Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: www.tandfonline.com/journals/raec20

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Aaron Semtner, Janet Dzator & Andrew Nadolny

APPLIED ECONOMICS
2025, VOL. 57, NO. 33, 4897–4915
https://doi.org/10.1080/00036846.2024.2364103

Is no (soft) skill left behind? Do soft skills enable job mobility

Aaron Semtner, Janet Dzator and Andrew Nadolny

Newcastle Business School, University of Newcastle (Australia), Callaghan, Australia

ABSTRACT

High job mobility or labour turnover is historically treated as detrimental for businesses and workers. With new technologies including artificial intelligence (AI) that further increase soft skill demand, there is an opportunity for beneficial job mobility of workers reallocating to productive businesses supported by transferable soft skills. However, Australian businesses risk missing these benefits as Australian workers have yet to reach pre-GFC mobility. We use the HILDA longitudinal dataset for Australia to test how the soft skill measures of communication skills, time management, and low task repetitiveness are associated with mobility for Australian workers measured using changing jobs directly and hourly wages as a measure of mobility success. The survival analysis for changing jobs finds soft skills have no significant effect on the expected employment duration prior to changing jobs, while measures of overall skills beyond soft skills increase this duration. Further, measures of soft skills and overall skills have mixed effects on wages by themselves, and when moderated with changing jobs these terms are almost completely insignificant. Overall, the potential transferability of soft skills does not translate into practical mobility, suggesting limitations for workers seeking to improve their working conditions via changing jobs.

KEYWORDS

Skill transferability; human capital; time management; communication skills; skill shortages

JEL CLASSIFICATION

J24; J62

I. Introduction

Job mobility, where workers change their employer or job (Carroll and Poehl 2007; Ferreira 2009; Ng et al. 2007; Sicherman and Galor 1990), has historically been researched from a labour turnover perspective, focusing on negative economic outcomes including increased production costs (Darmon 2004), additional training costs (Darmon 2004), loss of tacit knowledge (Avasthi and Dey 2015), and suggests 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 and Osborne 2017). Without job mobility, this constricts the ability for 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 and Chow 2022; Keith and McWilliams 1995) and shift from employers who are not adapting to these new technologies. Mobility is also an outcome of Schumpeter's theory of creative destruction, as workers reallocate to jobs that are of greater value (Andrews and Saia 2017). Further, the international trend of Baby Boomers leaving the workforce during and after the COVID pandemic (Agarwal and Bishop 2022) marks the start of the Baby Boomers exiting the labour force, with businesses left with key labour gaps. Altogether, these forces risk slower macroeconomic growth alongside business and individual detriments.

Australian job mobility at first appears to be doing well, with a decade-high job change rate in the post-COVID period (Australian Bureau of Statistics 2023b) combined with the tight labour market reaching 3.5% unemployment rate (Australian Bureau of Statistics 2023a). However, this current high job change rate is relatively weak compared to the pre-GFC period (Australian Bureau of Statistics 2023a). 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 emphasizing individual decisions for maximizing

CONTACT Aaron Semtner aaron.semtner@uon.edu.au University Drive, Callaghan, NSW 2308, Australia

lifelong returns (Ferreira 2009), and particularly human capital theory (Carroll and Poehl 2007; Sicherman and Galor 1990). Becker (1994) also considered human capital in this job mobility context, where individuals are less likely to move when trained in organization-specific skills compared to general skills, although it does not go into investigating the mobility likelihood of these skills. Few of these papers consider the use of transferable skills, and prior research on transferable skills covered transfer from education (Tran, Phan, and Bellgrove 2021) or occupational transition (Nawakitphaitoon 2014) instead of job mobility specifically. For this research, we focus on soft skills, including communication (Andreas 2018; Bacolod, Blum, and Strange 2009; National Careers Service, n.d.; Shakir 2009; Ubalde and Alarcón 2020), time management (Andreas 2018; Deng, Thomas, and Trembach 2014; National Careers Service, n.d.; Pang et al. 2019), and teamwork (Andreas 2018; Deng, Thomas, and Trembach 2014; Shakir 2009), as a key set of transferable skills (Cimatti 2016; Leighton and Speer 2020; Snell, Gekara, and Gatt 2016).

Soft skills have two additional benefits for our research on top of being transferable skills. First, soft skills are highly demanded by business leaders due to their productivity benefits and difficulty automating (Robles 2012; World Economic Forum, 2020), suggesting these skills are commonly demanded across a range of occupations and industries. This aligns with prior research on wage benefits when changing jobs with shared skills (Nawakitphaitoon 2014) and worker recruitment for alternate industries and occupations than originally educated for (Tsiligiris and Bowyer 2021). Second, workers can develop soft skills (Andreas 2018; National Careers Service, n.d.; Shakir 2009) if they want to improve their mobility.

To investigate the potential for soft skills to improve beneficial job mobility, we utilize the Household, Income and Labour Dynamics in Australia (HILDA) Survey from 2011 to 2019 using 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 mobility from unstable casualization (McGann, White, and Moss 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 communication skills are used to measure soft skills. We include further measures of education and skill intensity in the job for both comparing against overall skills and because soft skills primarily enhance additional worker skills (Cimatti 2016). The use of multiple measures for soft skills and overall skills 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 and Meekes 2021). To account for skills supporting job mobility in the wage regression, we moderate all skill terms on job mobility for certain specifications.

The results of both analyses suggest soft skills have an insignificant effect on job mobility. While overall skills increase the expected employment duration in the survival analysis, all soft skills are insignificant with no effect on the job change likelihood. Soft skills also have a mixed effect on wages broadly: time management has a negative effect, while lost task repetitiveness has a positive effect, and communication skills has no effect altogether. This aligns with the other skill measures, where job intensity contributes to wages, while education is associated with reduced wages. However, job change has no significant effect by itself, and there was limited significance at best when this term was moderated with the skill variables, suggesting mobility had no real effect on improving wages.

There are three primary contributions of this research. First, we deepen the understanding of skills transferability as theoretical transferability does not necessarily translate to active job mobility. This demonstrates limitations for workers to capture this potential mobility and the associated benefits. This study also deepens the understanding of how different types of skills operate in the labour market, including comparatively. The range of skill measures tested enables the research to draw upon both human capital theory and signalling theory (Lam, Ng, and Feldman 2012; Quintini 2011), demonstrating broader human capital via skill intensity and education is associated with remaining with the current employer. Second, the lack of association between soft skills and changing jobs suggests business owners have no particular tendency to hold onto soft skills nor can easily gain additional soft skills externally. What is relevant are the overall skills that soft skills support: these skills are associated with reduced job mobility. This is good for current employers who are able to utilize these skills, while creating difficulties for anyone seeking to recruit new workers with practical work experience and potentially slowing worker reallocation. Third, workers and governments gain a better understanding of potential weaknesses for skilled worker mobility, including for the job security of the worker and technological implementation. This could also include understanding why skilled workers tend to not get higher wages for moving, including a preference for non-monetary benefits (Masige 2023; PwC 2021). While one possible reason is the challenge in articulating transferable skills (Snell, Gekara, and Gatt 2016), the lack of mobility of and lower estimated wages for workers with easily visible education qualifications limits this explanation. 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.

The remaining sections are organized as follows. Section II further investigates how the literature defines soft skills to filter the specific characteristics relevant to this study, and detail the relevant hypotheses. Section III discusses the HILDA dataset and Section IV implemented the designs of both models along with initial tests. Section V discusses the primary results. Section VI concludes the article by considering how these results are applicable for theoretical contributions and practical applications.

II. Soft skills and hypotheses

Soft skills as a whole have a wide range of definitions in the literature, with few common characteristics. As such, we establish a definition prior to analysis, a process further complicated by the overlap of definitions and skills with other sets of skills (Cimatti 2016; Marin-Zapata et al. 2021; Robles 2012; Wats and Wats 2009; World Economic Forum, 2020). Among the literature, we consider two key questions for defining the type of skills we analyse. First, do these skills exclusively include interpersonal skills to work with colleagues and stakeholders to improve the group's effectiveness (Zhang 2012), or do they also include intrapersonal skills for self-management and improving one's own effectiveness (National Careers Service n.d.; Shakir 2009)? Second, do these skills also include broader personality and emotional aspects specific to the individual that are typically measured via psychometric tests (Heckman and Raut 2016)? Marin-Zapata et al. (2021) provides relevant discussions for both questions with their meta-analysis. For the first question, they found both interpersonal and intrapersonal skills were well considered across the literature and had similar characteristics as soft skills. For the second question, they noted that despite the inclusion of personality traits in some research, such aspects are not actually skills and thus should be excluded.

Both aspects align with the purpose of this article. For the first question, intrapersonal skills, including time management and emotional intelligence, as transferable between jobs and thus eligible for inclusion in this research. For the second question, personality traits are internal to a person and may be proxied using the Big Five personality traits (Cobb-Clark and Schurer 2013), with some research including these as soft skill or the similar category of noncognitive skills (Cobb-Clark and Schurer 2013; Maria, Stephanie, and Joanna 2021). These traits are transferrable between jobs (Maria, Stephanie, and Joanna 2021) and thus initially appear relevant for consideration. However, personality traits are typically stable for adults beyond major life events (Cobb-Clark and Schurer 2013), and thus development and training is improbable if a worker wishes to improve their soft skills. This means these traits are not considered skills at all (Marin-Zapata et al. 2021), in comparison to the ability to develop interpersonal and intrapersonal soft skills, even if these processes are broader than traditional education channels (Andreas 2018; National Careers Service n.d.; Shakir 2009).

We use this literature along with the data discussed in the next section to select three soft skill measures to analyse: time management as an intrapersonal soft skill (Andreas 2018; Deng, Thomas, and Trembach 2014; National Careers Service n.d.; Pang et al. 2019), communication as an interpersonal soft skill (Andreas 2018; Bacolod, Blum, and Strange 2009; National Careers Service n.d.; Shakir 2009; Ubalde and Alarcón 2020), and low task repetitiveness at the workplace as a broader measure (Robles 2012). As these soft skills are transferable across jobs (Cimatti 2016; Leighton and Speer 2020), we theorize workers with these skills will change jobs more regularly and thus have a higher likelihood of changing jobs each period, forming the basis for the following hypothesis:

H1: soft skills, as measured by time management, communication, and low task repetitiveness, have a significant and positive effect on the likelihood of changing jobs.

Further, we need to consider not only if these skills support mobility, but also support mobility to a greater degree than broader skill measures. Due to the breadth of skills and challenges when defining individual skills (Marin-Zapata et al. 2021; Matteson, Anderson, and Boyden 2016) and based on the data discussed in the next section, we use three measures of overall skills: the skill intensity of the job measured by the ability for the worker to decide what they do in their job, the skill intensity of the job measured by the ability for the worker to decide how to do their job, and their education level. This forms the basis for the following hypothesis:

H2: soft skills, as measured by time management, communication, and low task repetitiveness, have a larger effect on 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.

As some mobility may stem from job casualization and other problematic circumstances (McGann, White, and Moss 2016), we further test if workers with soft skills have an improved hourly wage from changing jobs as a measure of what workers seek from prospective employers (PwC 2021). This forms the basis for the following hypothesis:

H3: the moderation between changing jobs and soft skills, as measured by time management, communication, and low task repetitiveness, have a significant and positive effect on the hourly wage.

We also follow the previously mentioned comparison between soft skills and overall skills for the

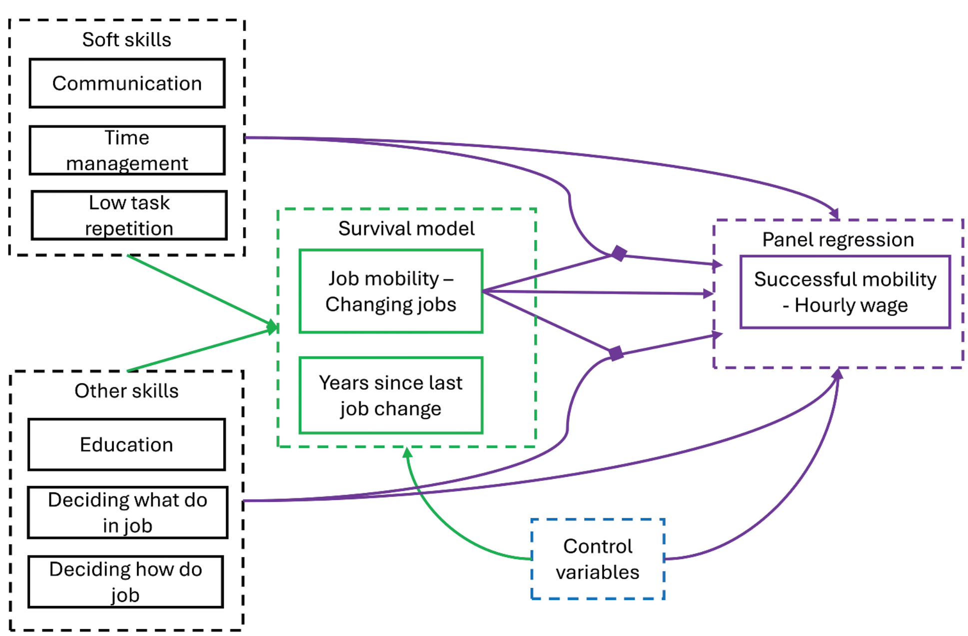

Figure 1. Conceptual model.
Source: Authors.

success of this job mobility using the following hypothesis:

H4: The moderation between changing jobs and soft skills, as measured by time management, communication, and low task repetitiveness, have a larger effect on 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 1 graphically displays the conceptual model for this research.

III. Data

The primary data source for this research 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 a range of topics relating to their socioeconomic status and employment. This survey is useful for our research due to its longitudinal nature, the low attrition rate of participants, and the inclusion of multiple measures for skills including both soft and overall. Underlying Likert variables for soft and overall skill measures are converted to binary variables as per Table 1 due to the ordinal nature of Likert data, and retention of all Likert categories results in an excessively large number of possible permutations, complicating the analysis (Jeong and Lee 2016).

We measure soft skills using three variables covering different aspects. The first soft skill variable is time management (Andreas 2018; Deng, Thomas, and Trembach 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) using the measure 'My job requires me to do the same things over and over again'. The third soft skill variable measures communication skills. One limitation of the HILDA dataset is the lack of a variable that captures workplace communication. We use four measures of participation in multiple social activities with the need for communication, as people can build communication skills beyond traditional education and workplace environments (Andreas 2018; National Careers Service n.d.; Shakir 2009). The four measures used are as follows: participation in a club using 'Currently an active member of a sporting/hobby/community based club or association', interaction with friends using 'How often get

Table 1. Likert to binary variable conversions.

Variable type	Analysis variable	Underlying variable	HILDA variable name	Good at skill	Poor at skill
Soft skills	Time management	'How often do you feel rushed or pressed for time?'	lsrush	4–5	1–3
	Low task repetitiveness	'My job requires me to do the same things over and over again'	jomrpt	1–3	4–7
	Communication – club	'Currently an active member of a sporting/hobby/community based club or association'	lsclub	Yes	No
	Communication – friends	'How often get together socially with friends/relatives not living with you'	lssocal	1–4 (at least 2–3 times a month)	5–7 (once a month or less)
	Communication – have close person	'When I need someone to help me out, I can usually find someone'	lssupsh	5–7	1–4
	Communication – part of community	'Feeling part of your local community'	losatlc	6–10	0–5
	Communication – overall	Prior four underlying communication variables	N/A	At least two of the four underlying variables are good	At most one of the underlying variables is good
Other skills	Deciding what do in job	'I have a lot of choice in deciding what I do at work'	jomdw	5–7	1–4
	Deciding how do job	'I have a lot of freedom to decide how I do my own work'	jomfd	5–7	1–4

We exclude education from this graph as we use three final categories. Underlying variable uses HILDA variable description where direct HILDA terms are utilized.

together socially with friends/relatives not living with you', having someone socially close to using 'When I need someone to help me out, I can usually find someone', and 'Feeling part of your local community'. As all four are partial measures of overall communication ability and people may not participate in all contexts, the final communication skill variable for this analysis considers someone to have good communication skills if they demonstrate good communication in at least two of the four contexts.

As previously discussed, soft skills alone are insufficient for production (Cimatti 2016), and thus three additional measures of overall skills are included, covering both skills readily demonstrated in external labour markets via qualifications and direct measures of a worker's capabilities to provide evidence across human capital theory and signalling theory perspectives (Lam, Ng, and Feldman 2012; Quintini 2011). The first measure 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 for this method: school level, vocational level, and university level. Even if these measures have notable restrictions as a single measure of skills (Cord and 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 their job and the ability to decide what to do in their job, measuring the skill intensity of the job as utilized by Fraser (2008). These Likert terms are converted to binary terms as per Table 1.

We use two different dependent variables to capture different aspects of the job mobility decision, each with their own structures resulting in the different methodologies. 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. Focusing on this movement over moves into unemployment or exiting the workforce is acceptable as prior research for Australia shows two-thirds of worker separations are followed by finding another employer (Carroll and Poehl 2007). This also enables consistent use of the provided skill metrics measured in the workplace. The second is the hourly wage, as this is commonly utilized in the literature (Kalb and Meekes 2021; Wen and Maani 2019) and captures a key part of remuneration, with workers emphasizing this aspect in their job search (PwC 2021). We estimate this hourly wage using the weekly wage divided by the usual number of hours the worker spends at their primary job each week, removing any workers with a positive weekly wage and zero hours worked. As this is an outcome of the job mobility decision, we include an additional set of coefficients generated using the interactions between the job mobility decision above and each skill term.

As this survey does not track people from workforce entry nor to their exit, we consider censoring for the survival analysis. For time prior to their measurement in the sample, including changing employers in an unobserved year, we use their 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. We treat individuals who do not change jobs within the sample as right censored. As the HILDA data is taken annually while the initial years employed measure may be in months or years employed, we round any individuals with less than one year of experience up to one year. This overall variable is called years since last job change to distinguish it from the underlying variables.

Finally, we include additional personal and workplace controls. These include gender, age, disability, 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, whether in a long-term relationship including marriage, life satisfaction, the stress of their job, whether the person is employed full-time, the natural log of their weekly wage, job satisfaction, years employed at the business, whether the person lives in an urban geographic region, whether the person feels they are underemployed or overemployed by hours worked, whether the employer is a medium or large business with at least 20 employees, the occupation and industry classifications at the first and second level, the regional unemployment rate, and the percent gap between the state-level GDP growth rate and the state-level industry value-added growth rate (percentage gap in growth rates). We also include 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 certain variables irrelevant to the wage: job stress, 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. We exclude observations with missing values for variables used in this research, 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, with details in Table 2.

There are two further aspects regarding the industry and regional controls. First, percentage gap in growth rates is not captured in the HILDA dataset, instead using the ABS Australian National Accounts: State Accounts dataset Tables 2–9 and comparing chain volume percentage change measures. This variable is also not lagged to account for the environment in the period when the movement decision occurred. Second, the occupation and industry controls are applied one at a time to provide comparisons while minimizing loss of parsimony.

Table 2 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 we only observe when there is right censoring or the person has an event of changing jobs; in comparison, two people are removed from the wage regression due to zero hours worked reported and thus an infinite hourly wage. A further point is the number of people with soft skills; less than 25% of observations have low task repetitiveness in their job and less than 15% have good time management, while over 90% of people have good communication skills. The underlying variables help explain this: using the wage data, 75% of observations have good community participation, 83% have someone they feel they can reasonably reach out to if there is a problem, and 97% have regular meetings with friends, while only 36% have club participation. This suggests people

Table 2. Variable descriptive statistics.

	Job change	Wage
Employment duration		
At least 10 years	0.273	
At least 5 years	0.545	
ln hourly wage		3.374
		(0.502)
Soft skills		
Communication Skills	0.931	0.94
Low task repetitiveness	0.217	0.235
Time management	0.145	0.143
Overall skills		
Highest education		
School	0.135	0.147
Vocational	0.282	0.294
University	0.583	0.56
What do in job	0.444	0.467
How do job	0.544	0.568
Change jobs	0.365	0.132
Control variables		
Age	38.229	39.79
	(14.219)	(13.594)
Aboriginal and Torres Strait Islander (ATSI)	0.022	0.019
Children	0.335	0.353
Disabled	0.162	0.158
Employment hour preferences		
Underemployed	0.232	0.243
Well Employed	0.595	0.612
Overemployed	0.173	0.144
Full-time	0.658	0.688
Gender	0.507	0.504
Job satisfaction	0.945	
Job stress	0.248	
ln weekly wage	6.768	
	(0.858)	
Medium-large business	0.587	0.631
Migrant (English-speaking background)	0.099	0.101
Migrant (non-English-speaking background)	0.086	0.085
Overall life quality	0.904	
Regional unemployment rate	5.226	5.397
	(0.865)	(0.863)
Relationship	0.608	0.644
Sector-GDP gap	0.32	0.204
	(4.374)	(4.182)
Urban	0.89	0.892
Years employed	6.145	7.259
	(7.792)	(8.175)
Year		
2012		0.12
2013		0.12
2014		0.121
2015		0.12
2016		0.125
2017		0.13
2018		0.13
2019		0.134
Observations	18684	51429
Individuals	12438	12436

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.
Source: HILDA dataset 2011–2019 and authors' calculations.

have good general socialization skills, and the increased interest in soft skills in the workplace (Robles 2012; World Economic Forum 2020) may stem from something other than low levels of general communication.

IV. Method

The two dependent variables of changing employers and hourly wage have different structures, as the former is binary while the latter is continuous. We use two different methods, one for each dependent variable.

For changing employers, we use the Cox proportional hazards survival model following the Andersen and Gill counting process, as this can handle repeat occurrences of the event of interest for each individual (Amorim and Cai 2014). This is represented using Equation 1 below:

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

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. 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, we make an exception for percentage gap in growth rates for time relevance as this measures macroeconomic conditions over the year of the decision. We use the Efron estimation approach to balance the discrete nature of years employed and the number of ties in the data (Therneau 1997), and cluster standard errors by individuals to account for the nature of repeat events of job mobility. We interpret results using 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). We test this using Table 3 column 1 below, and find seven variables with significant chi-square results for their Pearson product-movement correlation of the Schoenfeld residuals of the variables (Therneau 1997): regional unemployment, ability to decide what tasks perform, age, disability, whether the business is a small or medium-large employer, urban, and job satisfaction. Visual investigation of graphs of the Schoenfeld residuals, as displayed in Figure 2, suggests that these results do reflect underlying trends of concern. The graph for low task repetitiveness demonstrates a visible downturn in the hazard for the variable over longer periods of time despite an insignificant test statistic, and thus we also correct this variable. We choose to stratify the time variable (Therneau 1997) based on inflection points of the graphs, stratifying these results for year = 5 (regional unemployment, ability to decide what tasks perform, business employees) and year = 10 (age, disability, urban, job satisfaction, low task repetitiveness). The updated results with this stratification are displayed in Table 3 column 2 below, with most variables corrected and thus no longer violating the proportional hazards assumption, while the corrected terms for regional unemployment, age, and job satisfaction remain significant. Visual inspection of these graphs in Figure 3 suggests that there is no practical effect of these remaining violations on the results with the significant results stemming from the tight confidence intervals, and thus are left as-is due to no practical violation of the proportional hazards assumption.

All variables here have significant Pearson correlation, except for low task repetitiveness. 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.

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.

For hourly wage, we use a panel data regression for continuous variables. Two key model formats for this are random effects and fixed effects, where the former accounts for the individual variation in the error term

Table 3. 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		
Communication Skills	0.193 (0.66)	0.057 (0.812)
Low task repetitiveness	0.113 (0.737)	
Low task repetitiveness *10 years employed strata		3.952 (0.139)
Time management	0.001 (0.981)	0.813 (0.367)
Overall skills		
Highest education	3.588 (0.166)	5.738 (0.057)
What do in job	5.306* (0.021)	
What do in job *5 years employed strata		2.4 (0.301)
How do job	3.549 (0.06)	0.012 (0.912)
Control variables		
Age	133.648*** (0)	
Age *10 years employed strata		34.79*** (0)
ATSI	1.336 (0.248)	1.529 (0.216)
Children	0.455 (0.5)	0.123 (0.726)
Disabled	10.014** (0.002)	
Disabled *10 years employed strata		3.451 (0.178)
Employment hour preferences	1.111 (0.574)	0.334 (0.846)
Full-time	1.03 (0.31)	1.587 (0.208)
Gender	1.604 (0.205)	0.421 (0.516)
Gender * Relationship	0.251 (0.616)	0.248 (0.619)
Job satisfaction	18.758*** (0)	
Job satisfaction *10 years employed strata		11.598** (0.003)
Job stress	0.582 (0.446)	0.006 (0.94)
ln weekly wage	1.286 (0.257)	1.509 (0.219)
Medium-large business	8.326** (0.004)	
Medium-large business *5 years employed strata		3.67 (0.16)
Migrant (ESB)	1.022 (0.312)	0.608 (0.436)
Migrant (NESB)	0.073 (0.787)	0.316 (0.574)
Overall life quality	2.972 (0.085)	1.86 (0.173)
Regional unemployment rate	19.992*** (0)	
Regional unemployment *5 years employed strata		15.444*** (0)
Relationship	3.989* (0.046)	1.064 (0.302)
Sector-GDP gap	0.87 (0.351)	0.775 (0.379)
Urban	6.114* (0.013)	
Urban *10 years employed strata		5.622 (0.06)
Overall	227.338*** (0)	106.724*** (0)

*, **, *** Significant at 5%, 1%, and 0.1% levels respectively.
Source: HILDA dataset 2011–2019 and authors' calculations.

while the latter uses separate fixed intercepts for all individuals. As explanatory variables including education level are time-invariant terms inseparable from individual intercepts, we use a Durbin-Wu-Hausman test for endogeneity in the random effects model. The test on the model with all key explanatory terms and moderations and excluding any industry or occupational categories has a chi-squared of 158.69 with a p-value of ~ 0, signalling the random effects model by itself has problematic endogeneity. To correct this, we apply Mundlak corrections to all time variant terms (Bell and Jones 2015), also known as correlated random effects (Wooldridge 2019), to account for individual heterogeneity. We apply this process starting with the initial fixed effects model in Equation 2:

$$y_{it} = \beta_1^2 SS_{it-1} + \beta_2^2 OS_{it-1} + \beta_3^2 job_{it-1} + \beta_4^2 job_{it-1} * SS_{it-1} + \beta_5^2 job_{it-1} * OS_{it-1} + \gamma_1^2 X_{1it-1} + \alpha_1 + \alpha_{2i} + u_{it} \tag{2}$$

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. We then estimate the Mundlak corrections using Equation 3 (Bell and Jones 2015) along with the time invariant individual variables otherwise contained in the individual intercepts, and substitute them into Equation 4:

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

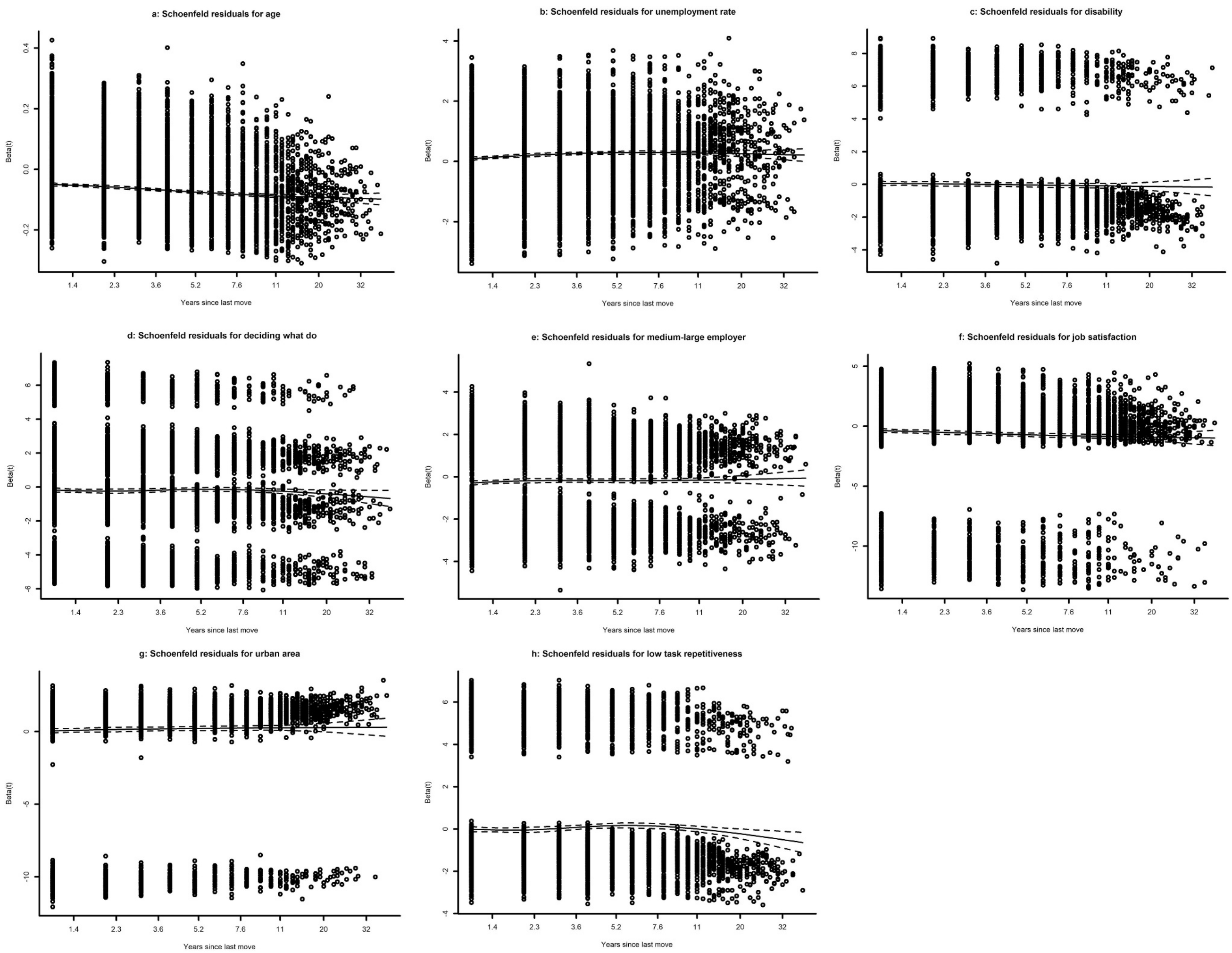

Figure 2. Schoenfeld residuals of concerning variables prior to correction.

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

We also remove the Mundlak correction for age due to extreme multicollinearity with the baseline term, affecting the model estimation.

V. Results

Job change

Table 4 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 typically display 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. When looking at the different specifications, these variables have some fluctuations in magnitude, particularly when including the skill terms but not any industry nor occupational classifications.

When we include the skill terms, both highest education terms have slightly significant hazard ratios, with similar reductions in job mobility between university education (hazard ratio = 0.895) and vocational education (0.891). Further, skill intensity measured by deciding what to do in their job also has reduced mobility, with a slightly

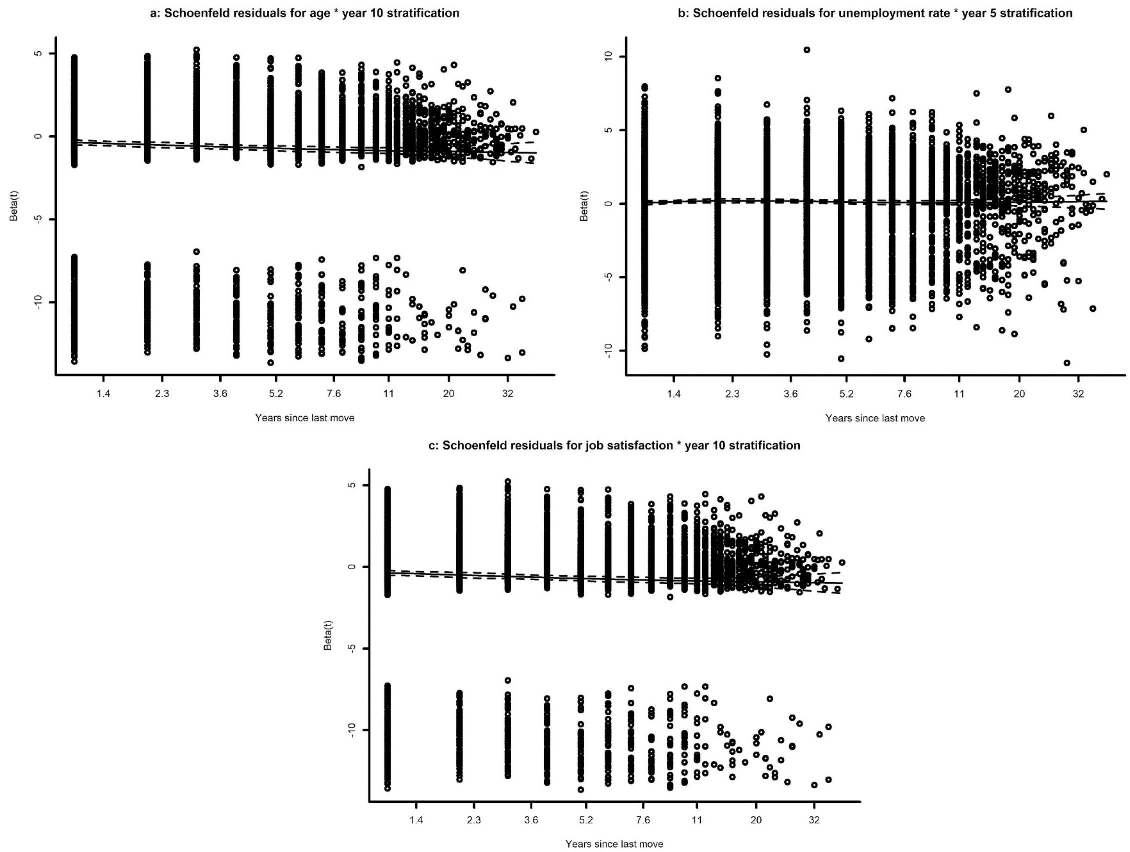

Figure 3. Schoenfeld residuals of concerning variables after correction through year stratification.

significant short employment duration ratio and increased significance and magnitude when remaining with the employer for at least 5 years. These results, along with the insignificant results for deciding how to do their job, suggest overall worker skills reduce the mobility for the worker. Prior Australian research has mixed evidence on education in particular, with Carroll and Poehl (2007) suggesting higher educated workers had fewer job separations or accessions. In comparison, Shah (2009) has their own mixed results, with a positive relationship between education and job separations for women and men with a bachelor degree, while higher education reduced occupational mobility for men and women. Further, none of the soft skill terms are significant, suggesting this group of skills are irrelevant to the mobility decision and thus do not confirm H1. Further, while lack of significance for soft skill hazard ratios might have a 'greater' contribution to mobility compared to significant and negative overall skill ratios, this is not considered good evidence in favour of H2.

When including the industry classifications, any insignificant skill terms remain insignificant. Further, the ability for the worker to decide what to do in their job further reduces the likelihood of changing employers for longer-duration employees, particularly at the 2-level classification (0.809 to 0.784) compared to the 1-level (0.809 to 0.791). Highest education have some particularly relevant changes, with greater reductions in mobility likelihood for both university and vocational workers so long as the industry classifications are included. Further, the university educated workers ratio has a particularly notable reduction in magnitude, now with an even greater increase in employment duration before moving compared to vocational educated workers. These ratios are reasonably consistent regardless of which industry classification level is used. Such changes are weaker when considering the occupation: the ratios for what do in their job only decrease notably when using the 2-level occupation classifications, with no practical change at the 1-level classifications. Further, education terms have only a slight reduction in

Table 4. 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						
Communication Skills		1.036	1.046	1.038	1.049	1.047
		(0.048)	(0.048)	(0.048)	(0.048)	(0.049)
Low task repetitiveness * Under 10 years		1.008	1.044	1.016	1.042	1.017
		(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Low task repetitiveness * At least 10 years		0.852	0.866	0.858	0.872	0.863
		(0.09)	(0.089)	(0.09)	(0.089)	(0.089)
Time management		1.012	1.01	1.007	1.015	1.012
		(0.036)	(0.035)	(0.036)	(0.035)	(0.035)
Overall skills						
Highest education						
Vocational		0.891 *	0.856 ***	0.887 **	0.859 ***	0.873 **
		(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
University		0.895 *	0.808 ***	0.88 **	0.801 ***	0.85 ***
		(0.045)	(0.047)	(0.048)	(0.048)	(0.049)
What do in job * Under 5 years		0.917 *	0.919 *	0.918 *	0.913 *	0.919 *
		(0.037)	(0.037)	(0.037)	(0.037)	(0.038)
What do in job * At least 5 years		0.809 ***	0.791 ***	0.808 ***	0.784 ***	0.795 ***
		(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
How do job		0.967	0.974	0.967	0.954	0.956
		(0.03)	(0.031)	(0.031)	(0.031)	(0.031)
Control variables						
Age *10 year (<10 years)	0.978 ***	0.978 ***	0.98 ***	0.978 ***	0.979 ***	0.978 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age *10 year (≥10 years)	0.912 ***	0.913 ***	0.915 ***	0.913 ***	0.915 ***	0.914 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ATSI	1.059	1.061	1.058	1.056	1.041	1.051
	(0.083)	(0.083)	(0.083)	(0.083)	(0.081)	(0.081)
Children	0.962	0.968	0.977	0.965	0.983	0.98
	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
Disabled *10 year (<10 years)	0.993	0.992	0.997	0.991	0.996	0.991
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Disabled *10 year (≥10 years)	0.909	0.9	0.917	0.9	0.897	0.906
	(0.103)	(0.102)	(0.102)	(0.102)	(0.102)	(0.101)
Employment hour preferences						
Underemployed	1.118 ***	1.118 ***	1.105 **	1.116 ***	1.099 **	1.104 **
	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)
Overemployed	1.248 ***	1.244 ***	1.236 ***	1.242 ***	1.238 ***	1.249 ***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Full-time	1.033	1.043	1.044	1.041	1.031	1.047
	(0.037)	(0.037)	(0.038)	(0.037)	(0.038)	(0.038)
Gender	1.127 **	1.117 **	1.161 ***	1.131 **	1.146 ***	1.121 **
	(0.039)	(0.039)	(0.04)	(0.041)	(0.041)	(0.041)
Gender * Relationship	0.72 ***	0.714 ***	0.724 ***	0.707 ***	0.734 ***	0.72 ***
	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)	(0.053)
Job satisfaction *10 year (<10 years)	0.597 ***	0.615 ***	0.629 ***	0.618 ***	0.633 ***	0.627 ***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.044)
Job satisfaction *10 year (≥10 years)	0.402 ***	0.433 ***	0.44 ***	0.434 ***	0.454 ***	0.443 ***
	(0.13)	(0.132)	(0.134)	(0.132)	(0.132)	(0.132)
Job stress	1.009	1.007	1.018	1.009	1.024	1.023
	(0.03)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
ln weekly wage	0.887 ***	0.891 ***	0.901 ***	0.894 ***	0.905 ***	0.882 ***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.023)	(0.023)
Medium-large business *5 year (<5 years)	0.853 ***	0.843 ***	0.867 ***	0.841 ***	0.875 ***	0.859 ***
	(0.031)	(0.031)	(0.032)	(0.031)	(0.033)	(0.032)
Medium-large business *5 year (≥5 years)	0.893 **	0.861 ***	0.894 *	0.858 ***	0.911 *	0.882 **
	(0.043)	(0.043)	(0.044)	(0.043)	(0.045)	(0.044)
Migrant (ESB)	1.148 **	1.151 **	1.136 **	1.149 **	1.134 **	1.136 **
	(0.045)	(0.045)	(0.046)	(0.045)	(0.046)	(0.045)
Migrant (NESB)	1.055	1.041	1.008	1.035	1.002	1.009
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.05)
Overall life quality	0.931	0.934	0.946	0.934	0.956	0.938
	(0.042)	(0.043)	(0.044)	(0.043)	(0.044)	(0.043)
Regional unemployment * Under 5 years	1.146 ***	1.146 ***	1.139 ***	1.146 ***	1.138 ***	1.14 ***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Regional unemployment * At least 5 years	1.305 ***	1.299 ***	1.292 ***	1.299 ***	1.291 ***	1.302 ***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Relationship	1.133 **	1.144 ***	1.143 **	1.151 ***	1.139 **	1.132 **
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)

(*Continued*)

Table 4. (Continued).

	Baseline	With skills	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Sector-GDP gap	0.998	0.998	0.999	0.999	0.999	0.997
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Urban *10 year (<10 years)	1.092	1.091	1.083	1.097 *	1.076	1.084
	(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)
Urban *10 year (≥10 years)	1.24	1.235	1.215	1.242	1.195	1.142
	(0.127)	(0.127)	(0.13)	(0.127)	(0.13)	(0.13)
Log likelihood	−54868.851	−54843.597	−54755.8	−54838.297	−54666.621	−54726.097

Industry and occupation classifications are not reported for space.
*, **, *** Significant at 5%, 1% and 0.1% levels, respectively.
Source: HILDA dataset 2011–2019 and authors' calculations.

mobility ratio under the 1-level occupation classifications and are moderately significant. Even under the 2-level occupation classifications, neither hazard ratio approaches the levels under either industry classification, with the ratio for university level under the 2-level occupation classification (0.85) closer to the ratios for vocational education under industry classifications (0.859 for 1-level, 0.856 for 2-level) than the university ratios for industry classifications (0.808 for 1-level, 0.801 for 2-level).

Finally, the log likelihood continues to approach 0 with additional variables, suggesting the skill terms and classifications are relevant. The log likelihood at each classification level is always closer to 0 for the industry version than the occupational version, with the strongest log likelihood particularly 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 0 compared to the 1-level industry classifications, suggesting granularity of work or employer type is valuable to understanding the mobility decision. This is reinforced by the relatively minor improvement in log likelihood from having no industry nor occupation classifications to the 1-level occupational classifications, suggesting broad occupations capture minimal additional detail.

Wages from changing jobs

Table 5 displays the coefficients for the regression on log hourly wages. Investigating the control variables, the main coefficients appear appropriate except for the negative coefficient for full-time workers (−0.064). Another relevant point is the high significance of the Mundlak corrections, particularly for insignificant or slightly significant variables including children, disability, years employed, and the percentage gap in growth rates. The correction for full-time is also positive and larger than the year-specific one (0.188), more than offsetting the unusual result. This suggests outcomes over the sample for the worker are of similar or greater relevance for wages over yearly variations. These coefficients generally retain or lose magnitude when including the skill terms, with few additional changes when including industry or occupational classifications.

Skill terms have varied effects. For soft skills, communication is insignificant for both the standard coefficient and the Mundlak correction, suggesting this skill is irrelevant. Both time management and low task repetitiveness are also insignificant as standard coefficients, while the Mundlak corrections are significant. The low task repetitive correction has a positive contribution of 0.1, while the time management correction has a negative contribution of 0.05, leading to overall mixed results on the effectiveness of soft skills generally on wage. Overall skills have multiple significant coefficients, with positive coefficients for both skill intensity Mundlak corrections (0.048 for deciding how to do their job, 0.076 for deciding what to do in their job) and the what to do in their job standard coefficient (0.014), while how to do their job has an insignificant standard coefficient. Contradicting this, vocational education has a negative coefficient of 0.095 and university education has a negative coefficient of 0.278. This differs from prior Australian research (Leigh 2008; Mavromaras et al. 2010) where education

Table 5. 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	2.71 ***	2.877 ***	2.876 ***	2.945 ***	2.971 ***	2.926 ***	3.004 ***
	(0.034)	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)	(0.037)
Soft skills							
Communication Skills		0.006	0.007	0.007	0.009	0.007	0.008
		(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Communication Skills (Mundlak)		0.027	0.027	0.019	0.019	0.02	0.016
		(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
Communication Skills * Change jobs			−0.003	−0.002	−0.004	−0.002	−0.004
			(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Low task repetitiveness		0.005	0.002	0.001	0.001	0.001	−0.001
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Low task repetitiveness (Mundlak)		0.1 ***	0.099 ***	0.089 ***	0.086 ***	0.086 ***	0.075 ***
		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Low task repetitiveness * Change jobs			0.026 *	0.019	0.021 *	0.019	0.02
			(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Time management		0.001	0.001	0.003	0.003	0.003	0.004
		(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Time management (Mundlak)		−0.05 ***	−0.05 ***	−0.05 ***	−0.038 **	−0.049 ***	−0.034 **
		(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Time management * Change jobs			−0.001	0.003	−0.002	0.006	0
			(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Overall skills							
Highest education							
Vocational		−0.095 ***	−0.093 ***	−0.094 ***	−0.078 ***	−0.09 ***	−0.075 ***
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
University		−0.278 ***	−0.278 ***	−0.26 ***	−0.218 ***	−0.249 ***	−0.193 ***
		(0.009)	(0.009)	(0.009)	(0.01)	(0.009)	(0.009)
Highest education * Change jobs							
Vocational * Change Jobs			−0.013	−0.009	−0.01	−0.005	−0.008
			(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
University * Change jobs			−0.003	0.006	−0.001	0.009	−0.001
			(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
What do in job		0.014 ***	0.015 ***	0.017 ***	0.013 **	0.018 ***	0.012 **
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
What do in job (Mundlak)		0.076 ***	0.076 ***	0.083 ***	0.069 ***	0.082 ***	0.065 ***
		(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
What do in job * Change jobs			−0.009	−0.01	−0.01	−0.012	−0.013
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
How do job		0.005	0.004	0.003	0.002	0.004	0.001
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
How do job (Mundlak)		0.048 ***	0.048 ***	0.04 **	0.034 **	0.037 **	0.03 **
		(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
How do job * Change jobs			0.004	0.002	0.003	0.002	0.004
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Change jobs		−0.004	0.001	0.001	0.003	0	0.005
		(0.005)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Change jobs (Mundlak)		−0.016	−0.015	−0.008	−0.013	−0.007	−0.012
		(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Control variables							
Age	0.009 ***	0.007 ***	0.007 ***	0.006 ***	0.007 ***	0.006 ***	0.007 ***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
ATSI	−0.028	−0.003	−0.003	−0.005	−0.001	−0.008	−0.002
	(0.024)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)
Children	−0.005	−0.006	−0.006	−0.007	−0.006	−0.007	−0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Children (Mundlak)	0.086 ***	0.072 ***	0.072 ***	0.065 ***	0.071 ***	0.066 ***	0.068 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.009)	(0.009)
Disabled	−0.002	−0.002	−0.002	−0.001	−0.002	−0.001	−0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Disabled (Mundlak)	−0.123 ***	−0.091 ***	−0.092 ***	−0.093 ***	−0.087 ***	−0.089 ***	−0.084 ***
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Employment hour preferences							
Underemployed	−0.052 ***	−0.051 ***	−0.051 ***	−0.048 ***	−0.051 ***	−0.048 ***	−0.051 ***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Underemployed (Mundlak)	0.085 ***	0.03 *	0.03 *	0.037 **	0.02	0.039 ***	0.021
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
Overemployed	0.022 ***	0.02 ***	0.02 ***	0.021 ***	0.021 ***	0.022 ***	0.021 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)

(*Continued*)

Table 5. (Continued).

	Baseline	With skills	Interactions	Industry 1-level classifications	Occupation 1-level classifications	Industry 2-level classifications	Occupation 2-level classifications
Overemployed (Mundlak)	−0.121 ***	−0.071 ***	−0.071 ***	−0.058 ***	−0.055 ***	−0.053 ***	−0.045 ***
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
Full-time	−0.064 ***	−0.082 ***	−0.082 ***	−0.1 ***	−0.099 ***	−0.105 ***	−0.111 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Full-time (Mundlak)	0.188 ***	0.179 ***	0.179 ***	0.156 ***	0.175 ***	0.148 ***	0.164 ***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Gender	−0.05 ***	−0.068 ***	−0.068 ***	−0.059 ***	−0.076 ***	−0.055 ***	−0.072 ***
	(0.01)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Gender * Relationship	−0.007	−0.011	−0.011	−0.017	−0.015	−0.016	−0.018
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Medium-large business	0.051 ***	0.048 ***	0.048 ***	0.041 ***	0.047 ***	0.037 ***	0.044 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Medium-large business (Mundlak)	0.184 ***	0.163 ***	0.163 ***	0.152 ***	0.157 ***	0.144 ***	0.149 ***
	(0.01)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Migrant (ESB)	0.015	−0.005	−0.005	−0.005	−0.005	−0.007	−0.007
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.01)	(0.01)
Migrant (NESB)	−0.03 *	−0.069 ***	−0.069 ***	−0.062 ***	−0.058 ***	−0.059 ***	−0.053 ***
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
Regional unemployment rate	−0.007 **	−0.006 **	−0.006 **	−0.006 **	−0.006 *	−0.007 **	−0.006 *
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Regional unemployment (Mundlak)	−0.039 ***	−0.025 ***	−0.025 ***	−0.022 ***	−0.023 ***	−0.021 ***	−0.022 ***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Relationship	0.079 ***	0.07 ***	0.07 ***	0.067 ***	0.066 ***	0.064 ***	0.064 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Relationship (Mundlak)	0.079 ***	0.05 ***	0.05 ***	0.045 ***	0.047 ***	0.043 ***	0.04 ***
	(0.011)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Sector-GDP gap	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Sector-GDP gap (Mundlak)	0.011 ***	0.008 ***	0.008 ***	0.006 ***	0.008 ***	0.004 ***	0.006 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Urban	0.031 **	0.031 **	0.031 **	0.029 **	0.03 **	0.032 **	0.029 **
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Urban (Mundlak)	0.075 ***	0.054 ***	0.054 ***	0.044 **	0.049 **	0.035 *	0.033 *
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Years employed	0.001 *	0.001 ***	0.001 ***	0.002 ***	0.001 **	0.002 ***	0.001 ***
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
Years employed (Mundlak)	0.003 ***	0.001 *	0.001 *	0.001 *	0.001	0.001 *	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year							
2013	0.039 ***	0.037 ***	0.037 ***	0.037 ***	0.036 ***	0.036 ***	0.036 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
2014	0.07 ***	0.067 ***	0.067 ***	0.068 ***	0.066 ***	0.068 ***	0.066 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
2015	0.1 ***	0.094 ***	0.095 ***	0.095 ***	0.093 ***	0.096 ***	0.094 ***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2016	0.129 ***	0.121 ***	0.122 ***	0.121 ***	0.121 ***	0.122 ***	0.121 ***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2017	0.158 ***	0.15 ***	0.15 ***	0.15 ***	0.148 ***	0.15 ***	0.147 ***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
2018	0.185 ***	0.177 ***	0.177 ***	0.176 ***	0.174 ***	0.176 ***	0.173 ***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
2019	0.226 ***	0.216 ***	0.216 ***	0.214 ***	0.212 ***	0.214 ***	0.21 ***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.513	0.538	0.538	0.55	0.547	0.56	0.558

Industry and occupation classifications are not reported for space.
*, **, *** Significant at 5%, 1% and 0.1% levels, respectively.
Source: HILDA dataset 2011–2019 and authors' calculations.

has a positive effect on wages. Our model does account for additional sources of skills that may offset this negative, although the sheer magnitude of the university-level job in particular is still unexpected. While correlation with the unobserved variable of overskilling might appear to be a reason, Mavromaras et al. (2010) suggests this is not the case as Australian university-educated workers are less likely to be overskilled compared to less educated workers.

Changing employers is also initially included with the skill terms and is found to be insignificant by itself, suggesting changing employers has no particular benefit to hourly wages. Knight and Wei (2014) found job mobility in Australia had different effects on wage depending on the sector, where public sector workers had 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. Further, this contrasts with expectations of workers using mobility to bargain for better conditions and wages (Black and Chow 2022; Keith and McWilliams 1995). When we include interactions between changing job and in our model, only the interaction with low task repetitiveness has any significance, and inclusion of the 2-level occupation classifications or any industry classifications also results in an insignificant coefficient for this term. This contrasts with Nawakitphaitoon (2014), where 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 helps offset this loss. Overall, this is not evidence in favour of either H3 or H4.

The adjusted R squared terms support these discussions. The inclusion of skill terms is beneficial to the R square (increase from 0.513 to 0.538), while the interactions with job change has no effect. Further improvements are seen when accounting for industry or occupation, with some benefit from 1-level classifications (0.55 for industry, 0.547 for occupation) and further benefit from using the 2-level classifications (0.56 and 0.558 respectively). Unlike in 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 are dependent more on visible characteristics including skills, with some effect from high-level classifications and limited additional effect from additional details in these classifications.

VI. Conclusion

Although the job mobility rate for Australia has recently increased above post-GFC levels, it has still yet to reach pre-GFC levels. This is a concern for Australia's future productivity and labour allocation. To investigate options for Australian workers to improve their mobility, we tested soft skills as a key set of transferable skills with broad demand by modern businesses, perceived to improve mobility by both allowing easier job mobility and by improving the quality of mobility by transferring these skills to their new workplace for additional monetary benefit. Using the HILDA dataset, we tested three soft skills of time management, low task repetitiveness, and communication against these two elements of job mobility using a survival model for changing jobs and a random effects model with Mundlak corrections for wages. Contrary to expectations, soft skills were insignificant for mobility in both models.

Further, job mobility has no significant effect on wages, suggesting even if workers were moving more due to soft skills, they would not get any additional monetary benefit. A further element of note is the reduction in job mobility likelihood from an increase in overall skills of any kind, suggesting skilled workers are less mobile from both human capital theory and signalling theory perspectives. This is mixed when it comes to wages beyond mobility: skill intensity measures and low task repetitiveness are associated with an increase in wages, while higher education and time management were associated with lower wages. We also noted the particular relevance of detailed industry classifications for job mobility.

Altogether, these results suggest soft skills have limited contributions to job mobility, while skills more broadly are less mobile, leading to no evidence in favour of any of the hypotheses. The lack of benefit of job mobility to wages also suggests limitations to workers moving jobs for this monetary benefit, although whether due to other preferences for jobs (Masige 2023; PwC 2021), increased incidence of negative mobility from casualization (McGann, White, and Moss 2016), or some alternate factor is not investigated in this research. The increased mobility duration from overall skills and mixed results for how all skills relate to wages also suggests barriers beyond the signalling of skills (Nawakitphaitoon 2014; Sicherman and Galor 1990). Further research into why these skilled workers are less mobile, including worker preferences, employer preferences, and the ability to match these two groups together, will be required to investigate other means to improve this low mobility, as workers will not always have such good economic conditions to take advantage of.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

We thank the HILDA Survey team for access to this data set. This article is financially supported by the Australian Government Research Training Program Scholarship.

ORCID

Aaron Semtner http://orcid.org/0000-0002-1407-986X
Janet Dzator http://orcid.org/0000-0002-9866-6323

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