OCCASIONAL PAPER

Does changing your job leave you better off? A study of labour mobility in Australia, 2002 to 2008

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NCVER

Australian Government
Department of Education, Employment and Workplace Relations

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The NVETRE program is based upon priorities approved by ministers with responsibility for vocational education and training (VET). This research aims to improve policy and practice in the VET sector. For further information about the program go to the NCVER website <http://www.ncver.edu.au>. The author/ project team was funded to undertake this research via a grant under the NVETRE program. These grants are awarded to organisations through a competitive process, in which NCVER does not participate.

ISBN 978 1 921809 79 8 web edition
ISBN 978 1 921809 80 4 print edition

TD/TNC 103.16

Published by NCVER
ABN 87 007 967 311

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About the research

NCVER

Does changing your job leave you better off? A study of labour mobility in Australia, 2002 to 2008

Ian Watson, Macquarie University and SPRC UNSW

The dynamics of labour mobility have been a matter of long-standing interest to researchers and policy-makers. It is a tricky subject, one that is afflicted by limitations in the information available and which can also pose dilemmas for social policy-makers who are concerned both to ensure a well-functioning labour market and people's welfare.

This paper is one of three commissioned by the National Centre for Vocational Education Research (NCVER) at the request of the Department of Education, Employment and Workplace Relations to tease out some of the issues connected to mobility in the Australian workforce. The related papers are:

- *The mobile worker: concepts, issues, implications* by Richard Sweet
- *Understanding and improving labour mobility* by John Buchanan, Susanna Baldwin and Sally Wright.

In this paper, using data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, Ian Watson explores the extent and consequences of labour market movement and the characteristics of people who change jobs. The analysis concentrates on adult employees who change their employer in the course of a year.

While around 17% of workers changed their jobs in 2008, most of those movements were within local labour markets. Interestingly, on average, workers who changed jobs were not better off financially, although they were better off in terms of happiness and job quality. Both the opportunity to acquire new skills and the use of existing skills are enhanced by changing jobs.

Watson argues, on the basis that wages are not a major element of labour mobility, that the labour market needs to be treated differently from simple commodity markets.

Tom Karmel
Managing Director, NCVER

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Executive summary

What is the extent of labour mobility in Australia? Why do workers change jobs? How far do workers move when they change jobs? What are the characteristics of those workers who do change jobs and how do they differ from those who don't? Finally, are workers better off after changing their job? These are the core questions which this report addresses.

We are fortunate in Australia to have a unique longitudinal dataset—the Household, Income and Labour Dynamics in Australia (HILDA) Survey—which is ideal for tracking changes over time and which provides a wealth of labour market information.[1] In following adult employees who changed their jobs from one year to the next, this survey can be used to answer these questions.

The 'Overview' chapter uses descriptive statistics to show that about 15–17% of workers change their jobs from one year to the next. Most of these workers change jobs because they are dissatisfied with their current job, or because they want a better job. Involuntary job loss—either through retrenchment or the temporary nature of the job—declined considerably over the period 2002–2008. When workers do change jobs, they are most likely to stay in the same residence or, if they do move, to stay in the same local labour market. Only a small proportion actually move interstate or move any considerable distance.

The 'Characteristics of job changers' chapter uses regression modelling to explore how job changers differ from those who stay put. The most distinctive characteristic of job changers is their age: changing jobs is very much the province of the young. Workers aged under 30 years have almost twice the probability of changing jobs as those in their 50s and upwards. Another demographic feature of job changers is their geographical location: workers living in the Northern Territory, the Australian Capital Territory and Perth are much more likely to change jobs, while those in Tasmania are much less likely.

Among the labour market characteristics, the most distinctive feature is the role of labour market insecurity. Those workers employed as casuals are far more likely to change jobs than those not so employed. Those workers with a prior history of unemployment, or who had spent time outside the labour market, are also more likely to change jobs. While occupational tenure does not count for much, job tenure certainly does. Those workers who have been in jobs for long periods are much less likely to change their job.

[1] This report 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 Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views reported in this report, however, are those of the author and should not be attributed to either FaHCSIA or the MIAESR.

Industries with high levels of job changing include accommodation, cafes and restaurants, construction and transport. Those with low levels include education, information services and health and community services. Among female workers there appears to be a sharp distinction between higher-skilled occupations—where job changing is more common—and lower-skilled occupations—where job changing is less common. Male workers do not follow this pattern.

Workers employed in large organisations—those with 500 or more employees—are much less likely to change jobs. Those in the smallest workplaces—those with under 20 employees—are much more likely to change jobs. Union membership and access to training appear to be only weakly associated with job changing.

The report also makes use of some unique personality and attitudinal data items which the Household, Income and Labour Dynamics in Australia Survey dataset provided. Analysis of these shows that 'extroverts' are much more likely to change jobs than are most other personality types. Workers who are dissatisfied with the nature of their job and with the level of job security are much more likely to change jobs. These factors are more important than satisfaction with the income from that job.

The chapter, 'The consequences of changing jobs', makes use of a matching estimators approach to provide a causal analysis of this issue. By regarding job changing as a treatment, and comparing job changers with a control group—those who don't change their jobs—it is possible to analyse the impact of job changing on earnings, satisfaction and skills. This analysis shows that job changing does not lead, on average, to an increase in earnings. This applies to both hourly rates of pay and annual earnings. On the other hand, job changing does lead, on average, to greater levels of job satisfaction. This applies to all areas—pay, hours, flexibility and the work itself—except for the issue of job security. This is largely unaffected by changing jobs, suggesting that those workers who are marginalised in the labour market, such as those working in short-term casual jobs, may be caught up in patterns of job churning, in which finding a new job does not lead to greater job security.

Finally, changing jobs has good outcomes in terms of productivity. Both the opportunity to acquire new skills and the use of existing skills are enhanced by changing jobs.

Overview

Introduction

There are a number of ways of looking at labour mobility. We could look at movements in and out of employment, or in and out of the labour market. We could also look at the situation where employees change their job, but stay with the same employer. Or we could look at employees who change employers. In this report I concentrate solely on the last category and examine adult employees who change their employer in the course of a year.[2] How many employees do indeed change their jobs, what kinds of job changes take place and what motivates this change? Finally, what is the geographical dimension to this?

In what follows I sketch some answers to these questions by drawing upon a unique dataset: the Household, Income and Labour Dynamics in Australia (HILDA) Survey. This is a longitudinal survey of Australian households, which is carefully sampled to be representative of the Australian population, and which has been collecting data since 2001.[3] It collects a large number of key labour market measures and is ideal for exploring a topic such as labour mobility. It allows us to 'track' individuals over time, examining how their circumstances change, as well as gaining insights into their attitudes.

The population examined in this report consists of adult employees who are not studying full-time. For ease of expression, I refer to this group as 'workers' throughout this report. Occasionally I use the term 'employee' in contexts where this is relevant and in the notes to tables where the specifics of this population are mentioned. These age and hours exclusions are important: both school students and tertiary students are often working in temporary jobs while they study and their labour market behaviour is not necessarily symptomatic of their longer-term behaviour. The volatility of this segment of the labour market is well known and is not a good indicator of labour market conditions more generally.[4] The measure of job change is the employment situation of a respondent in the annual survey interview. These are generally a year apart, but can be slightly longer than this. Respondents are asked if they work for the same employer (or in the same business) as they did at the last interview and if they are answer no, they fall into the 'job changer'

[2] This population of interest is thus restricted to employees who moved between jobs, rather than those who moved in and out of the labour market, whether into or out of unemployment or retirement (or other 'not in the labour force' states). In the case of the pooled data analysis (the random effects models), some respondents are in scope in some waves, but not in scope in other waves (an unbalanced panel). In the case of the matching estimators analysis, each distinct cohort is defined with respect to this population of interest, and so each cohort has a slightly different composition from the others.

[3] Because the sample recruits new members each year, it remains representative of the Australian population over time, thus allowing it to provide cross-section 'snapshots' for any particular year.

[4] For ease of expression, the term 'employee' will be used in the body of this report to refer to this population and the notes to figures and tables make it clear what further sub-populations are under consideration at any particular point in the analysis.

category for the this report. Multiple job holders are defined according to their main job. The strategy followed in this chapter involves comparing 2002 and 2008, since these form the bookends of the period under review. By comparing outcomes for both years, we can discern the general pattern, as well as observe any trends which may appear to be emerging.

Types of job change

Around 15–17% of workers changed jobs during the previous year, a group who numbered about 800 000 in 2002 and 1.2 million in 2008. These job changers were quite mobile when it came to changing industry or occupational category. Only about one-quarter to one-third of this group stayed in the same kind of job. That is, they changed only their employer, staying within the same occupational and industry locations (measured at ANZSCO Major Group and ANZSIC Divisional levels).[5] Around one-fifth changed their industry, but kept the same occupation, while just over 10% changed occupation, but stayed within the same industry. A larger proportion—around 30%—changed both industry and occupation. These patterns are shown in figure 1, with the inset showing all workers and the main graph showing the breakdown for those who changed jobs.

Figure 1 Changing jobs and type of job change, Australia 2002, 2008

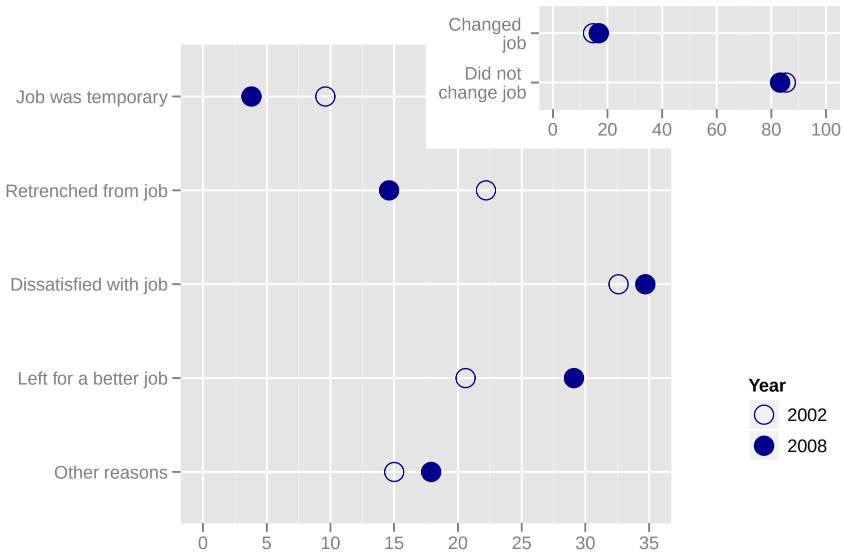
Note: Data weighted by cross-sectional weights. Totals in main graph do not equal 100% due to missing observations for the combination of job changing, occupation and industry.
Population: Adult employees not studying full-time. Sample sizes (inset): n = 4878 (2002); n = 5511 (2008).
Sample sizes (main) n = 721 (2002); n = 970 (2008).
Source: based on tables A1 and A2 in the appendix.

[5] ANZSCO is an abbreviation for Australian and New Zealand Standard Classification of Occupations and ANZSIC is an abbreviation for Australian and New Zealand Standard Industrial Classification. For further details of the current Australian Bureau of Statistics coding of these classifications see ABS (Australian Bureau of Statistics) (2005); ABS (Australian Bureau of Statistics) (2006).

Reasons for changing jobs

The respondents to the Household, Income and Labour Dynamics in Australia Survey are also asked for the main reason why they changed jobs, and the most prominent answers are shown in figure 2. During 2008, the main drivers for job change were job dissatisfaction and the search for a better job. The most notable change in these patterns over the period is an increase in the discretionary side of job changing and a consequent decline in involuntary job changing. The proportions of job changers who left because the job was temporary, or because they were retrenched, dropped markedly. In the case of the former, the proportion fell from nearly 10% to under 4%; for the latter the drop was from 22% to 15%. On the other hand, those leaving their job because of dissatisfaction stayed relatively stable, but those leaving for a better job rose from 21% to 29%.

Figure 2 Changing jobs and reasons for job change, Australia 2002, 2008



Note: Data weighted by cross-sectional weights.
Population: Adult employees not studying full-time. Sample sizes (inset): n = 4878 (2002); n = 5511 (2008).
Sample sizes (main) n = 721 (2002); n = 970 (2008).
Source: based on tables A3 and A4 in the appendix.

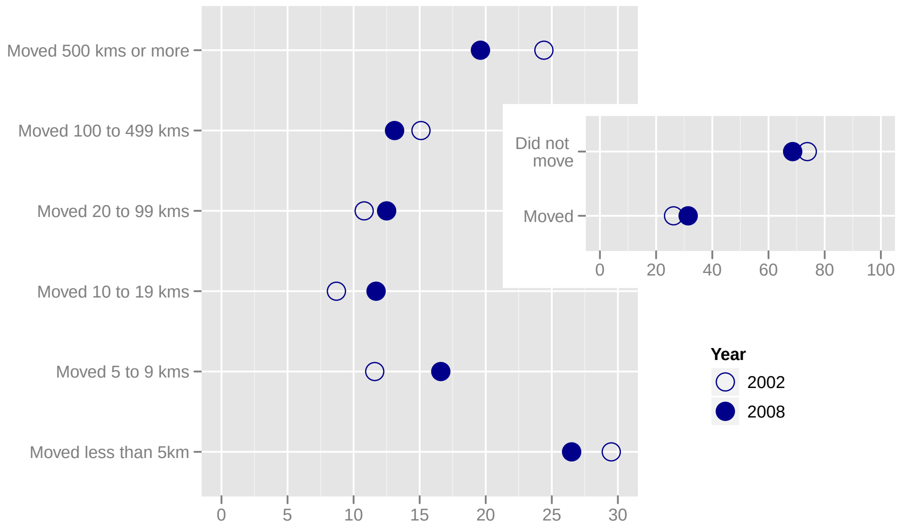
The geographical dimension

In changing jobs, did workers also relocate their places of residence? The data suggest that most job changers were immobile, with around 70% staying at the same address (see figure 3). Of those who did move, the largest proportion stayed within five kilometres of their former address. Clearly, this group was not changing local labour markets, as was the next distance group (those who moved five to nine kilometres), who constituted a further 10–17% of the job changers. In all, about 40% of job changers were likely to still be located within the same labour market. At the other extreme, between one-fifth and one-quarter of job changers moved 500 kilometres or more (and most of these were interstate moves), clearly relocating to a different labour market. The remaining group of job changers—around 30%—moved intermediate distances, with some changing to a different labour market and others simply commuting different distances to the same labour market.

Another take on geographical mobility is to look at the reasons workers give for moving. Looking at all workers (unrelated to job-changing behaviour), we see in figure 4 that about 16% moved residence during the year. The overwhelming motivation for this change in residence was housing-related (primarily moving to a bigger or better house), followed by family reasons (following a spouse or moving closer to family members). Moving house to take up a new job only accounted for about 6% of moves, while moving to look for work was less than 1%. Adding in other work-related reasons which did not involve changing jobs—such as taking a job transfer or moving closer to the workplace—the overall figure still only increased to about 17%.

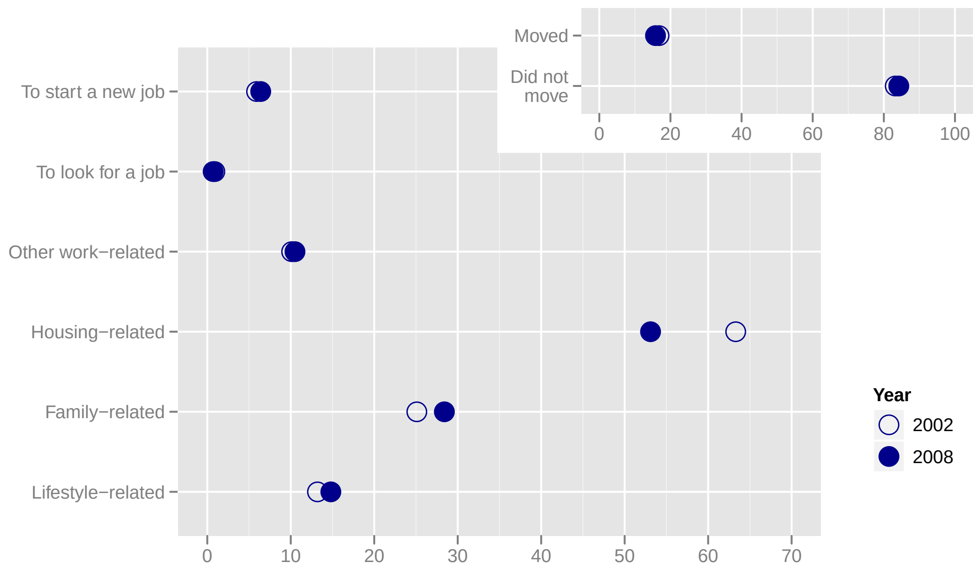
What kinds of numbers are we talking about here? In 2002 the number of workers who moved to take up a new job or to look for work was about 80 000. In 2008, the figure was about 93 000 (see tables A7 and A8 in the appendix). On the other hand, if we look at the group discussed above—job changers who moved—and examine those who moved a considerable distance, the figures are similar for 2002, but diverge for 2008. In 2002 the numbers of workers who changed jobs and moved 100 kilometres or more were about 84 000; in 2008 the relevant figure was about 126 000 (see tables A5 and A6 in the appendix).

Figure 3 Changing jobs and moving, distances moved by job changers, Australia 2008



Note: Data weighted by cross-sectional weights. Totals in main graph do not equal 100% due to missing observations for distance moved.
Population: Adult employees not studying full-time who changed jobs in the last year. Sample sizes (inset): n = 715 (2002); n = 965 (2008). Sample sizes (main) n = 230 (2002); n = 369 (2008).
Source: based on tables A5 and A6 in the appendix.

Figure 4 Reasons for persons moving, Australia 2008



Note: Data weighted by cross-sectional weights. Multiple responses allowed, so totals in main graph exceed 100%.
Population: Adult employees not studying full-time. Sample sizes (inset): n = 5205 (2002); n = 5780 (2008).
Sample sizes (main) n = 974 (2002); n = 1141 (2008).
Source: based on tables A7 and A8 in the appendix.

Characteristics of job changers

What demographic, labour market and workplace characteristics are associated with changing jobs? Are there some 'personality types' who are more likely to change their job? And how does an incumbent's satisfaction with their job influence job changing? In this chapter I look at each of these areas.

The approach taken is a multivariate regression modelling one, which seeks to identify the net effect of various factors on the probability of changing jobs. The characteristics are measured in the year prior to the job change, so in this sense, they definitely predate the job change. But these are still just *associations* which are being mapped, and whether they are causal is, of course, another matter. In the next chapter I adopt a strategy which is much more geared towards causal analysis. In this chapter I look only at the predictors of job changing in this more limited sense.

A multivariate regression modelling approach is necessary because a series of bivariate tables (such as cross-tabulations of characteristics with job changing) is vulnerable to confounding. A good illustration of this is the variable for household tenure. A simple cross-tabulation suggests that someone renting privately has a probability of changing their job of 22%. This is eight percentage points higher than the unconditional probability (14%) and more than twice the probability of someone who owns their house (10%). At the same time, as is well known, the probability of changing jobs is very high among young people. This happens for a range of reasons: trying out different jobs, mixing travelling and working, having fewer commitments, and so forth. And young people are much more likely to be renting privately; hence, one source of confounding.

Once we fit a regression model which controls for age (as well as a large number of other variables), the influence of differences in household tenure shrink considerably. The predicted probability from the regression model suggests that private renters have only a 15% probability of changing jobs, little different from the unconditional probability, and little different from home owners (13%). On the other hand, people in public housing have only a 9% probability of changing jobs, which contrasts with the simple cross-tabulation results (where their probability was 12%). In other words, some apparently obvious patterns disappear once a full set of controls are in place, while some other patterns may suggest themselves.[6]

The main data used for this modelling come from fives waves of the Household, Income and Labour Dynamics in Australia Survey dataset: from the years 2003 to 2007 (inclusive). The reason for the start date is that 2003 was the first year that a training variable was included in the questionnaire. The reason for the end date is that the outcome variable in this modelling—whether a person changed jobs or not—is

[6] As the confidence intervals shown in table A10 suggest, the difference between renting publicly and privately is statistically significant.

measured in the following year. So for looking at a job change which took place sometime in 2007–08, we need to consult the answer given in the 2008 interview.

The model which is fit to the data is a random effects probit model and the full set of model results are shown in the appendix as table A9. The main point about this particular model is that it makes the most of the panel data which the survey provides, that is, the longitudinal data on the same individuals. Such data have advantages and disadvantages. On the one hand, there is a problem when all these data are pooled because we now have multiple observations on the same individual. This leads to a lack of independence between observations and violates one of the core assumptions of regression modelling. This clustering of observations must be accommodated in some way and one approach is to make adjustments to the standard errors.

A more fruitful avenue involves incorporating random effects into the model, something which is only possible because of the repeated observations on the same individuals. In the case of this model, a random intercept is incorporated into the estimation procedure, a procedure which has several advantages. First, this deals with clustering in a more thorough fashion, adjusting not only the standard errors but also the coefficients. Secondly, and more importantly, employing random effects also helps to take account of what is called unobserved heterogeneity. These are the various unobserved aspects of individuals which may influence the outcome but which cannot be controlled for (because they go unmeasured). Usually they simply form part of the model's error term (the residual), but if they are correlated with any of the other regressors, then the problem of confounding (mentioned above) resurfaces. We may think we have a association between a certain regressor—such as education—and the outcome we are interested in, but if that regressor is correlated with an unobserved characteristic—such as ability—then we may ascribe a stronger effect to education than is warranted. By including random effects into the estimation process, we can partly control for potential confounders like these.

The results of this modelling are best presented as predicted probabilities. These are shown in the appendix for demographic (table A10), labour market and workplace characteristics (tables A11 and A12). As well as the predicted probabilities, these tables also show 95% confidence intervals. Unless otherwise noted, the differences discussed in the following sections are differences which are statistically significant.[7] Discussing predicted probabilities rather than coefficients makes the findings more accessible, and it also returns us to the original framework in which the analysis was begun. If the unconditional probability of job changing is about 14% for this sample, then the various predicted probabilities can be easily compared with this figure. These predicted probabilities are conditional probabilities, in the sense that they reflect the probability of changing jobs for someone in a particular category, with all other characteristics averaged across the sample.

In the case of categorical variables, the difference in the probability of job changing for being in one category—such as working as a casual—can be contrasted with the probability of not being in that category, and an average partial effect can be calculated as the difference in probabilities. In the case of a casual worker, for example, the probability of job changing is 17.3%, while the probability of job changing for someone who is not a

[7] Comparing whether confidence intervals overlap is one approach (and a conservative one) to gauging statistical significance and this has been used for this analysis.

casual is 12.6%. The average partial effect for casual status is thus 4.7 percentage points (or a 27% change).

In the case of continuous variables, such as job tenure, various measures of satisfaction and the personality rating scales, a different approach is taken for presenting the results. For technical reasons, these are all modelled as centred and standardised units, and the predicted probabilities are shown in this report as graphs. The x-axis depicts these units, as standard deviations, and the y-axis shows the percentage probability of job changing. The 0 position on the x-axis indicates where someone who is average on that characteristic, for example, having the mean number of years of job tenure, is to be found. A position at location 1 is someone who is 1 standard deviation above the average, while -1 is someone who is 1 standard deviation below the average. In the case of the extrovert personality rating scale, for example, the mean score in this sample was about 4.4 (on a rating scale from 1 to 7) and the standard deviation was about 1.1. So a 1 standard deviation position on the x-axis indicates someone who would have scored 5.5 on this personality rating scale. Table A13 in the appendix provides some guidance on interpreting these units in terms of their original rating scale measures.

Demographic characteristics

The most striking aspect of the demographic characteristic of job changers is their age (table A10). Changing jobs is very much the province of the young. Workers aged under 30 years have almost twice the probability of changing jobs as those in their 50s and upwards. There is little in the way of a gender difference when it comes to age. There is, however, a more interesting gender difference when it comes to birthplace. Women born in a non-English speaking country are less likely to change jobs than are those born in Australia or in an English-speaking country, a difference not shared by their male counterparts. Where one lives makes a some difference: workers living in the Northern Territory, the Australian Capital Territory and Perth are much more likely to change jobs, while those living in Tasmania are much less likely. An interesting gender difference is evident for the Northern Territory: the high probability for this territory is due entirely to women. Their predicted probability of changing jobs is 27% (compared with male Territorians at 12%).

As noted above, household tenure does make a difference when it comes to public housing. The probability of job changing is reduced among this group of people, something noted in other research and possibly due to some of the characteristics of public housing. There can be a disincentive towards increasing wage and salary income when rent is tied to household income levels and geographical mobility can also be constrained because of limited locational options.

Labour market and workplace characteristics

The most notable occupational differences are gender-based (table A11). For men there is only a modest variation in the predicted probability of changing jobs conditional on occupation—varying from 12% to 15%—whereas for women there is a pronounced difference between managerial-professional jobs and blue-collar jobs, such as machinery operators. Their predicted probability of leaving a job is just 7%, compared with figures of around 14–15% for managerial-professional jobs. Interestingly, salesworker jobs, while also less skilled, show higher predicted probabilities of job changing, though this may reflect the high job turnover traditionally associated with that occupation (which is high for both men and women).

Industry patterns are very distinctive, with quite low probabilities in education (9%) and government (11%) and quite high probabilities in accommodation, cafes and restaurants (19%) and construction (18%). Patterns of job changing conditional on earnings and hours are not distinctive, but employment status is. As noted above, casuals have a higher predicted probability of changing jobs (17%) than do non-casuals (13%). Both of these sets of findings suggest a certain amount of job churning in the labour market and this is confirmed by the labour market history of individuals. Those with some prior history of unemployment have higher predicted probabilities of job changing (17%), as do those with periods of time outside the labour force (although the latter differences are not statistically significant).

Some of the characteristics of individuals which are more specific to their workplaces are shown in table A12 and these suggest that job changing is less likely in larger organisations, with the predicted probability of job changing in organisations with 500 or more employees being 11%, compared with 17% in organisations with under 20 employees. Differences associated with union membership and supervisory roles are not particularly pronounced, nor is access to training strongly indicative of job changing outcomes.

Job tenure and occupational tenure are two of the variables presented here as graphs (see figure 5). As mentioned above, they are continuous variables and are measured in standard deviations. A word of caution is in order with all of these graphs. They present predictions across the x-axis from -2 to 2 standard deviations, but for some of the predictions, the extreme values are not realistic.[8] This is particularly the case for variables whose distribution is not symmetric.

Figure 5 Occupational tenure and job tenure and job changing, by sex

Note: Male = continuous, female = dashed. Shaded area = 95% confidence intervals. The x-axis units are explained in appendix table A13. Based on models shown in appendix table A9.

[8] For this reason, the reader should consult table A13 in the appendix to get a feel for the means and standard deviations of the raw scores of these variables.

Job tenure is one such variable: it is highly skewed to the right, with a mean for males of 7.7 years and a standard deviation of 8.4 years. Consequently, the predicted probabilities for job changing conditional on job tenure shown in figure 5 are quite meaningful for the range 0 to 2 standard deviations, but not so for for the range -1 to -2 (since a person cannot have negative job tenure!). This means that someone with about 20 years of job tenure—which is a realistic figure—would have a predicted probability of job changing of about 6%. However, nobody has predicted probabilities of job changing in the 20% and upward probability range because this would imply negative years of job tenure. Realistically, the highest probability of job changing is for someone with less than a year of job tenure and that figure is about 15% for females and 17% for males.

In other words, the low job tenure figures are quite close to the unconditional probability figures. So, having quite short job tenure does not imply an inclination to change jobs, but the opposite is definitely true: having quite long job tenure makes it much less likely that one will change jobs. Incumbency matters, a phenomenon captured in the notion of duration dependency. By way of contrast, occupational tenure counts for very little at all, illustrated by the graph lines in the left panel of figure 5 being essentially flat.

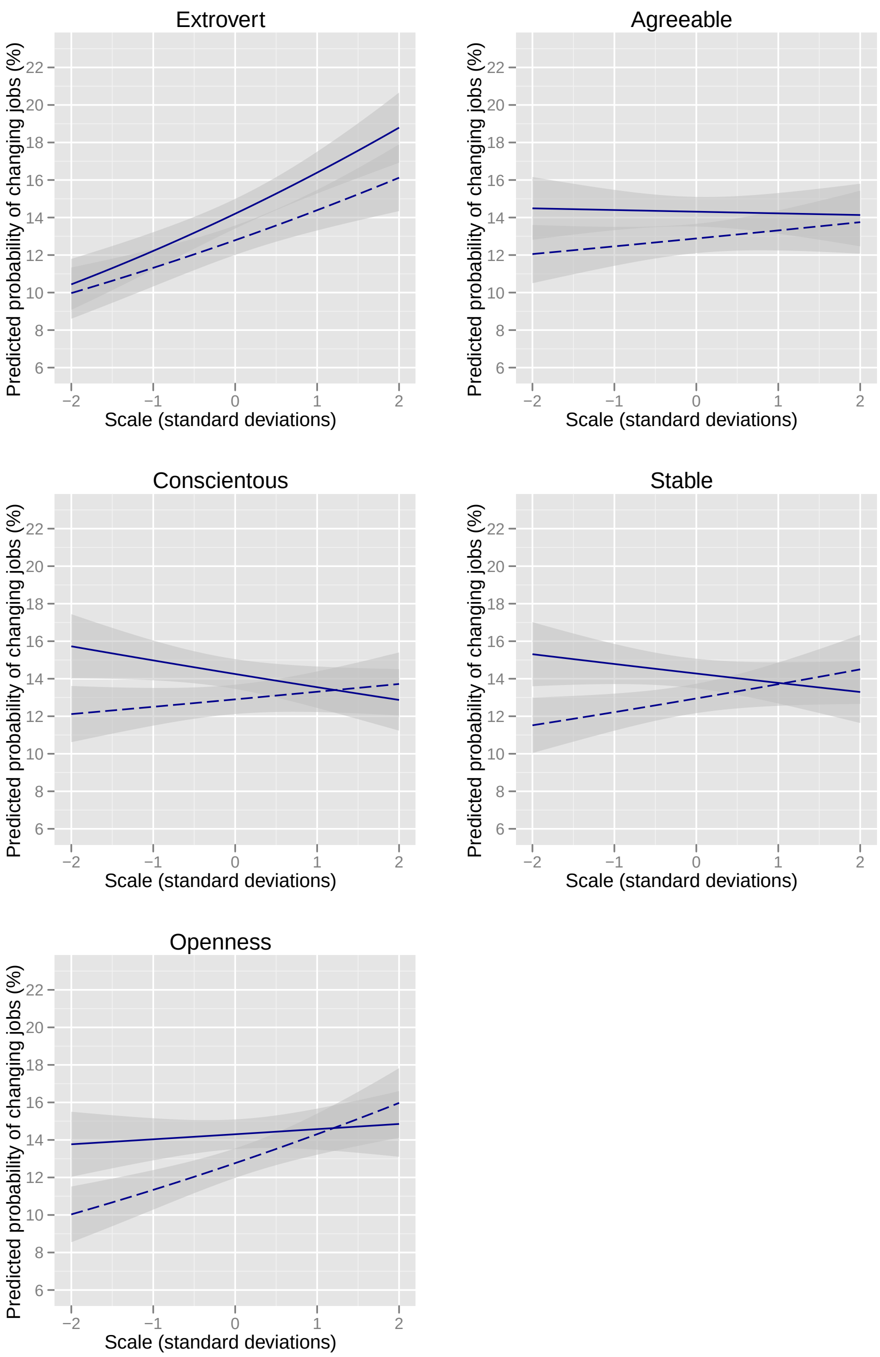
Personality types

In wave 5 the survey questionnaire contained a series of 36 test items which were based on Saucier personality test items. They were prefaced with the question: 'How well do the following words describe you?' and included terms like 'talkative', 'sympathetic', 'orderly', and so. They ranged from 1 (not describe at all) to 7 (describe very well). These items have been used by the survey team to construct personality measures for the so-called 'Big 5': extroversion, agreeableness, conscientiousness, emotional stability and openness to experience.

The most interesting findings for the inclusion of these personality types in the analysis are, firstly, how little difference most of these make to the outcome, and, secondly, the gendered nature of some of the responses. Extroversion is the one variable which shows a strong association with job changing, and this applies to both males and females. On the other hand, for nearly all of the other types, the associations are quite weak. This is not a uniform outcome, however, with gender differences sometimes pointing in opposite directions. For example, openness is associated with job changing among women, but not among men. An increase in either conscientiousness or stability among men inclines them to stay in their jobs, but not so for women.

To place these results in perspective, it's worth considering a few examples, as well as a contrast with one of the above findings. As just noted, most of these personality effects are quite mild, with only extroversion showing a notable impact. For example, among men the average score on the extroversion rating scale is 4.3 and the standard deviation is 1. Thus someone scoring 6 on this scale has a predicted probability of job changing of just over 18%, an increase of just four percentage points. By way of another example, for women the average score on openness is 4.2 and the standard deviation is also 1. A woman scoring 6 on this scale would increase her probability from a baseline figure of 13% to just under 16%. These two examples are among the more notable results, and yet by comparison with some of the demographic and labour market variables, these impacts are quite mild. Consider the case of job tenure, where staying in one's job for 20 years reduces the probability by more than a half, from about 14% to just 6%.

Figure 6 Personality type and job changing, by sex

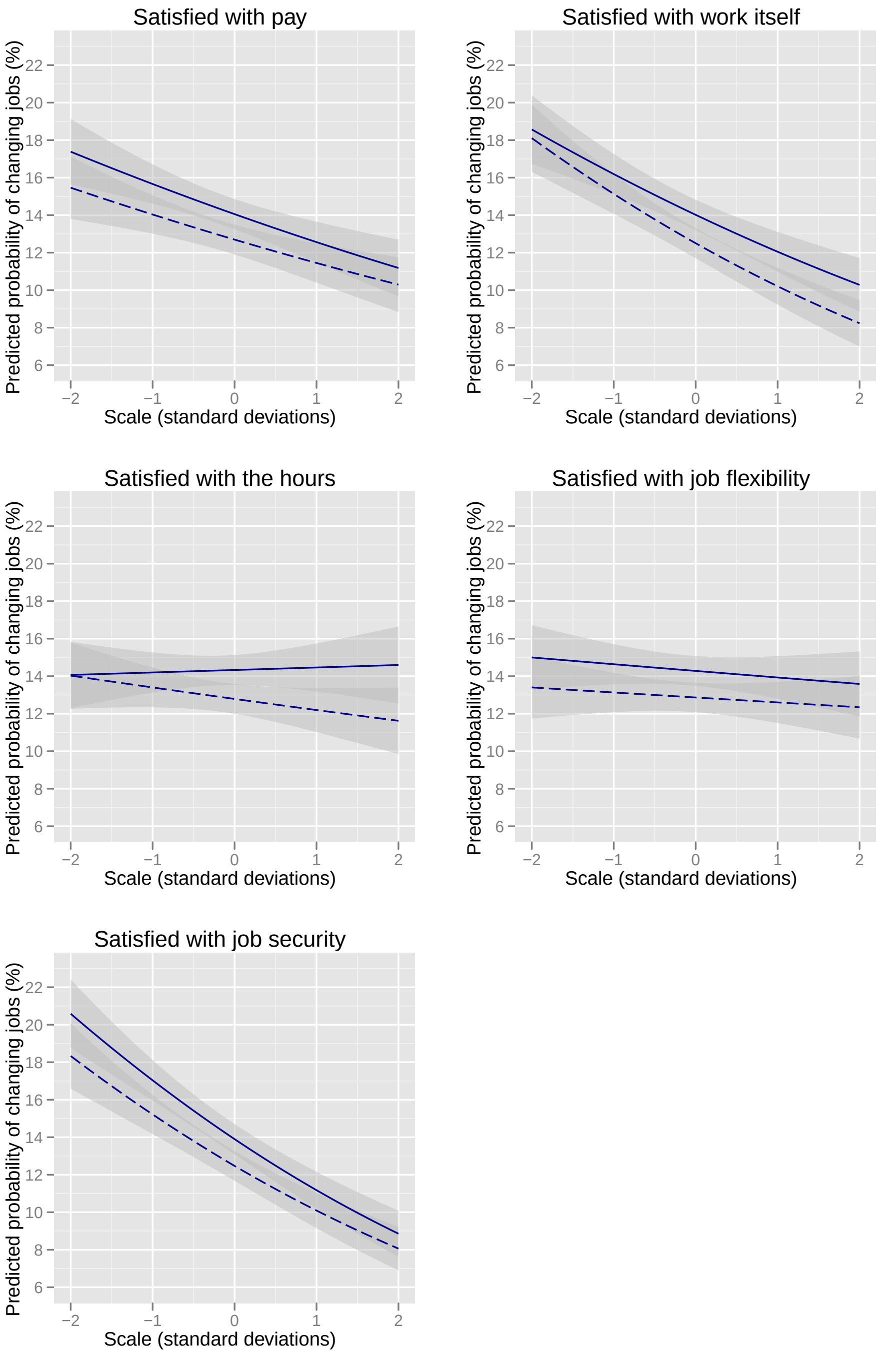


Note: Male = continuous, female = dashed. Shaded area = 95% confidence intervals. The x-axis units are explained in appendix table A13. Based on models shown in appendix Table A9.

Job satisfaction

Whereas personality might be regarded as reasonably stable—and hence only needing to be captured once in the survey—the same cannot be said for job satisfaction, which can rise and fall with one's labour market fortunes. A range of questions which tapped into this theme have a been a regular feature of the Household, Income and Labour Dynamics in Australia Survey since its inception and they have been extensively analysed over the years.

Figure 7 Job satisfaction and job changing, by sex



Note: Male = continuous, female = dashed. Shaded area = 95% confidence intervals. The x-axis units are explained in appendix table A13. Based on models shown in appendix table A9.

The main job-related satisfaction items measured by the survey are: the level of pay, job security, the nature of the work undertaken, the hours of work, and the flexibility to balance work and non-work commitments. These items range from 0 (low satisfaction) to 10 (high satisfaction), a rating scale which, despite being ordinal in nature, has been successfully used as interval data. In the case of the regression modelling in this paper, it is included as an explanatory variable, making this distinction less relevant. A finding of note is that most of the average scores for these satisfaction items are quite high: ranging from about 7 to 8.

The findings for job satisfaction are shown in figure 7 and it is clear that gender differences do not count for much. Only around hours of work is a gender difference discernible (although this difference is not statistically significant). Satisfaction with the hours worked makes it more likely that women will stay in their jobs than men. Job flexibility does not appear to be an issue at all, nor is satisfaction with hours of work particularly pertinent. On the other hand, workers who are dissatisfied with their pay are more likely to change jobs, as are workers less satisfied with the nature of the work.

It is job security, however, which has the most dramatic impact. While the average score on the satisfaction rating scale for job security is quite high (mean 8.1, standard deviation 2), the impact of being dissatisfied is noticeable. Someone scoring low on this rating scale (say 4) would have a predicted probability of changing jobs of about 19–20%. On the other hand, being more satisfied with job security does not necessarily count as much, since a one-standard-deviation change here is enough to take a person to the top of the rating scale, and this only serves to reduce the job changing probability to about 11%. In other words, job security mainly works in one direction, signalling an inclination to change jobs if things don't look secure. Better to move on, before being moved.

The consequences of changing jobs

Causal analysis with observational data

The set of questions I pursue in this chapter are: does changing jobs improve earnings? How does it influence a range of satisfaction scores related to workplace issues? And does changing one's job affect the extent to which a person uses their skills, or learns new skills?

These are all questions about the consequences of changing jobs. The focus so far in this report has been largely descriptive, with the first chapter providing an overview of the nature of job changing in Australia and the second chapter examining the characteristics associated with job changing. In this chapter, the focus shifts in two ways. First, the interest now lies in the aftermath of job changing—whether the job changer is better off or not. Secondly, the methodology is now explicitly causal. In the context of certain assumptions—to be outlined shortly—I will now make claims about what changing one's job does to an average person and how this differs from not changing one's job.

Of course, we cannot observe the same person both changing their job, and not changing their job. For this reason, the approach to causality, called the Neyman-Rubin causal model, 'conceptualizes causal inference in terms of potential outcomes under treatment and control, only one of which is observed for each unit ... A causal effect is defined as the difference between an observed outcome and its counterfactual' (Diamond & Sekhon 2008, p.4). In practice, this means constructing a control group of people who did not change their jobs and comparing their average outcomes with a treatment group who did change their jobs.

In an experimental setting the random assignment of individuals to treatment and control groups prior to the onset of treatment largely removes the problem of confounding and allows researchers to directly compare outcomes, confident that problems of selection bias are largely absent (Rosenbaum 2002, ch. 2). With observational data, especially that based on existing datasets (like HILDA), there is no scope for random assignment. Instead, the strategy which has evolved over the last few decades has been to identify a treatment group who are already in the sample, in this case, individuals who changed jobs during a certain period, and then to artificially construct a control group from a subset of all those in the sample who didn't undergo this treatment. Commonly—and this is the case with this current study—the potential control group is much larger than the treatment group, so there is considerable scope for selecting that subset in such a way that their characteristics closely match those of the treatment group. Matching the two groups on a wide range of relevant covariates is the core methodological challenge in this approach and the ultimate goal is to achieve good 'balance' across the two groups.

Matching on the actual covariate patterns is the most obvious way to get balance, and early classic studies like those of Freedman and Hawley (1949) pursued this approach.

However, this kind of matching is not always practical, particularly if there are a large number of covariates or if some of them are continuous rather than categorical. Without a massive sample, some patterns may simply lack matches between participants and non-participants. This is sometimes referred to as the problem of 'dimensionality'. Consequently, other approaches have become more common in recent years. One of these, propensity scores, makes use of a single measure which is based on the probability of receiving treatment, conditional on the covariates (Dehejia & Wahba 2002, p.153). Employing a logistic regression model, which predicts who will receive treatment and who won't, allows researchers to construct these probabilities and then carry out matching on the basis of closeness in propensity scores (Rosenbaum & Rubin 1983). Another common approach is to use various multivariate distance-measuring algorithms (based on the Mahalanobis distance, for example), or to use combinations of both (Rosenbaum & Rubin 1985).

The 'genetic matching' approach used in this report is based on software developed by Jasjeet Sekhon and makes use of genetic algorithms, which generalise the Mahalanobis distance method by employing a weighting matrix (Sekhon 2010; Sekhon forthcoming). While this approach tends to be computationally intensive[9] the balance achieved with this method has been shown to be superior to that achieved with the propensity score approach.

Irrespective of the specific algorithms used for matching, this overall approach of using matching estimators for causal analysis relies on two key assumptions. The first, termed 'selection on observables', requires that the assignment to treatment is independent of the outcomes, conditional on the covariates. The second assumption is the 'common support' or overlap condition. People with the same covariate values cannot all fall into one category (perfect predictability): they must have a positive probability of being either participants or non-participants (Abadie et al. 2004, p.292; Caliendo & Kopeinig 2005, p.4).

The selection on observables assumption is of central importance to causal analysis. It assumes that the effects of changing jobs, such as an increase in earnings, are not influenced by any correlation between unobserved factors, such as an instability in one's work history and the person's selection into the treatment group (that is, changing jobs). If there were to be such a correlation, then how would the researcher be able to separate out the earnings effects which are really due to job changing from the effects which are due to that work history? Clearly, encompassing as many relevant characteristics in the covariates used for matching becomes crucial. In the case of this study, for example, variables measuring the number of jobs held by an individual in the last two years, as well the number of weeks unemployed or outside the labour force during the last two years, are included in an attempt to capture some of the relevant work history.

At the same time, achieving a good match on these covariates between the treatment and control groups is also crucial: this is the idea of 'balance' mentioned above. As will be illustrated shortly, it is possible to compare the characteristics of the control and treatment groups before and after matching and to assess the extent to which balance has been achieved.

[9] Although the software used here makes use of parallel processing, allowing multiple computers (or processors) to be simultaneously employed. This speeds up the process considerably. The R package, `snow`, was used to parallelise the genetic matching, see Tierney et al. (2009); Tierney, Rossini & Li (2009).

Rosenbaum distinguishes between overt and hidden bias (Rosenbaum 2002, p.71). The former is present in the data that have been collected and is evident in the initial 'mismatches' between treatment and control groups. For example, in this study the job changers are younger, on average, than the control. As will be evident shortly, genetic matching can deal with this by bringing the two groups into closer alignment, thus reducing one aspect of overt bias. On the other hand, hidden bias is, by its nature, not observed in the data. As just noted, including a large range of relevant covariates can help to reduce the scope for hidden bias. However, the problem cannot be eliminated entirely because we can never be sure whether unobserved characteristics have a confounding influence on the findings. Fortunately, sensitivity analysis, which can be defined as giving 'quantitative expression to the magnitude of uncertainties about bias' (Rosenbaum 2002, p.11) can be used with matching estimators. The approach known as 'Rosenbaum bounds' allows us to test how sensitive the results are to hidden bias, and these tests are used in the final part of this chapter.

Implementation

As noted above, the key questions pursued in this chapter are whether job changing improves earnings, influences job satisfaction or affects skills utilisation. These various outcomes are measured in the job in one year, and compared with the job held in the previous year. For the treatment group, the job held in the previous year will be a different job; for the control group, it will be the same job they held the previous year. This approach is undertaken for three separate cohorts from the larger survey sample: 2002–03, 2005–06 and 2007–08. Each cohort provides a cross-sectional snapshot for that period. In other words, the data are not being pooled and used in a longitudinal framework.[10] However, the panel of the data are being utilised in order to assess the before and after situation of the respondents. This is the reason for using these 'twinned years' (that is, 2002–03). One needs a before and after interview to construct these various outcome measures. These are quantified as absolute changes in earnings (hourly and annual) in job satisfaction scores and in agreement scores related to skills use. Among the covariates used in the matching process are history variables, such as periods spent unemployed or outside the labour force. These are averaged over the two previous years (that is, 2001–02, 2004–05, and 2006–07) for each of the cohorts.

Thus for any particular cohort, three years worth of data are used to construct all of the relevant measures employed. Fortunately, the survey researchers recruit new panel members during each wave, thus compensating for survey attrition. Consequently, each of the cohorts can be regarded as a reasonably complete cross-section of the population during these three time blocks.[11] The relevant population, as with the earlier chapters in this report, consists of adult employees who are not studying full-time.

The covariates used for this matching process are based on the individual's circumstances in the previous year (that is, 2002 for the 2002–03 cohort), which means the characteristics of the job held prior to the change (for the treatment group) and the same job currently held (for the control group). These covariates are quite extensive and

[10] Because the data are used in this fashion, there are no repeated observations in the analysis, and hence no need to deal with issues of dependency (as there is for pooled data analysis).

[11] Because the analysis is not descriptive, no survey weights are employed. Rather, the analytical method is comparable with a regression modelling framework, in which survey weights are usually not employed. See Deaton (1997, pp.67–73) for a discussion of this issue.

attempt to control as much as possible for problems of confounding. Thus the previous level of earnings (and levels of satisfaction and skills use) are included, since better-paid workers may already be more 'productive' and thus inclined to have higher rates of earnings growth. Similarly, workers already utilising their skills to a high degree may be expected to have better chances of increasing their skills use. As mentioned above, the covariates also include aspects of the individual's work history, since job instability may be correlated with further job changing. Apart from these more obvious confounders, a full range of demographic, labour market and workplace covariates are also employed and include all of the covariates which the previous chapter showed to be associated with job changing.

The full set of covariates are shown in the appendix with their before and after matching characteristics (see table A14). It is clear from these figures that genetic matching goes a long way towards bringing the control group and the treatment group into close alignment (balance). For example, looking at the variable that measures whether the person had already changed jobs prior to the current job change, some 33% of the treatment group are in that category. Prior to matching, only 10% of the control group have previously changed jobs. This sharp difference suggests that job changers have a history of greater job changing than non-job changers, something noted in the previous chapter. However, after the process of genetic matching, the control group's figure is 27%, still slightly behind the treatment group, but only marginally so. Looking at the level of earnings of individuals prior to job changing shows that the treatment group earns, on average, $23.57 an hour, while the control group earns $25.88. Again, this is consistent with the overall tendency of job changing to be associated with low pay correlates like casual status and labour market churning. After matching, the control group's average earnings are $23.60, almost identical to the treatment group. As for the churning variable itself, which measures the number of jobs individuals have held over the last two years, this also suggests that the treatment group is more vulnerable: an average of 2.9 jobs compared with 2.4 jobs among the control group. After matching, the control group average has risen to 2.7 jobs. Finally, as we saw in the previous chapter, younger individuals are more likely to change jobs: the average age of the treatment group is 36.2 years; the average for the control group is 41.5. After matching, the average age of the control group is 37.6 years, considerably closer.

In summary, while a 'perfect match' on all covariates between the two samples is rarely found after genetic matching, the balance achieved is quite remarkable. A control group with characteristics which are not strongly associated with job changing can be brought into alignment with the treatment group, whose characteristics are strongly associated with job changing. After this process, they closely resemble each other across a large range of covariates. This suggests that any distinctive differences in outcomes (like earnings or satisfaction) are much more likely to be due to job changing itself and not pre-existing differences between the control group and the treatment group.

Findings

After a long exposition of the journey, the destination itself is quite succinct. The climax to this process of genetic matching is the finding that changing jobs does not improve an individual's earnings. On the other hand, changing jobs does lead to improvements in job satisfaction and skills use.

These results are summarised in tables 1, 2 and 3, which present estimates for the average causal effect of each item that changed between the two annual interviews for each of the three cohorts. The estimates are shown as average treatment effects on the treated (ATT), which is the absolute difference (in dollars for earnings, scores otherwise) between what the control group achieved and what the treatment group achieved. Very small changes are not only substantively unimportant, that is, not noteworthy, but they are also unlikely to be statistically significant. Whether an average causal effect is significant or not is based on the size of the standard errors, which in this case are derived using the Abadie-Imbens method, which takes account of the uncertainty involved in the matching process. The p-values in these tables indicate the probability that the estimates are significantly different from zero. These can be read as indicating the probability that there is *no* difference between the control and treatment groups, that is, no causal effect. By convention, only p-values of 0.05 or less are deemed to indicate statistically significant causal effects.

Table 1 Job changing and average causal effects: earnings

	2002	2005	2007
Hourly rates of pay			
Estimate (ATT)	0.19	0.86	-0.09
Abadie-Imbens SE	0.68	0.70	0.91
P value	0.78	0.22	0.92
Annual wage & salary earnings			
Estimate (ATT)	-1096.12	-1271.61	-1689.67
Abadie-Imbens SE	1122.85	1229.82	1066.93
P value	0.33	0.30	0.11

Notes: Figures (except for p-values) are expressed in dollars in real terms (CPI indexed to 2008). ATT = average treatment effect on the treated. SE = standard error. P value = probability value. Estimates are in real dollars (CPI indexed to 2008).
Number of observations in each treatment group: 427 (2002); 460 (2005); 472 (2007).
Population: adult employees not studying full-time.
Source: HILDA Release 8.

In terms of earnings, across all years shown, there are no statistically significant differences between the control group and the treatment group. In the case of hourly earnings, and without even considering the p-values, all these amounts are less than $1 per hour (19, 86 and –9 cents per hour respectively). When it comes to annual earnings, all of the estimates are negative (suggesting worse comparative outcomes for the treatment group) and statistically insignificant, again suggesting that changing jobs did not improve relative earnings.

On the other hand, the estimates for most of the job satisfaction measures are highly significant and of substantive magnitude. Looking at overall job satisfaction, on a rating scale of 0 to 10 (the satisfaction rating scale used in the survey questionnaire), these differences are in the range of 0.8 to 1.0, quite considerable margins over the control group.

Table 2 Job changing and average causal effects: satisfaction

	2002	2005	2007
Overall job satisfaction			
Estimate (ATT)	1.02	0.80	0.92
Abadie-Imbens SE	0.14	0.13	0.13
P value	0.00	0.00	0.00
Satisfaction with pay			
Estimate (ATT)	0.67	0.70	0.38
Abadie-Imbens SE	0.17	0.15	0.14
P value	0.00	0.00	0.01
Satisfaction with work itself			
Estimate (ATT)	0.59	0.52	0.71
Abadie-Imbens SE	0.15	0.14	0.14
P value	0.00	0.00	0.00
Satisfaction with hours			
Estimate (ATT)	0.44	0.29	0.54
Abadie-Imbens SE	0.18	0.15	0.14
P value	0.02	0.05	0.00
Satisfaction with job flexibility			
Estimate (ATT)	0.61	0.38	0.40
Abadie-Imbens SE	0.18	0.18	0.17
P value	0.00	0.03	0.02
Satisfaction with job security			
Estimate (ATT)	0.40	0.22	0.19
Abadie-Imbens SE	0.17	0.14	0.14
P value	0.02	0.13	0.17

Notes: ATT = average treatment effect on the treated. SE = standard error. P value = probability value.
All of the original scores for these items range from 0 (low satisfaction) to 10 (high satisfaction).
Number of observations in each treatment group: 427 (2002); 460 (2005); 472 (2007).
Population: adult employees not studying full-time.
Source: HILDA Release 8.

Table 3 Job changing and average causal effects: skills

	2002	2005	2007
Use of skills in job			
Estimate (ATT)	0.36	0.20	0.22
Abadie-Imbens SE	0.11	0.10	0.11
P value	0.00	0.05	0.05
Acquiring new skills in job			
Estimate (ATT)	0.24	0.40	0.33
Abadie-Imbens SE	0.12	0.12	0.12
P value	0.05	0.00	0.00

Notes: ATT = average treatment effect on the treated. SE = standard error. P value = probability value.
All of the original scores for the skills items range from 1 (low) to 7 (high).
Number of observations in each treatment group: 427 (2002); 460 (2005); 472 (2007).
Population: adult employees not studying full-time.
Source: HILDA Release 8.

In terms of particular dimensions of job satisfaction, several results are noteworthy. Satisfaction with the work itself shows a substantive margin over the control group, and as noted in the previous chapter, this item is an important consideration in the decision to change jobs. On the other hand, the weakest outcomes are for satisfaction with job security. Only in one year (2002) is this item statistically significant. It is the only dimension of job satisfaction which does not appear to confer any advantage on the treatment group. In other words, while a lack of job security may motivate individuals to change jobs, as we saw in the previous chapter, changing jobs does not, on average, improve the situation.

A more encouraging story is evident in the skills dimensions of job changing. Individuals who changed jobs got to make greater use of their skills and—an even stronger result—they got to learn new skills. The margins for individuals in the treatment group vis-a-vis the control group are quite considerable, ranging from 0.24 to 0.40 (keeping in mind that the rating scale for these skills items is 1 to 7).

In summary, job changers are certainly happier and more productive, on average, as a result of changing their jobs, but they fare no better in material terms.

Sensitivity to hidden bias

We can never be sure whether the results of directly comparing matched samples are influenced by hidden bias. After all, the matching is only based on observed characteristics. We can, however, extend that range of observed characteristics into as many domains as is feasible, which—with a dataset like the Household, Income and Labour Dynamics in Australia Survey—can be quite extensive. Unlike regression methods, where over-fitting of models can be the price paid for including too many covariates, with matching estimators the more covariates incorporated the better. Ultimately, the question of hidden bias remains unanswered, although sensitivity analysis can help quantify the likely influence of such bias.

The concept is quite simple: how much bias would need to be present for the results to change substantially? In the case of matching estimators this is implemented using the odds ratios for participation in the treatment. If the odds ratio (termed gamma) is equal to 1, then two matched individuals have the same probability of participating. As gamma rises, these individuals begin to differ in their odds of participating, despite the appearance of similarity.

When gamma reaches 2, for example, the odds of participating between these two individuals differ by a factor of 2, even though they appear to be well matched. Gamma thus measures the degree of departure from a study that is free of hidden bias. Rosenbaum bounds involve selecting a set of gamma values and examining how much the reported findings differ at each level of gamma. In a sense, one is estimating the magnitude of the hidden bias needed to reverse the findings.[12]

In the case of hourly earnings for the 2002 cohort, the gamma level at which the results become statistically significant is about 1.2 and, for the results to be highly statistically significant, the gamma level is about 1.5. For the overall job satisfaction item for the 2002 cohort, the gamma level at the point where this becomes statistically insignificant is 1.9, and for it to be conclusively insignificant the gamma level is about 2.1. In essence, we are measuring the cross-over point, from when a result which is not statistically significant (that is, no causal effect) becomes statistically significant (that is, there is a casual effect). Or vice versa, if the reported findings indicate a causal effect.

[12] The analysis of Rosenbaum bounds in this report was conducted using the R package, `rbounds` (Keele 2009).

Another approach to Rosenbaum bounds entails considering substantive findings, and pinpointing the gamma level at which the results would be actually *reversed*. In the case of the 2007 cohort, the annual earnings margin was about –$1700 (although not statistically significant). That is, changing jobs left individuals, on average, about $1700 per year *worse* off. For this figure to be reversed and for the average individual to be $1700 *better* off, the gamma level would need to be just under 1.6. In the case of the overall job satisfaction margin for the 2002 cohort, which was measured at 1.02 (see table 2), the gamma level needed to reverse this figure and make it –1.02 would be very large, namely 5.

In terms of sensitivity to hidden bias, what are small values for gamma and what are large? As Rosenbaum notes, a study is sensitive to hidden bias when values close to 1 'could lead to inferences that are very different from those obtained assuming the study is free of hidden bias' (Rosenbaum 2002, p.107). But how close to 1 is close? While observational studies in the health sciences typically find their results may not be subject to hidden bias until the gamma levels are quite large (as high as 6 in smoking and lung cancer studies), studies in the social sciences find much lower figures. Sensitivity analysis for the well-known Card and Krueger minimum wage studies found figures between 1.34 and 1.5 (Rosenbaum 2002, p.188), while DiPrete & Gangl (2004, p.36) found their results sensitive to values ranging from 1.1 to 2.2. Aakvik (2001), for example, examined the range from 1.25 to 2 in his study of a training program and he argued that a gamma level of 2 should be considered 'a very large number given that we have adjusted for many important observed background characteristics' (2001, pp.132–33). With this advice in mind, the results in this study are reasonably resistant to the effects of hidden bias, with the results for job satisfaction particularly robust.

Discussion

The context

There are several contexts for understanding the issue of labour mobility. There is a tradition stemming from industrial psychology which looks at issues like job search, training and careers, and focuses, in a practical way, on analysing successful job matching between firms and workers. There is also a tradition, within labour economics, which regards labour mobility as one of the key mechanisms by which labour markets work to redistribute labour 'resources' to areas of highest need. In the 1950s, both traditions overlapped, evident in the literature on 'manpower planning', which sought to achieve both optimum individual and social outcomes through unabashed state intervention. Since the late 1970s the two traditions have divorced, and the planning role of the state has been in retreat.

The context for understanding labour mobility in recent decades has been a quite polemical one and has often been subsumed within debates about 'flexibility' and labour market institutions (Freeman 2005). These debates have generally revolved around issues of unemployment, minimum wages and economic performance, and the driving ethos for the advocates of labour market 'flexibility' has been that labour markets should function more like *markets*. Such a perspective immediately conjures up the classic study by Karl Polanyi, *The great transformation: the political and economic origins of our time*. Writing in exile in the United States in 1944, Polanyi identified the essential contradiction at the heart of the markets for labour, land and money. While his insights concerning the latter two are particularly prescient—in the light of global warming and the Global Financial Crisis—my focus here is on his comments regarding labour:

> The crucial point is this: labor, land and money are essential elements of industry; they also must be organized in markets; in fact, these markets form an absolutely vital part of the economic system. But labor, land, and money are obviously *not* commodities; the postulate that anything that is bought and sold must have been produced for sale is emphatically untrue in regard to them. In other words, according to the empirical definition of a commodity they are not commodities. Labor is only another name for a human activity which goes with life itself, which in its turn is not produced for sale but for entirely different reasons, nor can that activity be detached from the rest of life, be stored or mobilized ... The commodity description of labor, land, and money is entirely fictitious.
>
> Nevertheless, it is with the help of this fiction that the actual markets for labor, land, and money are organized; they are being actually bought and sold on the market; their demand and supply are real magnitudes ... (Polanyi 1957, pp.72–73)

In other words, a labour market comparable with the market for oranges or white goods does not really exist, but the fiction that labour is a commodity is materialised in the everyday economic and social organisation of life. Employers advertise for labour, while workers scan the *Seek* website in search of a better job. Mobility between jobs is thus an everyday reality which provides a material basis for the fiction that labour is a commodity. Employers know they are buying labour power—the capacity to labour—while workers know they are selling it, and both are fully aware that labour power is only embodied in the person of a human being. Yet both unthinkingly regard themselves as engaged in a *market* transaction. Such is the lived reality of the fiction.

In this discussion chapter I draw together the key findings from the above chapters and I discuss them within the framework provided by Polanyi. I also look at the area termed 'behavioural economics', which is probably the closest mainstream economics comes to going beyond a narrow focus on market transactions. While the debates regarding labour market institutions and flexibility mentioned earlier are beyond the scope of this discussion, they hover in the background. After all, the question of whether labour markets should become more like markets has been a central preoccupation in these debates for the last four decades.

Behavioural economics

Over the last 30 years, the field of behavioural economics has thrown up a challenge to the nineteenth-century utilitarian philosophical roots of mainstream economics. The utility-maximising, rational economic actor at the centre of mainstream economics has been shown to provide an inadequate account of economic behaviour. Research using attitudinal surveys and experimental studies has emphasised the role of social preferences and 'irrational' choices in economic behaviour and has contested the notion that self-interest, rationality and self-control can explain everything (Rabin 2002, p.658). This research has emphasised the role of reciprocal fairness; of reference-based utility (changes matter more than absolutes); of unstable and ill-defined preferences; of hedonic adaptation (where material aspirations grow stronger the more one has already has); of status comparison ('keeping up with the Joneses'); and other psychological traits which appear to be 'illogical' (D'Orlando & Ferrante 2008; Fehr & Fischbacher 2002, pp.C29–C30; Rabin 2002, p.661; Easterlin 2004; Kahneman, Knetsch & Thaler 1991).

Summing up this literature in 2006, one of its early pioneers, Daniel Kahneman observed:

> A large literature from behavioural economics and psychology finds that people often make inconsistent choices, fail to learn from experience, exhibit reluctance to trade, base their own satisfaction on how their situation compares with the satisfaction of others and depart from the standard model of the rational economic agent in other ways. (Kahneman & Krueger 2006, p.3)

In other words, the core elements of 'rational choice theory' and the role of 'revealed preferences' are cast into doubt by the intervention of psychology into economics. This position has not gone uncontested and others have argued that when you observe people *interacting with institutions in particular settings*, they do behave according to the traditional economic model. Only when you ask them why they do things, or put them into experimental settings as isolated individuals, do they respond in the ways which psychologists report (Smith 1991).

Other economists have seen the growing interest in behavioural economics as a movement which can be accommodated within the mainstream, rather than as a challenge to its basic tenets. Commenting on the advent of 'second wave behavioural economics', Rabin (2002, p.658) has proposed a research program which replaces contestation about assumptions with a more systematic and formal approach. He does not want to abandon the 'correct insights of neoclassical economics', but rather to supplement them. His goal is to extend mainstream economics, not subvert it: 'the more realistic our assumptions about economic actors, the better our economics. Hence, economists should aspire to make our assumptions about humans as psychologically realistic as possible' (Rabin 2002, p.658).

This tradition of research throws light on the empirical findings in this report. It is important to appreciate just how few workers do actually change jobs: the figure was 17% in 2008. This relatively modest figure suggests considerable inertia, and implies that most people are reluctant to embrace change without a very good reason. The 'endowment effect', 'status quo bias' and 'loss aversion' are all part of the repertoire of behavioural economics which help to explain this inertia. As Kahneman, Knetsch & Thaler (1991, pp.197–8) noted: 'individuals have a strong tendency to remain at the status quo, because the disadvantages of leaving it loom larger than advantages'. One need only reflect on the myriad personal dislocations entailed in job changing to appreciate the force of this argument. Moreover, the studies of 'reference-based utility' have suggested that it is *changes* which matter more to individuals, than do *states*. And within this framework: 'changes that make things worse (losses) loom larger than improvements or gains' (Kahneman, Knetsch & Thaler 1991, p.199). Unless one is sure of a good outcome, why take the risk of changing.

But some workers do change jobs, and they usually have good reasons for so doing. As we have seen, workers are primarily motivated to change jobs because of dissatisfaction with their jobs and aspirations for a better job. But what is particularly interesting is that dissatisfaction with the 'nature of the work' and dissatisfaction with job insecurity were stronger motivators to change jobs than was dissatisfaction with the pay (figure 7). Clearly, in changing jobs individuals were looking beyond the immediate issue of the size of their pay packets and expressing a range of non-pecuniary preferences. Insecurity is particularly important. While the debate about the extent of labour market insecurity in Australia is far from settled,[13] it does appear that individual experiences of insecurity are the primary motivators for labour market behaviour. As shown in one of the previous chapters, workers in casual jobs were far more likely to change jobs. This partly reflects the temporary nature of many of these jobs, but it also reflects this flight from insecurity. The findings in this report have also emphasised the links between labour market churning, casualised employment and frequency of job changing. A fruitful future research task would be an exploration of the extent to which job changing among workers in these kinds of situations is voluntary—and might thereby reflect a strategy to escape insecurity—and how much it is involuntary—and simply reflects the extent of marginalisation among these workers.

The report has also demonstrated that personality traits mattered, although their influence is weaker than these labour market characteristics. The personality trait closest to the classic prescription of the economic actor is probably 'conscientousness'; yet this characteristic was associated with a tendency *not* to change jobs. The most likely person to change jobs was the extrovert. There seems to be no obvious economic reason for this, but there may be sound psychological reasons. Extroversion has been shown to be associated with high life satisfaction and happiness (Kahneman & Krueger 2006, p.9),

[13] See, for example, Australian Centre for Industrial Relations Research and Training (1999); Burgess & Campbell (1998); Wooden (2000); Wooden (2001).

suggesting that the focus here on fleeing a bad job must also be balanced with a recognition that some job moves are better considered as adventurism, seeing what else the labour market has to offer. This is certainly consistent with the findings in the first chapter, which showed that the desire for a better job was one of the main reasons to move on. Such a desire does not necessarily mean that the current job is a poor one; for many workers a job change may reflect this optimism to explore new possibilities. Again, future research might usefully explore these associations between personality types, job satisfaction scores and the stated reasons for changing jobs. Examining what is meant by changing to a 'better job' would also be a useful exercise.

Price signals and optimum outcomes

The first chapter in this report suggested considerable geographical immobility of labour in Australia. Only about 17% of workers changed their jobs in 2008 and of this group only about 31% actually moved their residence. In other words, only about 5% of workers both changed jobs and relocated during 2008. What's more, most of these movements were within local labour markets, with only about one-fifth moving more than 500 kilometres, and about one-third moving more than 100 kilometres.[14]

At the same time this report has shown that, on average, workers who changed jobs were *not* better off financially, although they were better off in terms of happiness and job quality. Other research, also using the survey data, concluded that job changers were unequivocally better off:

> substantial earnings increases are more prevalent for workers who change jobs than workers who do not. Changes in job are also associated with increases in job satisfaction. Together, these findings support the contention that job mobility leads to better labour market outcomes for the workers concerned.
>
> (Wilkins et al. 2010, p.63)

The satisfaction findings here are consistent with those in this report, but not the earnings results. The likely reasons for this discrepancy are differing populations and differing methodologies. The Wilkins et al. (2010) study did not restrict the population to adults and non-students, as has been done in this report. Movements from junior rates to adult rates, and from student jobs to graduate jobs, make such job changes more likely to lead to considerable increases in earnings. Secondly, Wilkins et al. (2010) relied on cross-tabulations and unadjusted summary statistics. By contrast, this report has made use of the matching estimators approach, which provides a far more robust method for assessing causality than do descriptive statistics.

Another study of labour mobility and earnings using survey data, that by Mitchell (2008), also found better earnings outcomes than reported here. He found that geographical mobility increased the likelihood of higher pay (2008, p.88). Unlike the

[14] It is likely that these figures under-estimate the true extent of geographical mobility for the labour force *as a whole*. Using ABS Labour Force data from 2004, Sweet (2010) shows that nearly 300 000 people who had been employed at some stage during the year had moved interstate during the year. This is a different population from the one considered in this report, since this analysis only tracks people who moved from job to job, while the ABS figures included movements into and out of work, and the in-scope population was anyone who held a job during the year. These larger ABS labour market flows are used by Sweet to highlight Australia's relatively high rates of geographical labour mobility in international terms (Sweet 2010). What this suggests is that the labour market as a whole may be characterised by greater mobility than is suggested by focusing on the currently employed adult employee workforce.

Wilkins et al. study, Mitchell modelled the data using a substantial number of covariates. However, the Mitchell study was focused on migration, rather than job changes per se, so again there is limited comparability with the present study.

Returning to this current report, if we combine the two key findings—no net financial benefit in job changing and limited geographical mobility among workers—we are immediately struck by the fact that the labour market does not seem to be working as a market might be expected to. In particular, price signals do not seem to be reallocating labour in the way that market theory presupposes. If the wage is the price for labour, and if all these movements between jobs don't lead, on average, to higher wages for those doing the moving, something seems to be amiss. The mainstream response to anomalies like these is not to question the fiction of labour as a commodity; rather, the response is to lament 'market failure', and to renew attempts to fashion policies which try to coerce labour to act more like a commodity.

Here is where Polanyi's insights have value. What matters about human economic activity is that it is embedded in human relationships, and that the location for activity—the workplace—is also a network of human relationships. Neither an orange nor a washing machine can form an attachment to its surroundings, let alone to other oranges or washing machines. But people do buy homes, grow to like their neighbourhood, try to live near their ageing parents, and are loath to move without very good reason. In many cases, they have little choice: if the value of their current house is well below the cost of housing in places with high labour demand—such as the large cities or the mining towns of outback Western Australia—then geographical movement is out of the question.

In a similar way, there is an inertia in place at the workplace because it is a site embedded in human relationships. Studies within the sociology of work have long shown that, apart from the money, the 'sociability' of the workplace is what motivates workers to show up each day, particularly those stuck in dead-end jobs. The expression of humanity through working—such as the exercise of skill or the derivation of satisfaction from a job well done—is integral to economic production. In this respect, the other important findings of this report are particularly relevant. People change jobs because they are unhappy in their current job, or aspire to a better job, and they find, on average, greater happiness in their new jobs and more opportunities to exercise their skills. These findings are more than just an endorsement of the behaviourist economics framework discussed in the last section. They undermine the notion that labour can be expended outside its embodiment in human relationships.

Polanyi was, of course, writing at the time of the Second World War, in the decade following the calamity of the Great Depression and on the eve of the welfare states constructed in the post-war decade. Faith in self-regulating markets, and the broader philosophy of laissez-faire, was in abeyance. Keynesian economics and the experience of war-time planned economies gave governments optimism that markets might be tamed. However, by the 1970s, with the emergence of neoliberalism, the concept of self-regulating markets was given a rebirth. Evident in many of the Organisation for Economic Co-operation and Development (OECD) publications over the last few decades has been the premise that labour markets should act more like self-regulating markets and less like the regulated welfare-state labour markets of the post-war period. The 1994 OECD *Jobs Study*, with its attack on labour market institutions and its radical calls for labour market deregulation, provided a classic restatement of this policy perspective (see the comments, for example, by Freeman 2005, p.3).

Not surprisingly, neoliberalism is blind to Polanyi's insights. Instead of realising that working and moving between jobs can never be forms of commodity expenditure nor commodity transactions, those labour market policies inspired by neoliberalism have sought in vain to 'fix' labour markets. The goal has been to make the labour market more self-regulating, in line with market deregulation in other fields. But two of the key findings in this report emphasise the futility of this aspiration.

Of course, a considerable amount of successful firm worker 'matching' does go on, and existing bad matches are replaced by better matches. These are certainly optimum outcomes in terms of efficiency and equity. But, on reflection, this can be seen as the useful working-out in practice of modern-day 'labour exchanges', like *Seek* or the classifieds. By any definition, it does not reflect the operations of a self-regulating market. The conclusion one draws from this analysis is that fostering the efficient functioning of these modern-day labour exchanges is a more realistic goal than trying to make labour markets 'work'.

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Appendix

Table A1 Changing jobs and type of job change, Australia 2002

	Changed job in last year		
	Population estimates	**Percentages**	**Sample size**
No	4,721,879	85.3	4,157
Yes	813,515	14.7	721
Total	5,535,394	100	4,878
	Type of job change		
	Changed ind & job	**Changed only job**	**Total**
Population estimates			
Changed occ. & job	264,382	97,917	362,299
Changed only job	160,688	241,923	402,611
Total	425,070	339,840	764,910
Percentages			
Changed occ. & job	32.5	12.0	44.5
Changed only job	19.8	29.7	49.5
Total	52.3	41.8	94.0
Sample size			
Changed occ. & job	234	87	321
Changed only job	142	217	359
Total	376	304	680

Notes: Weighted by cross-sectional weights.
Population: top panel = adult employees not studying full-time; bottom panel = adult employees not studying full-time who changed jobs in last year and provided relevant information.
Source: HILDA Release 8.

Table A2 Changing jobs and type of job change, Australia 2008

	Changed job in last year		
	Population estimates	Percentages	Sample size
No	6,132,856	83.2	4,541
Yes	1,236,749	16.8	970
Total	7,369,604	100	5,511

	Type of job change		
	Changed ind & job	Changed only job	Total
Population estimates			
Changed occ. & job	354,782	129,578	484,360
Changed only job	265,307	319,368	584,675
Total	620,089	448,946	1,069,035
Percentages			
Changed occ. & job	28.7	10.5	39.2
Changed only job	21.5	25.8	47.3
Total	50.1	36.3	86.4
Sample size			
Changed occ. & job	285	106	391
Changed only job	205	245	450
Total	490	351	841

Notes: Weighted by cross-sectional weights.
Population: top panel = adult employees not studying full-time; bottom panel = adult employees not studying full-time who changed jobs in last year and provided relevant information.
Source: HILDA Release 8.

Table A3 Reasons for changing jobs, Australia 2002

	Population estimates	Percentages	Sample size
	Persons who changed job in last year		
No	4,721,879	85.3	4,157
Yes	813,515	14.7	721
Total	5,535,394	100	4,878
	Reasons for changing job		
Job was temporary	77,801	9.6	65
Retrenched from job	180,938	22.2	152
Dissatisfied with job	265,177	32.6	234
Left for a better job	167,662	20.6	152
Other reasons	121,937	15	118
Total	813,515	100	721

Notes: Weighted by cross-sectional weights.
Population: top panel = adult employees not studying full-time; bottom panel = adult employees not studying full-time who changed jobs in last year.
Source: HILDA Release 8.

Table A4 Reasons for changing jobs, Australia 2008

	Population estimates	Percentages	Sample size
	Persons who changed job in last year		
No	6,132,856	83.2	4,541
Yes	1,236,749	16.8	970
Total	7,369,604	100	5,511
	Reasons for changing job		
Job was temporary	46,570	3.8	42
Retrenched from job	180,384	14.6	124
Dissatisfied with job	428,479	34.7	336
Left for a better job	359,057	29.1	276
Other reasons	220,532	17.9	191
Total	1,235,023	100	969

Notes: Weighted by cross-sectional weights.
Population: top panel = adult employees not studying full-time; bottom panel = adult employees not studying full-time who changed jobs in last year.
Source: HILDA Release 8.

Table A5 Changing jobs and moving, Australia 2002

	Population estimates	Percentages	Sample size
	Persons who changed job in last year		
Didn't move	596,548	73.8	485
Moved	212,317	26.2	230
Total	808,864	100	715
	Distance moved by job changers		
Moved less than 5 km	62,547	29.5	62
Moved 5 to 9 km	24,582	11.6	26
Moved 10 to 19 km	18,556	8.7	23
Moved 20 to 99 km	22,851	10.8	23
Moved 100 to 499 km	32,051	15.1	36
Moved 500 km or more	51,728	24.4	60
Total	212,317	100	230

Notes: Weighted by cross-sectional weights.
Population: top panel = adult employees not studying full-time who changed jobs in the last year; bottom panel = adult employees not studying full-time who changed jobs in last year and who moved residence.
Source: HILDA Release 8.

Table A6 Changing jobs and moving, Australia 2008

	Population estimates	Percentages	Sample size
	Persons who changed job in last year		
Didn't move	845,912	68.6	596
Moved	386,426	31.4	369
Total	1,232,338	100	965
	Distance moved by job changers		
Moved less than 5 km	102,416	26.5	96
Moved 5 to 9 km	64,080	16.6	48
Moved 10 to 19 km	45,334	11.7	46
Moved 20 to 99 km	48,132	12.5	46
Moved 100 to 499 km	50,609	13.1	59
Moved 500 km or more	75,856	19.6	74
Total	386,426	100	369

Notes: Weighted by cross-sectional weights.
Population: top panel = adult employees not studying full-time who changed jobs in the last year; bottom panel = adult employees not studying full-time who changed jobs in last year and who moved residence.
Source: HILDA Release 8.

Table A7 Reasons for persons moving, Australia 2002

	Population estimates	Percentages	Sample size
	Persons who moved in last year		
Didn't move	4,947,693	83.2	4,231
Moved	995,804	16.8	974
Total	5,943,498	100	5,205
	Reasons for moving		
Lifestyle-related	151,011	13.2	159
Family-related	287,936	25.1	326
Housing-related	726,396	63.3	702
Other work-related	115,600	10.1	119
To look for a job	10,619	0.9	13
To start a new job	67,241	5.9	66

Notes: Weighted by cross-sectional weights. Multiple responses allowed, so totals in bottom panel exceed 100%.
Population: top panel = adult employees not studying full-time; bottom panel = adult employees not studying full-time who moved in the last year.
Source: HILDA Release 8.

Table A8 Reasons for persons moving, Australia 2008

	Population estimates	Percentages	Sample size
	Persons who moved in last year		
Didn't move	6,479,636	84.2	4,639
Moved	1,218,695	15.8	1,141
Total	7,698,331	100	5,780
	Reasons for moving		
Lifestyle-related	193,379	14.8	170
Family-related	370,317	28.4	350
Housing-related	692,554	53.1	659
Other work-related	136,463	10.5	125
To look for a job	9,669	0.7	9
To start a new job	83,103	6.4	78

Notes: Weighted by cross-sectional weights. Multiple responses allowed, so totals in bottom panel exceed 100%.
Source: HILDA Release 8.
Population: top panel = adult employees not studying full-time; bottom panel = adult employees not studying full-time who moved in the last year.

Table A9 Characteristics of job changers—probit model results

	Male		Female		All persons	
	Coef.	P value	Coef.	P value	Coef.	P value
Female					-0.002	0.948
Aged 25–29	0.027	0.695	-0.043	0.554	-0.019	0.706
Aged 30–34	-0.044	0.541	-0.134	0.086	-0.102	0.053
Aged 35–39	-0.133	0.080	-0.119	0.144	-0.147	0.008
Aged 40–44	-0.234	0.003	-0.254	0.001	-0.260	0.000
Aged 45–49	-0.281	0.001	-0.427	0.000	-0.358	0.000
Aged 50–54	-0.360	0.000	-0.489	0.000	-0.412	0.000
Aged 55–59	-0.274	0.007	-0.632	0.000	-0.426	0.000
Aged 60–64	-0.810	0.000	-0.607	0.000	-0.667	0.000
Aged 65 plus	-0.392	0.049	-0.843	0.002	-0.531	0.001
Balance NSW	0.011	0.873	-0.080	0.300	-0.019	0.718
Melbourne	-0.019	0.753	0.084	0.186	0.028	0.530
Balance Vic.	-0.081	0.384	0.056	0.532	0.003	0.969
Brisbane	0.193	0.006	0.195	0.009	0.190	0.000
Balance Qld	0.110	0.116	0.165	0.023	0.134	0.008
Adelaide	0.161	0.065	-0.026	0.774	0.066	0.291
Balance SA	0.013	0.921	0.013	0.924	0.003	0.972
Perth	0.226	0.004	0.195	0.024	0.208	0.000
Balance WA	0.038	0.777	0.341	0.016	0.170	0.079
Tasmania	-0.107	0.382	-0.147	0.196	-0.129	0.120
NT	-0.080	0.681	0.701	0.000	0.362	0.004
ACT	0.287	0.024	0.362	0.006	0.306	0.001
Couple	0.064	0.165	-0.080	0.061	-0.012	0.688
One dependent child	0.019	0.722	-0.157	0.005	-0.061	0.110
Two dependent child	-0.046	0.400	-0.166	0.008	-0.096	0.019
Three or more dep child	0.015	0.843	-0.055	0.554	-0.005	0.927
Paying mortgage	0.087	0.105	-0.043	0.421	0.020	0.597
Renting private	0.143	0.016	0.047	0.440	0.090	0.033
Renting public	-0.185	0.179	-0.278	0.035	-0.218	0.022
Tenure: other	-0.066	0.618	0.016	0.908	-0.052	0.583
Born ES country	0.000	0.996	0.078	0.227	0.037	0.398
Born NESB country	-0.057	0.380	-0.183	0.006	-0.129	0.006
Not Indigenous	-0.081	0.626	-0.058	0.699	-0.077	0.487
Vocational qualifications	-0.031	0.578	0.015	0.790	-0.017	0.674
Year 12	-0.092	0.167	-0.049	0.461	-0.086	0.067
Year 11 or below	-0.093	0.175	-0.067	0.317	-0.096	0.045
Professionals	-0.040	0.542	-0.053	0.492	-0.033	0.509
Technicians & trades	-0.020	0.772	-0.241	0.045	-0.089	0.123
Service workers	-0.061	0.533	-0.176	0.047	-0.125	0.046
Clerical workers	-0.170	0.037	-0.143	0.062	-0.128	0.016
Salesworkers	0.002	0.985	-0.059	0.541	-0.017	0.801
Machinery & transport	-0.039	0.627	-0.506	0.016	-0.093	0.186
Labourers	-0.025	0.761	-0.227	0.028	-0.099	0.122
Mining	-0.021	0.889	0.394	0.205	0.059	0.655
Manufacturing	-0.128	0.265	0.039	0.841	-0.069	0.486
Electricity, gas, water etc.	-0.039	0.824	-0.091	0.767	-0.040	0.792
Construction	0.110	0.358	0.034	0.888	0.152	0.150
Wholesale trade	-0.080	0.549	0.072	0.731	-0.030	0.789
Retail trade	-0.091	0.474	-0.006	0.974	-0.054	0.607
Accommodation & food services	0.105	0.454	0.258	0.177	0.175	0.102
Transport, postal & warehousing	0.044	0.731	0.137	0.539	0.085	0.445
Information media & telecommunic	-0.170	0.265	-0.036	0.867	-0.118	0.331
Financial & insurance services	0.040	0.780	-0.087	0.669	-0.053	0.639
Rental, hiring & real estate serv.	0.097	0.595	0.111	0.629	0.105	0.448
Professional, scient & tech serv.	-0.187	0.148	0.001	0.995	-0.109	0.298

Table A9 Characteristics of job changers—probit model results (continued)

	Male		Female		All persons	
	Coef.	P value	Coef.	P value	Coef.	P value
Administrative & support services	0.082	0.607	0.107	0.594	0.072	0.538
Public administration & safety	-0.347	0.008	-0.105	0.598	-0.234	0.029
Education & training	-0.261	0.057	-0.375	0.052	-0.368	0.001
Health care & social assistance	-0.214	0.127	-0.104	0.580	-0.164	0.110
Arts & recreation services	-0.205	0.203	0.158	0.487	-0.038	0.769
Other services	-0.040	0.769	0.053	0.799	-0.000	0.998
Not casual	-0.202	0.001	-0.235	0.000	-0.233	0.000
Full-time	-0.038	0.594	0.094	0.060	0.094	0.016
Prefer same hours	-0.052	0.235	-0.079	0.095	-0.058	0.073
Prefer more hours	-0.024	0.722	0.111	0.093	0.071	0.129
Not union member	0.110	0.015	0.095	0.056	0.103	0.002
Org. size: 20 to 99	-0.110	0.045	-0.056	0.346	-0.094	0.019
Org. size: 100 to 499	-0.170	0.002	-0.142	0.015	-0.169	0.000
Org. size: 500 plus	-0.253	0.000	-0.279	0.000	-0.273	0.000
Occupational tenure (yrs)	-0.028	0.268	0.007	0.807	-0.009	0.626
Job tenure (yrs)	-0.280	0.000	-0.225	0.000	-0.255	0.000
Not supervisor	-0.061	0.113	-0.104	0.011	-0.080	0.004
Did not receive training	0.063	0.091	0.137	0.001	0.100	0.000
Second earnings quintile	0.049	0.389	-0.061	0.244	-0.006	0.882
Middle earnings quintile	0.050	0.397	-0.120	0.036	-0.026	0.518
Fourth earnings quintile	-0.072	0.271	-0.140	0.032	-0.093	0.043
Top earnings quintile	-0.006	0.935	-0.069	0.352	-0.027	0.588
NILF: under 6 mths	-0.040	0.635	0.033	0.644	0.000	0.993
NILF: 6 to under 12 mths	0.389	0.022	0.027	0.801	0.086	0.330
NILF: 12 mths	-0.081	0.846	0.364	0.046	0.269	0.101
Unemployed – some period	0.346	0.000	0.075	0.275	0.200	0.000
Extrovert	0.109	0.000	0.088	0.000	0.101	0.000
Agreeable	-0.005	0.813	0.024	0.240	0.005	0.734
Conscientous	-0.037	0.058	0.023	0.256	-0.008	0.558
Stable	-0.026	0.183	0.043	0.046	0.005	0.722
Open	0.014	0.495	0.085	0.000	0.051	0.001
Pay satisfaction	-0.081	0.000	-0.074	0.000	-0.079	0.000
Job security satisfaction	-0.152	0.000	-0.147	0.000	-0.152	0.000
Nature work satisfaction	-0.108	0.000	-0.141	0.000	-0.119	0.000
Hours satisfaction	0.007	0.765	-0.034	0.137	-0.015	0.347
Job flexibility satisfaction	-0.018	0.367	-0.015	0.480	-0.016	0.280
2004	0.003	0.948	0.022	0.704	0.013	0.738
2005	0.027	0.611	0.098	0.082	0.057	0.135
2006	0.015	0.775	0.099	0.082	0.050	0.196
2007	0.001	0.984	0.142	0.013	0.067	0.087
Intercept	-0.678	0.007	-0.491	0.081	-0.608	0.001
Sigma	0.301		0.344		0.345	
Rho	0.083		0.106		0.107	
Log likelihood	-3805.33		-3531.34		-7411.12	
Number of obs	10,574		10,501		21,075	
Number of groups	2,924		3,090		6,014	

Notes: Dependent variable: changed jobs between waves. Coef. = coefficients; P value = significance level. Models fitted using random effects probit using Stata's `xtprobit` command.

Omitted categories: male (in all persons); aged 21–24 years; Sydney; single; own house; born Australia; Indigenous; university qualifications; managers; agriculture, forestry & fishing; casual; part-time; prefer fewer hours; union member; org. size: under 20; received training; bottom earnings quintile; NILF: no period; Unemployed: no period; 2003.

Population: adult employees not studying full-time in Waves 3 to 8.

Source: HILDA Release 8.

Table A10 Demographic characteristics of job changers

	Male			Female			All persons		
	Est.	LB	UB	Est.	LB	UB	Est.	LB	UB
Aged 21–24	17.5	14.9	20.1	17.7	15.1	20.2	17.6	15.7	19.4
Aged 25–29	18.1	15.9	20.3	16.7	14.4	19.0	17.2	15.6	18.8
Aged 30–34	16.5	14.6	18.4	14.8	12.8	16.9	15.4	14.0	16.8
Aged 35–39	14.7	12.8	16.5	15.1	13.0	17.3	14.5	13.1	15.9
Aged 40–44	12.7	11.0	14.5	12.6	10.8	14.4	12.3	11.1	13.6
Aged 45–49	11.9	10.0	13.8	9.8	8.2	11.3	10.7	9.5	11.9
Aged 50–54	10.6	8.5	12.8	8.9	7.1	10.7	9.8	8.4	11.3
Aged 55–59	12.0	9.3	14.8	7.1	5.0	9.2	9.6	7.9	11.4
Aged 60–64	5.1	2.5	7.6	7.4	4.1	10.6	6.5	4.4	8.7
Aged 65 plus	10.1	4.4	15.8	5.0	0.4	9.5	8.2	4.2	12.1
Born Australia	14.4	13.5	15.3	13.1	12.2	13.9	13.6	13.0	14.3
Born ES country	14.4	12.3	16.6	14.5	12.2	16.8	14.3	12.8	15.9
Born NESB country	13.3	11.1	15.6	10.1	8.3	12.0	11.4	9.9	12.8
Indigenous	15.9	9.3	22.5	13.9	8.5	19.3	14.9	10.6	19.2
Not Indigenous	14.3	13.5	15.1	12.9	12.1	13.7	13.5	12.9	14.0
Sydney	13.2	11.5	14.9	11.5	9.9	13.0	12.2	11.1	13.4
Balance NSW	13.4	11.4	15.4	10.2	8.4	12.1	11.9	10.5	13.3
Melbourne	12.8	11.3	14.4	12.9	11.3	14.5	12.7	11.6	13.8
Balance Vic.	11.8	9.1	14.4	12.4	9.8	15.0	12.3	10.4	14.2
Brisbane	17.0	14.8	19.3	15.0	12.7	17.2	15.8	14.2	17.4
Balance Qld	15.3	13.2	17.3	14.4	12.3	16.4	14.7	13.2	16.1
Adelaide	16.3	13.3	19.4	11.1	8.6	13.5	13.4	11.4	15.4
Balance SA	13.4	9.0	17.8	11.7	7.5	15.9	12.3	9.2	15.3
Perth	17.8	15.0	20.6	15.0	12.2	17.8	16.2	14.2	18.2
Balance WA	13.9	9.3	18.5	18.0	12.3	23.7	15.4	11.8	19.0
Tasmania	11.3	7.7	15.0	9.3	6.4	12.1	10.1	7.8	12.4
NT	11.8	5.5	18.1	26.9	18.2	35.6	19.6	14.0	25.2
ACT	19.1	13.7	24.6	18.5	13.1	23.8	18.3	14.5	22.1
University qualifications	15.2	13.5	16.9	13.2	11.7	14.7	14.2	13.1	15.3
Vocational qualifications	14.6	13.3	15.8	13.5	12.1	14.8	13.9	13.0	14.8
Year 12	13.4	11.6	15.2	12.3	10.7	14.0	12.6	11.4	13.9
Year 11 or below	13.4	11.7	15.1	12.0	10.5	13.6	12.4	11.3	13.6
Single	13.5	12.1	14.9	13.8	12.5	15.1	13.6	12.7	14.6
Couple	14.7	13.7	15.7	12.4	11.5	13.3	13.4	12.7	14.1
No dependent child	14.4	13.4	15.4	13.9	12.8	15.0	14.0	13.2	14.7
One dependent child	14.8	13.0	16.6	11.2	9.7	12.7	12.8	11.7	14.0
Two dependent child	13.5	11.8	15.2	11.1	9.4	12.7	12.2	11.0	13.4
Three or more dep child	14.7	12.0	17.4	12.9	9.9	15.9	13.9	11.8	15.9
Own house	12.8	11.1	14.5	13.1	11.5	14.8	12.9	11.7	14.1
Paying mortgage	14.4	13.3	15.5	12.4	11.3	13.4	13.3	12.5	14.0
Renting private	15.5	14.1	16.9	14.0	12.6	15.4	14.6	13.6	15.6
Renting public	9.8	6.0	13.5	8.8	5.5	12.1	9.4	6.9	11.9
Tenure: other	11.6	7.6	15.7	13.4	8.8	18.0	12.0	9.0	15.0

Note: Est. = estimate; LB = lower bound; UB = upper bound (95% confidence interval). Numbers show predicted probabilities of job changing as percentages. Based on models shown in appendix table A9. Standard errors calculated using the delta method.

Table A11 Labour market characteristics of job changers

	Male			Female			All persons		
	Est.	LB	UB	Est.	LB	UB	Est.	LB	UB
Managers	15.1	13.0	17.1	15.0	12.5	17.5	14.8	13.2	16.4
Professionals	14.3	12.4	16.1	14.0	12.3	15.7	14.2	12.9	15.4
Technicians & trades	14.7	13.0	16.3	10.8	7.8	13.9	13.1	11.7	14.6
Service workers	13.9	10.8	16.9	11.9	10.0	13.7	12.5	10.9	14.1
Clerical workers	11.9	9.7	14.1	12.4	11.0	13.8	12.4	11.2	13.7
Salesworkers	15.1	11.9	18.3	13.9	11.3	16.5	14.5	12.5	16.5
Machinery & transport	14.3	12.1	16.5	7.3	2.8	11.7	13.1	11.1	15.0
Labourers	14.6	12.3	16.8	11.0	8.7	13.4	13.0	11.3	14.6
Agriculture, forestry, fishing	16.0	11.6	20.5	13.7	7.0	20.4	14.9	11.2	18.5
Mining	15.6	11.4	19.8	22.5	9.7	35.2	16.1	12.1	20.1
Manufacturing	13.5	11.8	15.2	14.4	11.3	17.6	13.5	12.0	15.1
Electricity, gas, water etc.	15.2	9.7	20.7	12.1	3.7	20.4	14.1	9.4	18.7
Construction	18.5	15.7	21.2	14.3	8.3	20.4	18.1	15.6	20.7
Wholesale trade	14.4	11.3	17.5	15.1	10.8	19.4	14.3	11.8	16.8
Retail trade	14.2	11.5	16.9	13.6	10.9	16.2	13.8	11.9	15.7
Accommodation & food services	18.3	14.2	22.5	19.1	15.7	22.6	18.7	16.0	21.3
Transport, postal & warehousing	17.0	13.9	20.1	16.4	11.1	21.8	16.6	13.9	19.3
Information media & telecommunic	12.7	9.0	16.5	13.0	9.1	17.0	12.6	9.9	15.3
Financial & insurance services	16.9	13.0	20.8	12.1	9.1	15.2	13.8	11.4	16.2
Rental, hiring & real estate services	18.2	11.6	24.7	15.9	10.0	21.7	17.1	12.7	21.5
Professional, scient & techl services	12.4	10.0	14.8	13.7	11.2	16.2	12.8	11.1	14.5
Administrative & support services	17.8	12.5	23.1	15.8	11.9	19.7	16.4	13.2	19.5
Public administration & safety	9.8	7.7	11.9	11.8	9.3	14.4	10.7	9.0	12.3
Education & training	11.2	8.4	13.9	7.9	6.3	9.4	8.7	7.3	10.0
Health care & social assistance	12.0	9.0	14.9	11.8	10.3	13.3	11.8	10.4	13.2
Arts & recreation services	12.1	8.0	16.2	16.9	11.0	22.8	14.1	10.7	17.6
Other services	15.2	11.7	18.7	14.7	10.6	18.8	14.9	12.2	17.5
First earnings quintile	14.2	12.4	16.0	14.2	12.7	15.7	14.0	12.8	15.1
Second earnings quintile	15.2	13.5	16.8	13.1	11.7	14.5	13.9	12.8	15.0
Middle earnings quintile	15.2	13.6	16.7	12.1	10.7	13.5	13.5	12.4	14.5
Fourth earnings quintile	12.9	11.4	14.4	11.7	10.1	13.3	12.3	11.2	13.4
Top earnings quintile	14.1	12.4	15.8	12.9	10.9	14.9	13.5	12.2	14.8
Casual	17.9	15.4	20.4	16.3	14.4	18.1	17.3	15.7	18.8
Not casual	13.7	12.9	14.6	11.9	11.0	12.8	12.6	12.0	13.3
Part-time	15.0	12.4	17.5	12.0	10.9	13.1	12.3	11.2	13.3
Full-time	14.2	13.4	15.1	13.6	12.5	14.8	14.0	13.2	14.7
Prefer fewer hours	14.9	13.5	16.4	13.3	11.9	14.7	13.9	12.9	14.9
Prefer same hours	13.9	12.9	14.9	11.9	11.0	12.9	12.8	12.1	13.5
Prefer more hours	14.5	12.4	16.6	15.4	13.4	17.5	15.2	13.8	16.7
NILF: none	14.3	13.5	15.1	12.8	11.9	13.6	13.4	12.8	14.0
NILF: under 6 mths	13.5	10.5	16.6	13.3	10.9	15.8	13.4	11.5	15.3
NILF: 6 to under 12 mths	23.0	14.5	31.6	13.2	9.6	16.9	15.0	11.7	18.4
NILF: 12 mths	12.8	-1.7	27.3	20.2	11.9	28.5	19.0	11.6	26.4
Unemployed: no period	13.8	13.0	14.6	12.8	12.0	13.6	13.2	12.6	13.7
Unemployed: some period	21.4	18.0	24.8	14.1	11.6	16.6	17.2	15.1	19.2

Note: Est. = estimate; LB = lower bound; UB = upper bound (95% confidence interval). NILF = Not in the labour force. Numbers show predicted probabilities of job changing as percentages. Based on models shown in appendix table A9. Standard errors calculated using the delta method.

Table A12 Workplace characteristics of job changers

	Male			Female			All persons		
	Est.	LB	UB	Est.	LB	UB	Est.	LB	UB
Org. size: under 20	17.4	15.7	19.2	15.8	14.0	17.5	16.6	15.4	17.8
Org. size: 20 to 99	15.1	13.4	16.8	14.6	12.9	16.4	14.7	13.5	15.9
Org. size: 100 to 499	13.9	12.4	15.5	13.0	11.5	14.6	13.2	12.2	14.3
Org. size: 500 plus	12.4	11.2	13.6	10.8	9.7	11.8	11.4	10.6	12.2
Supervisor	14.9	13.8	15.9	13.9	12.8	15.1	14.2	13.5	15.0
Not supervisor	13.7	12.6	14.8	12.1	11.1	13.1	12.8	12.0	13.5
Union member	12.7	11.3	14.2	11.6	10.2	13.1	12.0	11.0	13.1
Not union member	14.8	13.9	15.7	13.2	12.4	14.1	13.9	13.3	14.5
Received training	13.6	12.5	14.7	11.5	10.4	12.6	12.4	11.6	13.2
Did not receive training	14.8	13.8	15.8	13.9	12.9	14.9	14.2	13.5	14.9

Note:Est. = estimate; LB = lower bound; UB = upper bound (95% confidence interval). Numbers show predicted probabilities of job changing as percentages. Based on models shown in appendix table A9. Standard errors calculated using the delta method.

Table A13 Means and standard deviations of continuous variables

		Male		Female	
	Original measure	Mean	Standard deviation	Mean	Standard deviation
Occupational tenure	Years	10.2	10.1	9.2	9.5
Job tenure	Years	7.7	8.4	6.6	7.2
Extroversion	Scored1–7	4.3	1.0	4.6	1.1
Agreeableness	Scored 1–7	5.1	0.9	5.6	0.8
Conscientousness	Scored 1–7	5.0	1.0	5.3	1.0
Stability	Scored 1–7	5.1	1.1	5.2	1.1
Openness	Scored 1–7	4.3	1.0	4.2	1.0
Satisfaction with pay	Scored 0–10	7.1	2.0	7.0	2.1
Satisfaction with work itself	Scored 0–10	7.6	1.8	7.7	1.8
Satisfaction with the hours	Scored 0–10	7.2	2.0	7.4	2.1
Satisfaction with job flexibility	Scored 0–10	7.3	2.3	7.5	2.3
Satisfaction with job security	Scored 0–10	8.0	2.0	8.2	2.0

Notes: To appreciate the x-axis scales used in the graphs, one needs to relate the range of -2 to 2 shown there to the original measures. 0 on the x-axis is the mean, shown above, and the units on the x-axis are standard deviations, also shown above. The scores referred to here are rating scales in the HILDA questionnaire, where 0/1 is low and 7/10 are high.
Population: adult employees not studying full-time.
Source: HILDA Release 8.

Table A14 Balance statistics for genetic matching

	2002 Cohort			2005 Cohort			2007 Cohort		
	Treatment	Control before	Control after	Treatment	Control before	Control after	Treatment	Control before	Control after
Changed job last year	0.33	0.10	0.24	0.32	0.12	0.24	0.34	0.12	0.18
Prev hourly rate	23.58	25.87	23.71	25.29	27.56	25.06	25.38	28.63	26.19
Prev satis with job overall	6.80	7.75	7.71	7.01	7.75	7.59	6.85	7.84	7.62
Prev satis with pay	6.26	6.98	6.88	6.56	7.16	7.01	6.62	7.23	7.03
Prev satis with job security	7.15	8.12	7.85	7.52	8.19	7.99	7.64	8.36	8.11
Prev satis with nature work	7.02	7.73	7.61	7.12	7.71	7.42	7.05	7.75	7.52
Prev satis with hours	6.81	7.28	7.12	7.05	7.34	7.16	6.89	7.39	7.26
Prev satis with flexibility	6.94	7.38	7.41	7.25	7.38	7.37	7.10	7.49	7.50
Prev opportunity new skills	4.39	4.70	4.71	4.53	4.75	4.60	4.47	4.68	4.67
Prev use of skills	5.08	5.46	5.34	5.20	5.49	5.24	5.19	5.51	5.29
Prev occupational status	49.46	53.14	50.15	50.54	54.07	51.65	50.06	54.23	50.02
Prev annual wage	46240.00	52357.00	48047.00	50120.00	55108.00	51360.00	49354.00	57438.00	53104.00
Female	0.48	0.49	0.50	0.49	0.49	0.47	0.49	0.50	0.48
Age	36.25	41.55	37.51	35.61	42.06	39.12	36.84	42.46	37.32
Vic	0.23	0.27	0.23	0.26	0.26	0.27	0.25	0.26	0.26
Qld	0.20	0.20	0.22	0.23	0.21	0.23	0.27	0.22	0.21
SA	0.12	0.09	0.07	0.09	0.08	0.05	0.08	0.09	0.06
WA	0.12	0.09	0.11	0.10	0.09	0.09	0.10	0.08	0.10
Tas	0.03	0.03	0.03	0.02	0.04	0.01	0.03	0.04	0.02
NT	0.00	0.00	0.00	0.02	0.01	0.02	0.01	0.01	0.01
ACT	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03
Non-metropolitan	0.36	0.38	0.41	0.38	0.39	0.35	0.34	0.38	0.33
Married or defacto couple	0.68	0.73	0.70	0.67	0.74	0.68	0.66	0.75	0.71
One dependent child	0.14	0.15	0.11	0.12	0.16	0.10	0.14	0.17	0.11
Two dependent children	0.17	0.18	0.13	0.18	0.18	0.21	0.13	0.17	0.19
Three dependent children	0.07	0.08	0.07	0.05	0.06	0.06	0.04	0.05	0.03

Table A14 Balance statistics for genetic matching (continued)

	2002 Cohort			2005 Cohort			2007 Cohort		
	Treatment	Control before	Control after	Treatment	Control before	Control after	Treatment	Control before	Control after
Paying mortgage	0.51	0.54	0.56	0.49	0.56	0.55	0.45	0.54	0.51
Renting private	0.31	0.17	0.22	0.33	0.19	0.27	0.38	0.21	0.33
Renting public	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.00
Housing - other	0.02	0.02	0.01	0.02	0.02	0.02	0.01	0.02	0.01
Born English speaking country	0.12	0.11	0.08	0.10	0.11	0.08	0.08	0.10	0.05
Born Non-English speaking country	0.11	0.10	0.07	0.07	0.10	0.06	0.09	0.09	0.09
Not indigenous	0.99	0.99	0.99	0.98	0.99	0.98	0.97	0.99	0.97
University qualifications	0.27	0.31	0.32	0.31	0.33	0.28	0.34	0.32	0.32
Vocational qualifications	0.35	0.32	0.30	0.33	0.34	0.33	0.33	0.35	0.31
Year 11 or below	0.20	0.25	0.22	0.18	0.21	0.20	0.17	0.20	0.16
Managers	0.10	0.11	0.11	0.12	0.11	0.12	0.12	0.11	0.11
Professionals	0.27	0.29	0.27	0.26	0.30	0.28	0.26	0.30	0.23
Technicians & trades	0.13	0.12	0.11	0.13	0.11	0.13	0.13	0.12	0.12
Service workers	0.08	0.10	0.09	0.09	0.10	0.08	0.08	0.11	0.10
Salesworkers	0.07	0.05	0.06	0.10	0.06	0.09	0.09	0.06	0.08
Machinery & transport	0.07	0.07	0.06	0.06	0.07	0.06	0.07	0.05	0.06
Labourers	0.12	0.06	0.09	0.07	0.07	0.08	0.09	0.08	0.10
Primary industry	0.05	0.03	0.05	0.03	0.04	0.03	0.04	0.04	0.04
Utilities	0.01	0.01	0.01	0.00	0.02	0.00	0.01	0.01	0.01
Construction	0.06	0.03	0.06	0.06	0.04	0.05	0.08	0.04	0.07
Wholesale	0.05	0.03	0.03	0.07	0.03	0.05	0.05	0.02	0.04
Retail	0.08	0.07	0.07	0.12	0.07	0.11	0.09	0.07	0.08
Accommodation, cafes etc	0.09	0.03	0.05	0.07	0.03	0.05	0.08	0.03	0.07
Transport	0.04	0.05	0.03	0.04	0.05	0.04	0.04	0.05	0.02
Information services	0.07	0.03	0.04	0.02	0.02	0.01	0.03	0.03	0.03

Table A14 Balance statistics for genetic matching (continued)

	2002 Cohort			2005 Cohort			2007 Cohort		
	Treatment	Control before	Control after	Treatment	Control before	Control after	Treatment	Control before	Control after
Finance & insurance	0.04	0.03	0.04	0.03	0.04	0.03	0.04	0.04	0.06
Business services	0.12	0.09	0.12	0.14	0.09	0.13	0.14	0.11	0.16
Government	0.03	0.11	0.05	0.06	0.11	0.07	0.06	0.10	0.06
Education	0.07	0.15	0.11	0.08	0.16	0.09	0.05	0.15	0.05
Health & community	0.11	0.15	0.14	0.11	0.16	0.17	0.14	0.17	0.15
Other services	0.06	0.05	0.05	0.04	0.04	0.04	0.07	0.04	0.06
Casual	0.26	0.13	0.19	0.22	0.11	0.15	0.22	0.11	0.10
Usual weekly hours	36.97	38.22	38.45	37.73	38.04	38.27	38.32	37.94	39.37
Not union member	0.82	0.62	0.70	0.82	0.63	0.72	0.81	0.66	0.80
Organisation - under 20	0.27	0.17	0.21	0.27	0.15	0.20	0.28	0.15	0.22
Organisation - 20 to 99	0.19	0.15	0.17	0.21	0.14	0.14	0.18	0.14	0.13
Organisation - 100 to 499	0.20	0.20	0.19	0.20	0.19	0.16	0.16	0.19	0.15
Occupational tenure (yrs)	6.94	10.67	7.34	6.59	10.70	8.25	6.15	10.83	6.97
Job tenure (yrs)	3.46	8.04	4.60	3.74	8.31	5.12	3.59	8.18	4.58
Not supervisor	0.52	0.47	0.52	0.48	0.47	0.47	0.49	0.46	0.45
Wks unemp in last 2 yrs	2.55	0.85	1.81	2.21	0.85	1.17	2.42	0.80	1.52
Wks NILF last 2 yrs	1.92	1.36	1.55	1.66	1.43	1.45	2.04	1.38	1.76
Wks employed in last 2 yrs	98.03	101.29	100.07	97.28	100.06	100.43	98.14	101.34	100.99
Number jobs in last 2 yrs	2.86	2.43	2.56	2.83	2.44	2.59	2.92	2.44	2.54

Notes: Treatment statistics are the same both before and after matching. Earnings are in dollars (indexed to 2008); satisfaction and skills are measured on original scales (0 to 10, 1 to 7 respectively). Occupational status is scaled 1 to 100. All other variables are measured as proportions (i.e. 1 = 100%), unless indicated (for example, hours, weeks, years).

Population: Adult employees not studying full-time.

Source: HILDA Release 8.

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