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IZA DP No. 15869

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ISSN: 2365-9793

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ABSTRACT

Educational Job Mismatch, Job Satisfaction, On-the-Job Training, and Employee Quit Behavior: A Dynamic Analytical Approach

This paper extends the literature on the consequences of over-education, in particular quit outcomes. It is the first study that explicitly tests the impact of job satisfaction and on-the-job training for workers in educational mismatched jobs and on quit behavior using a longitudinal data set. Accounting for unobserved heterogeneity and endogeneity, the dynamic analytical framework examines labor market outcomes for job-mismatched workers. We find that over-education alone, or accompanied by skill under-utilization in combination with lower job satisfaction, increases the incidences of job quitting. Opportunities for training facilitate the retention of initially job-mismatched workers. These results have implications for interpreting mismatch data, retention, and resource allocation.

JEL Classification: J24, J28, J31, J63

Keywords: over-education, over-skilling, job satisfaction, on-the-job training, turnover

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1. Introduction

Over-education is prevalent across economies. For example, the most recent statistics across the OECD countries classify 35.7 percent of the workforce in qualification-mismatched jobs (e.g., 33.5 percent in the U.S., 38.7 percent in Australia, 41.0 percent in the U.K.) (OECD 2020). Yet the labor market trajectories for workers in mismatched jobs are not empirically resolved in economics or other related fields. In this paper, we examine quit outcomes for educational mismatched workers, compared to those in matched employment, and the interim impacts of job satisfaction and on-the-job training.

Understanding the relationship between over-education and career (or occupational) trajectories has required theoretical and empirical modifications since its inception (Freeman 1976; Rosen 1972; Sicherman and Galor 1990; Sicherman 1991; Groot and Maassen van Den Brink 2003). As an extension of human capital theory (Becker 1964), career mobility theory initially examined over-education mainly as a temporary supply-side phenomenon at the start of a worker's career (Rosen 1972). Specifically, the theory postulated that over-educated workers might accept temporary employment to gain specific skills or other types of human capital. The years of over-education, however, may compensate for lack of work experience and tenure (a form of compensating skill differential). Career mobility theory further predicted that over-educated workers are likely to have lower job satisfaction (Allen and van der Velden 2001), a higher likelihood of quits, and upward career mobility (Sicherman 1991; Alba-Ramírez 1993; Hersch 1995).[1]

Earlier studies found that over-educated workers have higher turnover rates and more active upward occupational mobility than workers with otherwise similar characteristics (Sicherman 1991; Hersch 1995; Robst 1995; Rubb 2006; Rogers and Creed 2011; Grunau and Pecoraro 2017). These studies employed static models. However, the pathways available and choices made by employees in mismatched jobs can change their career mobility and quit behavior. Static models omit the longitudinal dynamic effects for individuals' career development and choices.

In addition, the acceleration of technological change (Guironnet and Peypoch 2007), and the growing significance of information in the information age, means that over-educated workers may have a comparative advantage in receiving and benefiting from on-the-job training. This transition could change the dynamic employment trajectories of these workers, compared to the postulations and findings of the earlier seminal studies.

In fact, recent studies based on panel data analyses have cast further doubt on aspects relating to the transitory nature of over-education or occupational upward mobility outcomes (e.g., Mavromaras et al.

[1] This brief overview is not intended to be an exhaustive coverage of career theory or the related literature.

2013 (for university graduates); Meroni and Vera-Toscano 2017; Wen and Maani 2019). Wen and Maani (2019) further show that, in contrast to results from static models, a lower likelihood of upward occupational mobility is found among over-educated-and-over-skilled employees. These studies raise new questions about the dynamics of the choices available to employees in mismatched jobs. In particular, the drivers of quit behavior as opposed to remaining in the job. For example, are over-educated workers more likely to quit? Or does on-the-job training explain alternative outcomes, leading to retention?

Career theory and the existing literature support a negative association between educational job mismatch and job satisfaction (Tsang et al.1991; Allen and van der Velden 2001). For an employee in an over-education- or skill-mismatched position, an option is to quit and move to, or search for, a job that provides a closer match. Alternatively, the worker may remain in a mismatched position, but experience lower job satisfaction. A third option, if provided, is to receive on-the-job training to gain specific skills that can result in increased match with the current job and greater retention. Therefore, while over-education is a form of job mismatch, it may not, inevitably, lead to long-term job dissatisfaction or higher quit rates. In this dynamic setting, job satisfaction is adjusted in each scenario.

In this paper, we examine quit outcomes for employees in both matched and mismatched jobs in a dynamic analytical setting. An advantage of the longitudinal nature of the data is that it allows the observation of actual quit behavior, as opposed to quit intentions, which may or may not materialize. We expand our model to incorporate the adaptation process, as well as the choices available and made while in a job. These factors can, in turn, change quit outcomes. We hypothesize that participation in on-the-job training can assist individuals to remain in their present position of employment. As such, this paper provides analytical tools to examine the career trajectories for employees in mismatched jobs, through a dynamic setting. The analysis leads to new explanations for long-term (education and skill) job mismatches, rather than mismatch as a temporary phenomenon, as per career mobility theory.

There are two competing theoretical predictions on over-education and the uptake of on-the-job training. Human capital theory predicts that over-educated workers are less likely to take part in on-the-job training, because they already have more human capital than needed for the job. In contrast, career mobility theory recognizes that human capital requirements vary by occupation. It also recognizes potential dynamic changes in conditions for workers in mismatched jobs over time. For example, career mobility theory predicts that over-educated workers may take a job that does not match their credentials initially, but receive on-the-job training for further progress in that job (Rubb 2006). Empirical evidence on the relationship between over-education and on-the-job training is mixed, such as a negative effect is found in studies by Sicherman (1991) and Alba-Ramirez (1993), and a positive effect by Alba-Ramirez and Blazquez (2003). These two contrasting trajectories are worthy of careful examination. In particular, the combined effect of on-the-job-training and mismatched employment on future quit

outcomes is of special interest. In this setting, panel data and econometric modeling that can account for longitudinal job mismatches, dynamic changes, and employment outcomes, while adjusting for individual heterogeneity, can provide new and more definitive evidence. The models presented in this paper have been designed in relation to this gap, and we provide new findings.

In this paper, our focus is on quit outcomes for education and skill mismatched workers. We consider expanded categories based on both over-education and skill-utilization in our analysis of job mismatch. Over-education provides information derived based on the median education level of the employed workforce in the respondent's specific occupation. Over-education accompanied by skill under-utilization is a more severe form of mismatch. Over-skilling further provides a more direct measure between knowledge and skills accumulated by workers and the actual skill requirements of their jobs. Over-skilling has been shown to influence job satisfaction (Allen and van der Velden 2001) and job mobility (Mavromaras et al. 2010). The combined measure provides a more comprehensive measure of educational job mismatch than either measure alone. For an employee in a mismatched job, the degree of other overall job satisfaction and opportunities, such as on-the-job training, can affect decisions to remain on the job, or quit and search for a better matched employment. To examine the extent of job mismatches and quit outcomes across the labor market, we consider the sample across all education levels. In that respect, our approach is similar to Büchel and Mertens (2004), Linsley (2005), and Rubb (2006). [2]

In this setting, job satisfaction can play a significant role in an individual's decision to quit (Shields and Ward 2001; Lévy-Garboua et al. 2007; Wang et al. 2015), especially when individuals are in mismatched jobs due to over-education or over-skilling. In this setting, longitudinal data, as used in our analysis, is required for capturing these more realistic dynamics leading to quit outcomes. Likewise, but less studied, on-the-job training choices within skill-mismatched employment are relevant to quit behavior (e.g., Bartel and Borjas 1981; Bartel 1982; Weiss 1984; Munasinghe 2000; Batt and Valcour 2003; Dale-Olsen 2006; McGuinness et al. 2014).

[2] Our sample includes all education groups to allow a larger sample and a realistic representation of the groups and markets that workers operate in. By controlling for 'actual years of education', and over- or under-education, we are also able to effectively separate different education groups in our model. A number of existing studies incorporate all education groups. Examples are for the labor market in Germany evaluated by Büchel and Mertens (2004); the US labor market examined by Rubb (2006); and the Australian labor market investigated by Linsley (2005). Linsley (2005)'s study used data from the 1997 wave of the Negotiating the Life Course (NLC) survey. It's conclusion was disputed by Miller (2007), who argued that Linsley's results come from a small sample size which limits the power of the tests undertaken, and he suggested that alternative datasets should be used to test career mobility theory in Australia. Our analysis provides new information with a more recent and larger data set, and econometric methods to address individual heterogeneity. This approach extends the analyses that focus on one education group (e.g. university graduates) to capture mismatches for the wider labor force. In this research, we also expand the Mavromaras et al. (2010, 2013) sample from graduates to the entire range of working-age employees.

While earlier studies have examined the link between educational mismatch and job satisfaction, and also on-the-job training, the link between educational mismatch and quit outcomes is much less resolved in the literature. We advance the job mismatch literature by testing the following related hypotheses in relation to quit outcomes for workers in educational mismatched jobs:

Hypothesis 1. The effect of education and skill mismatch and job satisfaction will interact to affect job quitting (-).

Hypothesis 2. The effect of education and skill mismatch and on-the-job training will interact to affect job quitting (– or +).

Hypotheses 1 and 2 advance the understanding of career mobility theory by exploring the potential influences of individual workers' job satisfaction and on-the-job training decisions on the probability of quitting their jobs.

We employ a large-scale longitudinal data set, the Household, Income and Labor Dynamics in Australia (HILDA) Survey, which covers a large number of job positions and industry sectors.[3] The quality and breadth of the data set allows an enhanced dynamic analysis of career mobility theory. In addition, the panel features of the data and the dynamic econometric models we develop allow us to adjust for unobserved heterogeneity and potential endogeneity. With the dynamic modeling approach adopted in this paper, we can better utilize the longitudinal features of the data set and, for example, control for an individual's conditions over time, while initially in mismatched employment.

The contributions of the paper are as follows. First, it is the first study that explicitly tests the impact of on-the-job training and job satisfaction among job-mismatched employees on quit outcomes, extending, for example, findings in Chevalier (2003). A feature of the analysis is a comprehensive approach to the outcomes of job mismatch. These outcomes include the effect of on-the-job training opportunities once in a mismatched job, job satisfaction, and quit behavior over time. Second, from a modeling point of view, the dynamic panel data framework and the models we adopt allow us to make adjustments for endogeneity and individual heterogeneity – both of which are paramount to job mismatch analysis. Third, aiming to develop a more comprehensive examination of the types of triggering factors for job turnover, we incorporate elements across career mobility theory, and we find new insights. Specifically, the analysis provides additional understanding of how on-the-job training can be utilized to reduce recruitment and training costs (Robst 1995; McGuinness and Wooden 2009; Verhaest et al. 2018) that

[3] This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either FaHCSIA or the Melbourne Institute.

are concerned with over-education. We provide new evidence that on-the-job training contributes significantly, and specifically, to the retention of mismatched employees. This result extends the literature, adding to, for example, Melero's (2010) findings that promotions are, in general, the main contributor to job satisfaction for males.

Finally, job mismatch is an issue of international concern. Our analysis contributes to the literature and policy options on trajectories of job mismatches by providing new international evidence for other countries to consider. Specifically, Australia has a system in which industry standards requirements, prevalence of government financial support for training, and established training providers facilitate on-the-job training. Thereby, the study provides other countries with evidence for policy considerations from the Australian case in which on-the-job training receives widespread support and uptake.

The paper is organized as follows. The next section describes the data, followed by a discussion of variable specifications and summary statistics in Section 3. We introduce our analytical framework and econometric models in Section 4. We discuss the results in Section 5 and carry out a robustness check in Section 6. The last section concludes the study with recommendations for further research.

2. Data

The data are taken from the first nine waves of the HILDA Survey. This interview-based survey began in 2001 with a nationally representative sample, with annual interviews. The sample is restricted to an unbalanced panel of all working-aged (23-64 years old), male, full-time employees for 2001 to 2009. The period selected for this research provides continuous data and group inclusion in the data, and it is guided by some major changes in HILDA Survey data in later years.[4] A limitation of the selection of data for the initial nine years of the survey is that the predictive power of the model for current years is diminished. However, the advantages of the data selection are that it provides sufficient years for our analysis and it focuses on years of data collection before changes to some questions of interest and sampling groups were made in 2010 and 2011. Our focus in this paper is also on hypothesis testing and providing our modeling approach that adjusts for endogeneity to the questions of interest. Nonetheless, the availability of the HILDA survey wave data beyond year 2010 provides a good testbed to examine topics of interest.

Two major advantages of the HILDA Survey are (a) the features of the large-scale longitudinal data set that allow controls for potential endogeneity and unobserved heterogeneity and (b) rich coverage of

[4] For example, in 2010 some questions were not asked in anticipation of some changes made in 2011. In addition, we had already tested the 2001-2009 data set for suitability and robustness in previous data suitability tests. Therefore, we decided to conduct the analysis with the 2001-2009 cohort as a sufficiently long period for the current analysis.

relevant variables that provides information of research interest in this study. The data set includes detailed longitudinal information on human capital, personal characteristics, job tenure, hours of work, wages, detailed occupation categories, job satisfaction, training, and job separations, including the reason for quit behavior. We can also derive educational and skill mismatches based on detailed occupation, education, and skill utilization variables. This feature of the data set facilitates testing the main questions of interest in a dynamic setting. Detailed information on variable specifications and summary statistics is discussed in the next section.

Specifically, the survey asked workers who had changed jobs since the last interview, the main reason for stopping work in the job and was this a voluntary quit or an involuntary job separation. To test the effect of job mismatch on job separation, we match this variable with previous job mismatch status.[5] After considering quit outcomes and training variables, and by including the lagged variables into the model, the regression analysis consists of 5,439 observations for 1,613 individuals.[6]

We focus on the sample of male, full-time workers to trial our dynamic analysis of job mismatch outcomes for a relatively homogenous group of workers. This research area, however, lends itself to extensions in future studies that can address female employment choices within the dynamic setting.[7]

During the nine-year period of the panel data, the individuals in the sample move in and out of jobs. In terms of education and skill mismatch, a relatively large proportion of our sample has experienced at least one job mismatch change during the longitudinal period. For example, close to 60 percent of workers who were over-skilled and 26 percent of matched workers moved into another category. Likewise, 29 percent of only over-educated workers and 31 percent of only under-educated workers moved to a different category during the period of the study. This aspect of the longitudinal data provides variation across both time and employees, with changes for the same employees over time. This is an important feature of the data and the dynamic panel analysis, which would not have been

[5] Because we focus on the comparison between workers who stay in their current job and workers who leave voluntarily, we exclude workers who leave involuntarily or leave for other reasons are not classified as voluntary quit.

[6] In addition, self-employed workers and full-time or part-time students are excluded.

[7] To avoid potential selection biases, we first tested the sample selection impacts for inclusion into the sample, and full-time employment, in terms of unobserved circumstances such as having young children, etc., or unobserved personal characteristics by employing a Heckman (1979) selection adjustment.

Following Cutillo and Di Pietro (2006) and Green et al. (2007), we further applied a double selection probit model to estimate the incidence of over-education for full-time male workers. When sample selection correction for full-time employment was applied to our model, the 'invers of mills ratio' coefficient was very insignificant and the coefficients of interest were unchanged.

We also used an integrated approach by combining Wooldridge's approach (2005) and the Mundlak correction (1978), which controls for the initial condition and unobserved effects – worker's ability, quality, etc. The results were further not sensitive to the sample selection.

possible to account for in cross-section, static analyses or with short duration panel data sets.

We used an unbalanced panel as the initial data set to avoid deleting too much useful information, such as quit outcomes and job mismatches. In the econometric analyses of a specific model of interest, we adopted the procedure described by Wooldridge (2005), which states that the same conditional log-likelihood for the subset of observations can be used for unbalanced panels. If the dependent variable (not including the initial value) and selection indicator are independent conditional on initial value and exogenous explanatory variables, the consistency follows from the general argument in Chapter 10 in Wooldridge (2010).

3. Variables and summary statistics

Education and skill mismatch

Over-education measures the deviation between the formal education obtained by workers and the education required to perform a job. Over-education has been shown to impact wages. By contrast, over-skilling provides a more direct measure between knowledge and skills accumulated by workers and the actual skill requirements of their jobs. Over-skilling has been shown to impact satisfaction and job mobility (Allen and van der Velden, 2001; Mavromaras et al. 2010). In addition, Spearman's rank correlation coefficient between the over-educated and the over-skilled is 0.01, and the test for null hypotheses cannot reject the independence of over-education and over-skilling.

Six job-matching groups categorize the entire sample, according to the definitions of required education and over-skilling, and incorporating both education mismatch and skill mismatch. The over-education measure is based on the Mode method (Kiker et al. 1997). In this method, each individual's education level is compared to the Mode level of education for the occupation held (at the two-digit level of Australian and New Zealand Standard Classification of Occupations (ANZSCO) 2006 occupation categories) for each survey wave (year). For example, an individual is over-educated if their level of education is higher than the Mode.

Over-skilling is measured by following conventional approaches (e.g., Mavromaras et al. 2013) based on self-reported data on the degree to which an employee states that he is making adequate use of his skills and abilities in his job. In detail, over-skilling is derived from the HILDA data set by using the response, scored on a 7-point scale, to the statement: "I use many of my skills and abilities in my current job". A response of 1 corresponds with strongly disagree and 7 with strongly agree. We classified individuals with responses of 1, 2, 3, or 4 on the scale as "over-skilled" and those with responses of 5, 6, or 7 as "skill-matched". This cut-off point was shown to be appropriate in sensitivity tests, and this

was also confirmed in the work of McGuinness and Wooden (2009)[8] and Mavromaras et al. (2013). Some ambiguity in this variable based on self-reported data cannot be ruled out. However, it seems unlikely that workers who didn't utilize their skills reported a counterfactual answer. The validity of over-skilling was acknowledged in Allen and van der Velden (2001) and Green and McIntosh (2007).

Well-matched applies to the individual who works in a job where both education and skills match the job's requirements. Examples include individuals holding a professional degree (e.g., law, medicine) or a skill-specific certificate (e.g., the legal profession, plumbing) for work in their particular field.

Over-educated-and-over-skilled applies to the individual who works in a position where both education and skill level exceed those required. For example, an individual who has difficulty in locating a job, who then accepts employment that under uses both his education and skill. This is the most severe form of over-education and the group of most interest in this research.

Only over-educated applies to the individual who works in a job for which he is over-educated, but skill matched.

Only over-skilled applies to the individual who works in a job for which he is over-skilled, but does have a matched educational qualification. For example, with the increasing supply of educated workers, employers may raise their hiring requirements in relation to an education standard, but not update the actual technological working conditions.

Only under-educated applies to the individual who works in a job for which he is under-educated, but skill matched. This usually occurs when a worker has a long tenure with his current employer, a long period of work experience, and/or a considerable amount of on-the-job training.

Under-educated-and-over-skilled applies to the individual who works in a position where he is both under-educated for the job and also over-skilled. Usually, this type of worker is very capable, stays with the same job for a long time period, receives on-the-job training, and has a considerable amount of work experience.

Our study incorporates all mismatched groups specified above. However, our main interest is in the over-educated group on its own, and in particular jointly with over-skilled. This is in keeping with earlier studies of educational mismatch and links to labor allocation efficiency. Nonetheless, our study

[8] McGuinness and Wooden (2009) cross-tabulated the over-skilling variable with a measure of job complexity (responses to "my job is complex or difficult", which was scored on the same 7-point scale used to measure over-skilling) to confirm that the more over-skilled the worker, the less difficult they consider their job to be. They further refined that either the severely (individuals with responses of 1, 2, or 3 on this scale) or moderately over-skilled (those with responses of 4 or 5) must not report high levels (a score of more than 5) of job complexity. They claimed that this association showed that the over-skilling responses would not be biased by respondents having incorporated non-labour-market-relevant skills and abilities into these responses.

provides results on the effect of mismatch on quit outcomes for under-educated groups.

Chevalier (2003) also considers three categories of jobs based on education and skill combination levels of graduates, with two groups designated as over-educated based on skill. Since the data did not include skill information, job satisfaction was used as a proxy for over-skilling. More specifically, over-education accompanied by lower job satisfaction served as an indication of 'genuine mismatch', as opposed to 'apparent mismatch'. The study showed evidence of potential heterogeneity in skills, and that genuine mismatch was associated with greater wage penalties. In the current study, we utilize direct self-reported entries on skill utilization available in the data on the current job, and in association with educational mismatch data, creating six job mismatch variables based on education and skill utilization conditions.

Overall job satisfaction

Overall job satisfaction is derived from the responses to the question "All things considered, how satisfied are you with your job?". This question has a 10-point response scale.

Table 1 presents overall job satisfaction by types of job mismatch. Overall, the average job satisfaction is 7.6 out of 10 for males aged 23 to 64, which implies that most workers are generally satisfied with their jobs. When we split the entire sample by job mismatch, we find differences in job satisfaction among different types of job mismatch. Over-skilling on its own, or jointly with other educational mismatch, is associated with lower numbers, or less satisfaction. For example, the over-educated-and-over-skilled group of workers has the lowest average job satisfaction level on the 10-point scale (6.7), compared to those of well-matched (7.7). This evidence implies that skill under-utilization is associated with diminished job satisfaction.

Further statistical analysis shows that job satisfaction is, on average, higher at higher education levels, particularly with educational qualifications at university. Job satisfaction at the postgraduate level is 86.2 percent, job satisfaction is 83.6 percent with a bachelor degree, and the lowest satisfaction level of 80.3 percent is at no higher qualification. But the relationship is not linear, as employees with certificates have the second highest job satisfaction. Therefore, in our models we control for educational qualifications in a series of binary variables to allow differential effects.

[Table 1 here]

On-the-job training

On-the-job training is based on self-reported information in the annual HILDA surveys and derived from the responses to the question relating to having taken part in any work-related training in the past 12 months. On-the-job training is a dummy variable with a value of 1 if the worker has taken part in

any work-related training in the previous year, zero otherwise.

Various official and academic studies of Australian employment practices are consistent in documenting a supportive environment for work-related training. For example, in 2013, 27 percent of all individuals in Australia between the ages of 15 and 74 (4.6 million individuals) had received work-related training in the previous 12 months (Australian Bureau of Statistics 2013). Research on training practices in Australia concludes that employers are generally supportive of work-related/on-the-job training. Training provision or support is provided to boost productivity and sustainable growth, or to comply with industry standards and regulations, particularly related to hygiene, health, and safety. Availability of government subsidies and provision of quality and reliable information on training providers also support a positive training environment. A contribution for costs of training is observed for higher-level qualifications (Fowler 2017). In addition, research shows positive employee perceptions of on-the-job training uptake in Australia (Wood 2004).

Quit outcomes

A strength of The HILDA Survey for the purpose of this study is that it contains data about job separations, including the main reason the respondent had stopped working in that job or business. This variable provides detailed and comprehensive self-reported information on the reason for job separation based on 13 categories of options, identifying voluntary job-related quit outcomes from other voluntary and involuntary job separations.[9]

To test the effect of job mismatch on job separation, we match this variable with previous job mismatch status. Our analysis covers the two groups who had responded that they quit their job voluntarily, with responses in categories (1) not satisfied with job and (2) to obtain a better job/just wanted a change/to start a new business (see detailed information in Table A1).

As discussed previously, career mobility theory provides an explanation for the existence of over-education from a supply side perspective. Over-education may be a part of the career mobility process and a part of a phase of insertion and adaptation in the early stages of the individual's working life (Groot and Maassen van den Brink 2003). Over-educated workers may optimally choose a lower level of employment if the effect of education on the probability of being promoted for these jobs is higher than for other jobs. Over-educated workers may sacrifice a wage premium in their current jobs to gain specific skills, or other types of human capital, enabling them to move to higher-level jobs and higher

[9] Quit (voluntary leaving): (1) not satisfied with job, (2) to obtain a better job/just wanted a change/to start a new business, (3) retired/did not want to work any longer, (4) to study at home to look after children, house or someone else, (5) travel/have a holiday, (6) study/needed more time for study, (7) too much travel time/too far from public transport, (8) change of lifestyle, or (9) immigration. Involuntary leaving: (10) laid off, (11) no work available, (12) retrenched, or (13) redundant.

wages. Thus, it should be tested by comparing differences between workers who experience a voluntary separation (quit) and workers who experience 'no changes', rather than those experiencing involuntary separation (lay off). In deriving the quit binary variable of interest, workers who are laid-off or who leave their jobs for other reasons are not categorized as voluntary quitting.

Table 2 on job mobility in the first interview confirms that the over-educated-and-over-skilled group of workers has the highest incidence of job separation – 18.8 percent separate for all reasons and 11.1 percent of them experience voluntary job leaving (i.e., quit). The over-skilled, or jointly with the under-educated group, account for a higher proportion of voluntary job separation compared to the rest of the groups, ranging from 9.9 percent to 8.6 percent. The well-matched group of workers has a quit rate of 5.3 percent. The incidence of layoff is from 3.1 to 6.2 percent among the six groups. Job separation for other reasons is only a small proportion of the sample.

[Table 2 here]

Other control variables

In addition to the above variables, we account for personal characteristics such as healthy status (no serious illness or impairment), married, qualification, immigrant status, job characteristics such as work experience, current job tenure, union membership, current job hourly wage, current job occupational scale (socioeconomic index of occupation status), unemployment, state-fixed effects, and time periods. Further detailed information on variable specifications is available in the Appendix (Table A1).

Table 3 reports the means of the main variables used in the analysis. Younger workers with less experience, less occupational tenure, less current job tenure, and less earnings are more likely to experience voluntarily leaving (quitting) from their current jobs. The average hourly wage for the group who 'Quit' is less than that for the group belonging to 'Job no change' for each job mismatch category.

In four of the six groups, workers with higher occupational scale are less likely to quit. Table 3 also shows that education and skill mismatches are associated with higher quit rates. We note a wide range of group averages for on-the-job training (16 to 50 percent) are reported in Table 3.[10] Moreover, job satisfaction and on-the-job training are associated with lower quit rates across job mismatch categories. These statistics do not control for individual and occupational characteristics, which we address in our analytical section.

[10] This variable reports the completion of job-related training that enhances skills for the current or future jobs. In our data set, the cost of training was covered by the employer for 76 percent of the respondents who received training.

[Table 3 here]

4. Analytical framework and models

We apply the dynamic random-effects probit model to examine the relationships of interest in the longitudinal data set. In over-education analyses, an estimation issue arises from potential biases occurring in the correlation between explanatory variables and error terms due to unobservables, which is addressed by using the Mundlak correction. As a special case of the Chamberlain's correlated random effect model, the Mundlak correction is proposed by Mundlak (1978) and relaxed by Chamberlain (1980). These corrections in the dynamic setting serve as adjustments for unobserved factors to a greater extent than in static models. Notably, when the Mundlak correction is adopted on panel data, it can mitigate the problems of endogeneity and error correlation.

Mundlak's approach is used to control for endogeneity effects due to unobserved individual effects by additionally controlling for the impacts of time-invariant unobserved heterogeneity. It is considered as an alternative approach between the fixed and random effects models. It also provides a test for adjustment for endogeneity as an alternative to the Hausman test – if the coefficient on group mean δ is non-zero, that suggests that individual effects are not to be ignored (Greene 2010).

In the following model, the dependent variable y_{it}^{*} is a latent value and unobserved, depicting the probability of the labor outcome of interest for individual *i* at time *t*. Its observed counterpart y_{it} is a dummy variable. Variables X_{it}represent explanatory variables of interest and $\varepsilon_{i,t}$ denotes the disturbance terms, assumed to be independent and identically distributed. β is unbiased if explanatory variables x_{it} and individual specific effects μ_i are independent, that is

(1) $$y_{it}^{*} = x_{it}\,\beta + \mu_i + \varepsilon_{it}$$, where $E[\mu_i|X_i] = 0, and\ \varepsilon_i|\ X_i \sim \mathrm{N}\,(0,\sigma_\varepsilon^2)$.

To relax this assumption, the Mundlak (1978) model proposes individual effects μ_i as a function of individual means, that is $\mu_i = \overline{X}_\iota\,\delta + \eta_i$, where $\eta_i|\ X_i \sim \mathrm{N}(0,\sigma_\eta^2)$. The Mundlak (1978) model assumes the restricted specification that $\delta_1 = \delta_2 = \cdots = \delta_T = \delta$, implying that the individual-specific effect is equally correlated with all time-periods x_{it}. It assumes zero correlation between $\overline{X}_\iota$ and η_i.

Thus, we have $E[\mu_i|X_i] = \overline{X}_\iota\delta$, where $\overline{X}_\iota$ is an average of x_{it} over time for individual i, and it is time invariant.

We rewrite the above latent model as

(2) $$y_{it}^{*} = x_{it}\,\beta + \bar{X}_i\delta + \left[\varepsilon_{it} + \mu_i - E[\mu_i|X_i]\right] = x_{it}\,\beta + \bar{X}_i\delta + u_{it}$$, where

u_{it} is new error term for the whole model. Based on construction, we have

(3) $$E[u_{it}|X_i] = E[\varepsilon_{it} + \mu_i - E[\mu_i|X_i] \;\; |X_i] = 0$$

Combining Wooldridge's approach (2005) and the Mundlak correction (1978), the unobserved individual effect μ_i is conditional on the initial observed dependent variable y_{i0} and the mean of time-varying explanatory variables. Then, equation 4 represents the main model:

(4) $$y_{it}^{*} = \theta y_{it-1} + x_{it}\beta + \theta_0 y_{i0} + \overline{X_i}\delta + \eta_i + \varepsilon_{it}$$

As part of the design of dynamic models, Equation 4 controls for a lagged value pertaining to the previous time period, and an initial value related to an earlier time period. In this way, the dynamic model also controls for state dependence, and some otherwise unobserved personal traits or tendencies. Based on average values in the model across individuals and years of panel data, the added components $\bar{X}_i\delta$ address endogeneity, such that the coefficients β approximate unbiased fixed effects estimates (Wooldridge 2010). The estimates of θ control for the state dependence of the dependent variable.

All models are specified by controlling for educational attainment, as required in the educational mismatch formulation. In this setting, educationally matched workers with equal education levels are expected to work in occupations with similar educational requirements. Therefore, an over-educated worker must work in positions in a lower occupational rank than an educationally matched rank. Therefore, a comparison between an over-educated worker and an adequately educated worker happens in different occupations if their education level is the same.

The modeling approach of random-effects probit models with Mundlak correction has also been adopted in a few recent studies on labor outcomes such as wages and job satisfaction (Mavromaras and McGuinness 2012; Mavromaras et al. 2012, 2013). Wen and Maani (2019) also applied the approach to examine the career mobility theory.

The dynamic modeling approach and the variables of interest provide more detailed and realistic information on the options that are open for workers in mismatched jobs, leading to quit or retention outcomes.

Model of quit behavior

We apply a general dynamic random-effects probit model in Equation 5 (below), which is based on Equation 4, to the panel data to test our hypotheses of interest, as discussed in the Introduction. This model examines the quit behavior effects of job mismatch through interactions of job mismatch with job satisfaction and with on-the-job training. That is, the model investigates the effects of job satisfaction and on-the-job training on job quitting, across well-matched and job-mismatched workers. Results from these models show outcomes of job mismatches in interactions with the worker's job satisfaction and on-the-job training choices.

(5)

$$
\begin{aligned}
quit^{*}_{i,t} = {} & \theta quit_{i,(t-1)} + \theta_0 quit_{i,0} + \sum_{j=1}^{5} \alpha_j MTYP_{j,i,t} + \overline{\sum_{j=1}^{5} \alpha_j MTYP_{j,i}} \\
& + \sum_{j=1}^{6} \xi_j (Z_{1i,t} * MTYP_{j,i,t}) + \overline{\sum_{j=1}^{6} \psi_j (Z_{1i} * MTYP_{j,i})} \\
& + \sum_{j=1}^{6} \gamma_j (Z_{2i,t} * MTYP_{j,i,t}) + \overline{\sum_{j=1}^{6} \varphi_j (Z_{2i} * MTYP_{j,i})} \\
& + x_{it}\beta + \overline{X_i}\delta + \eta_i + \varepsilon_{it}
\end{aligned}
$$

The binary dependent variable $quit_{(i,t)}$ takes the value of 1 if workers experience voluntary quit at t, zero otherwise. The lagged job-quitting variable $quit_{i,(t-1)}$ is the value from the previous year's survey, and the initial value $quit_{(i,0)}$ is the quitting variable information relating to the respondent's latest job prior to the first survey. Variable $MTYP_{j,i,t}$ contains the types of mismatch that are occurring. Variable $Z_{1i,t}$ represents job satisfaction. Variable $Z_{2i,t}$ denotes on-the-job training. Each type of mismatch is a dummy variable. ξ_j (and γ_j) reveals the effect of job satisfaction (and on-the-job training) on job quitting at time *t* for job-mismatched workers, when compared to workers who have the same job mismatch status, but who are not satisfied with their job (or workers who have the same job mismatch status, but who haven't obtained on-the-job training). These extensions of the model allow a more realistic estimation approach to test hypotheses that are of interest with regard to the outcomes of job mismatch in labor markets. x_{it} is a set of personal or job characteristics for worker *i* at year *t* that are likely to affect individual's quit behavior, such as work experience, healthy status, married, current job tenure, union membership, current job occupational scales, and current job hourly wage. The models also include state-fixed effects, time periods, immigrant status, and unemployment. Variable η_i is an individual-specific effect. The variable $\varepsilon_{i,t}$ is the error term.

The other important feature of our analysis is the implementation of the Mundlak correction in our dynamic panel data analysis, which addresses potential endogeneity/bias concerns expressed. As

workers move through jobs and (or) as they experience new job conditions, the dynamic panel analysis enables us to separate the effect of changes in the variables of interest, while controlling for their individual unobserved characteristics.

As discussed in the Data section, it is noteworthy that the nine-year panel nature of our data set allows us to follow individuals, and this is an important feature of the analysis. This feature allows us to observe changes in job satisfaction associated with changes in job mismatch conditions and changes in receiving on-the-job training for the same individuals, while controlling for a number of other relevant variables.

5. Results

In this section, we summarize our results based on Equation 5 and provide robustness tests of our results. In Table 4, we first explore the main effects of job satisfaction and on-the-job training on quit behavior. We further assess whether these effects are significantly different between well-matched and job mismatched workers.

[Table 4 here]

Results from the dynamic random-effects probit (DREP) models in columns 1, 3, and 5 in Table 4 represent the results from the baseline model in which endogeneity is not taken into account. In contrast, results from the DREP-MC models in columns 2, 4, and 6 account for endogeneity by using the Mundlak correction. The results confirm that the study requires employment of the DREP-MC models to address endogeneity.

For ease of interpretation, 'marginal effects' (change of probability of the dependent variable caused by one unit change in the explanatory variable based on the mean value), instead of coefficients, are reported in , in Table 4. Marginal effects on job mismatch variables in the DREP and DREP-MC models are significantly different, indicating the existence of endogeneity among job mismatch variables. Robustness Likelihood Ratio (LR) tests also confirm that the DREP-MC estimation outperforms DREP.[11] Therefore, we focus on results from the DREP-MC models. Our results for job satisfaction and

[11] We use a likelihood ratio test to determine the better model between the DREP-MC and DREP. The statistic of the likelihood ratio test is $LR=2(\ln(L_{DREP-MC})-\ln(L_{DREP}))\sim\chi^2(m)$, where $\ln(L_{DREP-MC})$ is the natural logarithm of the model's likelihood for the less restrictive DREP-MC model, and $\ln(L_{DREP})$ is for the more restrictive DREP model. The statistic LR is distributed chi-squared with m degrees of freedom (i.e., the number of variables added to the model). The test statistics LR exceed the critical values when comparing between the DREP-MC and DREP models for Table 4, indicating that the null hypothesis of the DREP model is rejected, and that the DREP-MC model should be adopted for addressing the endogeneity issue.

on-the-job training effects on quits are new results, above controlling for the positive effect of promotion or wages (e.g., Hersch 1995). In addition, the results indicate evidence of a positive link between past and present quit outcomes.

Table 4 provides a summary of the results on the determinants of employee quit outcomes in relation to the hypotheses of interest in this paper. Columns 1 and 2 explore the marginal effect of overall job satisfaction and on-the-job training on quit outcomes. Columns 3-6 present results on based on the more comprehensive model of job mismatch and quit behavior (Equation 5). In the following sub-sections, we will discuss the impacts of interactions of job mismatch with job satisfaction and on-the-job training, and the impact of wage rate on quit outcomes.

The impact of mismatch and overall job satisfaction on quit outcomes

As shown in columns 1 and 2 of Table 4, job satisfaction has a significant and negative impact on quit outcome, confirming that, as expected, happy workers are more likely to stay in their current employment positions.

The impact of on-the-job training on turnover is a-priori undetermined. It would be negative if the greater investment of time on training specific to the firm makes quitting less advantageous. Alternatively, it could increase quit choices if it makes employees more desirable to other firms. Our results show a negative to insignificant effect on quit outcomes. But if training required by the employer is taken up for compliance requirements (e.g., hygiene, update of technical skills), a link between on-the-job training and quit outcomes may not exist. Results in columns 1 and 2 support a weak negative to insignificant effect of training on quit outcomes.

The results in all columns further confirm a significant state dependence effect of quit outcomes, meaning that those who had quit their previous job were also more likely to quit their job in the current period (i.e., a 13 percent higher probability to quit compared to those who had not quit their previous job).

Estimation results in columns 3 to 6 show the associated impact of job mismatch and job satisfaction, and on-the-job training on quit behavior. These results reveal a number of findings, including differentiated effects on quits from different types of job mismatch and in combination with these factors. First, according to results from the DREP-MC models (column 4, controlling for unobserved heterogeneity), significant effects of job satisfaction on job quitting are found for all types of mismatched workers. Specifically, job mismatch in combination with lower job satisfaction increases the incidences of job quitting. Second, the magnitude of marginal effects varies, ranging from 0.8 to 1.6

percent. The 'satisfied' over-educated-and-over-skilled workers have a 1.6 percent lower probability of quitting their job than 'not satisfied' workers who have the same job mismatch status. Compared to other mismatched workers, as expected, job satisfaction has the smallest estimated marginal effect (0.8 percent) on quit outcome among job-matched workers. The evidence reveals that job satisfaction is an important factor in determining workers' quit behavior in mismatched jobs.

The impact of mismatch and on-the-job training on quit outcomes

Column 4 in Table 4 shows that on-the-job training has drastically different effects on quits for different types of educational job mismatch. The marginal effects range between negative significant and insignificant effects. Notably, the group of over-educated-and-over-skilled job mismatched workers, who have obtained on-the-job training in their current job, are found to have a 2.5 or 2.6 percent lower probability of leaving their current jobs than workers who are in the same job mismatch groups, but who have not had on-the-job training. This finding is consistent with, for example, a group of workers who are high achievers, with more than the median level of education and skill, and who have experienced career changes, thriving with undertaking job specific on-the-job training. We find a similar negative effect on quits for under-educated and over-skilled employees who have received on-the-job training. This evidence is consistent with the hypothesis that organizations select workers for additional training as part of a strategy to reduce the turnover of skilled labor (Green and Heywood 2007).

In our view, these two groups are highly skilled workers who are in education and skilled mismatched jobs due to possible change in career or location, or highly skilled workers who find themselves undereducated in their occupation due to escalations in the educational requirements of their career. The evidence shows that offering on-the-job training to these two educationally mismatched and over-skilled groups (i.e., over-educated-and-over-skilled and under-educated-and-over-skilled workers) would reduce turnover of skilled workers and save the organizational cost associated with employee turnover.

Wage rates and quit outcomes

In the model specifications in columns 1-4 of Table 4, we control for the natural logarithm of the hourly wage rate. A higher wage rate is generally expected to result in a lower quit outcome. In addition, a job that is otherwise unsatisfactory may not lead to quit behavior if the wage rate is sufficiently high to cover economic needs. The results confirm this expectation with a marginal effect of -0.033 on the probability of quits of the current job (3.3 percent lower probability), for each 1 unit increase in the natural logarithm of the hourly wage rate (2.718 dollars increase in the hourly wage rate, where mean hourly wage is about $29.5 per hour).

6. Robustness tests

Test of multicollinearity of the wage rate and job satisfaction

Prior to examining the models in columns 1-4, we conducted tests to examine potential multicollinearity between the explanatory variables of overall job satisfaction and the wage rate. For example, a higher wage rate may increase overall job satisfaction. However, the variance inflation factors (VIFs) in this case had a very low value, indicating no multicollinearity. Overall job satisfaction results from several factors in combination, and the wage rate is just one of such factors.

We also did a sensitivity analysis based on the model in Table 4, by comparing results with and without the wage rate, to examine the impacts on the job satisfaction interaction variables. As columns 4 and 6 of Table 4 show, these results on both the hourly wage rate and the other coefficients of interest are very stable regardless of the inclusion or exclusion of the wage rate. This verifies the robustness of our results. Specifically, job satisfaction has impacts on quit outcomes in connection with educational job mismatch that are significant and distinguishable from the effect of the wage rate.

Examination of joint effects between job satisfaction and on-the-job training

Overall job satisfaction and on-the-job training are two major explanatory variables in our analysis, and in auxiliary tests we examined associations and potential impacts between them.

First, we provided a test of a potential joint effects from job satisfaction and on-the-job training on quit outcomes. For this test, we expanded the DREP-MC quit outcome model (such as in column 2 of Table 4) by adding an additional interaction term for the two explanatory variables, overall job satisfaction and on-the-job training. The coefficients for training continued to be small and insignificant, and the added interaction effect was small and statistically insignificant (a marginal effect of -0.004 and standard error of 0.003). Second, this result was also unchanged with a sensitivity test of the model excluding the hourly wage rate.

Test of the potential impact of training on overall job satisfaction

In auxiliary regressions, we considered job satisfaction as a dependent variable to test the assumption of independence of job satisfaction from training. Given the continuous nature of the overall job satisfaction variable, we applied fixed effects and random effects estimations, as summarized in Table A2. These results are consistent in confirming no statistically significant impact from on-the-job training on job satisfaction.

We further examined the robustness of this result by testing an alternative specification of the job satisfaction model, utilizing DREP estimation with the Mundlak correction, using an alternative dichotomous variation of the job satisfaction variable. For this additional auxiliary test, we transformed the continuous job satisfaction variable into a binary variable based on a threshold level to identify a high level of job satisfaction (i.e., a value of 1 was allocated for satisfaction responses levels of 7-10 on the 10-point scale, otherwise zero). The impact of on-the-job training on job satisfaction remained consistently statistically insignificant in this test, and in further sensitivity tests with alternative threshold levels for satisfaction value of 6 (on the 10-point scale).[12] Notably, the hourly wage has a significant and positive impact on job satisfaction.

Test of potential impact of overall job satisfaction on training

In these tests, we checked if job satisfaction, in turn, may increase on-the-job training. For this test we used our on-the-job training variable as the dependent variable and the DREP-MC estimation (with the Mundlak correction). These results are summarized in Table A3. Notably, these results show no evidence of a reverse impact from on-the-job training on job satisfaction.

The results on training in Table A3 show some additional findings on the determinants of on-the-job training. For example, both previous training and initial training increase the probability of undertaking future training. Accounting for job mismatch conditions experienced by employees, the results in column 2 reveal a complementary relationship between being over-educated and over-skilled, and the choice to receive on-the-job training. This result supports the postulation that workers with most serious job mismatch conditions are more likely to receive on-the-job training. This result is in contrast to some earlier studies (Sicherman 1991; Alba-Ramirez 1993), but in line with Alba-Ramirez and Blazquez (2003). Over-educated-and-over-skilled workers have about a 12 percent greater likelihood of obtaining on-the-job training than the average well-matched workers. As our results of quit outcomes in Table 4 had shown, for employees with the two most serious cases of mismatch (overeducated-and-over-skilled and undereducated-and-over-skilled groups) the combination of having training in these mismatch conditions may lower their propensity to leave their position of employment.

In summary, the auxiliary sensitivity tests we conducted support the robustness of our results.

7. Conclusions

Given the significant proportion of the workforce that is in mismatched jobs, across several countries, obtaining a better understanding of the employment outcomes from workers experiencing mismatched

[12] These results are available from the authors on request.

jobs is timely. In this paper we have focused on the drivers of job turnover (quit outcome) for this group.

The dynamic random-effects probit model accounting for unobserved heterogeneity and endogeneity is applied to examine the relationships of interest in the longitudinal data set. We find that over-education alone, or accompanied by skill under-utilization in combination with lower job satisfaction, increases the incidences of job quitting.

The dynamics of job satisfaction and on-the-job training choices explored in this paper have extended our understanding of the quit trajectories for employees in mismatched jobs beyond the existing literature. In particular, the analysis of the role of on-the-job training for workers in educational mismatched jobs, in a dynamic setting and that also accounts for endogeneity of job mismatches, has extended this literature. In addition, utilizing information across both education and skill mismatches has proven important in this setting, providing a more in-depth measure of the extent of job mismatches.

Our findings have added new insights to the existing literature. In particular, the combination of over-education and skill under-utilization – what could be considered as the most serious mismatch – imposes an added negative effect on an employee's job satisfaction. A related key finding is that the influence of job satisfaction surpasses that of job mismatch when employees make decisions on voluntary quitting. Specifically, employees experiencing job-mismatch do not necessarily quit their jobs voluntarily. Evidence from this study shows that over-educated-and-over-skilled employees may stay with their present employers if they otherwise have high overall job satisfaction. Importantly, this effect is present and significant after controlling for increased wage effects (reflecting promotions) and individual heterogeneity. We expect that the role of on-the-job training and its drivers (within a dynamic framework), such as productivity, also naturally leads to new research on employment outcomes.

The auxiliary robustness tests support the validity of our results, and these results further show that over-educated and over-skilled workers are more likely to take up on-the-job training. In addition, our results confirm that on-the-job training among employees who are in mismatched positions (over-education and skill underutilization) is a key factor that leads to greater retention in subsequent periods. This less-studied result explains why job mismatches may no longer be predominantly temporary for some groups of workers. Our results support the hypothesis that over-educated workers may be in stronger positions to take part in, and benefit from, on-the-job training, resulting in greater productivity and retention. As such, providing on-the-job training can lead to lower turnover and result in long-term cost savings, given the fact that high levels of employee turnover are inefficient and unsustainable.

Australian government employment regulations are, for example, supportive of on-the-job training to increase productivity and encourage economic growth. Our analysis provides evidence for international policy options to achieve positive outcomes with initial educational mismatches.

Finally, we believe that the dynamic framework opens further opportunities for research that advances the education and skill mismatch literature – in particular the trajectories for employees in mismatched jobs. Our analysis draws attention to the role of the drivers that enhance the productivity and retention of over-educated employees in dynamic settings.

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TABLE 1
Job Satisfaction by Job Mismatch

Overall job satisfaction [a]	Over-educated-and-Over-skilled	Only Over-educated	Under-educated-and-Over-skilled	Well-matched	Only Over-skilled	Only Under-educated	Total
10 point scale	*%*	*%*	*%*	*%*	*%*	*%*	*%*
0	1.0	0.0	0.6	0.1	0.1	0.3	0.2
1	0.9	0.2	1.5	0.3	0.7	0.5	0.5
2	1.9	0.7	1.8	0.7	1.0	0.7	0.9
3	4.0	0.9	3.0	1.1	3.1	0.8	1.4
4	4.8	1.6	3.7	1.7	4.5	1.4	2.1
5	9.1	4.2	8.8	4.4	10.9	4.7	5.4
6	14.2	7.2	11.7	7.6	12.3	6.1	8.0
7	27.7	23.3	23.7	21.5	22.6	19.0	21.8
8	22.6	34.3	25.9	33.8	25.0	33.3	32.1
9	10.0	21.2	11.5	20.8	13.3	22.0	19.5
10	3.8	6.3	7.9	8.0	6.6	11.1	8.1
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Mean of job satisfaction	6.7	7.7	7.0	7.7	7.0	7.8	7.6
Observations	682	2807	866	4045	807	3419	12626

Notes: a. Overall job satisfaction is derived from the responses to the question "If, all things considered, how satisfied are you with your job?". It is scored on a 10-point scale, in which 0 is totally dissatisfied and 10 is totally satisfied.
To present the complete information of overall job satisfaction by types of job mismatch, we use the data from wave 1 to wave 9, containing 12,626 observations.

Source: HILDA Release 9.

TABLE 2
Job Mobility in the First Interview by Job Mismatch

	Over-educated-and Over-skilled	Only Over-educated	Under-educated-and Over-skilled	Well-matched	Only Over-skilled	Only Under-educated
Job status	*%*	*%*	*%*	*%*	*%*	*%*
No change	81.1	89.2	85.2	89.4	81.5	90.2
Quit	11.1	4.7	8.6	5.3	9.9	5.4
Layoff	4.4	3.6	6.2	3.1	4.9	3.4
Other	3.3	2.5	0.0	2.2	3.7	1.0

Source: HILDA Release 9.

TABLE 3
Mean Values of Main Variables Used in the Analysis by Quit Status and Job Mismatch

	Over-educated-and-Over-skilled		Only Over-educated		Under-educated-and-Over-skilled		Well-matched		Only Over-skilled		Only Under-educated	
	Job no change	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*	*Job no change*	*Quit*
Variables	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean	mean
Personal Characteristics												
Age	41.18	33.71	43.33	38.01	42.60	36.76	41.86	36.71	40.84	36.79	43.48	38.90
ESB	0.15	0.07	0.14	0.14	0.13	0.05	0.11	0.17	0.13	0.09	0.12	0.11
NESB	0.15	0.10	0.11	0.07	0.06	0.05	0.06	0.03	0.04	0.05	0.06	0.05
Married	0.71	0.63	0.81	0.75	0.72	0.76	0.78	0.76	0.71	0.82	0.78	0.78
Unhealthy	0.15	0.17	0.11	0.19	0.17	0.16	0.13	0.13	0.15	0.11	0.13	0.14
Job Characteristics												
Union member	0.31	0.18	0.42	0.23	0.36	0.22	0.41	0.21	0.40	0.18	0.33	0.19
Years of experience	20.35	13.49	21.32	16.19	25.58	19.13	21.38	16.25	20.95	16.67	25.70	21.16
Occupation tenure	7.89	4.10	11.19	6.93	10.74	5.86	13.35	9.97	11.43	8.90	11.47	7.62
Job tenure	6.59	2.64	9.87	4.79	9.24	3.91	9.43	4.01	9.06	4.03	9.68	4.34
On-the-job training	0.34	0.27	0.50	0.42	0.25	0.16	0.47	0.41	0.33	0.38	0.44	0.34
Overall job satisfaction	6.98	5.73	7.74	6.81	7.07	6.29	7.77	7.08	7.24	6.06	7.88	6.99
Log hourly wage (2009 $)	3.19	3.07	3.48	3.33	3.14	3.08	3.38	3.29	3.29	3.18	3.28	3.15
Hourly wage (2009$)	24.28	21.54	32.45	27.93	23.10	21.75	29.36	26.83	26.83	24.04	26.57	23.33
Job occupational scale	40.63	32.27	61.20	55.56	36.57	39.01	50.48	45.29	42.10	42.71	50.86	48.17
Education												
Years of actual education	14.82	14.22	16.02	15.82	11.03	11.64	14.48	14.46	13.86	14.12	11.77	11.74
Years of required education	12.33	11.24	13.92	13.54	14.17	14.24	14.48	14.46	13.86	14.12	14.75	14.71
Observations	359	41	1,704	135	498	55	2,366	229	458	66	1,910	177

Notes: Age is a continuous variable, expressed in years. ESB and NESB are dummy variables; take value of 1 if born in an English-speaking or non-English-speaking country, 0 otherwise. Married is a dummy variable; takes value of 1 if married (or de facto), 0 otherwise. Unhealthy is a dummy variable; takes value of 1 if has a long-term health condition, disability, or impairment; 0 otherwise. Union member, on-the-job training, are dummy variables. Job satisfaction is an ordinal variable in response to the question, "If, all things considered, how satisfied are you with your job?" (10 point scale: 10 representing highest satisfaction). Years of experience, occupation tenure, job tenure, actual years of education, and years of required education are continuous variables, expressed in years. Variable job occupational scale provides Australian Socioeconomic Index 2006 occupational status scale of current main job. A higher value of this variable represents a higher occupational rank. The definition of variables is available in the Appendix (Table A1).
Sample size: Observations 7998, with 1980 individuals (before the regression).
Source: HILDA Release 9.

TABLE 4
Impacts of Job Satisfaction and on-the-job training on Quit Outcomes

Dynamic Random-effects Probit Models without and with Control for Endogeneity
Marginal effects (standard errors)

	Quit at t	Quit at t	Quit at t	Quit at t	Quit at t	Quit at t	
	(1)	(2)	(3)	(4)	(5)	(6)	
	Base Model		Full Model		Full Model (excluding wage rate)		
	DREP	DREP–MC With Mundlak correction	DREP	DREP–MC With Mundlak correction	DREP	DREP–MC With Mundlak correction	
Explanatory Variables	Pr(quit=1|u_i=0)=4.6%	Pr(quit=1|u_i=0)=3.6%	Pr(quit=1|u_i=0)=4.6%	Pr(quit=1|u_i=0)=3.6%	Pr(quit=1|u_i=0)=4.6%	Pr(quit=1|u_i=0)=3.6%	Mean of X
Lagged dependent variable							
Quit at t-1	0.030*	0.129***	0.030*	0.129***	0.031*	0.131***	0.076
	(0.017)	(0.031)	(0.017)	(0.031)	(0.017)	(0.024)	
Initial condition							
Quit at t=0	0.022	-0.009	0.022*	-0.009	0.022	-0.009	0.078
	(0.014)	(0.007)	(0.014)	(0.007)	(0.014)	(0.006)	
Overall job satisfaction $_t$	-0.014***	-0.014***	/	/	/	/	7.594
	(0.002)	(0.002)					
Training $_t$	-0.010*	-0.009	/	/	/	/	0.433
	(0.006)	(0.006)					
Panel A: Mismatched type interaction with overall job satisfaction							
Over-educated-and-Over-skilled $_t$ x Overall job satisfaction $_t$	/	/	-0.011	-0.016**	-0.011	-0.015**	0.343
			(0.007)	(0.008)	(0.007)	(0.008)	
Only Over-educated $_t$ x Overall job satisfaction $_t$	/	/	-0.016***	-0.018***	-0.017***	-0.019***	1.763
			(0.004)	(0.004)	(0.004)	(0.004)	
Under-educated and Over-skilled $_t$ x Overall job satisfaction $_t$	/	/	-0.009*	-0.015***	-0.009*	-0.015***	0.483
			(0.005)	(0.006)	(0.005)	(0.006)	
Job-matched $_t$ x Overall job satisfaction $_t$	/	/	-0.011***	-0.008**	-0.012***	-0.008***	2.502
			(0.003)	(0.003)	(0.003)	(0.003)	
Only Over-skilled $_t$ x Overall job satisfaction $_t$	/	/	-0.018***	-0.015***	-0.018***	-0.016***	0.465
			(0.005)	(0.005)	(0.005)	(0.005)	

TABLE 4 *(continued)*

Only Under-educated $_t$ x Overall job satisfaction $_t$	/	/	-0.014*** (0.003)	-0.016*** (0.004)	-0.014*** (0.003)	-0.016*** (0.004)	2.038
Panel B: Mismatched type interaction with on-the-job training							
Over-educated-and-Over-skilled $_t$ x on-the-job training $_t$	/	/	-0.021 (0.017)	-0.026** (0.011)	-0.022 (0.017)	-0.025** (0.011)	0.017
Only Over-educated $_t$ x on-the-job training $_t$	/	/	-0.000 (0.012)	-0.002 (0.013)	-0.000 (0.012)	-0.001 (0.013)	0.114
Under-educated-and-Over-skilled $_t$ x on-the-job training $_t$	/	/	-0.031*** (0.011)	-0.026** (0.010)	-0.032*** /(0.011)	-0.026*** //(0.010)	0.017
Job-matched $_t$ //x on-the-job training $_t$	/	/	-0.005 //(0.009)	-0.008 (0.009)	-0.005 //(0.009)	-0.008 //(0.009)	0.152
Only Over-skilled $_t$ x on-the-job training $_t$	/	/	-0.004 (0.019)	-0.002 (0.019)	-0.004 (0.019)	-0.003 (0.019)	0.022
Only Under-educated $_t$ //x on-the-job training $_t$	/	/	-0.016* (0.009)	-0.008 (0.010)	-0.016* (0.009)	-0.009 (0.010)	0.112
Log Hourly wage (2009$) $_t$	-0.010 (0.008)	-0.033*** (0.012)	-0.010 (0.008)	-0.033*** (0.012)	/	/	3.335
Mundlak correction	NO	YES	NO	YES	NO	YES	
Log likelihood	-1322	-1177	-1319	-1168	-1320	-1172	
Wald chi-squared	308.7	460.3	312.4	466.6	313.6	528.6	
Individuals	1,613	1,613	1,613	1,613	1,613	1,613	
Observations	5,439	5,439	5,439	5,439	5,439	5,439	

Notes: Dependent variable is a dummy variable; takes value of 1 if workers experience voluntary quit at t; 0 otherwise.

DREP represents a dynamic random-effects probit model. DREP–MC represents a dynamic random-effects probit model with Mundlak correction.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Overall job satisfaction is an ordinal variable, which is derived from the response to the question "If, all things considered, how satisfied are you with your job?" It is scored on a 10-point scale, in which 0 is totally dissatisfied and 10 is totally satisfied. Base-categories are: Native-born, Not Union member, healthy, No training, Year 2008 and QLD.

The models include job mismatch status (in Columns (3) to (6)), time periods, states fixed effects, unemployment, immigrant status, married status, actual years of education, union membership, health status, work experience, current job tenure, current occupational tenure, and job occupational scale. The complete set of results is available by request.

Source: HILDA Release 9

Appendix A

TABLE A1
Definition of Variables

Personal Characteristics	
General	
Married	1 if married (or de facto), zero otherwise.
Health Status	
Disability or impairment	1 if has a long-term health condition, disability, or impairment, zero otherwise.
Educational Mismatched Variables	
Actual years of education	Years of educational attainment.
Years of required education	Years of adequate education (based on two-digit occupational code and Mode method of educational requirements, used for the derivation of educational mismatch status variables).
Over-educated-and-Over-skilled	1 if over-educated and over-skilled, zero otherwise.
Only Over-educated	1 if over-educated and skill matched, zero otherwise.
Under-educated-and-Over-skilled	1 if under-educated and over-skilled, zero otherwise.
Well-matched	1 if both education and skill matched, zero otherwise.
Only Over-skilled	1 if education matched and over-skilled, zero otherwise.
Only Under-educated	1 if under-educated and skill matched, zero otherwise.
Job Mobility Variables	
No change	1 if respondent works in the same job as previous survey, zero otherwise.
Job separation reasons	Self-reported response on the reason for job change, if job had changed since previous job.A13-point set of responses identified voluntary or involuntary job separations:(1) not satisfied with job, (2) to obtain a better job/just wanted a change/to start a new business, (3) retired/did not want to work any longer, (4) to study at home to look after children, house or someone else, (5) travel/have a holiday, (6) returned to study/started study/needed more time for study, (7) too much time spent in travel/too far from public transport, (8) change of lifestyle, or (9) immigration.
Quit (voluntary leaving)	1 if workers experience voluntary quit categories, and due to job characteristics, (1) not satisfied with job, and (2) to obtain a better job/just wanted a change/to start a new business; zero otherwise. We focus on the comparison between workers who stay in their current job and workers who leave voluntarily. Therefore, workers who leave involuntarily or leave for other reasons are not classified as voluntary quit. In addition, self-employed workers and full-time or part-time students are excluded.
Involuntary leaving .	(10) laid off, (11) no work available, (12) retrenched, or (13) made redundant. Note: Not included in our analysis of quit behavior.
Others .	Including temporary or seasonal work, spouse transferred, pregnancy, sickness or disability, and any other reasons that cannot be classified. Note: Not included in our analysis of quit behavior.
Job Satisfaction Variables	
Overall job satisfaction	Overall job satisfaction is an ordinal variable, which is derived from the response to the question "If, all things considered, how satisfied are you with your job?" It is scored on a 10-point scale, in which 0 is totally dissatisfied and 10 is totally satisfied.

On-the-job Training Variables	
Training	1 if worker has taken part in any work-related training, zero otherwise. On-the-job training is a dummy variable, derived from the responses to the question relating to having taken part in any work-related training in the past 12 months.
Job Characteristics	
EXP	Experience: Potential years of working experience (age-actual years of education-5).
EXP^2	Experience squared.
Occupation tenure	Years of tenure in the current occupation.
Job tenure	Years of tenure in the current job.
Job occupational scale	Australian Socioeconomic Index 2006 (AUSEI06), which assigns sociologically occupational status scores to the official occupational classifications of the Australian Bureau of Statistics (ABS). This Ordinal control variable on the current job, on a scale of 1-100 is generated based on the 2006 Census of Population and Housing data. For example, medical practitioners are at the top of the scale (100); university lecturers and tutors (92); legal professionals (91); and laborers are placed at the lower end of the scale. More detailed information is available in McMillan et al. 2009.
Unemployment	Australian unemployment rate (annual), refer to 6202.0 - Labor Force, Australia, Australian Bureau of Statistics. This variable controls for the overall labor market conditions.
Log hourly wage	Natural logarithm of hourly wage from main job in constant 2009 $.
Union membership	1 if a union member, zero otherwise.
State	Dummy variables (NSW, VIC, QLD, SA, WA, TAS, NT, ACT)
Urban	1 if urban, zero otherwise.
Time	Dummy variables=1 for each year of survey, zero otherwise.
Country of birth	
Australian	1 if born in Australia, zero otherwise.
ESB	1 if born in an English-speaking country, zero otherwise.
NESB	1 if born in a non-English-speaking country, zero otherwise.

TABLE A2
Robustness Test 1: Testing Potential Impact of Training, and Job Mismatch, on Overall Job Satisfaction

Coefficients (standard errors)

Explanatory Variables	Overall job satisfaction (1) Pooled OLS	Overall job satisfaction (2) Fixed Effects	Overall job satisfaction (3) Random Effects
Main panel estimation results			
Training	0.016	0.041	0.028
	(0.034)	(0.039)	(0.035)
Mismatched status			
Over-educated-and-Over-skilled	-0.399***	-0.299***	-0.406***
	(0.082)	(0.108)	(0.088)
Only Over-educated	-0.027	-0.029	-0.025
	(0.046)	(0.073)	(0.052)
Under-educated and Over-skilled	-0.363***	-0.159	-0.336***
	(0.078)	(0.100)	(0.082)
Only Over-skilled	-0.242***	-0.113	-0.225***
	(0.069)	(0.078)	(0.071)
Only Under-educated	-0.032	-0.075	-0.044
	(0.055)	(0.076)	(0.060)
Log Hourly wage (2009$)	0.184***	0.398***	0.232***
	(0.043)	(0.081)	(0.050)
Hausman fe/re test: Chi2	/	1847.98	
Prob>Chi2=	/	0	
Individuals	1,613	1,613	1,613
Observations	5,439	5,439	5,439

Notes: Overall job satisfaction is an ordinal variable, which is derived from the response to the question "If, all things considered, how satisfied are you with your job?" It is scored on a 10-point scale, in which 0 is totally dissatisfied and 10 is totally satisfied.

The models also include time periods, states fixed effects, unemployment, immigrant status, married status, actual years of education, union membership, health status, work experience, current job tenure, current occupational tenure, and Job occupational scale. Base-categories are: Native-born, Not Union member, healthy, No training, Well-matched, Year 2008 and QLD.

The complete set of results is available by request.

Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Source: HILDA-Release 9.

TABLE A3
Robustness Test 2: Testing Potential Impact of Overall Job Satisfaction, and Job Mismatch, on on-the-Job Training

Dynamic Random-effects Probit Models without and with Control for Endogeneity
Marginal effects (standard errors)

	With wage variable **Training at t**		***Without wage variable*** **Training at t**		
	(1)	(2)	(3)	(4)	
	DREP	DREP-MC With Mundlak correction	DREP	DREP-MC With Mundlak correction	
Explanatory Variables	Pr(Training=1|u_i=0)=41%	Pr(Training=1 |u_i=0)=41%	Pr(TRaining= 1|u_i=0)=41%	Pr(Training=1 |u_i=0)=41%	Mean of X
Main panel estimation results					
Lagged dependent variable					
Training at t-1	0.182***	0.177***	0.182***	0.177***	0.448
	(0.022)	(0.022)	(0.022)	(0.022)	
Initial condition					
Training at t=0	0.209***	0.204***	0.209***	0.204***	0.402
	(0.023)	(0.023)	(0.023)	(0.023)	
Overall job satisfaction $_t$	0.004	0.000	0.005	0.000	7.594
	(0.006)	(0.008)	(0.006)	(0.008)	
Mismatched status					
Over-educated-and-Over-skilled $_t$	0.011	0.116**	0.008	0.116*	0.050
	(0.043)	(0.060)	(0.043)	(0.060)	
Only Over-educated $_t$	0.006	0.011	0.006	0.011	0.230
	(0.024)	(0.039)	(0.024)	(0.039)	
Under-educated-and-Over-skilled $_t$	-0.063	0.001	-0.064	0.002	0.069
	(0.040)	(0.055)	(0.040)	(0.055)	
Only Over-skilled $_t$	-0.073**	-0.064	-0.074**	-0.065	0.066
	(0.034)	(0.041)	(0.034)	(0.041)	
Only Under-educated $_t$	0.033	0.026	0.031	0.026	0.261
	(0.029)	(0.041)	(0.029)	(0.041)	
Log Hourly wage (2009$) $_t$	0.051**	0.023	/	/	3.335
	(0.023)	(0.043)	/	/	
Mundlak correction	NO	YES	NO	YES	
Log likelihood	-3151	-3126	-3153	-3128	
Wald chi-squared	664.1	691.4	661.2	689.2	
Individuals	1,613	1,613	1,613	1,613	
Observations	5,439	5439	5,439	5439	

Notes: DREP represents a dynamic random-effects probit model.

DREP-MC represents a dynamic random-effects probit model with Mundlak correction.

Dependent variable is a dummy variable; takes value of 1 if worker has taken part in any work related training in the past 12 months at interview time t; 0 otherwise.

Overall job satisfaction is an ordinal variable.

The models include time periods, states fixed effects, unemployment, immigrant status, married status, union membership, health status, work experience, current job tenure, current occupational tenure, actual years of education, and Job occupational scale.

The complete set of results is available by request. Standard errors in brackets; ***, **, and * denote statistical significance at the 1%, 5 % and 10% levels respectively.

Source: HILDA-Release 9.