Gender and Geographical Differences in Australian Job-to-Job Mobility

Diego Machillanda Flechas

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Abstract

This paper investigates gender and geographical differences in the factors associated with job-to-job mobility for the average Australian worker. Using a Generalised Estimating Equations approach and waves 11 to 21 of the Household, Income and Labour Dynamics in Australia (HILDA) survey, I estimate marginal models for workers' probability of voluntary employer change, promotion, occupation change, and industry change. I find several but disparate gender differences, including in the effect associated with immigration from a non-English speaking background, postgraduate education, and employment in gender-concentrated industries. I also find that household characteristics have limited associations with job-to-job mobility in general and that there are few geographical differences in the factors associated with mobility. These findings highlight the individual characteristics through which group differences in job-to-job mobility do and do not manifest, identifying areas for further research to understand the underlying causal mechanisms and inform targeted policy opportunities.

Contents

1. Introduction

Job mobility, referring to when an employee moves from one job to another, is an important feature of how labour markets operate. Voluntary job changes allow workers to change the nature of their participation in the labour market over time, such as in response to personal developments or economic circumstances. They allow workers to meet changing needs – whether financial, lifestyle, or otherwise – and to be recognised and rewarded, as in the case of promotions. Even when involuntary, job changes enable the productive reallocation of labour resources in the economy. As employers terminate low-quality matches, workers are compelled to seek new employment opportunities that may better utilise their skills, including in alternative occupations or industries.

However, not all Australians experience the labour market equally. This inequality is well-documented, with persistent (albeit moderating) differences in employment and earnings between men and women (Coelli & Borland, 2016). Similarly, growth in the Australian economy over the past few decades has not been distributed equally across the country, with regional labour markets diverging from metropolitan centres in employment and income growth (Sobyra et al., 2022). Given the association between job switching and wage growth in Australia (Treasury, 2017), it is worth understanding whether there are similar inequalities in workers' likelihood of job mobility and through which characteristics they may manifest.

This paper seeks to answer which individual characteristics are associated with different types of job mobility in Australia and whether these differ by gender and geography. I use data from waves 11 to 21 of the Household, Income and Labour Dynamics in Australia (HILDA) survey, comprising a nationally representative sample of Australian workers from 2011 to 2021.[1] I estimate population average models for voluntary employer changes, promotions, occupation changes, and industry changes, estimating the average effect on workers' probability of mobility that is associated with a range of demographic, household, and employment characteristics. I then re-estimate these models with gender and geography

[1] This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute. DOI: 10.26193/24EJST

interaction terms, testing the difference in the effect associated with each characteristic between male and female workers and between regional and urban workers. I find few geographical differences but several gender differences, notably among immigrants from non-English speaking backgrounds, workers with postgraduate education, and those employed in industries with high gender concentration.

My contribution to the job mobility literature in Australia is four-fold. The existing body of work is relatively small, focussed, and centred in the early 2000s. I build upon this work by investigating four types of job mobility simultaneously, whereas previous work has tended to examine these in isolation. I also expand its scope by considering geographical differences in the factors associated with mobility, which have received little attention in the literature. Furthermore, I update previous findings with a large sample from 2011-2021 and use a novel estimation technique designed for longitudinal data that is commonly used in health studies.

The rest of the paper is structured as follows. Section 2 reviews the literature on job mobility, focussing on gender and geographical differences and salient Australian studies. Section 3 describes the data used in the empirical analysis and Section 4 outlines the estimation technique. Section 5 presents the main results with a discussion thereof. Section 6 acknowledges the limitations of this study and Section 7 concludes the paper.

2. Literature Review

The conceptual literature on job mobility distinguishes between different dimensions across which mobility can occur. Nicholson & West (1998) propose a tripartite typology consisting of status, function, and employer. Here status refers to a change in prestige or rank between jobs, function refers to a change in work activities or output, and employer refers to whether a job change is within- or between-employer. The four mobility types investigated in this paper cut across all three dimensions – voluntary employer changes are defined as between-employer, promotions as within-employer and upwards in status, and occupation and industry moves as changes in function.

The literature also distinguishes between the perspectives that can explain the determinants of job mobility. Ng et al. (2007) categorise these into structural factors, individual differences, and decisional factors. Structural factors include economic conditions and societal characteristics, encompassing those factors influencing workers’ likelihood of job mobility that are beyond their immediate control. These include regional differences in economic development, which historically affect rates of job mobility (Ladinsky, 1967).

Conversely, individual differences are those personal characteristics that may affect workers' preferences towards jobs and chances of successfully changing jobs, such as career interests and work experience. Decisional factors are those related to the decision to actually pursue any job mobility, including attitudes towards risk and confidence in one's success. I draw on all three perspectives in selecting variables for my empirical analysis, with a focus on demographic, household, and job characteristics.

The following subsections summarise the empirical literature on gender differences in job mobility, geographical differences in job mobility, and Australian job mobility.

2.1 Gender differences

The empirical literature on gender differences in employer and status mobility is mixed. Some studies find that women have higher rates of voluntary employer separation than men (Kronberg, 2013), while others find only higher rates of involuntary separation (Booth & Francesconi, 2002). More recently, Avram et al. (2023) use longitudinal data from the United Kingdom to test for gender differences in job mobility. They find similar levels of overall mobility for men and women, but with important differences driven by motherhood.[2]

The literature on upwards status mobility is similarly mixed. Some studies find lower promotion rates for women than men with similar characteristics (Ransom & Oaxaca, 2005; Blau & DeVaro, 2007), while others find no gender differences (Giuliano, Levine & Leonard, 2009) or higher promotion rates for women (Hersh & Viscusi, 1996). The explanations given for these results vary, including gender differences in labour productivity, gender-based discrimination, and gender differences in career trajectories.

Nonetheless, the literature on gender differences in functional mobility is less mixed. Historically, women experience greater rates of occupational mobility – typically downward in status and towards lower-paid occupations – in particular following the birth of a child (Perry, 1988). Portuguese evidence suggests that this effect applies more broadly for women already in low-paying occupations (Crespo et al., 2014). Moreover, Australian evidence suggests it is pronounced for migrant women relative to migrant men, and qualitatively attributed to family responsibilities in the home (Ressia et al., 2017).

[2] Avram et al. (2023) find that mothers are a third less likely to change jobs within-employer and twice as likely to change employers for family related reasons, relative to men and women without children. They find no impact on mobility associated with fatherhood.

2.2 Geographical differences

On geographical differences in job mobility (i.e. between urban and regional labour markets), the literature identifies two main effects. Regional labour markets may benefit from 'localisation economies', referring to increased job mobility due to a concentration of similar activities (Eriksson, Lindgren & Malmberg, 2008). As many economic resources such as raw materials and production facilities are geographical in their creation and use, regional areas tend to specialise (Neffke et al., 2018). This may locally reduce the barriers to mobility across employers and functions. However, some studies find no regional effects on voluntary employer change (Steenackers, 2015) and others are inconclusive. Henning & Kekezi (2023) find competing localisation effects in Sweden, where regions with a dominant industry are associated with more upwards mobility while regions with a few concentrated industries are associated with less. They also find the opposite effects for occupational concentration.

The other effect is 'urbanisation economies', referring to advantages in productivity and economic variety that arise from the size of metropolitan economies and typically benefit urban labour markets (Jacobs, 1969). This effect has been found to increase rates of employer mobility in the United States (Finney & Kohlhase, 2008) and upwards mobility in Sweden (Henning & Kekezi, 2023). Moreover, studies have found strong evidence of 'escalator regions' – metropolitan centres that are associated with upwards and function mobility for workers originating from regional areas (Champion, 2012; van Ham et al., 2012). More broadly, Bachmann et al. (2020) find that differences in occupational mobility across Europe are better explained by labour market institutions than individual characteristics.

2.3 Australian job mobility

The mixed results in Sections 2.1 and 2.2 may be due to institutional, economic, and cultural differences between countries, differences in datasets, and changes in labour markets over time. This motivates my project's focus on job mobility in Australia between 2011 and 2021 using a nationally representative longitudinal study. Moreover, the research on the determinants of different job mobility types in Australia is limited. This is especially the case for job mobility research using HILDA – Wooden's (2021) review describes this as a "very significant research gap" that is surprising given the long-term decline of mobility rates in Australia (ABS, 2023). Therefore, my paper builds directly on the following work.

Watson (2011) overviews Australian workers' job mobility between 2002 and 2008 using HILDA data. He finds that 15-17% of workers changed jobs from one year to the next within this period, which contrasts with declining job mobility over the past decade (ABS, 2023).[3] Younger workers and those living in the Northern Territory, Australian Capital Territory, and Perth are more likely to change jobs, followed by casual workers and those with short employer tenures. On occupation, Watson finds a female-specific effect – high mobility for women in high-skilled occupations and low mobility in low-skilled occupations.

However, a key limitation of this study is that it does not distinguish between voluntary and involuntary job mobility. This conceals differences in separation rates and their associated drivers, which Carroll & Poehl (2007) find are significant. They use HILDA data from 2001 to 2005 to investigate which groups in the Australian labour market were relatively more likely to separate from their employers. Using a multinomial logit framework, they find that employment in the public sector, union membership, and longer employer tenure are associated with lower probabilities of voluntary job separation. Although they find that the effect of these factors is similar for both men and women, their focus is on job separations rather than job-to-job transitions. Moreover, they do not consider geographical differences and neither study considers mobility outcomes beyond employer changes.

Johnston & Lee (2012) do examine gender differences in promotions and its wage benefits between 2001 and 2008 using a random effects probit model. They find that women are less likely to be promoted than men – but only among university-educated workers with fewer than 20 years of experience. Similarly, Lodewijks (2010) finds that low levels of wealth, liquidity, and financial satisfaction are associated with higher rates of voluntary job mobility – but only among Australian men under 40. Neither study controls for geographical differences nor do they find significant results outside of the aforementioned cohorts.

On geographical differences, Bill et al. (2007) examine whether Australian cities promote greater levels of mobility than non-metropolitan areas using HILDA data from 2001 and 2004. Using clustered logit regression, they find that job mobility is higher in metropolitan areas, where workers appear to have increased confidence that they can find a new job and a greater fear of losing their current job. They investigate the relationship between individual characteristics and job mobility indirectly, via their relationship to confidence and fear of job loss. Kilpatrick & Felmingham (1996) also investigate differences in job mobility patterns between Australian states, finding higher rates of job mobility in the

[3] The national job mobility rate in February 2023 and February 2022 was 9.5%, the highest since February 2012 at 10.5%.

growing economies of New South Wales, Queensland, and Western Australia. They find that male mobility is correlated with tenure and the unemployment rate of a worker's industry, but they do not compare metropolitan workers to those in rural areas in their analysis. To my knowledge, there is no Australian study comparing the determinants of job mobility between regional and metropolitan workers.

3. Data

This paper uses Release 21 of the HILDA survey to examine the factors associated with job-to-job mobility. HILDA is a household-based panel study that began in 2001, tracking a national probability sample of 13,969 individuals in 7,682 households. It collects detailed annual information on Australians' economic wellbeing, labour market dynamics, and family life, making it well-suited to explore the determinants of different types of mobility. HILDA's Restricted Release includes more granular geographic coding than the General Release and is thus used for this inquiry.

I focus on waves 11 to 21 of the HILDA survey to distinguish my analysis from previous work in this area, which has largely examined the period up to 2010. In wave 11, a top-up sample of 4,009 individuals in 2,153 households was added to address panel attrition and the effect of immigration since wave 1. I use this augmented dataset alongside HILDA's longitudinal weights to construct a nationally representative sample between 2011 and 2021. The total sample for this period comprises 255,176 observations from 34,803 unique individuals across 11 time periods.[4]

Table 1 summarises the exclusion decisions turning this total dataset into the final sample. First, I limit my scope to individuals aged between 22 and 65 inclusive to centre my inquiry among the prime working-age population in Australia. I exclude observations where individuals did not answer HILDA's self-completion questionnaire (SCQ) – as this is where promotions are reported – and where workers reported no industry of employment. Since any realised job mobility in wave $t + 1$ is assumed to be informed by factors observed in wave t, I also exclude observations without a matched observation from the same individual in the previous or following wave.[5] This includes eliminating individuals who are not

[4] The number of unique individuals exceeds the sum of wave 1 individuals and the top-up sample because of non-participating members in some respondents' households and changes in household composition over time.
[5] Each observation pair is collapsed into one observation, eliminating a mobility outcome in wave t when there are no characteristics in wave $t - 1$ and likewise eliminating characteristics in wave t when there is no mobility outcome in wave $t + 1$.

employed in wave t and thus missing job characteristics, as my focus is on job-to-job transitions. However, I allow individuals employed in wave t who become unemployed or leave the labour force in wave $t+1$ to remain in the sample.

Table 1. Exclusion decisions in order taking total dataset down to final sample.

Exclusions	**Observations**	**Individuals**
No exclusions	255,176	34,803
Respondents aged <22 and >65	137,066	20,138
Undetermined geographic location	137,032	20,138
Observations without SCQ	123,187	19,220
Observations without industry reported	122,374	19,200
Observations without a neighbouring wave	116,129	16,050
Missing characteristics in t or mobility in $t+1$	97,834	16,050
Not employed in wave t	75,717	13,725
Average longitudinal weight of zero	75,324	13,622

Finally, I eliminate observations with a mean longitudinal weight of zero. The estimation tool used requires time-invariant weights, so I average across the time observations for each individual.[6] Individuals with mean zero weight are excluded.[7] The summary statistics below describe the paired 75,324 observations actually used in the empirical analysis.

3.1 Variables of Interest

This paper's focus is on whether the factors that affect job mobility and their impact differ by gender and geography. Table 2 shows the number of observations along these metrics.

Table 2. Dataset composition by gender and geography.

Sex \ Regionality	**Major City**	**Regional**	**Total**
Male	26,416	11,297	37,713
Female	26,563	11,048	37,611
Total	52,979	22,345	75,324

Gender is measured directly in HILDA through a binary male-female classification and geography is measured using the Australia Bureau of Statistics' Remoteness Areas. This

[6] This is a technical limitation of the estimation commands for Generalised Estimating Equations that cannot be currently overcome (Hardin, 1997). Note that averaging to derive a constant person-weight gives lower weight to late observations from individuals who are likely to drop out of the survey, and higher weight to early observations from individuals who are likely to remain, than ought to be the case.

[7] While HILDA is representative of Australia overall, wave 1 excluded people living in institutions (e.g. hospitals, corrections, hotels) and people living in very remote areas. Individuals who enter these cohorts during HILDA are thus given a longitudinal weight of zero.

classification divides Australia into five classes of remoteness, ranging from Major Cities of Australia to Very Remote Australia, based on road distance to populated service centres. HILDA only includes the 2001 version of this classification, the 2011 version is derived using respondents' Statistical Areas Level 2 and the Australian Bureau of Statistics' data correspondence documentation (ABS, 2012).

3.2 Outcome Variables

This paper models four types of job mobility as separate outcomes – voluntary employer changes, promotions, occupation changes, and industry changes. These represent different degrees of mobility that are not always mutually exclusive and may differ in likelihood of occurring according to individual characteristics. Table 3 summarises the proportion of observations in the sample that exhibit each mobility type.

Table 3: Average rate and standard deviation of each type of job mobility observed in the sample.

Job Mobility	Mean	Standard Deviation
Voluntary employer change	8.36%	0.277
Promotion	8.52%	0.279
Occupation change	24.98%	0.433
Industry change	16.81%	0.374

Between-employer mobility is captured directly in HILDA by asking respondents whether they "still work for the same employer" as they did in the last wave. HILDA also captures a wide range of reasons for these employer changes. To capture the complete spectrum of workers' agency and self-initiated movements between jobs, voluntary employer changes are defined as all that are not explicitly involuntary.[8]

Promotions are captured directly in HILDA's self-completion questionnaire by asking respondents whether they were "promoted at work" in the past 12 months. Promotions are deemed employee-initiated because employees must voluntarily accept any new position offered to them and may even have to apply for it in the first place.

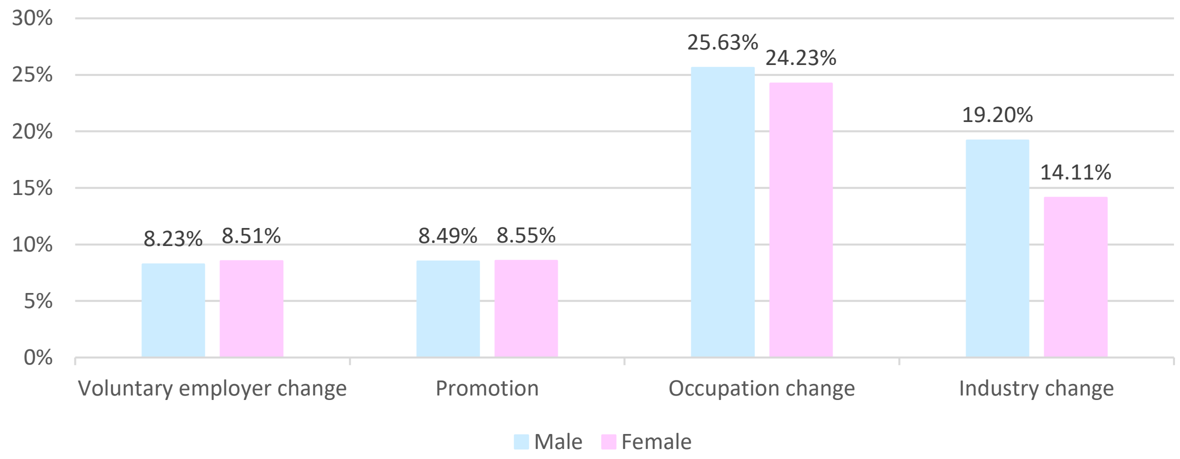
In addition to these voluntary mobility definitions, two outcome variables track mobility in individuals' occupation and industry of employment. I define an occupation change as a change in a respondent's Australian and New Zealand Standard Classification of Occupations (ANZSCO) code from one wave to the next. Likewise, an industry change is

[8] This definition excludes firm-side reasons like layoffs, redundancies, and business closures but includes worker-side reasons ranging from job dissatisfaction to sickness, pregnancy, and travel.

defined as a change in a respondent's Australian and New Zealand Standard Industrial Classification (ANZSIC) code between waves. These changes are measured at the 2-digit code for occupation and the 1-digit code for industry.

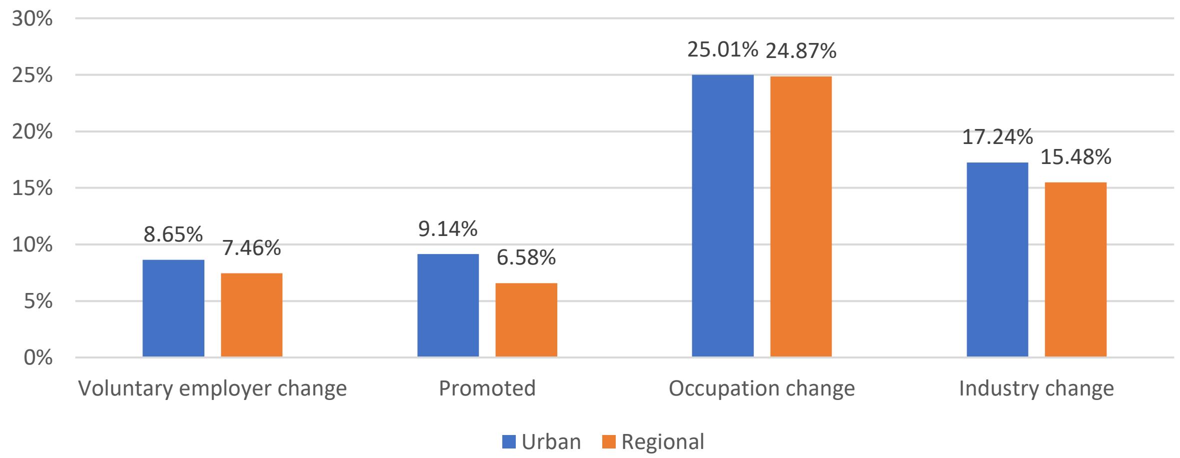
Figures 1 and 2 illustrate how these outcomes differ by gender and geography.

Figure 1: Average rate of each type of job mobility observed in the sample, by gender.



The rates of job mobility between male and female workers are broadly comparable, as per Figure 1. The only exception is the rate of industry change, where male workers are 5.09 percentage points (pp) more likely to change industry than female workers when changing jobs. On the other mobility types, female workers are marginally more likely to voluntarily change employer and male workers are marginally more likely to change occupation.

Figure 2: Average rate of each type of job mobility observed in the sample, by geography.



Workers in regional areas have slightly lower rates of job mobility on average than those in urban areas, as per Figure 2. Urban workers are 2.56pp more likely to be promoted, 1.76pp more likely to change industry, and 1.19pp more likely to change employer voluntarily.

3.3 Explanatory Variables

Tables 4 to 8 show summary statistics for all explanatory variables, organised by gender and geographical sub-groups and into several regression blocks to be tested sequentially.

The non-responding column counts the number of missing values for any reason except when a question is not applicable or not asked of a respondent. In the empirical analysis, non-responding values exceeding 100 observations are set to a separate dummy variable while those below 100 observations are set to the relevant base category. Variables marked with an asterisk are included quadratically in the regression specification.

Table 4: Demographic explanatory variables; mean values and non-responding count for all by gender and geography.

Demographics	**Mean (All)**	**Urban Male**	**Urban Female**	**Regional Male**	**Regional Female**	**Non-Resp.**
Female	46.94%	0.00%	100.00%	0.00%	100.00%	0
Age (years)*	41.35	40.70	40.86	43.23	43.09	0
Married or partnered	71.41%	71.88%	68.19%	75.03%	75.80%	7
Divorced, separated, or widowed	8.29%	5.47%	10.93%	7.33%	11.03%	7
Immigrant (English-speaking background)	10.37%	12.12%	10.58%	8.25%	5.89%	24
Immigrant (non-English-speaking background)	19.74%	24.06%	23.68%	6.51%	7.13%	24
Regional	24.22%	0.00%	0.00%	100.00%	100.00%	0
Health (self-assessed, scale of 1-7)	2.43	2.38	2.42	2.55	2.49	574
Long-term health condition	16.00%	14.11%	16.39%	18.78%	18.26%	11
- Health condition limits work	8.18%	6.50%	8.44%	10.22%	10.98%	7
Highest Education						0
Year 12	14.20%	14.34%	13.96%	15.08%	13.47%	
Certificate/Diploma	35.06%	36.10%	28.37%	47.58%	38.14%	
Undergraduate	21.27%	21.18%	26.38%	10.58%	17.73%	
Postgraduate	16.39%	17.60%	19.68%	7.22%	12.21%	

As per Table 4, there are some notable demographic differences between the four sub-groups. There are different patterns in respondents' highest educational attainment, with those in urban areas more likely to have an undergraduate or postgraduate qualification. Moreover, female workers tend to have higher education than male workers regardless of geography. There are also fewer immigrants in regional areas – particularly those from non-English speaking backgrounds – and more respondents who report long-term health conditions.

Table 5: Job characteristic explanatory variables; mean values and non-responding count for all by gender and geography.

Job Characteristics (Main Job)	**Mean (All)**	**Urban Male**	**Urban Female**	**Regional Male**	**Regional Female**	**Non-Resp.**
Casual	13.97%	10.97%	16.01%	13.24%	18.99%	19
Fixed term	8.65%	7.59%	10.37%	6.81%	9.10%	19
Public sector	22.72%	16.76%	28.45%	18.25%	30.99%	74
Non-profit	7.98%	4.45%	12.03%	4.10%	12.18%	74
Small Firm (<19)	40.11%	39.67%	34.31%	52.46%	45.84%	173
Large Firm (>99)	32.51%	33.83%	37.40%	22.96%	23.31%	173
Tenure with employer (years)*	7.34	7.43	6.73	8.52	7.59	31
Pay set by Enterprise Bargaining Agreement	28.32%	25.81%	30.68%	28.76%	29.24%	1,042
Pay set by award	19.22%	12.82%	23.01%	17.63%	31.83%	1,042
Average weekly hours work from home	3.34	3.37	3.41	3.33	3.05	4
Average commute time per week (hours)	4.40	5.25	4.22	3.73	2.68	1,996
Average weekly hours[9]	36.82	40.62	32.49	42.58	30.33	150
Hourly wage[9]	34.69	37.44	33.91	31.77	30.73	150
Industry (ANSZIC Division)						0
Agriculture, Forestry and Fishing	2.05%	0.53%	0.33%	9.36%	4.49%	
Mining	2.01%	2.34%	0.71%	5.48%	0.96%	
Manufacturing	8.04%	11.09%	4.29%	12.45%	3.99%	
Electricity, Gas, Water and Waste Services	1.09%	1.24%	0.41%	3.08%	0.45%	
Construction	7.96%	12.91%	1.76%	15.04%	1.83%	
Wholesale Trade	3.37%	4.76%	2.28%	3.69%	1.48%	
Retail Trade	7.94%	6.65%	8.92%	7.09%	10.41%	
Accommodation and Food Services	4.09%	3.57%	4.33%	2.89%	6.61%	
Transport, Postal and Warehousing	5.15%	7.51%	2.69%	7.40%	1.92%	
Information Media and Telecommunications	1.73%	2.29%	1.67%	0.66%	1.15%	
Financial and Insurance Services	4.35%	5.18%	5.16%	1.20%	2.49%	
Rental, Hiring, and Real Estate Services	1.34%	1.29%	1.52%	1.09%	1.25%	
Professional, Scientific and Technical Services	8.64%	11.46%	8.76%	3.40%	4.29%	
Administrative and Support Services	3.19%	3.15%	3.22%	3.11%	3.31%	
Public Administration and Safety	6.70%	7.59%	6.05%	7.11%	5.10%	
Education and Training	10.61%	5.82%	16.13%	5.07%	16.52%	
Health Care and Social Assistance	16.28%	6.69%	26.87%	5.92%	28.83%	
Arts and Recreation Services	1.72%	2.02%	1.51%	1.75%	1.25%	
Other Services	3.73%	3.90%	3.39%	4.20%	3.68%	

[9] Weekly hours top-coded at 80. Inflation-adjusted to 2021 AUD using annual average CPI.

Table 5 illustrates the relatively more pronounced differences in main job characteristics between the groups. Female workers are close to twice as likely to be employed in the public sector and almost thrice as likely to be employed in the not-for-profit sector, regardless of geography. They are also more likely to have their pay set by an award, especially in regional areas where award wages are more common. Weekly hours and hourly wages tend to be higher for men, especially in regional areas. In regional areas workers are also significantly more likely to be employed in small firms, with the same applying for urban workers and large firms.

There are few geographical differences in industry of employment, aside from Agriculture, Forestry, and Fishing and Professional, Scientific, and Technical Services which are concentrated in regional and urban areas respectively. However, there are striking gender differences. For example, the proportion of female workers in Health Care and Social Assistance and in Education and Training is around 20pp and 10pp greater than that of male workers, respectively. Also striking is Construction, where fewer than 2% of female workers are employed compared to around 14% of male workers.

There are only marginal group differences in household characteristics within the sample, as per Table 6. Noteworthy are the differences in other household income, which captures the total disposable income of a respondent's household minus their personal income in each financial year. Female workers and urban workers report higher other household income on average.

Turning to Table 7, the group differences in other employment characteristics are slightly larger. The largest difference is in paid parental leave, which is more common in urban areas and significantly more common for female workers. Similarly, union membership is more common among female workers but less common in urban areas. Regional workers also tend to have more a couple more years of work experience than urban workers and female workers tend to have access to carer leave more often than male workers.

Finally, there are some notable differences in the personality and lifestyle variables in Table 8. Male workers are about twice as likely to be risk-seeking and are less likely to be risk averse than female workers. Male workers are also slightly more likely to belong to a club or community organisation, which is more common in regional areas for both genders. Female workers are more likely to have caring responsibilities, with no significant regional differences.

Table 6: Household characteristic explanatory variables; mean values and non-responding count for all by gender and geography.

Household Characteristics	**Mean (All)**	**Urban Male**	**Urban Female**	**Regional Male**	**Regional Female**	**Non-Resp.**
Number of resident children	0.91	0.89	0.92	0.88	1.03	0
- aged 0	0.04	0.05	0.03	0.04	0.03	
- aged 1-4	0.20	0.23	0.17	0.22	0.17	
- aged 5-14	0.41	0.39	0.40	0.42	0.49	
- aged 15-24	0.31	0.27	0.35	0.25	0.36	
Uses childcare	0.20	0.18	0.21	0.16	0.22	35
Pays rent	0.30	0.32	0.29	0.27	0.26	28
Has no housing costs	0.02	0.01	0.02	0.04	0.03	28
Other disposable household income (AUD in past financial year)[10]	63,654	57,401	77,553	45,186	63,117	0

Table 7: Other employment characteristic and workplace entitlements explanatory variables; mean values and non-responding count for all by gender and geography.

Other Employment Characteristics	**Mean (All)**	**Urban Male**	**Urban Female**	**Regional Male**	**Regional Female**	**Non-Resp.**
Has multiple jobs	7.52%	6.10%	8.33%	7.39%	10.18%	11
Work experience (years)*	19.81	20.08	17.89	23.77	20.36	1,271
Is a union member	23.78%	21.00%	25.53%	24.52%	27.27%	4
Wants to work less hours	24.60%	24.46%	25.43%	24.70%	22.34%	115
Wants to work more hours	14.78%	13.77%	15.31%	14.53%	17.00%	115
Workplace Entitlements						
Workplace childcare	7.09%	7.20%	8.51%	4.46%	5.23%	13,511
Carer leave	60.36%	58.33%	63.23%	56.92%	62.48%	11,701
Paid parental Leave	43.56%	37.92%	52.43%	32.97%	47.76%	16,524

Table 8: Personality & lifestyle explanatory variables; mean values and non-responding count for all by gender and geography.

Personality & Lifestyle	**Mean (All)**	**Urban Male**	**Urban Female**	**Regional Male**	**Regional Female**	**Non-Resp.**
Risk seeking	11.03%	15.63%	7.07%	12.83%	5.06%	720
Risk averse	43.39%	35.26%	49.62%	41.35%	54.90%	720
Has caring responsibilities	7.77%	6.14%	9.78%	6.06%	9.10%	7,737
Has a lot of friends (self-assessed, scale of 1-7)	4.37	4.28	4.50	4.26	4.36	398
Participates in club or community organisation	32.86%	34.59%	29.37%	36.98%	33.03%	535
Identifies as other than heterosexual (imputed)[11]	6.55%	6.58%	7.12%	5.95%	5.29%	170

[10] Inflation-adjusted to 2021 AUD using annual average CPI.

[11] Asked every four HILDA waves. In-between values imputed 'downup' from nearest responding value.

4. Methodology

To assess gender and geographical differences in the factors associated with job-to-job mobility, I use population-averaged (PA) models constructed via Generalised Estimating Equations (GEE).

Orthodox regression methods are inappropriate for this inquiry because job mobility is a binary outcome that is likely correlated within individuals across time. Estimating the effect on mobility associated with individual characteristics thus requires predicting probabilities for job mobility occurring that are constrained between zero and one, which ordinary least squares does not impose (Ballinger, 2004). While nonlinear models like probit and logit regression do, they rely on assumptions about serial independence of outcomes that are often violated in longitudinal data. Moreover, whether an individual engages in job mobility likely depends on time-invariant characteristics. Although fixed-effects estimators can address the effect of unobservable factors that are individual-specific, they also prevent the estimation of the effects associated with time-invariant characteristics of interest like gender.

I use the GEE method popularised by Liang & Zeger (1986) to overcome these limitations. This method extends generalised linear models to longitudinal data and can estimate marginal or population-averaged models where the average for a particular outcome depends only on the covariates of interest and not on random effects (Lipsitz & Fitzmaurice, 2008). For this study, Australians' average probability of engaging in job mobility is estimated as a function of individual characteristics.

The estimation procedure is moment-based, requiring only the correct specification of the conditional mean (i.e. the first moment) to provide consistent estimators of the marginal regression parameters. Then, a relationship between this mean function and the variance structure of an individuals' observations is proposed (i.e. the second moment), which is augmented using a correlation matrix to account for serial correlation within individuals. GEE estimates have been proven to be robust to mis-specification in this matrix (Cui & Qian, 2007). The final estimating equations draw these components into the structure of Wedderburn's (1974) quasi-likelihood approach to be solved numerically by an iterative process that converges to the marginal parameter estimates. The theoretical details underpinning the GEE method are outlined in an online appendix.[12]

[12] Online appendix available here.

To the extent that GEE models do not require fully specifying the joint distribution of individuals' outcome variables across time, they are often described as semi-parametric (Davis, 1991). By comparison, similar models estimated by maximum likelihood would require fully specifying the joint distribution of an individual's job mobility outcomes, including correct assumptions about the correlations between periods, to yield asymptotically unbiased estimators (Lipsitz & Fitzmaurice, 2008).

Let X_{it} denote a vector of individual characteristics, β its associated vector of coefficients, and π_{it} the probability of job mobility for individual i at wave t. Let an individual's job mobility outcome be denoted by the binary indicator Y_{it+1}, which may be correlated across time but is assumed independent across individuals. A model estimated by GEE is specified by three components: a link function, a variance function, and a proposed correlation structure (Hardin & Hilbe, 2013). In the context of this paper, these are as follows.

Link function

The link function relates the probability of job mobility occurring to an unrestricted linear predictor:

$$g(\pi_{it}) = X_{it}'\beta.$$

This is the core parametric component of GEE, requiring a correct regression specification to obtain unbiased estimators. I use the logistic cumulative density function as this is the canonical – computationally efficient and conventionally used – link for binary data (Hardin & Hilbe, 2013). Formally,

$$g(\pi_{it}) = \ln\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = X_{it}'\beta,$$

$$\Longrightarrow \pi_{it} = \frac{\exp(X_{it}'\beta)}{1+\exp(X_{it}'\beta)} = (1+\exp(-X_{it}'\beta))^{-1} \equiv \Lambda^{-1}(X_{it}'\beta),$$

where $\Lambda^{-1}(\cdot)$ denotes the inverse-logistic function.

Variance function

The variance function equates the variance of the outcomes to a transformation of their mean,

$$\mathrm{var}(Y_{it}) = \phi V(\pi_{it}),$$

where $\phi \in (0,1]$ is a scale parameter and $V(\cdot)$ the variance function. The scale parameter is also referred to as a nuisance parameter, as its value does not actually affect the estimation (Lipsitz & Fitzmaurice, 2008). Since job mobility is a binary outcome, the variance of Y_{it} is easily defined:

$$\mathrm{var}(Y_{it}) = \phi V(\pi_{it}) = \phi\pi_{it}(1-\pi_{it}),$$
$$\Longrightarrow V(\pi_{it}) = \pi_{it}(1-\pi_{it}),$$

or alternatively in matrix form:

$$\boldsymbol{V}_i = \begin{bmatrix} \pi_{i1}(1-\pi_{i1}) & 0 & \cdots & 0 \\ 0 & \pi_{i2}(1-\pi_{i2}) & \cdots & 0 \\ \vdots & \vdots & \ddots & \cdots \\ 0 & 0 & \cdots & \pi_{it}(1-\pi_{it}) \end{bmatrix}.$$

Correlation structure

The proposed correlation structure captures the correlation of each individuals' outcomes over time. It is a matrix expressed as a function of a parameter vector, $\boldsymbol{R}(\boldsymbol{\alpha})$.

I use the simplest correlation structure for computational convenience, given GEE's robustness to mis-specification in this matrix. This is the 'exchangeable' structure, where the within-individual correlations are estimated as constant and equal for all individuals. While an individual's likelihood of job mobility plausibly depends on whether they have recently moved jobs, GEE's parameter estimates are consistent even without this level of detail (Hardin & Hilbe, 2013). Formally, using the three-observation case for illustration,

$$\boldsymbol{R}(\alpha) = \begin{bmatrix} 1 & \alpha & \alpha \\ \alpha & 1 & \alpha \\ \alpha & \alpha & 1 \end{bmatrix}.$$

Augmenting the variance matrix with the proposed correlation structure obtains the covariance structure needed for GEE estimation:

$$\boldsymbol{C}_i = \boldsymbol{V}_i^{1/2}\boldsymbol{R}(\alpha)\boldsymbol{V}_i^{1/2}.$$

Together, these features allow me to estimate the coefficients of the conditional expectation function using the following estimating equation:

$$\sum_{i=1}^{n} \frac{\partial \Lambda^{-1}(X_{it}'\beta)}{\partial \beta} \boldsymbol{C}_i^{-1}[Y_{it} - \Lambda^{-1}(X_{it}'\beta)] = \mathbf{0},$$

which takes its structure from Wedderburn's (1974) quasi-likelihood theory (see online appendix). The estimated coefficients have a population-level interpretation, describing the average effect on Australians' job mobility associated with each characteristic relative to those who do not exhibit it, holding all else constant (Hubbard et al., 2010). For the clearest interpretation of group differences (Long & Mustillo, 2021), I compute the marginal effect on the predicted probability of mobility associated with each characteristic.

I present Discrete Changes at the Mean (DCM), calculating the effect associated with changing a variable when all are set to their mean values. For binary variables this is the effect associated with the variable itself. For continuous variables, I compute the one-unit effect as well as the one standard deviation effect. The exceptions are the effect of resident children, ordinal variables (i.e. self-reported health and friends), and other household income. For these I calculate the effect associated with having 1 child relative to no children, the effect associated with a one-unit increase from the mean, and the effect associated with a $10,000AUD increase in other disposable household income, respectively.

4.1 Estimation procedure

I estimate separate PA-GEE models for each type of job mobility using the list of explanatory regressors presented in Section 3.3 and year fixed effects. In addition to a baseline model, gender and geographical differences are estimated in separate models by interacting all regressors with a female and rural dummy respectively. These group difference models have no base category specified for gender and region respectively, with the intercept term suppressed for the clearest calculation of group differences. Formally, the conditional expectation functions are:

$$E[Y_{it+1}|X_{it}] = \beta_0 + \beta X_{it} + \gamma_t, \quad (1)$$

$$E[Y_{it+1}|X_{it}] = \beta^F(F_i \times X_{it}) + \beta^M(M_i \times X_{it}) + \gamma_t, \quad (2)$$

$$E[Y_{it+1}|X_{it}] = \beta^R(R_{it} \times X_{it}) + \beta^U(U_{it} \times X_{it}) + \gamma_t, \quad (3)$$

where Y_{it+1} denotes a mobility outcome in wave $t+1$, X_{it} denotes individual characteristics in wave t, F_i and M_i are dummy variables for female and male, and R_{it} and U_{it} are dummy variables for regional and urban. γ_t represents year fixed effects.

I include only eight industry dummy variables to avoid problems with collinearity and setting an industry base category. These are the eight industries with employment shares exceeding 5% in the sample, constituting 71.32% of all workers. They are Manufacturing, Construction, Retail Trade, Transport, Postal and Warehousing, Professional, Scientific and Technical Services, Public Administration and Safety, Education and Training, and Health Care and Social Assistance. The interpretation of their marginal effects is relative to the other eleven industries in Table 5, employing 28.68% of workers in the sample.

Twenty-one models are estimated for each mobility type – seven without interactions, seven for gender, and seven for geography – by adding the covariate blocks sequentially and testing the joint significance of each addition using Wald tests. This procedure leads to a preferred regression specification for each type of mobility and both types of group differences, resulting in the twelve final PA-GEE models summarised in Table 9.

Table 9: Results of Wald testing covariate blocks sequentially for baseline, gender, and geographical difference models for all mobility types.

	Voluntary employer change			Promotion			Occupation change			Industry change		
	Base	M/F	R/U	Base	M/F	R/U	Base	M/F	R/U	Base	M/F	R/U
Demographics	X	X	X	X	X	X	X	X	X	X	X	X
Job Characteristics	X	X	X	X	X	X	X	X	X	X	X	X
Industry	X	X	X	X	X	X	X	X	X	X	X	X
Household Characteristics	X	X	X	X	X	X	X	X	X	X	X	X
Other Employment Characteristics	X	X	X	X	X	X	X	X	X	X	X	X
Workplace Entitlements				X	X	X				X		
Lifestyle & Personality				X	X	X						

The covariate blocks associated with job mobility are relatively common across mobility types. Demographic factors, job characteristics, industry of employment, household characteristics, and other employment characteristics are each collectively statistically significant in the baseline and group difference models at the 5% level. Workplace entitlements and lifestyle and personality factors are statistically significant only for the promotion models. Additionally, workplace entitlements are statistically significant in the baseline model for industry changes but not in the group difference models. This is likely to due many non-responding values for some variables in this block, reducing the sample sizes for each sub-group to the point that the estimated coefficients are no longer jointly significant.

5. Results

The following results should be interpreted with reference to the average probability of each type of job mobility.[13] Each marginal effect is additive not multiplicative – that is,

[13] Recall that the average probability of job mobility in the sample is 8.36% for voluntary employer changes, 8.52% for promotions, 24.98% for occupation changes, and 16.81% for industry changes.

expressed in percentage point (pp) differences from the average probability. Moreover, each marginal effect is calculated with all other factors held constant at their mean values.

5.1 Baseline results

Tables 10 to 15 present the marginal effects by covariate block for all mobility types estimated using the baseline model. To focus on the most notable results, I include only the variables of interest (i.e. gender and geography) and those associated with an effect on at least one mobility type that exceeds a magnitude of 1pp at the 5% level of significance.

Table 10: Demographic factors associated with workers' probability of job-to-job mobility and their impact, for all types. Gender, geography, and variables associated with at least a 1pp effect.

	Employer Change		**Promotion**		**Occupation Change**		**Industry Change**	
Demographics	DCM	p	DCM	p	DCM	p	DCM	p
Female	0.4pp	0.106	0.3pp	0.318	-0.2pp	0.771	-2.3pp***	0.000
Regional	-0.1pp	0.672	-0.7pp	0.011	-0.1pp	0.845	-0.7pp	0.182
Age (+11.67 years)	-2.8pp***	0.000	-3.2pp***	0.000	-5.2pp***	0.000	-2.3pp***	0.000
Separated, divorced, or widowed	0.6pp	0.217	2.4pp**	0.016	2.2pp	0.160	0.3pp	0.728
Immigrant (non-English speaking background)	-0.5pp	0.112	-1.6pp***	0.000	0.4pp	0.726	0.9pp	0.298
Health condition limits work	-0.3pp	0.499	-1.0pp**	0.047	0.1pp	0.908	-1.0pp	0.287
Certificate/Diploma	0.6pp*	0.099	1.8pp**	0.001	0.5pp	0.553	0.2pp	0.760
Undergraduate	1.1pp**	0.013	2.9pp***	0.000	-2.0pp*	0.084	1.9pp*	0.064
Postgraduate	1.8pp**	0.002	3.4pp***	0.000	0.3pp	0.819	2.4pp**	0.038

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.001$

Table 10 shows that age and tertiary education are the demographic factors most associated with differences in Australians' probability of job mobility. A standard deviation increase in age (11.67 years) is associated with large decreases in occupation change (-5.2pp) and promotion (-3.2pp) probabilities. Tertiary education is associated with increased rates of mobility relative to workers who did not complete Year 12, especially postgraduate education which is associated with higher rates of employer change (1.8pp), promotion (3.4pp), and industry change (2.4pp). These factors may be associated with different preferences towards mobility, differentiators of worker quality, or some other mechanism.

Being female and living in a regional area are associated with significant and negative effects on workers' probability of industry change (-2.3pp) and promotion (-0.7pp), respectively. These findings may reflect the high degree of industry gender segregation in

Australia's labour market and suggest lower upwards mobility in regional areas (WGEA, 2019). Moreover, formerly partnered workers tend to be promoted at higher rates (2.4pp) than single workers, which may reflect changes in priorities or enhanced resilience after the loss of a relationship. No such effects are found for partnered workers, perhaps due to aggregating the effect across male and female workers.

There are also negative promotion effects associated with immigration from non-English speaking backgrounds (-1.6pp) and with health conditions that limit the type or amount of work that respondents can do (-1.0pp). It is unclear whether this effect is related to workplace discrimination, personal preferences towards lower status employment (which may allow greater flexibility and less responsibility), or other mechanisms.

Table 11: Job characteristics associated with workers' probability of job-to-job mobility and their impact, for all types. Variables associated with at least a 1pp effect.

	Employer Change		**Promotion**		**Occupation Change**		**Industry Change**	
Job Characteristics	DCM	p	DCM	p	DCM	p	DCM	p
Casual	2.3pp***	0.000	-0.7pp*	0.071	2.5pp**	0.005	3.2pp***	0.000
Fixed term	0.1pp	0.832	0.7pp*	0.093	2.6pp**	0.010	1.4pp*	0.090
Public sector	-2.4pp***	0.000	0.5pp	0.315	-0.7pp	0.504	-1.4pp	0.133
Small firm (<19)	-0.2pp	0.390	-1.1pp**	0.001	2.1pp**	0.003	-0.2pp	0.702
Large firm (>99)	-0.6pp**	0.021	0.6pp**	0.049	1.5pp**	0.040	-0.9pp	0.116
Tenure with employer (+1 year)	-0.4pp***	0.000	-0.2pp***	0.000	-0.1pp	0.367	-0.3pp***	0.000
Tenure with employer (+8.08 years)	-2.3pp***	0.000	-1.1pp***	0.000	-0.5pp	0.201	-1.7pp***	0.000
Average weekly hours (+13.48 hours)	0.0pp	0.815	1.5pp***	0.000	-1.0pp**	0.001	-0.7pp**	0.003

$* p < 0.1$, $** p < 0.05$, $*** p < 0.001$

The job characteristics in Table 11 have varied effects across the mobility types. Casual workers have lower rates of promotion and higher rates of other mobility relative to continuing workers, as expected from their weaker job security. Tenure has a negative effect on all mobility types except occupation change and is strongest for employer change (-2.3pp) and industry change (-1.7pp) considering a standard deviation increase in tenure (8.08 years). This likely reflects the effect of firm-specific and industry-specific human capital, which reduces mobility between employers and industries for employees with longer tenure.

Workers in the public sector are less likely (2.4pp) to change employer voluntarily, in line with previous research on the factors associated with voluntary employer separation (Carroll & Poehl, 2007). Workers who work approximately 13.5 weekly hours more than the average of 36.82 are also 1.5pp more likely to be promoted, suggesting that workers are rewarded on average for working additional hours and that most jobs with upwards progression are full-time rather than part-time.

Table 12: Industries associated with workers' probability of job-to-job mobility and their impact, for all types. Variables associated with at least a 1pp effect.

	Employer Change		**Promotion**		**Occupation Change**		**Industry Change**	
Industry	DCM	p	DCM	p	DCM	p	DCM	p
Manufacturing	-0.7pp*	0.075	-1.2pp**	0.008	2.5pp**	0.028	-2.0pp**	0.018
Construction	-0.6pp*	0.087	-1.4pp**	0.002	-1.9pp*	0.083	-4.0pp***	0.000
Retail Trade	-0.5pp	0.115	0.3pp	0.566	4.3pp***	0.000	-2.1pp**	0.009
Transport, Postal and Warehousing	-0.6pp	0.268	-1.9pp***	0.000	-3.6pp**	0.008	-2.0pp**	0.036
Education and Training	-1.3pp**	0.003	-2.4pp***	0.000	-8.5pp***	0.000	-9.2pp***	0.000
Health Care and Social Assistance	-0.6pp*	0.084	-1.0pp**	0.025	-6.7pp***	0.000	-10.9pp***	0.000

$* p < 0.1, \quad ** p < 0.05, \quad *** p < 0.001$

Employment in the industries in Table 12 is broadly associated with decreased mobility relative to the industries with employment shares below 5%. While only Education and Training has a significant association with employer changes (-1.3pp), all are associated with lower rates of industry change. This is strongest for Health Care and Social Assistance (-10.9pp), Education and Training (-9.2pp), and Construction (-4.0pp), which may involve high levels of industry-specific human capital, qualification requirements, or other barriers to mobility. This is supported by Education and Training (-8.5pp) and Health Care and Social Assistance (-6.7pp) having the lowest occupation change rates. Education and Training is also associated with lower promotion rates (-2.4pp), followed by Transport, Postal and Warehousing (-1.9pp).

Table 13: Household characteristics associated with workers' probability of job-to-job mobility and their impact, for all types. Variables associated with at least a 1pp effect.

	Employer Change		**Promotion**		**Occupation Change**		**Industry Change**	
Household Characteristics	DCM	p	DCM	p	DCM	p	DCM	p
Resident child aged 1-4	-1.1pp***	0.000	-0.3pp	0.257	-1.2pp*	0.060	-1.3pp**	0.015
Pays rent	1.4pp***	0.000	0.8pp**	0.014	1.4pp*	0.056	1.4pp**	0.017

$* p < 0.1, \quad ** p < 0.05, \quad *** p < 0.001$

Table 13 shows that household characteristics have no significant association with job mobility, aside from having a resident child aged 1-4 and paying rent. Workers living with a young child are less likely to change employer (-1.1pp), occupation (-1.2pp), and industry (-1.3pp), potentially prioritising stability over mobility. Conversely, renters are more likely to do so (1.4pp) relative to owner-occupiers, likely due to greater spatial flexibility.

As for Table 14, having multiple jobs, belonging to a union, and wanting more or less hours are associated with job mobility. The effect associated with having multiple jobs is positive across all mobility types, perhaps capturing ongoing job adjustment for Australians with multiple jobs. Union membership is associated with lower occupation change (-5.4pp), industry change (-2.6pp), and employer change rates (-1.0pp), extending previous findings that union membership is associated with decreased employer mobility to occupation and industry mobility as well (Carroll & Poehl, 2007). Wanting less hours at work is associated with higher mobility rates except for promotions, while wanting more hours is associated with higher mobility across the board including promotions (1.0pp). This supports the conjecture that full-time jobs with longer hours are more likely to lead to promotion. The effect associated with the other mobility types is slightly larger in magnitude for wanting less hours than for wanting more hours.

Table 14: Other employment characteristics associated with workers' probability of job-to-job mobility and their impact, for all types. Variables associated with at least a 1pp effect.

Other Employment Characteristics	**Employer Change**		**Promotion**		**Occupation Change**		**Industry Change**	
	DCM	p	DCM	p	DCM	p	DCM	p
Has multiple jobs	2.1pp***	0.000	1.5pp**	0.001	5.2pp***	0.000	6.4pp***	0.000
Work experience (+12.16 years)	1.6pp***	0.000	0.2pp	0.642	2.4pp**	0.006	1.0pp	0.141
Belongs to a union	-1.0pp***	0.000	0.1pp	0.662	-5.4pp***	0.000	-2.6pp***	0.000
Wants less hours	1.2pp***	0.000	-0.4pp	0.115	1.9pp**	0.001	1.3pp**	0.010
Wants more hours	0.8pp**	0.019	1.0pp**	0.033	1.7pp**	0.043	1.2pp*	0.065

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.001$

Finally, only the two variables in Table 15 from the Workplace Entitlements and Personality & Lifestyle blocks have a statistically significant association with job mobility. Workers with access to paid parental leave are 2.1pp more likely to be promoted and 1.8pp less likely to change industry, perhaps reflecting differences in workplace cultures and self-selection into industries where this entitlement is offered. Strikingly, a one-category increase from the mean in a workers' assessment of whether they "seem to have a lot of friends" on a scale of one to seven is associated with a 6.5pp increase in promotion probability. This variable operates as a proxy for extroverted behaviours or social self-assuredness, suggesting a strong relationship between such traits and upwards status mobility at work.

Table 15: Workplace entitlements and personality & lifestyle factors associated with workers' probability of job-to-job mobility and their impact, for promotion and industry change. Variables associated with at least a 1pp effect.

Workplace Entitlements, Personality & Lifestyle	**Promotion**		**Industry Change**	
	DCM	p	DCM	p
Paid parental leave	2.1pp***	0.000	-1.8pp**	0.012
Has a lot of friends	6.5pp***	0.000		

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.001$

5.2 Gender differences

Tables 16 to 19 present the factors associated with gender differences in the probability of each mobility type separately. I include only the variables associated with an effect that differs between male and female workers at the 5% significance level.[14]

Voluntary employer change

Table 16 shows that wanting more hours, being an immigrant from a non-English speaking background, and being employed in the public sector are associated with gender-based effects on voluntary employer change.

Female workers who want more hours are more likely to change employer (1.8pp), with no such effect detected for male workers. Given that higher average weekly commutes are also associated with slightly higher employer mobility for female workers, these results suggest a higher degree of sensitivity to working hour preferences for female relative to male workers. Female workers with an average weekly commute that is 1 hour above the mean are 0.2pp more likely to change employer, aligning with arguments that women have a smaller job search radius because they bear a greater share of household and child-rearing responsibilities (Gutierrez, 2018). Conversely, female workers from non-English backgrounds are less likely to change employer than Australian-born women (-1.3pp) with no effect for similar male counterparts. This finding echoes qualitative work on how cultural norms affect the negotiation of labour for women in some migrant households (Lemma et al., 2022).

[14] Note that the estimated p-values tend to be lower for the female DCMs than the male DCMs, indicating greater confidence in the association between female workers' characteristics and job mobility.

Table 16: Individual characteristics associated with gender differences in workers' probability of voluntary employer change. Variables associated with a difference at the 5% sig. level.

	Female		**Male**		**Difference**	
Employer change	DCM^F	p	DCM^M	p	$DCM^{F\text{-}M}$	p
Married or partnered	-0.4pp	0.285	0.7pp*	0.054	-1.1pp**	0.034
Immigrant (non-English speaking background)	-1.3pp**	0.005	0.2pp	0.708	-1.5pp**	0.032
Public sector	-3.0pp***	0.000	-1.6pp***	0.000	-1.4pp**	0.034
Average weekly commute (+1 hour)	0.2pp**	0.001	0.0pp	0.667	0.1pp**	0.018
Average weekly commute (+4.18 hours)	0.6pp**	0.002	0.1pp	0.668	0.6pp**	0.019
Public Administration and Safety	-3.0pp***	0.000	-1.6pp***	0.000	-1.4pp**	0.034
Wants more hours	1.8pp***	0.000	0.1pp	0.874	1.7pp**	0.016

$* p < 0.1, \quad ** p < 0.05, \quad *** p < 0.001$

Employment in the public sector and in Public Administration and Safety is associated with lower mobility rates for men (-1.6pp) and women (-3.0pp), though the effect is almost double in magnitude for women. This lends further credibility to the hypothesis on female workers' sensitivity to employer conditions on average, as the public sector is often regarded as a model employer for women, especially on flexible arrangements (Powell & Cortis, 2017).

Promotion

Table 17 shows that the greatest gender differences in the factors associated with promotions are in postgraduate education, health conditions that limit one's ability to work, and employment in gender-concentrated industries.

Table 17: Individual characteristics associated with gender differences in workers' probability of promotion. Variables associated with a difference at the 5% sig. level.

	Female		**Male**		**Difference**	
Promotion	DCM^F	p	DCM^M	p	$DCM^{F\text{-}M}$	p
Health condition limits work	-2.2pp***	0.000	0.3pp	0.664	-2.6pp**	0.009
Postgraduate	6.1pp***	0.000	2.0pp**	0.038	4.0pp**	0.016
Construction	-3.3pp**	0.002	-0.9pp*	0.068	-2.4pp**	0.047
Professional, Scientific and Technical Services	-0.4pp	0.470	1.3pp**	0.044	-1.7pp*	0.050
Health Care and Social Assistance	-1.8pp**	0.002	0.6pp	0.484	-2.4pp**	0.017

$* p < 0.1, \quad ** p < 0.05, \quad *** p < 0.001$

Postgraduate education is associated with a strong positive effect for female workers (6.1pp) and a weaker effect for male workers (2.0pp) relative to workers who completed Year

12. This may capture self-selection bias if women who pursue postgraduate education are particularly career-driven, or it may suggest that postgraduate education is highly impactful for women's career trajectories, perhaps due to its large investment cost disincentivising workers from turning away from work and towards domestic duties. Conversely, female workers who have a long-term health condition that limits their ability to work tend to be promoted less often (-2.2pp) than similar male workers, who have no such effect. It is unclear whether this captures gender differences in the extent to which long-term health conditions limit workers' careers or gender differences in health-based discrimination.

Additionally, female workers employed in Construction and Health Care and Social Assistance are both 2.4pp less likely to be promoted that similar male counterparts. This is a curious similarity that points to nuanced gender effects in industry composition, given that the former industry is female-dominated and the latter male-dominated. It may be the case that female workers in male-dominated industries are overlooked for promotions while male workers in female-dominated industries stand out.

Occupation and industry change

Some industries are associated with relatively high gender differences in occupation change rates, as outlined in Table 18. Female workers are more likely to change occupation than male workers in Public Administration and Safety (by 9.2pp), Manufacturing (by 6.4pp), and Construction (by 6.1pp). One explanation is that male workers in these industries may be concentrated in some occupations whereas female workers may be relatively dispersed, especially in the latter industries where physical labour is concerned.

Table 18: Individual characteristics associated with gender differences in workers' probability of occupation change. Variables associated with a difference at the 5% sig. level.

	Female		**Male**		**Difference**	
Occupation change	DCM^{F}	p	DCM^{M}	p	$DCM^{F\text{-}M}$	p
Manufacturing	7.2pp**	0.001	0.8pp	0.540	6.4pp**	0.013
Construction	3.4pp	0.208	-2.7pp**	0.026	6.1pp**	0.038
Public Administration and Safety	7.7pp***	0.000	-1.5pp	0.412	9.2pp**	0.001
Belongs to a union	-7.1pp***	0.000	-3.9pp***	0.000	-3.2pp**	0.026

$* p < 0.1, \quad ** p < 0.05, \quad *** p < 0.001$

Membership in a union is also negatively associated with occupation change for both genders, but almost double so for women (-7.1pp) relative to men (-3.9pp). This may reflect occupational segregation with women selecting into more unionised industries (WGEA, 2019), but it is curious given the lack of a similar result associated with other mobility types.

Turning to Table 19, employment in Construction and Retail Trade are the factors associated with industry changes that exhibit the strongest gender differences. Male workers in Construction are less likely (-5.1pp) to change industry relative to the other industries while female workers in Retail Trade (-4.2pp) are less likely to change. There are no statistically significant effects for the opposite gender in either case, highlighting these two as particularly 'sticky' industries for each gender respectively. These industries are also male- and female-dominated respectively, echoing the results in Table 18. It could be that the minority gender in each industry tend to be in roles requiring skills that are more easily transferrable between industries.

Table 19: Individual characteristics associated with gender differences in workers' probability of industry change. Variables associated with a difference at the 5% sig. level.

	Female		**Male**		**Difference**	
Industry change	DCM^{F}	p	DCM^{M}	p	DCM^{F-M}	p
Married or partnered	-1.7pp*	0.056	1.5pp	0.113	-3.1pp**	0.013
Immigrant (non-English speaking background)	-0.8pp	0.417	2.8pp*	0.054	-3.6pp**	0.041
Tenure with employer (+1 year)	-0.2pp**	0.016	-0.3pp***	0.000	0.2pp**	0.048
Tenure with employer (+8.08 years)	-1.3pp***	0.000	-2.2pp***	0.000	0.8pp*	0.098
Hourly wage (+1 AUD)	0.0pp	0.127	0.0pp**	0.028	-0.1pp**	0.008
Hourly wage (+21.20 AUD)	-0.4pp	0.123	0.6pp**	0.030	-0.9pp**	0.008
Construction	2.2pp	0.255	-5.1pp***	0.000	7.3pp**	0.001
Retail Trade	-4.2pp***	0.000	0.4pp	0.782	-4.5pp**	0.004

$* p < 0.1, \quad ** p < 0.05, \quad *** p < 0.001$

Finally, there are significant gender differences in the effect associated with being partnered and being an immigrant from a non-English speaking background. Women with these characteristics are 3.1pp and 3.6pp less likely to change industry than men, respectively. Both effects mirror similar gender differences for employer changes in Table 16. The first may also align with research that men experience a greater 'marriage premium' in earnings than women, which may extend to mobility (Breusch & Gray, 2004).

5.3 Geographical differences

Tables 20 to 22 present the factors associated with geographical differences in the probability of each mobility type separately. I include only the variables associated with an effect that differs between urban and regional workers at the 5% level of significance.[15]

Voluntary employer change

Few factors are associated with geographical differences in voluntary employer change rates, as shown in Table 20. Workers with a postgraduate education change employer more often if they live in urban areas (4.0pp), with the associated effect in regional areas (1.2pp) failing to be significant at the 5% level. This may reflect differences between urban and regional areas in the demand for high-skilled employment (Hajkowicz et al., 2016).

Table 20: Individual characteristics associated with geographical differences in workers' probability of voluntary employer change. Variables associated with a difference at the 5% sig. level.

	Urban		Regional		Difference	
Employer change	DCM^{U}	p	DCM^{R}	p	$DCM^{U\text{-}R}$	p
Postgraduate	4.0pp***	0.000	1.2pp*	0.063	2.8pp**	0.023
Transport, Postal and Warehousing	2.0pp**	0.046	-1.2pp**	0.033	3.1pp**	0.005
Resident child aged 15-24	-0.3pp	0.275	0.5pp*	0.077	-0.8pp**	0.047

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.001$

Workers in Transport, Postal and Warehousing are also 3.1pp more likely to change employer in urban areas than regional areas, suggesting different geographical conditions.

Promotion

Table 21 shows there are small differences in the factors associated with promotion. Employment in Education and Training is associated with a negative effect (-2.8pp) for regional workers and no significant effect for urban workers. This suggests that the dampening effect of the industry on promotions may be driven by regional areas, where worker shortages are well-documented (Kline et al., 2013), despite the conventional wisdom that worker shortages should encourage promotions to attract and retain workers.

There are also small differences in the effect associated with age, which is negative for both areas but more so in regional areas. Likewise, there are small differences in the effect associated with higher hourly wages, which is stronger in urban areas than regional areas.

[15] Note that the responses from urban areas are more than double those from regional areas. This makes it comparatively difficult to estimate regional effects and may partially explain the few differences identified.

Table 21: Individual characteristics associated with geographical differences in workers' probability of promotion. Variables associated with a difference at the 5% sig. level.

	Urban		Regional		Difference	
Promotion	DCM^{U}	p	DCM^{R}	p	$DCM^{U\text{-}R}$	p
Age (+1 year)	-0.2pp***	0.000	-0.4pp***	0.000	0.2pp**	0.022
Age (+11.67 years)	-2.2pp***	0.000	-3.5pp***	0.000	1.2pp*	0.050
Hourly wage (+21.20 AUD)	0.9pp***	0.000	0.3pp**	0.010	0.6pp**	0.048
Education and Training	-0.7pp	0.344	-2.8pp***	0.000	2.1pp**	0.018
Other disposable household income (+$10,000 AUD)	-0.1pp*	0.074	0.0pp	0.170	-0.1pp**	0.027
Other disposable household income (+$55,222 AUD)	-0.4pp*	0.065	0.2pp	0.176	-0.7pp**	0.023

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.001$

Occupation and industry change

Table 22 shows the only significant differences in the factors associated with occupation and industry change between urban and regional workers. Having a resident child aged 1-4 is associated with a dampening effect on occupation change (-3.3pp) for urban workers alone. Likewise, the negative effect on industry change (-4.1pp) associated with a standard deviation increase in age is only significant at the 5% level for urban workers. Given the similar aggregate mobility rates shown in Figure 2, these limited findings suggest there are few geographical differences in function mobility between urban and regional areas.

Table 22: Individual characteristics associated with geographical differences in workers' probability of occupation and industry change. Variables associated with a difference at the 5% sig. level.

	Urban		Regional		Difference	
Occupation change	DCM^{U}	p	DCM^{R}	p	$DCM^{U\text{-}R}$	p
Resident child aged 1-4	-3.3pp**	0.001	-0.5pp	0.544	-2.9pp**	0.028
Industry change						
Age (+1 year)	-0.4pp***	0.000	-0.2pp**	0.024	-0.2pp**	0.036
Age (+11.67 years)	-4.1pp***	0.000	-1.5pp*	0.065	-2.6pp**	0.024

$* \, p < 0.1, \quad ** \, p < 0.05, \quad *** \, p < 0.001$

6. Limitations

This study has focussed on gender and geographical differences in the factors associated with job-to-job mobility for the *average* Australian worker. That is, the marginal effect of individual characteristics on the predicted probability of job mobility for the mean Australian worker and the mean female, male, urban, and regional Australian worker. The effect of individual characteristics may differ substantially along other metrics, which this paper does not capture and may misattribute to gender and geography.

Likewise, DCMs may obscure heterogeneity across the non-mean values of the characteristics in the sample. Other result formats, such as Average Discrete Changes and plotting predicted probabilities at representative values would illustrate this heterogeneity (Long & Mustillo, 2021), but they are omitted due to space constraints.

This study has not identified causal relationships between individual characteristics and job mobility. Crucially, I am unable to determine whether the effect associated with a characteristic is the result of different preferences and choices between individuals with different characteristics or the response of hiring firms to said characteristics. My work only overviews the distribution of job-to-job mobility in contemporary Australia along individual factors, summarising key differences for future research to examine more closely.

There are also some threats to this study's external and internal validity. HILDA only captures respondents' job characteristics in each wave, limiting the analysis for workers who held multiple jobs between waves. Moreover, I exclude from my sample respondents who did not complete HILDA's SCQ as this is where promotions are recorded, which may constitute non-random sample selection and violate the independence assumption between individuals underpinning the asymptotic consistency of my empirical analysis. Excluding promotions from the analysis may indicate whether the results are sensitive to this.

Likewise, sampling only employed workers at wave t may further induce non-random selection. Each observation consists of pre-mobility characteristics at wave t and realised job mobility in wave $t+1$, such that individuals who leave the labour force are omitted from the sample until they become employed again. To the extent that an individuals' missing observations can be explained by previously observed characteristics, there may be bias in the parameter estimates (Lipsitz & Fitzmaurice, 2008). Advanced simulation techniques can address this, including multiple and mean imputation (Paik, 1997), but they are beyond the scope of the thesis.

Finally, there are limitations inherent to my estimation technique. The core parametric component of GEE is the conditional mean, which is assumed to be correctly specified. To the extent that this is violated – whether due to omitted variables not in HILDA, endogeneity between covariates, or an incorrect choice of the logistic link function – the estimates will be biased and may be inconsistent (Lipsitz & Fitzmaurice, 2008).

7. Conclusion

This paper has identified which individual characteristics are associated with differences in Australian workers' average probability of four types of job-to-job mobility, as well as whether these characteristics and their impact differ by workers' gender and region.

I find several but disparate associations that cannot be easily tied into an overarching narrative. Demographic factors and employment characteristics have explanatory power over all types of job mobility, notably workers' age and tertiary education qualifications. Household characteristics have limited explanatory power aside from the number of young resident children in a workers' household, which has a small dampening effect on mobility except for promotions. Surprisingly, this effect does not differ by gender which runs contrary to conventional narratives about the effect of household responsibilities on women's labour outcomes. Promotions are also the only mobility associated with personality and lifestyle factors, driven strongly by workers' self-perception of how many friends they seem to have.

Examining gender differences in the factors associated with job-to-job mobility reveals the nuanced effect associated with immigration from a non-English speaking background and employment in gender-concentrated industries. Such immigrant women tend to have lower rates of voluntary employer changes and industry changes relative to male counterparts. Likewise, female workers in some gender-concentrated industries – including male-dominated Construction *and* female-dominated Health Care and Social Assistance – tend to be promoted at lower rates than male workers and have lower rates of occupation change.

Conversely, I find few significant differences in job mobility and its associated characteristics between urban and regional workers. The positive effect on employer mobility associated with postgraduate education is stronger in urban areas, as is the negative effect on promotions associated with age in regional areas. There are only small geographical differences in occupation and industry changes associated with young resident children and workers' age, failing to align with the localisation hypothesis that a concentration of similar economic activities should decrease local barriers to job-to-job mobility.

These results illuminate inequalities concealed in the aggregate rates of job-to-job mobility in Australia. They highlight the role of gender, but not geography, in mediating the effect on mobility associated with individual characteristics. In particular, they highlight immigrants from non-English speaking backgrounds and workers in gender-concentrated industries as areas of further study, to understand the mechanisms behind these findings.

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[16] Links have been omitted in this reference list due to space constraints. The reference list with links included is available here.

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