0.654	-0.508	-0.637	-0.611
School			(0.489)	(0.482)	(0.482)	(0.478)
2011 * Highest education -			-0.819	-0.704	-0.74	-0.625
School			(0.503)	(0.498)	(0.497)	(0.496)
2012 * Highest education -			-0.625	-0.516	-0.468	-0.494
School			(0.512)	(0.504)	(0.508)	(0.503)
2013 * Highest education -			-0.481	-0.381	-0.372	-0.35
School			(0.49)	(0.482)	(0.484)	(0.479)
2014 * Highest education -			-1.076*	-1.013*	-0.992*	-0.926
School			(0.507)	(0.501)	(0.501)	(0.498)
2015 * Highest education -			-1.079*	-0.889	-0.822	-0.859
School			(0.534)	(0.528)	(0.527)	(0.526)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
2016 * Highest education -			-1.218*	-1.192*	-1.065*	-1.093*
School			(0.507)	(0.502)	(0.504)	(0.5)
2007 * Highest education -			-0.143	-0.084	-0.028	-0.09
Vocational			(0.541)	(0.537)	(0.536)	(0.532)
2008 * Highest education -			-0.748	-0.643	-0.644	-0.676
Vocational			(0.533)	(0.528)	(0.528)	(0.523)
2009 * Highest education -			-0.595	-0.475	-0.494	-0.572
Vocational			(0.508)	(0.501)	(0.5)	(0.496)
2010 * Highest education -			-0.453	-0.323	-0.403	-0.479
Vocational			(0.53)	(0.523)	(0.521)	(0.515)
2011 * Highest education -			-0.345	-0.177	-0.285	-0.253
Vocational			(0.533)	(0.527)	(0.528)	(0.523)
2012 * Highest education -			-0.016	0.068	0.13	0.006
Vocational			(0.531)	(0.523)	(0.525)	(0.518)
2013 * Highest education -			-0.3	-0.16	-0.16	-0.28
Vocational			(0.527)	(0.518)	(0.519)	(0.513)
2014 * Highest education -			-0.476	-0.387	-0.445	-0.448
Vocational			(0.521)	(0.514)	(0.514)	(0.509)
2015 * Highest education -			-0.919	-0.713	-0.693	-0.799
Vocational			(0.56)	(0.552)	(0.553)	(0.547)
2016 * Highest education -			-0.826	-0.711	-0.596	-0.759
Vocational			(0.521)	(0.512)	(0.514)	(0.508)
2007 * Decide what do in job			0.072	0.111	0.127	0.119
			(0.14)	(0.141)	(0.14)	(0.14)
2008 * Decide what do in job			0.088	0.15	0.148	0.114
			(0.133)	(0.134)	(0.133)	(0.132)
2009 * Decide what do in job			0.038	0.075	0.083	0.073
			(0.13)	(0.13)	(0.129)	(0.129)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
2010 * Decide what do in job			0.295*	0.304*	0.341*	0.303*
			(0.145)	(0.145)	(0.144)	(0.144)
2011 * Decide what do in job			0.142	0.182	0.207	0.181
			(0.15)	(0.15)	(0.15)	(0.149)
2012 * Decide what do in job			0.075	0.136	0.161	0.125
			(0.148)	(0.149)	(0.148)	(0.148)
2013 * Decide what do in job			0.252	0.284	0.311*	0.279
			(0.145)	(0.145)	(0.144)	(0.144)
2014 * Decide what do in job			0.099	0.132	0.151	0.119
			(0.152)	(0.152)	(0.151)	(0.151)
2015 * Decide what do in job			0.274	0.309	0.314	0.276
			(0.166)	(0.167)	(0.166)	(0.165)
2016 * Decide what do in job			0.161	0.184	0.22	0.188
			(0.154)	(0.154)	(0.153)	(0.153)
2007 * Decide how do job			0.066	0.053	0.026	0.042
			(0.142)	(0.141)	(0.141)	(0.14)
2008 * Decide how do job			-0.027	-0.056	-0.052	-0.038
			(0.131)	(0.131)	(0.131)	(0.13)
2009 * Decide how do job			0.026	0.042	0.008	0.017
			(0.129)	(0.129)	(0.128)	(0.128)
2010 * Decide how do job			-0.333*	-0.306*	-0.353*	-0.325*
			(0.142)	(0.141)	(0.141)	(0.14)
2011 * Decide how do job			-0.168	-0.173	-0.211	-0.195
			(0.15)	(0.15)	(0.15)	(0.149)
2012 * Decide how do job			0.03	0.016	-0.03	0.008
			(0.149)	(0.149)	(0.149)	(0.148)
2013 * Decide how do job			-0.205	-0.202	-0.255	-0.221
			(0.143)	(0.142)	(0.142)	(0.141)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
2014 * Decide how do job			0.12	0.132	0.071	0.115
			(0.154)	(0.154)	(0.154)	(0.153)
2015 * Decide how do job			0.064	0.063	0.023	0.069
			(0.168)	(0.168)	(0.167)	(0.167)
2016 * Decide how do job			-0.059	-0.048	-0.102	-0.059
			(0.155)	(0.154)	(0.154)	(0.154)
Controls						
Job stress		0.104**	0.109***	0.11***	0.117***	0.117***
		(0.032)	(0.033)	(0.033)	(0.033)	(0.033)
Job stress (Mundlak)		-0.11	-0.1	-0.101	-0.096	-0.091
		(0.057)	(0.058)	(0.058)	(0.057)	(0.057)
Total hours busy		-0.087	-0.092	-0.092	-0.074	-0.068
		(0.068)	(0.069)	(0.069)	(0.069)	(0.069)
Total hours busy (Mundlak)		-0.242*	-0.242*	-0.241*	-0.232*	-0.258*
		(0.1)	(0.101)	(0.102)	(0.101)	(0.101)
Gender (female)	0.073***	0.167	0.195	0.209	0.275*	0.212
	(0.001)	(0.106)	(0.108)	(0.109)	(0.114)	(0.114)
Age						
Under 30	0.365***	0.168	0.185	0.155	0.162	0.151
	(0.001)	(0.144)	(0.148)	(0.148)	(0.148)	(0.147)
40-49	-0.642***	-0.424**	-0.354*	-0.397**	-0.313*	-0.392**
	(0.001)	(0.142)	(0.144)	(0.144)	(0.143)	(0.143)
50-59	-0.11***	0.041	0.113	0.078	0.167	0.055
	(0.001)	(0.152)	(0.155)	(0.155)	(0.155)	(0.153)
60 and over	0.05***	0.306	0.364	0.341	0.407*	0.297
	(0.001)	(0.201)	(0.204)	(0.205)	(0.204)	(0.202)
Disabled	0.405***	0.29*	0.206	0.248	0.217	0.241
	(0.001)	(0.139)	(0.141)	(0.141)	(0.141)	(0.14)

	Pre-GFC control	Pre-GFC independent	Pre-GFC interactions	Pre-GFC structural unemployment	Pre-GFC industry classifications	Pre-GFC occupation classifications
Disabled (Mundlak)	0.553***	0.394	0.516*	0.447*	0.508*	0.418
	(0.001)	(0.221)	(0.224)	(0.225)	(0.223)	(0.223)
Relationship	-0.597***	-0.259	-0.223	-0.243	-0.228	-0.24
	(0.001)	(0.176)	(0.18)	(0.18)	(0.181)	(0.18)
Relationship (Mundlak)	-0.049***	-0.098	-0.156	-0.14	-0.121	-0.113
	(0.001)	(0.215)	(0.22)	(0.22)	(0.219)	(0.218)
Children	0.24***	0.22	0.159	0.131	0.181	0.175
	(0.001)	(0.148)	(0.151)	(0.151)	(0.15)	(0.15)
Children (Mundlak)	-0.249***	-0.101	0.006	0.033	-0.047	-0.066
	(0.001)	(0.209)	(0.212)	(0.213)	(0.21)	(0.21)
Aboriginal and Torres Strait	1.023***	0.764*	0.854*	0.858*	0.899*	0.871*
Islanders (ATSI)	(0.001)	(0.359)	(0.361)	(0.363)	(0.354)	(0.354)
Migrant (ESB)	-0.126***	0.069	-0.011	0	0.034	0.018
	(0.001)	(0.167)	(0.171)	(0.171)	(0.168)	(0.168)
Migrant (NESB)	-0.347***	0.121	0.096	0.078	0.106	0.097
	(0.001)	(0.197)	(0.2)	(0.202)	(0.197)	(0.197)
Urban	0.185***	-0.139	-0.157	-0.178	-0.085	-0.126
	(0.001)	(0.271)	(0.275)	(0.275)	(0.279)	(0.274)
Urban (Mundlak)	-0.529***	-0.045	-0.015	0.01	0.053	-0.053
	(0.001)	(0.324)	(0.329)	(0.33)	(0.333)	(0.327)
Observations	31730	31730	31730	31730	31730	31730
Log likelihood	-4016.973	-3941.428	-3899.898	-3898.488	-3870.168	-3888.819
AIC	8095.947	7976.857	8033.797	8032.976	8012.335	8027.638

Industry and occupation classifications are not reported for space. Structural unemployment in the industry and occupation models is treated as an industry or occupation classification respectively. *, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.

Next, the three further sets of employment state controls are tested in the year effects specification to determine which is best suited: occupation classifications, industry classifications, or structural unemployment by itself, with relevant coefficients and statistics included in Table 3-4. All AICs are slightly smaller than the interaction model, suggesting these all have some contribution. However, the structural unemployment model has very minimal reduction in AIC, suggesting longer durations of unemployment by themselves have limited further contribution. One notable element is the reduction of significance of the significance of some variables, including school-level education and the Mundlak correction for social capital, in the industry and occupation model, reinforcing that these components do provide additional explanatory power. Of the industry and occupation models, the industry model has a slightly lower AIC along with higher significance for its base skill terms and the interaction terms compared to the occupation model, suggesting that the industry component better synergises with the skill analysis of interest. The final models and interpretation are discussed in Chapter 5.

3.4. Soft skills, technology, and productivity of Australian industries

3.4.1. Data

Soft skills as the primary independent variable of interest are drawn from the Australian Skills Classification (ASC) 2023 data as a base and are tested on the Australian and New Zealand Standard Classification of Occupations (ANZSCO) 2006 standard 4-level occupations, improving the ability to calculate the overall soft skill measure compared to broad 1-level occupations. While the ASC has been decommissioned due to restrictions including timeliness and the importance of external validation (Jobs and Skills Australia, n.d.), these data are still the best available data known to the author for the skill content of Australian occupations specifically, particularly for sufficient breadth for this thesis.

From the ASC data, this analysis draws on the core competency data, consisting of ten total skills across a range of types including soft skills and skills outside of this category, with Likert scores on all skills varying from 1 to 10. As described earlier, seven of these ten skills are selected based on the soft skills literature: initiative and innovation, learning ability, oral communication, planning and organising, problem solving, teamwork, and writing as a measure of written communication. Although writing is sometimes considered a basic or foundation skill along with mathematics and literacy (Newton, 2016), it is treated as a soft skill for this analysis due to the importance of communication generally in research on soft skills as previously discussed, and using only oral communication results in an imbalance. The remaining four skills not utilised as soft skills (digital engagement, learning, numeracy, and reading) are instead considered basic or foundation skills more directly used in production (Department of Employment and Workplace Relations, 2025; European Education Area, 2025; Newton, 2016), or more broadly as the other key skills a worker may use in their employment. While it would be preferable to investigate these skills individually, the relatively limited number of observations in the sample utilised and the inclusion of moderating relationships between soft skills and ICT investment as discussed in the following Section 3.4.2 makes the combined usage of individual skills and moderating relationships unviable with the data available. As such, an initial test is run on a CFA analysis of the ten skills into two dimensions based on their skill grouping they represent: a soft skill dimension and a hard skill dimension, using correlated factors. The use of CFA is to ensure model parsimony when including the moderating interaction between skills and ICT. This model has a comparative fit index (CFI) of 0.927 and a Tucker-Lewis Index (TLI) of 0.903, suggesting reasonable fit. However, the root mean square error of approximation (RMSEA) is 0.145, which is not particularly strong. However, initial testing of models with these variables found variance inflation factors (VIFs) over 150 between the soft skill and hard skill measures, suggesting excessive correlation that distorts interpretation of this key independent variable. As the removal of the correlation between factors negative affects all the CFA fit metrics, a soft skill only CFA is instead tested. This model has very similar statistics to the initial model (CFI=0.949, TLI=0.923, RMSEA=0.153), further confirming the limited value of including hard skills as a distinct component. Overall, the soft skill model is considered sufficient for analysis thanks to the reasonable CFI and TLI, while the VIFs for all variables are sufficiently low for analysis. Standardised factor loadings for the soft skill variables are reported in Table 3-5 to investigate the similarity of these elements as a further check. Of the seven skill terms included, six of the seven skill terms (initiative and innovation, learning, oral communication, planning, problem solving, writing) have loadings above 0.7 and thus are appropriate for use. Only teamwork has a relatively low factor loading of 0.36; due to the theoretical relevance of this factor, it is also retained.

Table 3-5: Skill term factor loadings

	Soft skill loading
Initiative and innovation	0.709
Learning	0.927
Oral communication	0.916
Planning	0.791
Problem solving	0.890
Teamwork	0.363
Writing	0.941

To link these occupation 4-level measures to the Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006 1-level industries the other data utilise, two steps are applied. First, a weighted average is created by total hours worked of these skills from the ANZSCO 4-level occupations to the ANZCO 1-level occupations. Second, these ANZSCO 1-level skills are weighted by the proportion of total hours worked by each 1-level occupation in each 1-level industry. Both steps use the Australian Bureau of Statistics (ABS) Detailed Labour Force data calculated annually, averaging the quarterly data available over each year to remove irrelevant volatility within each year. As not all 4-level occupations are included in both datasets, only occupations common to the ASC data and the Detailed Labour Force data are utilised for both the CFA and the weightings. This includes 278 unique occupations, out of 296 total occupations in the ASC data and 471 in the Detailed Labour Force data. Of the 193 occupations only included in the Detailed Labour Force data, 113 of these are for occupations that are not further defined beyond 1-level, 2-level, or 3-level codes and thus excluded from the ASC data, with a further 31 coming from miscellaneous occupation groups that can be difficult to attach specific skill information to. In comparison, the final occupations retained only include 42 occupations classified under any level of miscellaneous, and the ASC data contain only one occupation classified as miscellaneous that is not included in the Detailed Labour Force data. When investigating the distribution of 4-level occupations excluded from the final sample, seven sets of 2-level occupations (12, 36, 44, 51, 52, 54, 84) exclude at least half of the occupations measures in at least one category. Three of these are under clerical and administrative workers, suggesting some limits to this category; however, the remaining 2-level sets of clerical and administrative workers (55, 56, 59) all have less than 30% of occupations under this level, suggesting this is not systemic to the overall 1-level category. One further important element of this soft skill measure is the initial 4-level occupation measures are time-invariant, while the industry weighted measures are time-variant due to changes in occupational employment. This means changes in the soft skill term are interpreted as changes to the employment share rather than changes in the skills within occupations.

The remaining data are drawn from different ABS datasets and linked by year and ANZSIC 1-level industry codes for all specifications. The data used for each specification are discussed in the following sub-sections.

3.4.1.1. Industry MFP

The capital, labour, energy, materials, and services (KLEMS) dataset provides many additional variables, including change in the natural log of multifactor productivity (MFP) as the dependent variable, intermediate goods usage as an additional independent variable, information communication technology (ICT) capital usage, and non-ICT capital usage. MFP in these data is calculated using labour quality adjusted hours (Australian Bureau of Statistics, 2021); thus, some skill components are already controlled for. This measure utilises education level and experience to control for skills, suggesting further detailed skill measures can further explain the model. The two capital variables are used to calculate the ICT capital ratio of the proportion of ICT used compared with total capital, which prior research suggests is relevant for productivity analysis (Leung & Zheng, 2012). Imports and exports by industry are drawn from the International Trade in Goods tables, while research and development (R&D) investment by each industry is drawn from the Research and Experimental Development Business dataset. To ensure comparability between industries and over time, both variables are divided by the total value added of each industry in each year, as calculated by the chain value measure from the National Accounts dataset. Further, to account for skill-biased technological change and routine-biased technological change, this analysis also utilises the interaction between the ICT-capital ratio and the soft skill measure. This analysis uses the years 2006–2021 to maximise the observations with the available data for the industry standard utilised, while also keeping the analysis to relatively recent years. As all industries are measured in each year, this forms a balanced panel data set of 256 observations before incorporating lags or differencing.

Summary statistics for these data and stationarity tests are provided in Table 3-6. One key point to note is the missing data for R&D due to the biannual collection of these data by the ABS after 2014. Due to this, predictive mean matching (PMM) multiple imputation is applied for these missing values, with five imputations generated. Stationarity of the data is tested using both the Im, Pesaran, & Shin (2003) (IPS) method to test for stationarity and Hadri (2000) to test for nonstationarity, with all variables excluding MFP non-stationary according to both tests. When first differencing is applied to the variables, the ICT/capital ratio and intermediate goods have significant results for both measures, which are further investigated using Figure 3-3. The ICT-capital ratio appears stationary except for during the GFC and one industry during the COVID pandemic, suggesting these are unusual years rather than nonstationary data; thus, this variable is appropriate for use without further adjustments. Intermediate goods usage has some industries with larger fluctuations or fluctuations that take a couple periods to return to normal levels; as these measures do not go on systemic random walks this variable is also appropriate for use. As such, both variables are treated as integrated of order 1, or I(1). All other variables are stationary according to both methods after this transformation, and thus are I(1).

Table 3-6: Summary statistics and stationarity tests – empirical chapter 3, MFP analysis

	Min	Max	Mean	Median	Standard deviation	Missing count	Final count	IPS base	Hadri base	IPS first difference	Hadri first difference
MFP	-7.02	8.59	0.143	0.325	1.867	0	256	-9.612***	0.664		
Soft skills (occupation)	-1.36	1.32	0	-0.028	0.635	0	278				
Soft skills (industry)	-0.377	0.386	0	-0.033	0.175	0	256	-1.542	16.879***	-15.56***	-2.007
ICT capital ratio	0.351	36.242	9.99	8.032	7.732	0	256	-8.031***	22.503***	-7.297***	4.003***
R&D – base	0.04	4.217	1.061	0.542	1.099	83	173				
R&D – imputed			1.062	0	1.106		256	-5.437***	9.513***	-23.26***	-2.562
Imports	0	234.806	11.685	0	43.380	0	256	2.411	17.007***	-5.922***	-0.746
Exports	0	101.585	10.006	0	22.907	0	256	2.042	12.575***	-5.619***	-0.498
Intermediate goods	34.62	72.62	53.061	52.69	9.628	0	256	-2.198*	15.217***	-6.151***	6.719***
Year	2006	2021					15				

Soft skills (occupation) are the original occupation-level skills data and thus lack IPS or Hadri test estimates for these results. *, **, *** Significant at 5%, 1%, and 0.1% levels respectively.

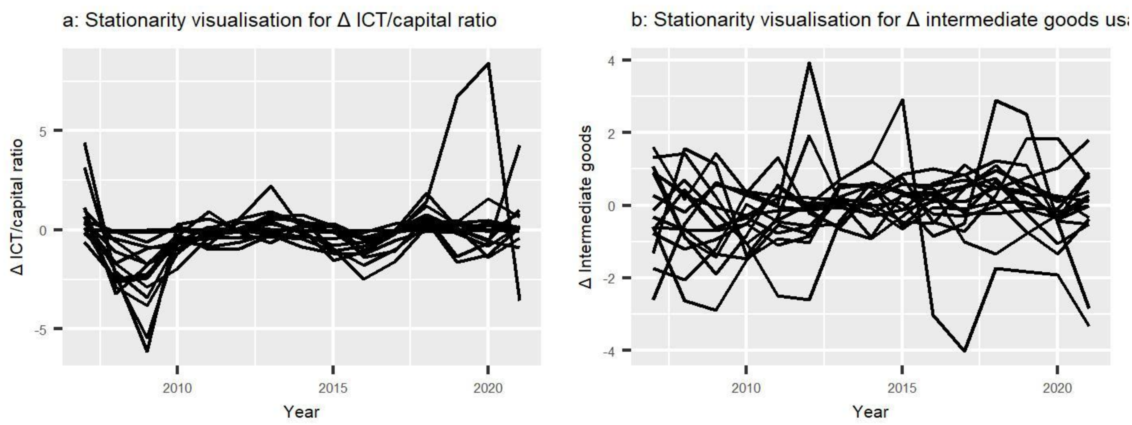

Figure 3-3: Stationarity graphs – MFP differenced variables
The variables included have mixed results between the Hadri and IPS statistics after correction.

3.4.1.2. Industry output

While the ABS KLEMS data also provide production growth statistics for a range of inputs, this increases the complexity of interpretation for long-run analysis if the method proves useful. As such, alternate data are utilised that can be directly interpreted in a long-run framework. Value-added output utilises the industry value added measured using chained values as previously discussed. Capital is measured using the ABS System of National Accounts (SNA) Table 64 for gross capital formation for each industry and Table 70 for gross ICT capital formation. Intermediate goods are measured using the National Accounts Input-Output Table 5 for total use of intermediate goods among private industries as a measure of industry specialisation. As the intermediate goods data have missing values for some years, multiple imputation using PMM is also applied for these years. For labour, total hours worked are utilised as a direct measure of production using the previously discussed Detailed Labour Force hours worked measures. Soft skills utilise the same data as before; however, as the base measures include zero or negative values, these measures are all shifted so the lowest value possible is 1 prior to log transformation (0 when log transformed). Imports and exports instead had only zero values shifted prior to log transformation due to the larger scale of the variables. Summary statistics for these data for the market sector are included in Table 3-7. A further benefit of using these data is the ability to adjust for total worker counts in industries to determine per worker production via using the Detailed Labour Force tables previously utilised. This ratio is not applied to soft skills as these skills are endowed for each worker rather than being rivalrous like physical capital.

As in the MFP analysis, the IPS and Hadri tests for stationarity are applied for both data sets. All variables for this analysis have significant Hadri statistics while only output, R&D, and other capital have significant IPS statistics. As such, all variables are first differenced, resulting in significant IPS statistics for all variables and no significant Hadri statistics, suggesting all variables are I(1). Monetary units are utilised for all relevant terms to align with prior research on production growth (Agbenyegah & Bloch, 2010; Graetz & Michaels, 2018).

Table 3-7: Summary statistics and stationarity tests – empirical chapter 3, value added analyses

	Min	Max	Mean	Median	Standard deviation	Missing count	Final count	IPS base	Hadri base	IPS first difference	Hadri first difference
Industry value added	23.158	26.534	24.922	24.894	0.705	0	256	1.216	31.864***	-10.86***	-0.068
Soft skills (industry)	0	0.567	0.312	0.296	0.128	0	256	-1.29	16.902***	-14.887***	-2.044
ICT capital	19.209	22.421	20.789	20.797	0.725	0	256	2.88	27.886***	-12.477***	-1.212
Non-ICT capital	20.292	25.911	22.963	22.833	1.086	0	256	-1.458	20.065***	-12.357***	-0.759
Labour hours	15.175	17.613	16.523	16.508	0.647	0	256	-1.506	23.726***	-12.492***	-0.692
R&D – base	16.315	22.665	19.776	19.569	1.544	83	173				
R&D – imputed			19.775	0	1.553	0	256	-4.771***	12.917***	-21.849***	-2.337
Imports	0	26.412	5.699	0	9.952	0	256	1.229	14.81***	-6***	-0.541
Exports	0	26.232	5.839	0	10.216	0	256	-0.642	11.577***	-4.95***	-0.384
Intermediate goods – base	23.136	26.556	24.809	24.774	0.725	32	224				
Intermediate goods – imputed			24.795	0	0.722	0	256	2.354	31.066***	-13.249***	-0.985

All variables are in natural log terms. *, **, *** Significant at 5%, 1%, and 0.1% levels respectively.

3.4.2. Method

Before model testing can be done, two further steps are required: determining whether a long-run model is appropriate, and what format of model is suited for the data. The long-run aspect is investigated via testing whether cointegration exists in the data: if cointegration is found, long-run methodologies can be applied that are considered some of the main ways human capital (Égert et al., 2024) and technology investment (Basu et al., 2003) affect MFP and production as a whole. To address this, the Pedroni (1999) series of tests are applied to all three models. As the base MFP variable is stationary, a log index version is generated from the data; while the ABS do provide an MFP index as part of the SNA data, the KLEMS MFP uses more detailed data (Australian Bureau of Statistics, 2025) and thus index calculation using the KLEMS data is preferred. Results are presented in Table 3-8, where only the panel parametric t statistic is found to be significant while all other statistics are insignificant. Based on this, a short-run model using differenced variables is best suited. While not preferable due to the aforementioned effects of interest, analyses on production and productivity are occasionally conducted in the short-run (Ali et al., 2018), suggesting some relevance. A fixed effects panel data model is considered well suited to handling potential endogeneity within the data, while the limited size of the data risk overly reducing degrees of freedom when attempting to use Mundlak corrections in a random effects model as utilised elsewhere in this thesis. However, there is still the question of which estimator is suitable: the OLS estimator or a generalised method of moments (GMM) estimator. For this, the system GMM estimator was tested: although the difference GMM estimator is preferred for smaller samples of observed individuals by some (Arellano & Bond, 1991), more recent research suggests the system GMM estimator is as good or better even in small samples so long as there is moderate persistence of the dependent variable (Soto, 2009). This testing found only limited persistence in any of the models tested, with the coefficients of autoregressive components reaching at largest 0.195 and are at best significant at the 5% level, suggesting too low levels of persistence for suitable interpretation. As such, the models tested for all analyses are short-run fixed effects models using the OLS estimator.

Table 3-8: Pedroni (1999) cointegration standardised statistics

	MFP	Value added	Value added per worker
Panel ν	-4.933	-6.272	-6.269
Panel ρ	4.055	7.628	7.852
Panel t nonparametric	5.662	12.527	13.593
Panel t parametric	-8505.685***	-17270.111***	-3026.346***
Group ρ	7.915	9.906	10.042
Group t nonparametric	12.357	16.455	17.24
Group t parametric	12.883	16.494	17.186

*, **, *** Significant at 5%, 1%, and 0.1% levels respectively.

The base productivity model takes the form specified in Equation 8:

$$\Delta\ln MFP_{\iota\tau} = b_1\Delta Soft_{\iota\tau-1} + b_2\Delta ICT_{\iota\tau-1} + b_3\Delta Soft_{\iota\tau-1} * \Delta ICT_{\iota\tau-1} + b_4\Delta Imports_{\iota\tau-1} + b_5\Delta Exports_{\iota\tau-1} + b_6\Delta Intermediate_{\iota\tau-1} + b_7\Delta R\&D_{\iota\tau-1} + a_i + \varepsilon_{it} \tag{8}$$

where $\Delta lnMFP_{\iota\tau}$ is the MFP dependent variable for industry i at time t, $Soft_{\iota\tau}$ is the soft skill measure, ICT is the ICT-capital ratio, $Imports$ is the imports as a proportion of total value added, $Exports$ is the exports as a proportion of total value added, $Intermediate$ is the intermediate goods as a proportion of factor inputs, $R\&D$ is the R&D as a proportion of total value added, the b terms are the short-run coefficients, a_i is the short-run industry intercept, and ε is the overall error term.

This same process is applied for the production model, using a log-log transformation of a Cobb-Douglas function, including the human capital components (Bowlus & Robinson, 2012; Égert et al., 2024). This results in the form specified in Equation 9:

$$\begin{aligned} \Delta lnValueadd_{\iota\tau} &= b_1\Delta lnSoft_{\iota\tau-1} + b_2\Delta lnICTcap_{\iota\tau-1} + b_3\Delta lnSoft_{\iota\tau-1} * \Delta lnICTcap_{\iota\tau-1} \\ &+ b_4\Delta lnOthercap_{\iota\tau-1} + b_5\Delta lnLabourhrs_{\iota\tau-1} + b_6\Delta lnImports_{\iota\tau-1} \\ &+ b_7\Delta lnExports_{\iota\tau-1} + b_8\Delta lnIntermediate_{\iota\tau-1} + b_9\Delta lnR\&D_{\iota\tau-1} + a_i + \varepsilon_{it} \end{aligned} \tag{9}$$

where $Valueadd$ is the value-added output for the industry, $ICTcap$ is the ICT capital investment, $Othercap$ is the non-ICT capital investment, and $Labourhrs$ is the labour hours. As raised above, R&D, imports, intermediate goods, and exports are no longer in intensity terms as a proportion of total value added, but instead in the same log monetary units as the capital terms. The per worker version takes the same form as equation 9, with all variables excluding soft skills adjusted to use per worker measures.

3.5. Conclusion

This section has detailed the underlying data and models applied to answer the research questions posed previously. Each of these methods further incorporates each of the key theories in some manner to account for the productive value of soft skills and the technological changes occurring in the Australian economy. Further, the different methods provide alternative lenses and focal points to develop a fuller picture of how these skills interact with the Australian economy. The first method prioritises individual benefits to human capital in the broader context of the technological changes and resulting skill and routine biases, along with multiple skill measures for soft and other skills for comparative purposes and to provide an angle on potential signalling. The second method further builds on this by investigating the link between unemployment risk and the GFC, using SBTC and RBTC as a base while studying a key indicator relevant for businesses and governments. The third method changes approach to focus on business usage of soft skills for comparison against the labour benefits, while also including technological synergies with soft skills for further details on technological biases.

Chapter 4. Soft skills and job mobility[3]

4.1. Introduction

This empirical chapter seeks to answer RQ1 from Section 1.6. Section 4.2 begins this chapter with further background on the specific issue of job mobility and its relevance in the Australian economy, along with the hypotheses tested. This is followed by Section 4.3 detailing the results of the empirical methodology detailed in Section 3.2. Section 4.4 concludes this chapter with the overall conclusion of this chapter, including contributions and results.

4.2. Background and hypotheses

Job mobility, where workers change their employer or job (Carroll & Poehl, 2007; Ferreira, 2009; Ng et al., 2007; Sicherman & Galor, 1990), has historically been researched from a labour turnover perspective. This has resulted in a focus on associated negative outcomes including increased production costs (Darmon, 2004), additional training costs (Darmon, 2004), loss of tacit knowledge (Avasthi & Dey, 2015), and low job satisfaction in the workplace (Green, 2010). However, the emergence of new technologies, including artificial intelligence (AI), is changing this image, potentially disrupting up to 19% of employment (Frey & Osborne, 2017). Without job mobility, this constricts the ability of businesses to fill skill gaps as they implement new technologies (Ng et al., 2007), and for workers to both bargain for better wages and conditions (Black & Chow, 2022; Keith & McWilliams, 1995) and shift from employers who are not adapting to these new technologies. Further, the Baby Boomers have begun exiting the labour force internationally since the COVID pandemic (Agarwal & Bishop, 2022), risking leaving key skill gaps and labour shortages for businesses. Taken together, these forces risk slower macroeconomic growth alongside detrimental effects for businesses and individuals.

However, while Australia currently has a decade-high job change rate since the COVID pandemic (Australian Bureau of Statistics, 2023a), it is still relatively weak compared to

[3] This chapter has been published as: Semtner, A., Dzator, J., & Nadolny, A. (2025). Is no (soft) skill left behind? Do soft skills enable job mobility. *Applied Economics, 57*(33), 4897-4915. https://doi.org/10.1080/00036846.2024.2364103. This chapter is based on the specified paper, with methodological updates and relevant adaptations made in this thesis at the behest of reviewers.

the pre-GFC period (Australian Bureau of Statistics, 2023b). This is curious considering Australia did not have a technical recession during the GFC (Debelle, 2018) despite its status as a moderately sized OECD country. Prior research has investigated job mobility using a range of theories, including job shopping theory where workers new to the labour market test out multiple jobs over time (Ferreira, 2009), neoclassical theory emphasising individual decisions for maximising lifelong returns (Ferreira, 2009), and particularly human capital theory (Becker, 1994; Carroll & Poehl, 2007; Sicherman & Galor, 1990). Further, prior research on transferable skills has focused on knowledge transfer from education (Tran et al., 2021) or occupational transition (Nawakitphaitoon, 2014), leaving a resulting gap for job mobility as a whole. This chapter focuses on the value of soft skills as a key set of transferable skills (Cimatti, 2016; Leighton & Speer, 2020; Snell et al., 2016). Further, soft skills are considered valuable among a range of occupations and industries (Robles, 2012; Whiting, 2020), thus suggesting endowments of these skills could provide wage benefits when changing jobs and even additional flexibility with moving across industries and occupations (Tsiligiris & Bowyer, 2021).

This study seeks to answer RQ1 by investigating four hypotheses. The first hypothesis follows the expectation of soft skills enabling workers to utilise job mobility, while the second compares this to overall skills that should be less mobile than soft skills specifically:

H1.1: Soft skills, as measured by time management, social capital, and low task repetitiveness, have a significant and positive association with the likelihood of changing jobs.

H1.2: Soft skills, as measured by time management, social capital, and low task repetitiveness, have a larger association with the likelihood of changing jobs compared to overall skills, as measured by the skill intensity of the job and the education level of the worker.

Further, some mobility may stem from job insecurity and other problematic circumstances (McGann et al., 2016). The third hypothesis considers whether workers with soft skills have an improved hourly wage from changing jobs as a measure of what workers seek from prospective employers (PwC, 2021), while the fourth hypothesis again compares this to overall skills:

H1.3: The moderation between changing jobs and soft skills, as measured by time management, social capital, and low task repetitiveness, has a significant and positive association with the hourly wage.

H1.4: The moderation between changing jobs and soft skills, as measured by time management, social capital, and low task repetitiveness, has a larger association with the hourly wage compared to the moderation between changing jobs and overall skills, as measured by the skill intensity of the job and the education level of the worker.

Figure 4-1 graphically displays the conceptual model for this research.

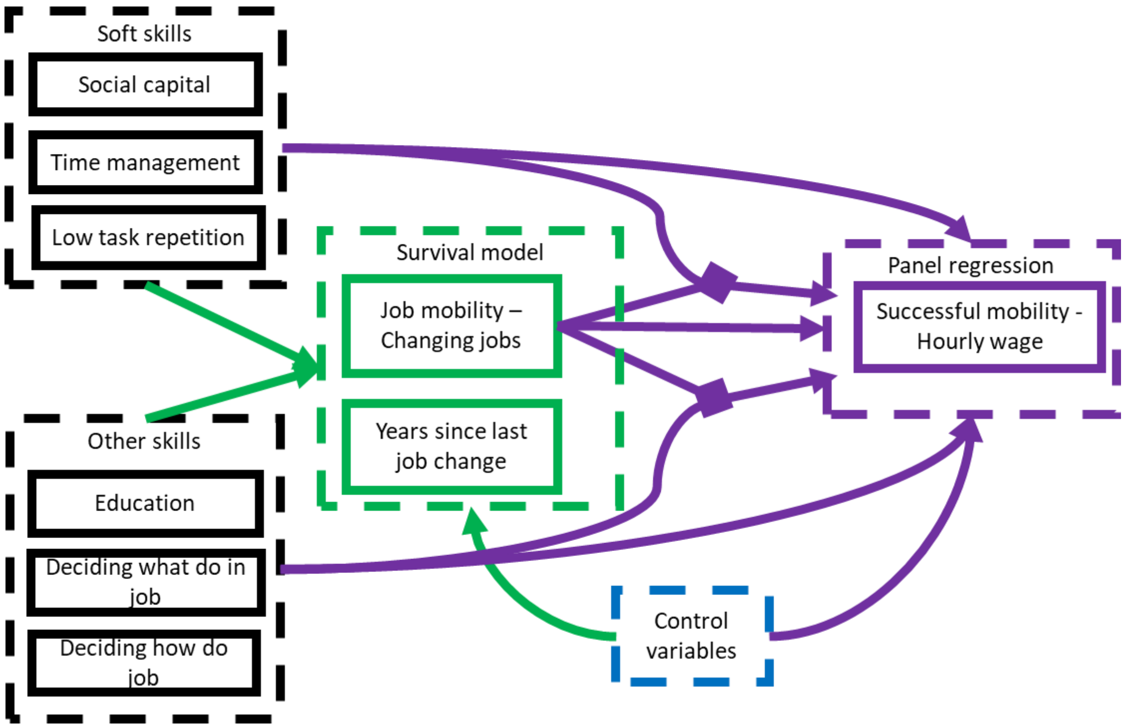

Figure 4-1: Conceptual model
Source: thesis author, original study authors.

To investigate these hypotheses, this chapter follows the data and method previously discussed in Section 3.2. This involves employing the Household, Income and Labour Dynamics in Australia (HILDA) Survey from 2011 to 2019 in two models: a survival model to test how soft skills are associated with changing employers, and a random effects model to test how soft skills are associated with log hourly wages. This second model is particularly useful to separate detrimental mobility from unstable casualisation (McGann et al., 2016) from the beneficial mobility of interest by using a key job requirement prospective workers consider (PwC, 2021). Self-reported measures of time management, low task repetitiveness, and social capital are used to measure soft skills. The use of multiple measures for soft skills, along with multiple measures of overall skills for comparison, help to investigate different aspects of each skill group, including comparisons between baseline human capital and job signalling theory perspectives using readily observed education variables (Burdett, 1978; Kalb & Meekes, 2021). To account for skills supporting job mobility in the wage regression, job mobility acts as a moderator for all skill terms within certain specifications.

4.3. Results

4.3.1. Job change

Table 4-1 displays the hazard ratios of changing jobs for the Cox proportional hazards survival model, where a result greater than 1 suggests an increased likelihood of mobility and a result less than 1 suggests a reduced likelihood of mobility. The significant hazard ratios of the baseline model without any skill terms display primarily expected ratios. One unusual element is the relatively large reduced mobility likelihood that the gender-relationship moderation provides, as this effectively removes the positive mobility benefits of both gender and relationship by themselves. Most hazard ratios only have slight variations in magnitude across specifications, with the most variation occurring when introducing skill terms.

Table 4-1: Changing jobs Cox model results

	Baseline	With skills	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Soft skills						
Social capital		1.024	1.024	1.024	1.029*	1.022
		(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Time management * 5 year (>=5 years)		0.977	0.975	0.976	0.98	0.976
		(0.029)	(0.029)	(0.029)	(0.029)	(0.028)
Time management * 5 year (<5 years)		1.01	1.01	1.009	1.015	1.015
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Low task repetitiveness		0.997	1.006	0.998	1.006	0.999
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Overall skills						
Highest education						
School * 5 year (>=5 years)		0.919	0.858*	0.913	0.86*	0.897
		(0.064)	(0.065)	(0.067)	(0.066)	(0.067)
School * 5 year (<5 years)		1.05	0.965	1.046	0.95	1.015
		(0.048)	(0.05)	(0.051)	(0.05)	(0.052)
Vocational * 5 year (>=5 years)		0.848**	0.792***	0.848**	0.794***	0.842**
		(0.058)	(0.06)	(0.062)	(0.061)	(0.062)
Vocational * 5 year (<5 years)		1.06	0.999	1.059	0.98	1.053
		(0.049)	(0.05)	(0.052)	(0.051)	(0.052)
Decide what do in job		0.962**	0.956***	0.961**	0.954***	0.96***
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Decide how do job		1.023	1.026*	1.022	1.018	1.02
		(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Controls						
Job stress		0.973**	0.976*	0.973**	0.978*	0.978*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Total hours busy		0.935***	0.935***	0.933***	0.935***	0.938***
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)

	Baseline	With skills	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Gender (female)	1.138**	1.141**	1.194***	1.154**	1.178***	1.153**
	(0.043)	(0.044)	(0.045)	(0.046)	(0.046)	(0.046)
Gender (female) * Relationship	0.718***	0.72***	0.724***	0.713***	0.736***	0.721***
	(0.059)	(0.059)	(0.06)	(0.06)	(0.06)	(0.06)
Age						
Under 30 * 10 year (>=10 years)	2.634***	2.611***	2.646***	2.62***	2.625***	2.622***
	(0.195)	(0.195)	(0.193)	(0.196)	(0.196)	(0.195)
Under 30 * 10 year (<10 years)	1.218***	1.182***	1.182***	1.187***	1.189***	1.202***
	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
40-49 * 10 year (>=10 years)	0.408***	0.398***	0.406***	0.396***	0.411***	0.402***
	(0.123)	(0.123)	(0.123)	(0.123)	(0.124)	(0.123)
40-49 * 10 year (<10 years)	0.869**	0.864**	0.882*	0.86**	0.872**	0.866**
	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)	(0.053)
50-59 * 10 year (>=10 years)	0.186***	0.182***	0.189***	0.182***	0.189***	0.187***
	(0.144)	(0.144)	(0.144)	(0.144)	(0.145)	(0.143)
50-59 * 10 year (<10 years)	0.677***	0.676***	0.701***	0.672***	0.685***	0.682***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)	(0.067)
60 and over * 10 year (>=10 years)	0.093***	0.091***	0.095***	0.09***	0.093***	0.093***
	(0.205)	(0.206)	(0.206)	(0.206)	(0.207)	(0.205)
60 and over * 10 year (<10 years)	0.265***	0.264***	0.275***	0.262***	0.268***	0.267***
	(0.141)	(0.142)	(0.141)	(0.142)	(0.142)	(0.143)
Disabled * 10 year (>=10 years)	0.771*	0.774*	0.785*	0.773*	0.752*	0.77*
	(0.122)	(0.122)	(0.122)	(0.122)	(0.124)	(0.122)
Disabled * 10 year (<10 years)	0.992	1.003	1.009	1.002	1.009	1.002
	(0.042)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Relationship	1.1*	1.129**	1.133**	1.134**	1.132**	1.122*
	(0.046)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Children	0.91**	0.951	0.958	0.949	0.961	0.966
	(0.035)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)

	Baseline	With skills	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Aboriginal and Torres Strait Islanders	1.058	1.084	1.08	1.082	1.083	1.068
(ATSI)	(0.1)	(0.1)	(0.099)	(0.099)	(0.095)	(0.098)
Migrant (ESB)	1.088	1.096	1.072	1.094	1.071	1.076
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Migrant (NESB)	1.032	1.038	1.016	1.036	1.003	1.018
	(0.055)	(0.055)	(0.055)	(0.055)	(0.056)	(0.056)
Overall life quality	1.025*	1.009	1.012	1.008	1.012	1.012
	(0.012)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Urban * 5 year (>=5 years)	1.375***	1.343**	1.325**	1.346**	1.325**	1.307**
	(0.092)	(0.091)	(0.092)	(0.091)	(0.093)	(0.092)
Urban * 5 year (<5 years)	1.031	1.029	1.025	1.036	1.018	1.028
	(0.061)	(0.061)	(0.062)	(0.062)	(0.062)	(0.062)
Hour preference						
Underemployed	1.024	1.049	1.049	1.047	1.05	1.044
	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Overemployed	1.181***	1.177***	1.174***	1.178***	1.174***	1.185***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Full time	0.998	1.044	1.044	1.037	1.033	1.041
	(0.041)	(0.042)	(0.043)	(0.043)	(0.044)	(0.043)
Job satisfaction * 5 year (>=5 years)	0.819***	0.819***	0.822***	0.819***	0.826***	0.822***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Job satisfaction * 5 year (<5 years)	0.879***	0.877***	0.884***	0.877***	0.885***	0.883***
	(0.009)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ln weekly wage * 10 year (>=10 years)	0.894	0.908	0.908	0.909	0.919	0.896
	(0.069)	(0.068)	(0.068)	(0.068)	(0.068)	(0.067)
ln weekly wage * 10 year (<10 years)	0.858***	0.894***	0.898***	0.893***	0.901***	0.878***
	(0.025)	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)
Medium-large business * 5 year (>=5	0.815***	0.791***	0.831***	0.789***	0.841***	0.813***
years)	(0.049)	(0.049)	(0.05)	(0.049)	(0.051)	(0.05)

	Baseline	With skills	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Medium-large business * 5 year (<5 years)	0.837***	0.838***	0.861***	0.836***	0.869***	0.855***
	(0.035)	(0.035)	(0.037)	(0.036)	(0.037)	(0.036)
Regional unemployment * 5 year (>=5 years)	1.227***	1.237***	1.229***	1.238***	1.233***	1.24***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.028)	(0.027)
Regional unemployment * 5 year (<5 years)	1.107***	1.105***	1.098***	1.105***	1.095***	1.099***
	(0.019)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Sector-GDP gap	0.997	0.998	0.996	0.998	0.996	0.996
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Observations	16386	16386	16386	16386	16386	16386
Log likelihood	-42970.6	-42944	-42868.7	-42941.3	-42789.1	-42852.7

Industry and occupation classifications are not reported for space. *, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.

When including the skill terms, vocational education as the highest education level has significantly smaller hazard ratios for changing jobs after at least 5 years that suggest workers with these qualifications are less likely to change jobs after at least 5 years with their current employer. By comparison, school-level workers lack a significant effect for either duration when no industry nor occupation controls are included, although the coefficients are consistently below 1 and thus suggest relatively mobility for workers with university-level qualifications. Deciding what to do in the job is also significant; however, the coefficient is below 1, suggesting workers in these jobs have lower mobility. Together, these provide mixed effects in line with prior Australian research by Shah (2009), where a positive relationship was found between education and job separations for women and men with a bachelor's degree while higher education reduced occupational mobility for men and women. However, they differ from research by Carroll and Poehl (2007), who found higher educated workers had fewer job separations. Compared to overall skills, soft skill factors lack any significant coefficients across all specifications, suggesting these mobility effects do not apply and thus do not support H1.1. Further, between these insignificant results for soft skills and the mixed effects of overall skill measures, there is a lack of evidence supporting H1.2.

When the industry classifications are included, the magnitude of these effects stay relatively consistent. However, there is a notable reduction in the coefficients for vocational education over 5 years, suggesting that vocationally trained workers are even less mobile depending on industry. Further, school-level education also has significant coefficients less than 1 when either level of industry classification is utilised. This reinforces the prior element of lower skills being generally associated with lower mobility and thus university-educated workers being associated with the highest mobility, albeit with the lowest mobility still found for moderately skilled workers. Other skill factors are also significant in specific specifications: the ability to decide how to do the job is significantly associated with increased mobility for industry 1-level classifications, while social capital is significantly associated with increased mobility for industry 2-level classifications. When occupation classifications are included, results do not notably change from the baseline case, suggesting industry of employment is more relevant for job mobility compared to the occupation employed in. As this is a singular case of a single soft skill measure having a significant association and the skill results have minimal significant changes, the results still fail to support H1.1 and H1.2

Finally, the log likelihood continues to approach zero with additional variables, suggesting the skill terms and classifications are relevant. The log likelihood at each classification level is always closer to zero for the industry version than the occupational version, with the strongest log likelihood when 2-level industry classifications are included, reinforcing the relevance of industry distinctions for job mobility decisions. The 2-level occupation classifications are closer to zero compared to the 1-level industry classifications, suggesting granularity of work or employer type is valuable to understanding the mobility decision.

4.3.2. Wages from changing jobs

Table 4-2 displays the coefficients for the regression on log hourly wages. Investigating the control variables, the main coefficients appear appropriate. Further, the majority of Mundlak corrections for the variables have significant coefficients, particularly for those with low or insignificant coefficients for the base variables. This suggests the comparisons between workers are of greater relevance than the changes for each worker. Coefficients generally retain or lose magnitude when including the skill terms, while there are few additional changes when including industry or occupational classifications, suggesting skills are important in determining wages.

Table 4-2: Wage random effects model results

	Baseline	With skills	Interactions	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Intercept	3.143***	2.808***	2.807***	2.86***	2.965***	2.837***	2.999***
	(0.035)	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)
Soft skills							
Social capital		-0.002	-0.003	-0.003	-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Social capital (Mundlak)		0	0	0	-0.001	0	-0.001
		(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Time management		0.001	0.001	0.001	0.001	0.001	0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Time management (Mundlak)		-0.007	-0.007	-0.009	-0.004	-0.008	-0.003
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Low task repetitiveness		0.002	0.002	0.001	0	0	-0.001
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Low task repetitiveness (Mundlak)		0.039***	0.039***	0.036***	0.035***	0.035***	0.033***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Overall skills							
Highest education							
Vocational		0.072***	0.076***	0.064***	0.069***	0.062***	0.062***
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
University		0.239***	0.246***	0.228***	0.2***	0.218***	0.177***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Decide what do in job		0.004*	0.003*	0.003	0.002	0.004*	0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decide what do in job (Mundlak)		0.011**	0.011**	0.014***	0.01*	0.014***	0.009*
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Decide how do job		0	0.001	0	0	0	-0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Decide how do job (Mundlak)		0.009*	0.009*	0.006	0.006	0.006	0.005
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

	Baseline	With skills	Interactions	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Controls							
Change jobs		0.004	0.009	-0.004	0.011	-0.003	0.011
		(0.005)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Change jobs (Mundlak)		0.035*	0.033	0.039*	0.033*	0.039*	0.033*
		(0.017)	(0.017)	(0.016)	(0.017)	(0.016)	(0.016)
Change jobs * Time management			0.002	0.002	0.001	0.004	0.002
			(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Change jobs * Social capital			0.003	0.003	0.003	0.002	0.003
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Change jobs * Low task repetitiveness			0.001	0	0	0	-0.001
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Change jobs * Decide what do in job			0.006	0.008	0.007	0.009*	0.007
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Change jobs * Decide how do job			-0.008*	-0.008*	-0.009*	-0.009*	-0.009*
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Change jobs * University			-0.046***	-0.047***	-0.045***	-0.046***	-0.047***
			(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Change jobs * Vocational			-0.023	-0.021	-0.022	-0.022	-0.023
			(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Job stress		0	0	-0.001	-0.001	-0.001	-0.002
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Job stress (Mundlak)		0.002	0.002	0.002	0	0.004	0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total hours busy		0.01***	0.01***	0.006*	0.008**	0.005	0.005
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total hours busy (Mundlak)		0.03***	0.03***	0.025***	0.03***	0.024***	0.029***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Gender (female)	-0.037***	-0.052***	-0.052***	-0.047***	-0.061***	-0.049***	-0.057***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

	Baseline	With skills	Interactions	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Gender (female) * Relationship	-0.025*	-0.039***	-0.038***	-0.043***	-0.04***	-0.038***	-0.042***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.01)	(0.01)
Age							
Under 30	-0.134***	-0.099***	-0.1***	-0.094***	-0.099***	-0.095***	-0.098***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
40-49	0.02**	0.015*	0.015*	0.013*	0.016*	0.014*	0.014*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
50-59	-0.007	-0.007	-0.006	-0.008	-0.003	-0.006	-0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
60 and over	-0.01	-0.012	-0.012	-0.015	-0.007	-0.013	-0.006
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Disabled	0.004	0.004	0.004	0.004	0.003	0.004	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Disabled (Mundlak)	-0.105***	-0.089***	-0.089***	-0.092***	-0.086***	-0.089***	-0.083***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Relationship	0.075***	0.066***	0.067***	0.064***	0.063***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Relationship (Mundlak)	0.088***	0.045***	0.045***	0.042***	0.043***	0.041***	0.04***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Children	-0.007	-0.006	-0.006	-0.006	-0.006	-0.006	-0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Children (Mundlak)	0.032**	-0.005	-0.005	-0.002	-0.003	0.001	-0.004
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Aboriginal and Torres Strait	-0.015	0	-0.001	-0.005	0	-0.008	0
Islanders (ATSI)	(0.025)	(0.024)	(0.024)	(0.023)	(0.023)	(0.022)	(0.022)
Migrant (ESB)	0.046***	0.019	0.019	0.015	0.017	0.013	0.014
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.01)
Migrant (NESB)	-0.013	-0.057***	-0.058***	-0.057***	-0.049***	-0.056***	-0.046***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)

	Baseline	With skills	Interactions	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Urban	0.037**	0.036**	0.036**	0.035**	0.036**	0.037**	0.034**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Urban (Mundlak)	0.058***	0.049**	0.049**	0.039*	0.041*	0.028	0.03
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Years employed	0.001	0.001**	0.001**	0.001**	0.001*	0.001**	0.001*
	(0)	(0)	(0)	(0.001)	(0.001)	(0.001)	(0.001)
Years employed (Mundlak)	0.006***	0.005***	0.005***	0.005***	0.004***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hour preference							
Underemployed	-0.001	-0.001	-0.002	0.001	-0.002	0.002	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Underemployed (Mundlak)	0.053***	0	0	0.005	-0.007	0.006	-0.009
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Overemployed	0.003	0	-0.001	0	0	0	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Overemployed (Mundlak)	-0.137***	-0.084***	-0.084***	-0.069***	-0.07***	-0.064***	-0.059***
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Full time	0.043***	0.015*	0.015*	0.001	0.003	-0.001	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Full time (Mundlak)	0.066***	0.022	0.022	0.01	0.02	0.006	0.015
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Medium-large business	0.03***	0.026***	0.027***	0.022***	0.026***	0.021***	0.024***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Medium-large business (Mundlak)	0.193***	0.172***	0.172***	0.165***	0.167***	0.158***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.009)
Regional unemployment	-0.008**	-0.006*	-0.006*	-0.006*	-0.006*	-0.007**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Regional unemployment (Mundlak)	-0.036***	-0.028***	-0.028***	-0.025***	-0.025***	-0.023***	-0.025***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)

	Baseline	With skills	Interactions	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Sector-GDP gap	0.001	0.001	0.001	0	0.001	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Sector-GDP gap (Mundlak)	0.009***	0.006***	0.006***	0.004**	0.006***	0.003*	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year							
2013	0.033***	0.03***	0.03***	0.029***	0.029***	0.029***	0.027***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2014	0.059***	0.053***	0.053***	0.052***	0.051***	0.052***	0.05***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2015	0.107***	0.096***	0.096***	0.095***	0.094***	0.096***	0.094***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
2016	0.142***	0.13***	0.13***	0.128***	0.129***	0.128***	0.127***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2017	0.162***	0.148***	0.148***	0.145***	0.145***	0.145***	0.142***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2018	0.203***	0.187***	0.187***	0.184***	0.183***	0.184***	0.18***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2019	0.247***	0.231***	0.231***	0.226***	0.227***	0.225***	0.222***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	39745	39745	39745	39745	39745	39745	39745
Adj. R^2	0.582	0.606	0.606	0.615	0.612	0.621	0.62

Industry and occupation classifications are not reported for space. *, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.

Skill measure have consistently positive returns in the skill model without interactions. In particular, overall skills are consistently associated with higher returns through the coefficients for vocational and university education, and the Mundlak corrections for the ability to decide what tasks to perform in the job and how to perform the job. These results are aligned with prior research on the effects of education on wages (Leigh, 2008; Mavromaras et al., 2010). Further, the coefficient for the year-to-year measure of ability to decide what job to perform is significant and positive as well, reinforcing this. However, soft skills lack significant effects for any of the base coefficients nor Mundlak corrections with the sole exception of the Mundlak correction for low task repetitiveness, suggesting soft skills also do not provide relevant wage benefits let alone any over broader skills.

The variable for changing employers is also added alongside the skill terms and has no effect, suggesting workers who change employers have no significant wage benefit. Knight and Wei (2014) found job mobility in Australia had different effects on wage depending on the sector, with public sector workers experiencing a wage loss in the short-term while private sector workers offset their underlying wage disadvantage, thus demonstrating limited benefit to job mobility for Australian workers. However, the Mundlak correction for changing employers is significant and positive, suggesting that those who change jobs at some point have higher wages. Whether this is workers who are using mobility to bargain for better conditions and wages (Black & Chow, 2022; Keith & McWilliams, 1995) or potentially workers having higher wages before moving is unknown from this information alone. When the interactions between changing job and skills are added, only the interaction with university-level education is significant, and this is consistently insignificant regardless of model. This does partially align with Nawakitphaitoon (2014), who found US workers have some decline in wages whenever they change occupations due to lost job-specific human capital, while shared skills with their new occupation help offset this loss, potentially suggesting these university qualifications are seen as job or career specific rather than readily transferable. Overall, this is not evidence in favour of either H1.3 or H1.4.

The adjusted R-squared terms support these discussions. The inclusion of skill terms is beneficial to the R-squared, while including the interactions with job change does not affect the R-squared. Further improvements are seen when accounting for industry or occupation, with some benefit from 1-level classifications and further benefit from using the 2-level classifications. Unlike the changing job model, there is limited difference between using industry or occupational classifications and the improvements from including these terms are smaller than the benefit from the skill terms. This suggests wage characteristics do depend on the skills of the worker while the type of employment has limited further effect.

4.4. Conclusion

Although the job mobility rate for Australia has recently increased above typical post-GFC levels, it has still yet to reach pre-GFC levels. This is a concern for Australia's future productivity and labour allocation. Soft skills are theoretically useful for this as a key set of transferable skills, with broad demand by modern businesses, forming the basis for RQ1. This chapter seeks to apply the empirical analyses discussed earlier to modern Australia data to answer this research question by investigating if employees utilise these theoretical benefits of soft skills for mobility, and whether the combination of skills and mobility improves their wages. Three soft skills of time management, low task repetitiveness, and social capital are measured using the HILDA dataset, and are applied in a survival model for whether workers change jobs and in a random effects model with Mundlak corrections for wage benefits, particularly from worker transitions.

Contrary to expectations, soft skills as a whole were insignificant for mobility in both models. Further, the only time changing employers was significantly associated with wage was when university workers had reduced incomes, with no monetary benefit for workers with soft skills changing employers. Whether this is due to workers preferring other characteristics over wages for changing jobs (Masige, 2023; PwC, 2021), increased incidence of negative mobility from casualisation (McGann et al., 2016), or some other factor is not investigated in this study, forming one avenue for further research. A further element of note is the mixed effect of overall skills on job mobility likelihood, with non-university education and the job element of the ability to decide what to do in the job reducing mobility overall. Higher levels of overall skills have positive associations with wages, while the only soft skill factor associated with wages was low task repetitiveness, which by itself does not act as evidence for the value of soft skills. This chapter overall provides a negative answer for RQ1 while also reinforcing the value of overall skills for general wages. Despite this, soft skills as a whole lack a strong association with these components, suggesting they are limited as individual skills developed through different channels and with the ability to support workers in different ways.

There are three primary contributions from this chapter. First, these results deepen the understanding of skills transferability as potential transferability does not necessarily translate to active job mobility, potentially constraining workers to their current employment. This study also deepens the understanding of differences between individual skills and skill measures in the labour market. The range of skill measures tested enables this research to draw upon both human capital theory and signalling theory (Lam et al., 2012; Quintini, 2011), with some additional mobility shown by university qualifications supporting signalling theory while the lower wages of moving with these university qualifications act as evidence against this. Second, these results suggest a lack of bias for business to gain or retain soft skills, compared to the bias for retaining overall skills. This may create complications for businesses seeking skilled workers, particularly as overall skills are required for production (Cimatti, 2016). Further, although university-educated workers may be relatively mobile they risk facing a wage penalty from moving. However, the lack of wage gain for workers with characteristics associated with soft skills suggests limits with how valued these skills are by businesses, whether due to alternate ways these skills are valued or how businesses identify the presence of soft skills. Third, governments and workers gain a better understanding of potential weaknesses for skilled worker mobility, including for the job security of the worker and technological implementation. Governments in particular should understand the potential benefits of improving the mobility of skilled workers would likely be macroeconomic from improving the allocation and productivity of labour overall, while skilled individuals have no monetary benefit from mobility.

Finally, this research offers a base for further analysis of why these soft skill metrics are not associated with additional worker value through neither improved job mobility options nor higher wages. An additional avenue to explore is what skills businesses seek to acquire and how they go about it, including what skills they see as transferable and thus potentially costly to train in-house. These are important as workers will not always have strong wage bargaining powers and businesses will need to continue acquiring the necessary skills for their continued functioning.

Chapter 5. Soft skills, unemployment risk, and Australian economic downturns[4]

5.1. Introduction

Recessions have grown costlier for Australia and other modern developed economies, in part due to consistent government deficits seen years after the Global Financial Crisis (GFC) in particular (Quiggin, 2014) and the degradation of human capital when potential workers are structurally unemployed (Cardona-Arenas, 2024). Further, research in the USA also suggests recessions in modern economies risk structural unemployment of workers due to changes in the types of skills businesses demand (Jaimovich & Siu, 2020). The retirement of Baby Boomers from the labour market has also commenced in recent years (Agarwal & Bishop, 2022), emphasising the importance of keeping the remaining workers employed to maintain output. Combined, this suggests the Australian Government can apply skill development policies to both improve productivity and reduce the cost of future recessions. Soft skills are a set of relevant skills that could support workers with remaining employed or finding new and better-suited employment sooner while further improving productivity, forming the basis for RQ2. This chapter aims to answer this research question by investigating whether soft skills reduce the risk of unemployment in the Australian labour market, particularly during an economic downturn. The first sub-hypothesis is the association between soft skill endowments and a reduction in unemployment likelihood:

> *H2.1: Soft skills, as measured by time management, social capital, and low task repetitiveness, have a significant and negative association with unemployment, underemployment, and overskilling risk.*

This has particular relevance for Australian workers due to the relatively high and growing proportion of jobs with nonrepetitive tasks (Borland & Coelli, 2024) along with the aforementioned benefits of soft skills.

There is a further aspect of particular interest that this chapter investigates: the ability for soft skills to act as a hedge against unemployment during economic downturns. Internationally, the

[4] This chapter has been published as: Semtner, A., & Dzator, J. (2024) Soft skills, unemployment risk, and Australian economic downturns. The Economic and Labour Relations Review. https://doi.org/10.1017/elr.2025.10039. This chapter is based on the specified paper, with methodological updates and relevant adaptations made in this thesis at the behest of reviewers.

GFC resulted in a shock of skill-biased technological change (SBTC) and routine-biased technological change (RBTC) that affected the type of employment in other developed nations (Hershbein & Kahn, 2018; Jaimovich & Siu, 2020), resulting in perpetual effects beyond the crisis itself. This can potentially stem from creative destruction occurring during the GFC, acting as a cleansing effect. While Australia did not have a technical recession for this period, there was still an increase in unemployment for specific groups (Junankar, 2015) and the labour market overall (Mackey et al., 2022), suggesting SBTC, RBTC, or creative destruction may have perpetually affected the relevance of soft skills. To test this, data are drawn from the years 2006–2016 to provide both years prior to the GFC for comparison and sufficient years after the GFC to investigate these perpetual effects. In particular, interactions between skill terms and year effects provide detailed information on the impact perpetual effects of this crisis have on the relationship between soft skills and unemployment. This forms the base for the second sub-hypothesis:

> *H2.2: Soft skills, as measured by time management, social capital, and low task repetitiveness, have additional significant and negative associations with unemployment, underemployment, and overskilling risk for the years 2010-2016.*

These effects are graphically displayed in Figure 5-1.

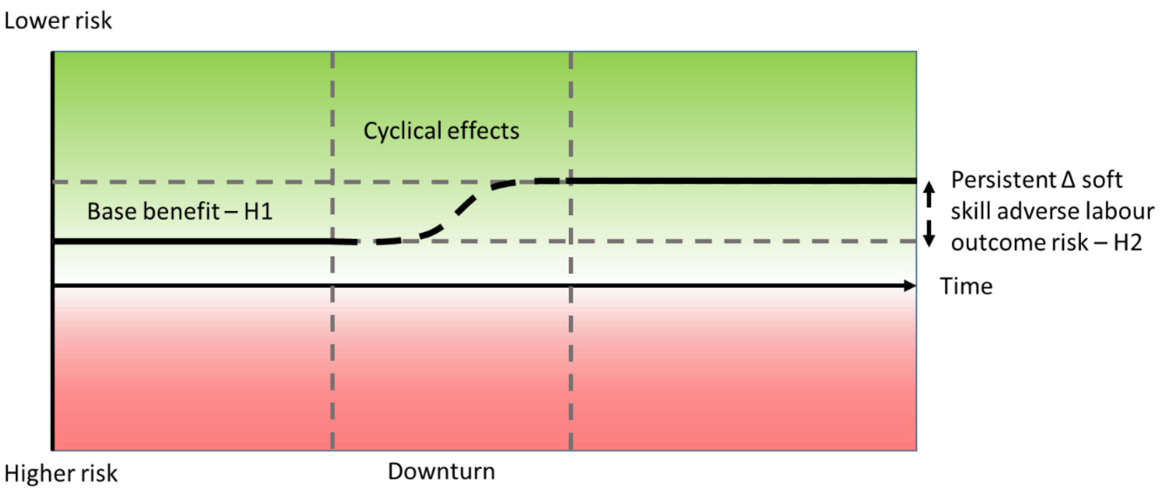

Figure 5-1: Theoretical expectations of soft skill effect on unemployment likelihood
Source: thesis author, original study authors.

This analysis uses the Household, Income and Labour Dynamics in Australia (HILDA) Survey to measure self-reported social capital, time management, and task repetitiveness for the lead-up to, during, and after the GFC, as described in Section 3.3.1. These data are applied in a random effects logit regression to determine the association between these soft skills and the likelihood of unemployment, underemployment, or overskilling as potential negative outcomes from economic downturns as discussed in 2.2.1. This analysis also specifically tests for perpetual elements as per H2.2. The focus of this research is on these cyclical and persisting effects of the GFC on skills, with SBTC and RBTC applied as theoretical drivers, rather than investigating theses tech biases from specific technological investments.

This chapter begins with Section 5.2 covering the results using the two final models in the specified data sample to test these hypotheses across three dependent variables. This is followed by Section 5.3 discussing applications and contributions.

5.2. Results

Relevant coefficients for all models are included in Table 5-1. Base skill terms are almost entirely insignificant for both the unemployment and underemployment models, with the exception of the positive association between school-level education as the highest education and risk of unemployment and underemployment compared to university education. The Mundlak corrections in these models do provide further information, with significant coefficients for the social capital and deciding what do in the job corrections. All three significant coefficients are also of higher significance in the underemployment model compared to the unemployment model, suggesting they are only somewhat relevant for unemployment and have greater relevance when accounting for poor match states. However, time management and low task repetitiveness have no significant coefficients for their base variables nor their Mundlak corrections. The latter is particularly unusual considering the relatively high and growing proportion of nonroutine jobs in the Australian labour market (Borland & Coelli, 2024). When looking at the interactions for the unemployment and underemployment models, there are limited trends to be found: the unemployment model has limited significant effects with no trends visible, while the underemployment model has significant interactions for social capital prior to the GFC, before losing significance after this period. Overall, these results do not align with H2.1 nor H2.2.

Table 5-1: Unemployment, underemployment, and overskilling binary and ordered random effects results

	Unemployment only	Unemployment or overskilled	Unemployment or underemployed
Intercepts and thresholds			
Intercept	-1.383		
	(1.06)		
Well employed | underemployed			0.303
			(0.526)
Underemployed | unemployed			2.216***
			(0.526)
Well skilled | overskilled		-2.011***	
		(0)	
Overskilled | unemployed		0.735***	
		(0)	
Soft skills			
Social capital	-0.064	0.004***	0.071
	(0.098)	(0)	(0.051)
Social capital (Mundlak)	-0.154*	-0.238***	-0.166***
	(0.068)	(0)	(0.035)
Time management	0.03	0.022***	-0.003
	(0.157)	(0)	(0.079)
Time management (Mundlak)	0.029	0.089***	0.049
	(0.109)	(0)	(0.054)
Low task repetitiveness	-0.056	-0.028***	-0.068
	(0.083)	(0)	(0.041)
Low task repetitiveness (Mundlak)	0.096	-0.134***	-0.008
	(0.054)	(0)	(0.027)
Other skills			
Highest education			
School	0.805*	0.332***	0.595***
	(0.372)	(0.081)	(0.175)
Vocational	0.394	0.036***	0.275
	(0.406)	(0)	(0.191)
Decide what do in job	-0.184	-0.051***	-0.068
	(0.102)	(0)	(0.052)
Decide what do in job (Mundlak)	-0.227**	-0.3***	-0.175***
	(0.076)	(0)	(0.038)
Decide how do job	0.014	0.016***	-0.004
	(0.101)	(0)	(0.052)
Decide how do job (Mundlak)	0.135	-0.001***	0.056
	(0.076)	(0)	(0.038)
Prior employment state			
Unemployed	-0.346	0.371	0.732*
	(0.627)	(0.311)	(0.317)
Overskilled		1.019***	
		(0)	
Underemployed			1.349***
			(0.053)

	Unemployment only	Unemployment or overskilled	Unemployment or underemployed
Structurally unemployed	1.399	1.527*	1.497*
	(0.975)	(0.658)	(0.609)
Regional unemployment	0.236***	0.028***	0.09**
	(0.066)	(0)	(0.034)
Regional unemployment (Mundlak)	-0.484***	-0.078***	-0.102*
	(0.088)	(0)	(0.044)
Year			
2007	0.094	-0.706	0.951
	(1.163)	(0.379)	(0.605)
2008	1.422	-0.225	0.46
	(1.113)	(0.322)	(0.561)
2009	0.358	0.235***	0.08
	(1.104)	(0)	(0.568)
2010	-0.513	-0.14***	0.068
	(1.189)	(0)	(0.606)
2011	1.156	0.404***	-0.055
	(1.219)	(0)	(0.613)
2012	-1.759	-0.531***	-0.286
	(1.249)	(0)	(0.635)
2013	-0.215	0.325***	-0.304
	(1.235)	(0)	(0.637)
2014	-1.201	-0.235***	-0.192
	(1.227)	(0)	(0.628)
2015	1.144	0.275***	0.365
	(1.303)	(0)	(0.672)
2016	1.229	0.642	0.819
	(1.201)	(0.397)	(0.639)
Year effects			
2007 * Social capital	-0.119	0.058	-0.132*
	(0.126)	(0.043)	(0.067)
2008 * Social capital	-0.134	-0.039	-0.146*
	(0.118)	(0.035)	(0.061)
2009 * Social capital	0.073	-0.01***	0.028
	(0.119)	(0)	(0.062)
2010 * Social capital	0.108	0.013***	-0.023
	(0.131)	(0)	(0.067)
2011 * Social capital	0.011	-0.042***	-0.01
	(0.131)	(0)	(0.067)
2012 * Social capital	0.122	0.03***	-0.031
	(0.135)	(0)	(0.069)
2013 * Social capital	0.087	-0.074***	0.008
	(0.131)	(0)	(0.068)
2014 * Social capital	0.049	-0.042***	-0.033
	(0.135)	(0)	(0.069)
2015 * Social capital	-0.295*	-0.043***	-0.144
	(0.15)	(0)	(0.075)
2016 * Social capital	-0.168	-0.099*	-0.121
	(0.136)	(0.046)	(0.072)

	Unemployment only	Unemployment or overskilled	Unemployment or underemployed
2007 * Time management	0.153	-0.034	-0.015
	(0.199)	(0.063)	(0.103)
2008 * Time management	0.05	-0.02	0.061
	(0.193)	(0.055)	(0.096)
2009 * Time management	-0.036	-0.062***	-0.029
	(0.188)	(0)	(0.096)
2010 * Time management	0.11	-0.096***	-0.047
	(0.202)	(0)	(0.103)
2011 * Time management	-0.089	-0.016***	-0.005
	(0.212)	(0)	(0.104)
2012 * Time management	0.198	0.011***	0.145
	(0.217)	(0)	(0.11)
2013 * Time management	0.163	-0.011***	0.141
	(0.207)	(0)	(0.106)
2014 * Time management	0.265	0.037***	0.139
	(0.212)	(0)	(0.105)
2015 * Time management	0.024	-0.039***	0.129
	(0.229)	(0)	(0.113)
2016 * Time management	0.091	-0.076	-0.038
	(0.216)	(0.071)	(0.111)
2007 * Low task repetitiveness	0.024	0.025	0.04
	(0.111)	(0.035)	(0.057)
2008 * Low task repetitiveness	-0.145	0.012	0.001
	(0.109)	(0.03)	(0.053)
2009 * Low task repetitiveness	-0.116	-0.038***	-0.011
	(0.105)	(0)	(0.053)
2010 * Low task repetitiveness	0.031	-0.019***	0.055
	(0.11)	(0)	(0.056)
2011 * Low task repetitiveness	-0.128	-0.022***	0.036
	(0.118)	(0)	(0.057)
2012 * Low task repetitiveness	0.031	0.004***	0.011
	(0.114)	(0)	(0.059)
2013 * Low task repetitiveness	-0.127	0.015***	-0.007
	(0.113)	(0)	(0.058)
2014 * Low task repetitiveness	-0.038	0.014***	0.015
	(0.117)	(0)	(0.058)
2015 * Low task repetitiveness	-0.06	-0.021***	-0.003
	(0.129)	(0)	(0.063)
2016 * Low task repetitiveness	0.043	0.028	0.011
	(0.117)	(0.039)	(0.06)
2007 * Highest education - School	-0.18	-0.07	-0.083
	(0.49)	(0.16)	(0.244)
2008 * Highest education - School	-0.496	0.155	0.19
	(0.469)	(0.148)	(0.232)
2009 * Highest education - School	-0.54	-0.203*	-0.029
	(0.449)	(0.099)	(0.225)
2010 * Highest education - School	-0.637	-0.033	-0.106
	(0.482)	(0.106)	(0.245)

	Unemployment only	Unemployment or overskilled	Unemployment or underemployed
2011 * Highest education - School	-0.74	-0.103	0.104
	(0.497)	(0.11)	(0.242)
2012 * Highest education - School	-0.468	0.021	-0.215
	(0.508)	(0.111)	(0.252)
2013 * Highest education - School	-0.372	-0.058	-0.02
	(0.484)	(0.114)	(0.243)
2014 * Highest education - School	-0.992*	-0.108	-0.295
	(0.501)	(0.121)	(0.244)
2015 * Highest education - School	-0.822	-0.29*	-0.256
	(0.527)	(0.127)	(0.254)
2016 * Highest education - School	-1.065*	-0.084	-0.228
	(0.504)	(0.168)	(0.252)
2007 * Highest education - Vocational	-0.028	0.104	0.211
	(0.536)	(0.155)	(0.264)
2008 * Highest education - Vocational	-0.644	0.071	0.229
	(0.528)	(0.138)	(0.252)
2009 * Highest education - Vocational	-0.494	-0.024***	0.126
	(0.5)	(0)	(0.244)
2010 * Highest education - Vocational	-0.403	0.045***	0.564*
	(0.521)	(0)	(0.256)
2011 * Highest education - Vocational	-0.285	-0.033***	0.151
	(0.528)	(0)	(0.258)
2012 * Highest education - Vocational	0.13	0.203***	0.459
	(0.525)	(0)	(0.259)
2013 * Highest education - Vocational	-0.16	-0.042***	0.123
	(0.519)	(0)	(0.254)
2014 * Highest education - Vocational	-0.445	0.147***	0.002
	(0.514)	(0)	(0.253)
2015 * Highest education - Vocational	-0.693	-0.212***	-0.298
	(0.553)	(0)	(0.263)
2016 * Highest education - Vocational	-0.596	-0.083	-0.004
	(0.514)	(0.148)	(0.256)
2007 * Decide what do in job	0.127	-0.037	0.041
	(0.14)	(0.044)	(0.072)
2008 * Decide what do in job	0.148	0.048	0.12
	(0.133)	(0.037)	(0.066)
2009 * Decide what do in job	0.083	0.004***	0.005
	(0.129)	(0)	(0.067)
2010 * Decide what do in job	0.341*	0.077***	0.107
	(0.144)	(0)	(0.072)
2011 * Decide what do in job	0.207	0.031***	0.032
	(0.15)	(0)	(0.074)
2012 * Decide what do in job	0.161	0.06***	0.061
	(0.148)	(0)	(0.075)
2013 * Decide what do in job	0.311*	0.045***	0.036
	(0.144)	(0)	(0.074)
2014 * Decide what do in job	0.151	0.03***	0.021
	(0.151)	(0)	(0.075)

	Unemployment only	Unemployment or overskilled	Unemployment or underemployed
2015 * Decide what do in job	0.314	0.084***	0.126
	(0.166)	(0)	(0.081)
2016 * Decide what do in job	0.22	0.046	0.124
	(0.153)	(0.05)	(0.078)
2007 * Decide how do job	0.026	0.081	-0.044
	(0.141)	(0.044)	(0.072)
2008 * Decide how do job	-0.052	0.024	-0.025
	(0.131)	(0.037)	(0.067)
2009 * Decide how do job	0.008	0.065***	0.006
	(0.128)	(0)	(0.067)
2010 * Decide how do job	-0.353*	-0.011***	-0.12
	(0.141)	(0)	(0.072)
2011 * Decide how do job	-0.211	-0.053***	-0.026
	(0.15)	(0)	(0.074)
2012 * Decide how do job	-0.03	-0.032***	-0.061
	(0.149)	(0)	(0.075)
2013 * Decide how do job	-0.255	0.01***	-0.03
	(0.142)	(0)	(0.074)
2014 * Decide how do job	0.071	0.045***	0.023
	(0.154)	(0)	(0.076)
2015 * Decide how do job	0.023	-0.038***	-0.029
	(0.167)	(0)	(0.081)
2016 * Decide how do job	-0.102	-0.005	-0.052
	(0.154)	(0.05)	(0.079)
Controls			
Job stress	0.117***	0.034***	0.025
	(0.033)	(0)	(0.017)
Job stress (Mundlak)	-0.096	-0.169***	-0.108***
	(0.057)	(0)	(0.029)
Total hours busy	-0.074	-0.029***	0.021
	(0.069)	(0)	(0.034)
Total hours busy (Mundlak)	-0.232*	-0.167***	-0.286***
	(0.101)	(0)	(0.05)
Gender (female)	0.275*	0.189***	0.178**
	(0.114)	(0)	(0.056)
Age			
Under 30	0.162	0.079	0.233**
	(0.148)	(0.047)	(0.071)
40-49	-0.313*	-0.081***	-0.111
	(0.143)	(0)	(0.066)
50-59	0.167	0.03	-0.106
	(0.155)	(0.049)	(0.077)
60 and over	0.407*	0.069	-0.208
	(0.204)	(0.081)	(0.113)
Disabled	0.217	0.064	0.18*
	(0.141)	(0.064)	(0.075)
Disabled (Mundlak)	0.508*	0.113	0.363**
	(0.223)	(0.097)	(0.116)

	Unemployment only	Unemployment or overskilled	Unemployment or underemployed
Relationship	-0.228	-0.243***	-0.186*
	(0.181)	(0)	(0.088)
Relationship (Mundlak)	-0.121	0.166***	-0.188
	(0.219)	(0)	(0.107)
Children	0.181	0.021	0.154*
	(0.15)	(0.062)	(0.074)
Children (Mundlak)	-0.047	0.176*	0.185
	(0.21)	(0.078)	(0.102)
Aboriginal and Torres Strait Islanders	0.899*	0.505**	0.529**
(ATSI)	(0.354)	(0.164)	(0.18)
Migrant (ESB)	0.034	-0.007	0.023
	(0.168)	(0.068)	(0.083)
Migrant (NESB)	0.106	0.236**	0.43***
	(0.197)	(0.078)	(0.092)
Urban	-0.085	0.093***	0.148
	(0.279)	(0)	(0.142)
Urban (Mundlak)	0.053	-0.016***	-0.129
	(0.333)	(0)	(0.167)
Observations	31730	31730	31730
Log likelihood	-3870.17	-16194.8	-12479.2

Industry classifications are not reported for space. *, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.

In comparison to the prior two models, the overskilling model has a far wider range of significant variables, with all skill measures having highly significant coefficients for the base variables and the Mundlak terms. Before discussing these, the two notable controls of total hours busy and job stress are relevant to consider, as both Mundlak corrections and the base coefficient for total hours busy have significant and negative coefficients. This suggests these aspects may be controlling for underskilling risk, itself considered part of the well-matched category, rather than the suitability of the person for their job and their base level of busyness as intended. The job stress element affects three of the six skill proxies that are measures of the workplace itself (low task repetitiveness, deciding what to do in the job, deciding how to do the job): while it is supposed to control for if someone is well-suited for these workplace, the stress component and the negative coefficients for the ability to decide what to do in the job and low task repetitiveness suggest these are all job elements rather than soft skills. A similar aspect can be seen for time management: as this measure is based on time pressure, the positive coefficient suggests that lower time management ability, and thus higher time pressure, is associated with a lower risk of overskilling and unemployment and thus a higher likelihood of being well skilled or underskilled. As such, this is not considered a strong base for investigating time management itself in this specific situation. For the remaining soft skill measure, social capital has a significant and negative Mundlak correction, while the base variable has a significant and positive coefficient. This base coefficient is practically very small compared to the coefficient for the Mundlak correction (0.004 compared to -0.238), thus the overall association between social capital and unemployment or overskilling is negative. Overall, the combination of one soft skill measure being associated with higher unemployment and overskilling risk while the other is more likely a measure of underlying work quality ultimately does not provide evidence in favour of H2.1.

When looking at the interaction effects, the year interactions between 2009 and 2015 are highly significant for all variables excluding school-level education. This aligns with the significant year effects for 2009-2015 but not for 2007, 2008, nor 2016, suggesting the post-GFC period through to 2016 has a noticeable association with overskilling risk. However, the reason for this high level of significance stems from standard errors that approach 0 for these periods, and with the harsh cut-off in significance from 2015 to 2016 this may at least partially stem from other model fit elements. Progressing with the analysis of the variables, both time management and social capital have generally negative year effects during this time period: social capital is significant and negative excluding 2010 and 2012, and time management is significant and negative excluding 2012 and 2014. These are more consistent than low task repetitiveness with a 2012-2014 stretch of significant and positive coefficients, and the very mixed signs for vocational education and deciding how to do the job. By comparison, the ability to decide what to do in the job has only significant and positive year effects, suggesting a limited bias against skills in this period. While these effects may be at least partially overestimated, the consistent negative coefficients for social capital and time management do provide partial support for H2.2.

Overall, this model does align with the mixed evidence from local literature (Coelli & Borland, 2016). The evidence for H2.2 partially aligns with international literature for SBTC and particularly RBTC (Hershbein & Kahn, 2018; Jaimovich & Siu, 2020), albeit for the overskilling model only. Further, it suggests the GFC is the point of change, as opposed to the economic slowdown at the end of the mining boom in 2012-13.

5.3. Conclusion

The progress of technology has continued to affect skill demand and usage, particularly through skill and routine biases. Further, these technologies affect unemployment during and after economic downturns, slowing the labour recovery. One theoretical method Australian workers could utilise to prepare for these shocks is soft skill development, as these skills are demanded by a broad range of employers and are difficult to automate, forming the basis for RQ2. This chapter seeks to answer RQ2 by testing three soft skill measures of social capital, time management, and low task repetitiveness using the HILDA dataset on years covering before, during, and after the GFC. Measures of unemployment, along with underemployment and overskilling as intermediate negative employment outcomes, were also drawn from these data, with methods applied to test whether the GFC resulted in a persistent change in association between soft skills and these negative labour market outcomes.

The results show that social capital is generally associated with a reduction in negative employment state risk regardless of model. While a useful base, it is not enough to support H2.1. However, the remaining soft skill proxies of time management and low task repetitiveness do not provide the same support: both are fully insignificant in the unemployment and underemployment models. Further, in the overskilling and unemployment model, time management has consistently positive associations with unemployment and overskilling risk, likely due to its underlying time pressure measure, while low task repetitiveness is most likely due to the employment aspects rather than the skill aspects. This is relevant due to the job stress and time management controls implying an association with underskilling as a sub category of well-skilled, rather than as direct controls for ability to manage their time or to perform well in a job with higher skill requirements as intended. The limited significance of skill components generally in the unemployment and underemployment models suggests that while some base level of skills and social capital are important for retaining employment in a decent job, additional skills have limited further relationship with achieving higher quality employment in the broader labour market.

When investigating the year interactions, there is a lack of consistent trend across the unemployment and underemployment models, reinforcing the limits of skills as a way to reduce the risks of entering these lower quality states. For overskilling, all three soft skill variables have consistently significant year interactions between 2009 and 2015. While there are some potential restrictions on interpretation due to the model fit, the interactions for social capital and time management have generally positive and significant coefficients through this time period, suggesting the GFC did increase the benefits of these skills for overskilling and thus providing partial support for H2.2. In particular, other skills and work measures including low task repetitiveness had mixed signs during this period, suggesting these soft skill aligned factors specifically are associated with overskilling risk. This further suggests RBTC and SBTC could be associated with soft skills specifically. Overall, this research provides some evidence in favour of RQ2, albeit limited due to the weaker interpretation of soft skills for H2.1 and the overskilling model acting as the primary driver of this relationship.

This chapter makes multiple theoretical contributions. First, it appears the GFC shock affected the association between Australian workers' skills and their unemployment and overskilling risk. As this was mostly with overskilling as opposed to new technology, it is still likely to a lesser degree than other countries studied internationally. Second, there is evidence of some RBTC during the GFC, when the business cycle had a shock and the Australian government stepped in, as opposed to after 2012 when the Australian Government's stimulus packages had concluded and the mining boom that supported the Australian economy petered out. These effects suggest that while the Australian Government's support helped to reduce the impact of this initial shock, there were still some lingering effects well after the initial crisis with higher tendency of overskilling to be considered. Third, this research reinforces the value of at least moderate human capital for supporting workers even outside of an economic crisis, as seen with social capital's significant effects and the importance of tertiary education compared with only receiving school-level education.

There are also practical contributions from this research. In particular, it demonstrates the importance of social networks beyond work and home for maintaining quality employment. These may be developed by governments via education policies; further, to enable workers to maintain their social capital, seemingly unrelated policies may be considered, including physical "third places" to promote in-person interactions beyond the immediate household and workplace (Pettersen et al., 2024) while employers support work-life balance. Further, the speed of response of the effects in 2009 for the overskilling model while the unemployment and underemployment models demonstrated no trend reinforce the importance of governments acting promptly during a crisis to support the economy to protect against the worst possible outcomes.

Chapter 6. Soft skills, technology, and productivity of Australian industries

6.1. Introduction

This empirical chapter investigates RQ3 from Section 1.6. To begin, Section 6.2 covers some further background on prior research on multifactor productivity (MFP) and how RQ3 is answered. Section 6.3 then applies the methodologies from Section 3.4 and provides the results. Finally, Section 6.4 concludes the chapter by summarising the theory and results and providing contributions and applications.

6.2. Background

A key driver of economic production has been the growth of MFP, or the change in output when accounting for changes in the inputs used. A growth in MFP means workers and machinery are more efficient or producing higher value output and thus enables further economic production and value without additional inputs. Three interrelated concepts that enable MFP and economic output growth in modern economies are information communication technology (ICT) (Leung & Zheng, 2012), research and development (R&D) (Égert et al., 2024; Leung & Zheng, 2012), and human capital (Romer, 1994). Human capital in particular is typically utilised for analysing output directly, either as a weighting for the labour input (Bowlus & Robinson, 2012) or via dichotomous categorisation of workers (Balleer & van Rens, 2013; Violante, 2008).

However, the weightings utilised for the human capital in labour are commonly based on education and years of work (Australian Bureau of Statistics, 2021). While these are useful tools that are relatively easy to gather annually, they are broad proxies for underlying skill (Cord & Clements, 2010; Hanushek et al., 2015), leaving room for investigation of more detailed skills on top of these base measures. Further, modern and emerging technologies, including artificial intelligence (AI), can be biased towards different types of human capital, potentially causing skill-biased technological change (SBTC) or routine-biased technological change (RBTC) depending on the technology and use case. Limited research has investigated these components together for productivity; Égert et al. (2024) is one of the most detailed studies as they test the use of the Programme for International Student Assessment (PISA) and Progress for the International Assessment of Adult Competencies (PIAAC) as an alternative estimation of human capital affecting MFP, alongside R&D in their modelling. A relevant set of skills to further investigate are soft skills, as discussed previously; whether soft skills benefit production forms the basis of RQ3. This chapter seeks to answer this research question by using two sets of analyses to investigate the use of soft skills in industry production for the years 2006-2021: the direct effect of soft skills on MFP, and the effect of soft skills on overall value-added production. In both analyses, seven individual soft skills are used to build a single overall soft skill metric: initiative and innovation, learning ability, oral communication, planning and organising, problem solving, teamwork, and writing as a measure of written communication. This analysis further investigates skill-biased and routine-biased technological change via a moderating relationship between ICT investment and soft skill endowments.

This chapter follows the data and method previously discussed in Section 3.4, drawing on data from the Australian Skills Classification (ASC) for the soft skill components and the Australian Bureau of Statistics (ABS) for all other sources. After the testing discussed in Section 3.4.2, both the productivity and production models are investigated in a short-run fixed effects model, along with a per-worker version of the value added model as a third model.

6.3. Results

All results for this soft skill analysis are displayed in Table 6-1. Across all models, few variables are significant, and most have a negative association: exports have a negative association with value-added production and MFP, non-ICT capital has a negative association with per worker value added, labour hours has a negative association with per worker value added, and imports have a positive association with value-added production. Imports makes some sense from an intermediate goods perspective, although the insignificant coefficient for intermediate goods limits the explanation of this method. Further, the negative association between exports and production is unusual, considering the GDP accounting identity specifies that higher exports increase GDP, which itself is an economy-wide measure of value added. Labour hours makes some sense in a per worker model if workers are working too many hours, although this is unlikely considering underemployment is a rising issue in the Australian economy during this period (Chambers et al., 2021). For the variables of interest, soft skills, ICT and their interaction are insignificant across all model specifications, suggesting they lack a significant effect on short-run production.

Table 6-1: Productivity and production regression results on overall soft skills

	MFP	Value added	Value added per worker
Soft skills	-0.13	0.242	-0.137
	(6.042)	(0.211)	(0.296)
Soft skills * ICT capital ratio	0.03		
	(4.148)		
Soft skills * ICT capital		0.517	1.117
		(1.308)	(1.815)
ICT capital ratio	0.115		
	(0.087)		
ICT capital		-0.003	-0.057
		(0.021)	(0.03)
Non-ICT capital		-0.02	-0.082**
		(0.019)	(0.027)
Labour hours		-0.101	-0.516*
		(0.058)	(0.219)
R&D	-0.165	0.004	0.004
	(0.305)	(0.006)	(0.009)
Imports	0.029	0.123**	0.01
	(0.044)	(0.041)	(0.06)
Exports	-0.11**	-0.114**	-0.115
	(0.042)	(0.04)	(0.059)
Intermediate goods	-0.043	0.025	-0.019
	(0.117)	(0.035)	(0.055)
Observations	226	226	226

Imports, exports, intermediate goods, and R&D are measured as a proportion of value added in the MFP model, while all variables use natural log form for the value added models. All independent variables are lagged by one year, and all variables excluding MFP are differenced. *, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.

These results are rather unusual with the significant coefficients and their signs, while other researchers have found significant effects in the short-run (Égert et al., 2024). While investigating the long-run would be preferable, the previously discussed lack of cointegrating relationship makes estimation and interpretation particularly difficult. One area that can be tested within the short-run is the value of the individual soft skills instead of soft skills as a whole to determine if there are individual skill relationships not suitably captured by the CFA estimation. To do this, the base skills are applied using their Likert scores. The models are the same as the individual soft skill model, with the exception of no interactions with ICT. These results are displayed in Table 6-2, with the significant coefficients from the previous models sharing the same signs and generally similar magnitudes with the exception of exports now being significant and negative in the per worker model. When looking at skills, only the overall value-added model has significant coefficients for any skills. This is unusual, as skills would typically operate at the worker or group level and thus be more likely to have a significant effect on MFP or per worker value added. The significant coefficients only for industry value added suggests there is some value of skills at the industry level that is unrelated to per-worker capabilities that the other models focus on. Of these skills, oral communication has a significant and positive association with value added production, while writing skills has a negative and slightly significant association along with slightly lower magnitude. This mismatch in two measures of communication skills is interesting, suggesting some skills are valued at the industry level in the short-run while others may be undervalued.

Table 6-2: Productivity and production regression results on individual soft skills

	MFP	**Value added**	**Value added per worker**
Initiative and innovation	12.14	0.217	0.225
	(15.701)	(0.509)	(0.758)
Oral communication	20.816	1.399**	0.977
	(15.141)	(0.488)	(0.714)
Learning ability	-11.654	0.813	0.637
	(14.775)	(0.532)	(0.79)
Planning	3.47	-0.329	-0.66
	(12.132)	(0.423)	(0.621)
Problem solving	13.322	-0.373	-0.102
	(18.41)	(0.593)	(0.875)
Teamwork	-2.442	-0.242	-0.26
	(9.189)	(0.288)	(0.426)
Writing	-25.493	-1.213*	-0.769
	(14.485)	(0.492)	(0.725)
ICT capital ratio	0.106		
	(0.093)		
ICT capital		0.004	-0.051
		(0.021)	(0.03)
Non-ICT capital		-0.017	-0.077**
		(0.019)	(0.028)
Labour hours		-0.091	-0.503*
		(0.058)	(0.227)
R&D	-0.207	0.006	0.002
	(0.36)	(0.006)	(0.01)
Imports	0.034	0.136***	0.026
	(0.044)	(0.04)	(0.061)
Exports	-0.109**	-0.127**	-0.124*
	(0.042)	(0.039)	(0.059)
Intermediate goods	-0.022		
	(0.118)		
Intermediate goods		0.037	-0.009
		(0.035)	(0.053)
Observations	226	226	226

Imports, exports, intermediate goods, and R&D are measured as a proportion of value added in the MFP model, while all variables use natural log form for the value added models. All independent variables are lagged by one year, and all variables excluding MFP are differenced. *, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.

6.4. Conclusion

Australian productivity growth has slowed since the GFC, limiting long-run growth potential. Further, while relatively broad measures of skills have been tested internationally for productivity and economic growth, further detailed skill measures have not been tested to the same degree, forming the basis for RQ3. To investigate this gap further and answer the associated research question, this chapter uses Australian occupational skills data to analyse how multiple soft skills loaded onto a single soft skill metric are associated with industry level MFP and value-added output in a short-run specification relevant to the data utilised. A further aspect of interest is the moderating relationship between soft skills and ICT to investigate potential synergies between these variables from a technological bias perspective. The output analysis also uses an additional specification for per-worker output. The results show that soft skills for high-level industries are insignificant across the majority of specifications for both MFP and value-added output, as are the interactions between soft skills and ICT, suggesting soft skills have a limited measurable association with macroeconomic-level growth. This insignificant interaction between ICT and soft skills also provides evidence against SBTC and RBTC in the short-run, albeit limited due to the insignificance of ICT in any model and thus the relevance of technological biases at all in the short-run. When breaking it down to specific skills, only two skills were significant, with writing having a negative association while oral communication has a positive association. Further, both were significant in the overall industry production model, rather than in the models focused on worker-level production or productivity. These results ultimately suggest a negative answer for RQ3, suggesting that broadly increasing skill accumulation has limited value for industries.

This analysis comes with three notable limitations. First, the skill data were only available for two years towards the end of the time period, restricting longitudinal research to only changes in occupational employment without the ability to investigate changes within occupations. Further, the ASC data utilised were discontinued due to timeliness issues and problems with external validation; while these were not of significant concern for this research, they still suggest limits to the broader applicability of this analysis. Second, this model was restricted to short-run analysis due to the lack of cointegrating relationship; while still a useful perspective, the importance of human capital and ICT in the long-run is relevant in the broader literature, limiting the ability for this research to fully investigate the skill and technological aspects of relevance. The unexpected coefficient directions do suggest unusual aspects for this short-run analysis that could be reshaped in a long-run model. Third, there are data availability limits for both years and industries available for study: the former is limited as the majority of data are only available annually along with the change in industry standards from ANZSIC 1993 to ANZSIC 2006, while the latter is due to most data sources only being available for the highest level of industries. While the data are sufficient for analysis, additional years or more detailed industries would be beneficial.

This research makes multiple contributions to the broader productivity literature. First, the total value added model was the only model to demonstrate significant associations with any skill terms, as opposed to the MFP or the per worker value-added production models. This suggests the value of average skills across the whole of an industry's workforce stems from a broader level than the worker level. One potential reason is that industries derive value from broader talent pools, similar to agglomeration of human capital within urban regions (Eriksson & Hansen, 2013), meaning higher access to skills is relevant as opposed to the actual skill level of their workers. Second, the negative association between value-added and certain elements including exports and other capital investment suggests there are trade-offs in the short-run to achieve productivity, suggesting additional incentives may be required for businesses to improve long-run productivity. Third, the lack of significance found in this model suggests there are limited short-run benefits from soft skills as a whole; however, depending on further research long-run benefits may be available, and require some support for businesses and industries in the short-run to implement training and recruitment. There is also the potential for skill benefits to manifest not through changes in the occupations hired but instead within occupations.

Chapter 7. Conclusion

7.1. Introduction

With the empirical results from the prior three chapters, it is now possible to investigate the conclusions these provide for the overall research question raised in Section 1.6. This begins with Section 7.2 summarising the core issue this thesis seeks to answer and how this is done. Section 7.3 then summarises the results of Chapters 4–6, specifically in terms of RQ1, RQ2, and RQ3. Section 7.4 then notes the limitations of this research and future directions for research. This section concludes with the implications of the study, with Section 7.5 discussing the contributions to research while Section 7.6 discusses the practical applications, including discussions on how this can apply to AI.

7.2. Review of the research questions and methods

In the modern Australian economy, automation via emerging technologies risks disrupting employment. Further, these technologies do not affect all workers evenly, with low-skilled and highly routine jobs, including more traditional jobs and some middle-wage employment, more likely to be displaced. This, along with lower career stability, suggests key changes are required in the skills Australian workers bring as one form of protection against these shocks. Development of relevant skills would also help boost Australian productivity, providing further protections against other external shocks including a slowdown in Chinese manufacturing affecting demand for mineral exports (Leahy & Lockett, 2024). One key set of skills that could support workers during these transitions and into the future is soft skills, which are theorised to boost productivity, be readily transferrable between jobs, and be in demand from employers. This area has not been researched in Australia to the same degree as in other countries, and thus this thesis addresses this gap by investigating soft skills from multiple perspectives in the Australian economy to determine if these skills are economically relevant. Three overall research questions and objectives are specified for particular areas: workers using these skills to support positive job mobility, workers using these skills to reduce unemployment risk, and industries improving their productivity using these skills.

The first empirical chapter investigates labour endowments of soft skills among Australian workers utilising detailed labour panel data from the HILDA dataset.

Specifically, it investigates how these endowments are associated with changes between employers and how these job changes affect wage growth, based on the hypothesis that soft skills would enable proactive mobility while job mobility further supports wage growth. Three soft skill measures are utilised: time pressure to measure time management (Andreas, 2018; Deng et al., 2014; National Careers Service, n.d.; Pang et al., 2019), a social capital measure (Andreas, 2018; Jackson, 2020; Rungo et al., 2024) built from multiple individual socialisation measures, and low task repetitiveness as an overall measure (Robles, 2012; Tamm, 2018). Job changes are analysed using a Cox proportional hazards survival analysis with the Andersen and Gill counting process. This is followed by a random effects regression to investigate natural log wages. Mundlak corrections are implemented over fixed effects in this model to include both time-invariant variables and to enable comparisons between the variations within individuals over time and the variations between individuals in the sample (Bell & Jones, 2015). These corrections also account for the endogeneity found in the random effects model without Mundlak corrections (Bell & Jones, 2015). Moderating interactions between skills and job mobility are also included to provide important information on whether soft skills are associated with higher wages when a worker changes employer.

The second empirical chapter investigates how soft skill endowments for Australian workers are associated with the risk of negative labour force outcomes for workers, including unemployment, underemployment, and overskilling. This applies a random effects logistic regression to the same HILDA panel data utilised for the prior analysis with a different time period. The same soft skills as in the first empirical chapter are retained for comparative purposes. Mundlak effects are included for the same reasons as for the first method. Of particular interest was how the GFC could have acted as a structural shock in unemployment risk; this is tested using moderated interactions between soft skills and the years 2006–2016, with particular interest in the significance of the interactions after 2010. Technological shocks, in particular SBTC and RBTC, are of particular interest, with the GFC shock being used as a theoretical boundary for their implementation and as a likely driver of shifting skill relationships for this time period.

The third empirical chapter takes a different approach by investigating the employer side through Australian industry usage of soft skills. This study utilises occupational skills data and CFA to build a measure of soft skills at the occupation level, with this being weighted to develop an industry level metric of soft skills. This analysis applies further industry data to investigate how these skills are associated with industry-level MFP and value-added output in both absolute form and per-worker output form. Tests are conducted for stationarity, cointegration, and persistence of the dependent variable, with a short-run fixed effects model estimated using OLS selected as best suiting the data. This study further tests for SBTC and RBTC by including ICT capital investment, along with a moderating relationship between soft skills and ICT. Individual soft skills are also considered to further investigate if particular components have different associations of relevance.

7.3. Research findings

The first empirical chapter found that soft skill proxies have a statistically insignificant relationship with job duration, while overall skill measures have no association beyond non-university education and the ability to decide what to do in the job having positive associations with employment duration. Meanwhile, the log wage analysis finds that changing jobs has an insignificant effect on wages outside of one case where the moderating relationship between university education and changing jobs is associated with lower wages. This suggests soft skills directly are not associated with job mobility decisions in contrast to the theory. In comparison, overall skills are mixed between the vocational and lesser degree school education associations providing a mixed to positive relationship between skills and mobility, while the ability to decide what to do in the job may suggest some bias for skills, albeit dependent on the underlying skills versus the desire to maintain quality employment. These results provide a negative answer to RQ1. When it comes to broader effects on wages, the low task repetitiveness Mundlak correction was the only soft skill element associated with higher wages, while all other soft skill measures were insignificant. As this is a single soft skill measure and other job quality measures have significant and positive associations with employment, this is insufficient to say that soft skills are associated with higher wages. These results broadly suggest soft skills developed outside of formal processes do not provide the worker with additional job mobility nor wages, with the main value coming from broader skill packages.

The second empirical chapter found that the social capital Mundlak correction was the only one to be significantly associated with the risk of unemployment or underemployment; while this is a negative association, by itself it is insufficient to say anything about soft skills as a whole. Further, as school-level education's positive coefficient and the ability to decide what to do's negative Mundlak correction are the only other significant skill terms in these models, this suggests a base level of skills are of use and further skill development is of limited value. The overskilling model has all skill elements significant and positive, with the overall directions between the base coefficients and the Mundlak corrections showing time management is associated with higher overskilling and unemployment while social capital and low task repetitiveness are associated with lower overskilling and unemployment. While this model has two significant soft skill measures with negative coefficients, the fact that low task repetitiveness is primarily associated with overskilling risk and the two additional controls for job stress and total hours busy were likely aligned with underskilling as a subcategory of well-matched suggests low task repetitiveness is likely aligned with job quality rather than underlying skills. Similarly, time management appears to have the positive association with unemployment and higher overskilling in part because of the underlying time pressure measure sharing a similar pattern with job stress, suggesting a common underlying driver. Thus, this leaves only social capital for interpreted as a measure for soft skills with a significant and negative coefficient, providing limited evidence for overall soft skills contributing to lower unemployment risk. When looking at the moderating relationships between skills and these negative employment risks, social capital and time management have significant and negative coefficients only in the overskilling model between 2009 and 2015, suggesting soft skills did have a greater association with reduced negative outcome likelihood and these effects persisted for some time. Curiously for the overskilling model, all skill terms and the year interactions for skill terms between 2009 and 2015 have standard errors close or equal to 0, suggesting some unusual model fit elements for the overskilling model specifically. Overall, this is a partially positive answer for RQ2, albeit with the conditionality of only applying when in the overskilling model with its fitting quirk and with limited support for soft skills having a base effect on reducing unemployment risk.

The third empirical chapter found that soft skills lack a significant association with MFP and both value-added output measures. Further, all models have insignificant ICT-soft skill interaction coefficients. When looking at individual skills, written communication and oral communication were the only significant skills, albeit with opposing relationships. Further, they were only significant in the overall industry value added specification, rather than one of the specifications that better accounted for worker-level production. Overall, this suggests soft skills have no significant association in the short-run, providing a mostly negative answer for RQ3. This suggests industries as a whole derive limited additional value from broader skill acquisition in the short-run, with some potential for specific skills to be relevant for overall industry value instead of contributing directly to individual production or productivity.

In summary, these results suggest that soft skills have a limited econometric effect on Australian businesses and workers. While there are some specific cases where soft skills have some significance, as demonstrated with overskilling risk between 2009 and 2015 and individual components having significant associations, the macroeconomic effect is limited. This suggests soft skills primarily have an impact on specific businesses and workers, rather than broader level effects, answering the overall research question. One exception is communication or social capital having significant coefficients in a range of model formats, suggesting communication skills and potentially other interpersonal skills are relevant for the Australian economy over other soft skills.

7.4. Limitations and future research

While both datasets provide relevant contributions, each has certain limitations. One common limitation is the limited coverage of the COVID shock, with the job change and unemployment analyses explicitly excluding the COVID period and after, while only a handful of these years are included in the productivity analysis. This is readily addressed even within these types of methods as new waves of the data are released over time to allow investigation of not only the shock itself but also perpetuating effects or other general changes after COVID. Additional observations would also support further investigations into SBTC and RBTC, as the COVID pandemic provides another form of economic and technological shock. The HILDA survey and several key ABS data are annual, potentially missing smaller changes during the year for the productivity study, missing additional job changes during the year for the job mobility study, or missing particularly short spells of unemployment for the unemployment study.

There are further limitations for each dataset: the HILDA data lack specific workplace measures for skills broadly and particularly interpersonal soft skills, the ABS data are primarily at higher industry levels and thus lack further breakdowns, and the ASC skills data lack a sufficient longitudinal component and have further restrictions on deeper use due to their discontinuation. The lack of dedicated skill measures for HILDA data further constrain the first two papers: without sufficiently shared significance and directions individual metrics cannot be readily interpreted as commonly measuring soft skills within the model, and even when multiple are detected they must be interpreted cautiously without detailed linkages to specific soft skills. This results in only H2.2 being accepted despite significance of at least one of the three measures across every model excluding the movement likelihood model. A business perspective on skills would also prove useful to supplement the individual survey of the HILDA data and the expert opinions of the ASC data. The reliance on task data for the workplace may also constrict some analyses, as seen with the endogeneity risks for the overskilling model.

The methods also come with certain limitations. The mobility study made certain assumptions about workers changing jobs to seek improved wages; however, if workers instead seek alternative characteristics in employment (Masige, 2023; PwC, 2021), this would go undetected. Further, longer duration effects of wages were not tested in this model. The unemployment study instead faces limitations with potential endogeneity, particularly in the overskilling specification , as several skill components such as low task repetitiveness are measured via workplace attributes. This is despite attempts to control these aspects using additional controls for the workplace to provide greater confidence that these variables capture worker capability. Finally, the third analysis also presumes the lagged terms affect industry production sufficiently and follow the neoclassical Cobb-Douglas model; if one or both assumptions are inaccurate then it may have impacted the significance of the results. Further, this analysis also lacked long-run elements due to the data not containing the relevant cointegrating relationships, forming another restriction on the effects investigated. All models also share the common weakness of lacking specific investigation of causality, resulting in models only being interpretable from a correlational aspect. Overall, this thesis tests a range of methods and specifications of common interest for soft skills; however, this is not an exhaustive investigation of all possible specifications for soft skills, nor of the macroeconomic measures that are of relevance for workers and employers.

Future studies may utilise alternative surveys that better measure skills directly and perhaps have more frequent measurement intervals to provide additional data over a period of time. However, the structure of such surveys may result in different limits for both longitudinal analysis of trends and breadth of workers and organisations studied compared to the data utilised here that can analyse longer trends and through times that are recent but still very difficult to collect new data on, such as the GFC. These limitations may be worthwhile, as both the wage and unemployment models suggest skills primarily affect outcomes between individuals rather than changes within individuals, somewhat reducing the value of the longitudinal element.

7.5. Research contributions

A primary contribution of this thesis is to better understand the benefits of a specific form of human capital at the macroeconomic level, including where human capital is not beneficial. The main example is time management by itself: its only significance was in the overskilling model, where higher time management ability is associated with a higher risk of overskilling or unemployment. Similar results have been seen in some prior research on other soft skills, including Ubalde and Alarcón's (2020) finding that foreign language ability significantly reduced wages in one model. Unlike those cases, time management here is proxied as an inverse of time pressure; considering how both job stress and total hours busy were positively associated with lower unemployment and overskilling risk, this may suggest the underlying measure was not well-suited to this specific model. The significance of skill measures varies between models: even between the shared data in the first two models, social capital is insignificant for both analyses in Chapter 4 while significant in all specifications in Chapter 5, suggesting even skills that have macroeconomic relevance may not be detected depending on the variable investigating. This further limits the value of wider measures of broad skill clusters within overall human capital, as seen with the insignificant overall soft skill metric across all models in chapter 6. There is some wider macroeconomic value seen in medium-level skill clusters: communication and social capital were significant across a range of model formats, suggesting interpersonal skills may have greater macroeconomic relevance.

For SBTC and RBTC, the second and third empirical chapters provide limited evidence in favour of these theories. The second empirical analysis suggests some SBTC and RBTC for soft skills due to the significant and negative year interactions with social capital and time management; however, this was only in the model with overskilling risk. Meanwhile, the third empirical chapter shows no significant short-run effects for ICT nor even R&D across the different specifications, along with insignificant interactions between soft skills and ICT. The restrictions of relying on the business cycle to detect social capital in the first model and the second model failing to detect short-run value from ICT investments do not rule out SBTC nor RBTC for the modern Australian economy, although they are less apparent from this research.

7.6. Practical applications

This research provides guidance for businesses and governments seeking to utilise a skilled workforce in Australia. In particular, soft skills appear to have limited to no significant associations at a macroeconomic level; when combined with prior literature, this suggests training in soft skills is most valuable in courses and jobs that most benefit from them, with select skills and training methods utilised more broadly. This is relevant for the Australian Federal Government's University Accords: while these accords do not discuss soft skills specifically, they do discuss general skills for tertiary education broadly (Department of Education, 2024). Further, the significance of social capital in the unemployment study and communication skills in the production study, even writing with its negative coefficient, suggests governments should consider supporting projects for people to maintain and build interpersonal capabilities. This may even extend to seemingly unrelated areas, including physical "third places" to promote in-person interactions beyond the immediate household and workplace (Pettersen et al., 2024).

This research also has some guidance on how to reduce unemployment, with tertiary education and social capital being positively associated with lower risk of all negative outcomes and thus potentially useful. However, other skill measures are irrelevant outside of the overskilling model, suggesting a base level of education and social capital may be relevant while further skilling has limited additional value for supporting workers who are unemployed or working insufficient hours in their current job. The inclusion of inactive yet interested people means the unemployment results also extend to people who have disconnected from active job search yet are interested in returning to the labour market.

For businesses, decisions on whether to externally acquire or internally develop soft skills and even skills more broadly should come down to the other skills they want to acquire. If they seek to acquire skills related to jobs with notable freedom to decide what to do in their role or those associated with vocational education, they should seek to recruit workers as they exit education or develop these skills internally due to associated lower employer movement. Meanwhile, if they seek to recruit skills associated with university-level workers, they may be able to acquire those skills from worker mobility, albeit with the need to provide suitable reasons for the worker to remain with them. The limited measured association between these skills and aspects of interest to workers including higher wages and reduced unemployment risk could also suggest businesses have room to re-evaluate their approach to rewarding these skills. An additional aspect is the significance of skill measures for overall production and not per worker production nor MFP, suggesting businesses should investigate measures of capturing the benefits of skills at this broader level, such as developing deep talent pools to draw from.

7.6.1. AI applications

One rapidly developing area of interest is in the application of AI in the workplace, in particular generative AI (GAI) that includes large language models (LLMs). This technology is purported to replace tasks that soft skill are applied to, including email writing, report generation, and schedule management. Due to relevant literature on this topic being relatively new and sparse, the results of this thesis cannot be directly applied to this technology. Instead, I provide some relevant history of AI development, some information on its current usage, and potential limitations. This is followed by a brief discussion of how this technology could affect technological disruption and soft skills with relation to the results of this thesis where relevant.

Early versions of artificial neural networks, which underpin a range of modern AI tools, were conceptualised as early as the 1960s (Macukow, 2016). However, it would take multiple developments before GAI would become viable; two of these include sufficiently large corpora of text data or tokens to be available for training (Penedo et al., 2023), and the development of Transformers to simplify the network structure and enable the models to be scaled more effectively (Hao, 2025; Vaswani et al., 2023). Despite these developments, there was still a lack of widespread use of these GAI models until November 2022 when OpenAI released ChatGPT for public usage, with it soon becoming the fastest-growing consumer app at the time to reach 100 million users (Hu, 2023). This relatively recent spike in interest suggests this technology is early in the Gartner hype cycle process (Gartner, 2024), where the initial promise of an emerging technology leads to overly high expectations and applications before interest collapses due to the reality of implementations, with an eventual level of final usage applying the technology where it is relatively efficient.

Early reports on AI usage in the workplace suggest applications globally are already relatively high, with 58% of survey respondents to one international survey using them regularly (Gillespie et al., 2025) and 37% of respondents to a US survey using AI in some way for work tasks (AP-NORC Center, 2025). The latter poll also noted usage rates for AI were higher for those under 30, with 52% of respondents using it for work tasks (AP-NORC Center, 2025). Further, the first report noted particularly high GAI usage in the workplace that are not specific to the organisation (Gillespie et al., 2025), varying from 73% of AI-using workers utilising general-purpose GAI or LLM tools to 26% utilising specific-purpose GAI. This compares to 18% usage of specific-purpose AI tools or AI systems specific to the organisation, overall suggesting broadly recognisable tools including ChatGPT are the primary ones utilised. Despite this breadth, there are notable concerns with current applications: 66% of AI-using workers do not critically review AI-generated outputs, 56% report mistakes in their work related to AI usage, and 48% use sensitive company data in public AI tools (Gillespie et al., 2025).

A further set of concerns stem from recent developments in new GAI models potentially restricting future potential for growth and thus emphasise the risk of a hype cycle collapse in interest, with three of these restrictions considered here. First, these models require massive amounts of data, with modern models requiring billions of text tokens for training (Penedo et al., 2023). However, the introduction of widely-used GAI may risk model collapse for future generations (Shumailov et al., 2024), resulting in these models potentially deviating from actual inputs and compounding prior errors. This is particularly problematic in the context of the costs of curating the broader web data utilised for these models (Penedo et al., 2023) and even the use of GAI in traditionally quality training data such as academic papers (Snoswell et al., 2025). Second, there are increasing energy requirements for these models for both the training and the processing of queries (O'Donnell & Crownhart, 2025). While alternate models including Deepseek have reported lower costs for training (Liu, 2025), the opacity of the current AI industry as a whole makes it difficult to know the full costs of models (Hao, 2025; O'Donnell & Crownhart, 2025). Third, despite these development costs recent models have made limited technical improvements, as seen with success rates only reaching 30% for the TheAgentCompany benchmark (Xu et al., 2024). When looking at the success rates of certain models on specific tasks in this benchmark, models typically perform worse at data science, administrative, and financial tasks, with the models performing best at project management tasks with success rates between 21% and 43%.

Overall, while AI may temporarily substitute some tasks dependent on soft skills, the combination of GAI currently being at the peak of the hype cycle, the risks with modern tools, and the limits being encountered with training the data all suggest long-term usage will be more targeted than at present. Even with this, if AI is applied towards tasks that benefit from communication skills it may still have a macroeconomic effect on the use of skills. Further, the type of effect will depend on how AI is applied: for example, using AI to provide recommendations for report editing may reduce the importance of communication skills for adjusting language for the audience, but still require a good understanding of how to communicate to the audience to interpret the AI-provided feedback and convey the information desired. There is also the potential for TBTC to affect tasks that may not directly use soft skills, but where they are commonly with soft skills within a role and thus lead to soft skills being relatively important for associated roles. Another element is whether new AI tools are developed that fall outside these GAI tools, creating a further layer of uncertainty on how these technologies will affect employment. And beyond the skills themselves is their development mechanisms: depending on how AI implementation works, it may increase the skill level of entry level jobs or even cut out traditional pathways for employment, forcing other aspects of education or life experience to develop these additional skills previously developed on the job.

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Appendix A. Wage regression comparison of interval vs categorical variables

	Numeric	Categorical
Intercept	2.808***	2.892***
	(0.046)	(0.047)
Soft skills		
Social capital	-0.002	-0.002
	(0.002)	(0.002)
Social capital (Mundlak)	0	0.002
	(0.004)	(0.004)
Time management	0.001	
	(0.003)	
Likert category: 2		-0.001
		(0.007)
3		-0.002
		(0.008)
4		0.005
		(0.009)
5		-0.005
		(0.021)
Time management (Mundlak)	-0.007	
	(0.006)	
Likert category: 2		-0.008
		(0.017)
3		-0.008
		(0.017)
4		-0.021
		(0.021)
5		-0.084
		(0.049)
Low task repetitiveness	0.002	
	(0.001)	
Likert category: 2		0.007
		(0.006)
3		0.005
		(0.007)
4		0.006
		(0.007)
5		0.011
		(0.008)
6		0.014
		(0.009)
7		0.004
		(0.012)
Low task repetitiveness (Mundlak)	0.039***	
	(0.003)	

	Numeric	Categorical
Likert category: 2		0.046**
		(0.017)
3		0.113***
		(0.017)
4		0.119***
		(0.018)
5		0.158***
		(0.021)
6		0.208***
		(0.023)
7		0.236***
		(0.028)
Overall skills		
Highest education - Vocational	0.072***	0.071***
	(0.007)	(0.007)
Highest education - University	0.239***	0.236***
	(0.008)	(0.008)
Decide what do in job	0.004*	
	(0.002)	
Likert category: 2		-0.01
		(0.009)
3		0.012
		(0.01)
4		0.02*
		(0.01)
5		0.016
		(0.01)
6		0.022*
		(0.011)
7		0.007
		(0.013)
Decide what do in job (Mundlak)	0.011**	
	(0.004)	
Likert category: 2		0.009
		(0.028)
3		-0.012
		(0.028)
4		-0.004
		(0.028)
5		0.074*
		(0.029)
6		0.079**
		(0.03)
7		-0.015
		(0.034)
Decide how do job	0	
	(0.002)	
Likert category: 2		0.007
		(0.01)

	Numeric	Categorical
3		-0.006
		(0.011)
4		-0.003
		(0.01)
5		0.002
		(0.011)
6		-0.001
		(0.011)
7		-0.001
		(0.012)
Decide how do job (Mundlak)	0.009*	
	(0.004)	
Likert category: 2		-0.047
		(0.032)
3		-0.047
		(0.032)
4		-0.011
		(0.031)
5		-0.01
		(0.031)
6		0.012
		(0.032)
7		0.027
		(0.035)
Controls		
Change jobs	0.004	0.004
	(0.005)	(0.005)
Change jobs (Mundlak)	0.035*	0.038*
	(0.017)	(0.017)
Job stress	0	
	(0.001)	
Likert category: 2		0.002
		(0.006)
3		0.008
		(0.007)
4		0.008
		(0.007)
5		0
		(0.007)
6		-0.002
		(0.009)
7		-0.004
		(0.012)
Job stress (Mundlak)	0.002	
	(0.003)	
Likert category: 2		0.011
		(0.016)
3		0.007
		(0.017)

	Numeric	Categorical
4		0.013
		(0.018)
5		0.017
		(0.019)
6		0.019
		(0.024)
7		-0.043
		(0.033)
Total hours busy	0.01***	0.01***
	(0.003)	(0.003)
Total hours busy (Mundlak)	0.03***	0.03***
	(0.006)	(0.006)
Gender (female)	-0.052***	-0.05***
	(0.01)	(0.01)
Gender (female) * Relationship	-0.039***	-0.037***
	(0.011)	(0.011)
Age		
Under 30	-0.099***	-0.098***
	(0.007)	(0.007)
40-49	0.015*	0.014*
	(0.007)	(0.007)
50-59	-0.007	-0.008
	(0.009)	(0.009)
60 and over	-0.012	-0.012
	(0.012)	(0.012)
Disabled	0.004	0.004
	(0.006)	(0.006)
Disabled (Mundlak)	-0.089***	-0.087***
	(0.013)	(0.013)
Relationship	0.066***	0.066***
	(0.01)	(0.01)
Relationship (Mundlak)	0.045***	0.044***
	(0.011)	(0.011)
Children	-0.006	-0.007
	(0.007)	(0.007)
Children (Mundlak)	-0.005	-0.006
	(0.011)	(0.011)
Aboriginal and Torres Strait Islanders (ATSI)	0	0.002
	(0.024)	(0.024)
Migrant (ESB)	0.019	0.02
	(0.011)	(0.011)
Migrant (NESB)	-0.057***	-0.054***
	(0.012)	(0.012)
Urban	0.036**	0.036**
	(0.012)	(0.012)
Urban (Mundlak)	0.049**	0.048**
	(0.017)	(0.017)
Years employed	0.001**	0.001**
	(0)	(0)

	Numeric	Categorical
Years employed (Mundlak)	0.005***	0.005***
	(0.001)	(0.001)
Hour preference		
Underemployed	-0.001	-0.001
	(0.005)	(0.005)
Underemployed (Mundlak)	0	-0.002
	(0.012)	(0.012)
Overemployed	0	0
	(0.006)	(0.006)
Overemployed (Mundlak)	-0.084***	-0.083***
	(0.014)	(0.014)
Full time	0.015*	0.015*
	(0.006)	(0.006)
Full time (Mundlak)	0.022	0.019
	(0.012)	(0.012)
Medium-large business	0.026***	0.026***
	(0.005)	(0.005)
Medium-large business (Mundlak)	0.172***	0.168***
	(0.01)	(0.01)
Regional unemployment	-0.006*	-0.006*
	(0.003)	(0.003)
Regional unemployment (Mundlak)	-0.028***	-0.027***
	(0.006)	(0.006)
Sector-GDP gap	0.001	0.001
	(0)	(0)
Sector-GDP gap (Mundlak)	0.006***	0.006***
	(0.001)	(0.001)
Year		
2013	0.03***	0.03***
	(0.006)	(0.006)
2014	0.053***	0.053***
	(0.006)	(0.006)
2015	0.096***	0.095***
	(0.007)	(0.007)
2016	0.13***	0.13***
	(0.006)	(0.006)
2017	0.148***	0.148***
	(0.006)	(0.006)
2018	0.187***	0.187***
	(0.006)	(0.006)
2019	0.231***	0.231***
	(0.006)	(0.006)
Observations	39745	39745
Adj. R^2	0.606	0.607

*, **, *** Significant at 5%, 1%, and 0.1% levels, respectively.