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UNDERSTANDING THE ROLE OF KEY SOCIO-DEMOGRAPHIC CHARACTERISTICS IN LABOUR FORCE AND INDUSTRY EMPLOYMENT OUTCOMES

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Understanding the Role of Key Socio-Demographic Characteristics in Labour Force and Industry Employment Outcomes

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Industry and Small Business Policy Division

Department of Innovation, Industry, Science and Research
Working Paper

November 2008

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Working papers are prepared by the Industry Policy and Economic Analysis Branch in the Industry and Small Business Policy Division of the Department of Innovation, Industry, Science and Research. Working papers and other publications are available through the research link on the department's internet website at www.innovation.gov.au.

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Understanding the Role of Key Socio-demographic Characteristics in Labour Force and Industry Employment Outcomes[2]

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Abstract

The aim of this paper is to improve understanding of the impact of socio-demographic characteristics in labour force and industry employment outcomes in Australia. The paper presents results of multivariate econometric modelling of the relationship between an individual's socio-demographic characteristics and the probability of being in one of 19 labour market outcomes: employed in any of the 17 one-digit ANZSIC industry sectors, unemployed, or not in the labour force. Through the creation of stylised socio-demographic profiles, the model serves as a tool with which to probe the impacts across industries of changes by gender in ageing, education and age of children. The data set is based on Wave 4 of the Living in Australia: Household Income and Labour Dynamics in Australia (HILDA) Survey. Brief descriptions of the data and cross-tabulations of variables used in the model are provided in the appendix.

[2] We gratefully acknowledge the intellectual contribution of Dr Donald Brunker of the Productivity Commission (formerly, General Manager, Industry Analysis Branch, Industry Policy Division, Department of Industry, Tourism and Resources), whose ideas, comments and suggestions greatly added to the rigour of the paper. Colin Lyons, policy economist in Industry Policy Section, is appreciated for his assistance with editing earlier drafts of the paper as are the helpful comments of our present general manager, Mr Richard Snabel. We also gratefully acknowledge the helpful comments on econometric methodology provided by Associate Professor Robert Breunig, Research School of Social Sciences, Australian National University (ANU) and, on an earlier draft, Professor Trevor Breusch, Crawford School of Economics, ANU.

The HILDA Project was initiated and is funded by the Commonwealth 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 paper, however, do not reflect those of FaHCSIA or the MIAESR.

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Key Points

Background

In this paper we analyse individual socio-demographic characteristics and their association with 19 possible labour market outcomes: industry of employment for each of 17 one-digit ANZSIC industries; ‘unemployed’; and, ‘not in the labour force’.

- Previous studies have identified demographic change as a key factor influencing labour participation and the structure of the labour force across industries. They also have highlighted how labour force characteristics are associated with forms of employment.
- We build an econometric model of the probability or 'likelihood' of an individual worker being employed in a particular industry based on some specific characteristics of that individual (15 in total). The model overcomes the limitation of existing analysis using cross tabulations in predicting an individual's labour market outcome.
- We examine the impact of five key characteristics—age, gender, age of children under care, educational attainment and English skill—on the probability of an individual being: not in the labour force, unemployed, and employed in one of the 17 one-digit ANZSIC industries.
- The value of the work beyond other studies is that its unit of analysis focuses on employment outcomes by industry (as opposed to occupation or full-time/part-time status). The robust model infrastructure facilitates the ability to isolate the impact of individual characteristics on employment likelihood across different industries. Examining differences between industries can help inform policy.
- Our analysis uses confidentialised unit record data from Release 4.1, Wave 4 of the Living in Australia: Household Income and Labour Dynamics in Australia (HILDA) Survey.

Major highlights

- An association is found between age and the probability of employment in every industry, although the relationship is not uniform across industries and gender.
- Males and females face different employment prospects in different industries. The likelihood of females being employed in retail trade, property and business services, education and health and community services is much larger than their male counterpart. On the other hand, males have much better chances in electricity, gas and water, construction, transport and storage and manufacturing.
- The age of the child under care is an important determinant of a mother's labour market outcomes. Women's workforce participation probability almost halves as a result of caring for pre-school aged children. The probability generally starts to rise with the rise

in the age of the child.

- In levels, this rise varies dramatically by industry. Among the industries reported, retail trade shows the highest rise in employment prospects for women as the child under their care grows older, followed by health and community services.
- The sensitivity of employment probability to industry by age of the child under care may be reflective of greater flexibility of working hours in these industries.
- The impact of higher education varies across industries and by gender. Some industries show positive impacts consistently at each level of higher education. Similarly, some industries show consistently negative impacts, with some industries showing mixed outcomes.
- There is a strong positive relationship between the workforce participation rate for females and higher levels of educational attainment, both for those born in English speaking and in non-English speaking countries. For males, the relationship is much weaker.

1 Overview

1.1 Background

The challenges posed by the ageing of the Australian population were brought to prominence in the *Intergenerational Report* published by the Treasury in Budget Paper No. 5 (2002–03) and, more recently, by the Treasury's *Intergenerational Report 2007*. The 2005 Productivity Commission research report *Economic Implications of an Ageing Australia* assessed the implications of Australia's ageing population for productivity, labour force and fiscal outcomes across the three tiers of government, building on and complementing Treasury's work.

Demographic change, in particular the ageing of the population, was identified by the then Department of Education, Science and Training in *The National Industry Skills Report* (2006) as a key factor influencing labour participation and the structure of the labour force in most industries. The report suggested that Australian industries with a concentration of skilled workers near retirement age, or with traditionally-recruited younger workers, are likely to experience shortages of both labour and skills due to the ageing population. The nature of the shortages differs between industries, sometimes significantly, suggesting a need to explore more deeply the correlations between labour characteristics and labour market outcomes. More recently, a paper by Geisecke and Meagher (2008) considers how the structure of the economy is likely to be affected by population ageing. In particular, it analyses the effects on 64 skill groups, 81 occupations and 106 industries.

In recent years, a number of studies have used HILDA to analyse the Australian labour market. A paper released by the Productivity Commission (2006) used HILDA to analyse the characteristics of labour participation in major forms of 'non-traditional' work including casual, fixed-term employment, self-employed contractors and labour-hire employment. The study identified personal characteristics associated with non-traditional work. For example, casual employees tend to be young, female and less skilled; males are more likely to be fixed-term employees or self-employed contractors. In addition, the study noted different mixes of non-traditional and traditional work across industries. For instance, in accommodation, cafes and restaurants, 53 per cent of all employees are casual compared to only about 5 per cent in electricity, gas and water.

Several studies have also been conducted in Australia, analysing the labour characteristics associated with forms of employment (Kryger 2004, Waite and Will 2002, Wooden and Warren 2003, Productivity Commission 2006), while Nicholas (2006) examined the probability of a university graduate finding a full-time job within six months of graduation.

1.2 The present study

The present study complements this earlier work but focuses on the individual socio-

demographic characteristics associated with likelihood of employment in different industries, of being unemployed or of not being in the labour force. This is accomplished by establishing a model of the likelihood of an individual worker being employed in a particular industry based on some specific characteristics of that individual (15 in total)—for example, age, gender, educational qualifications, and age of children under care. Such a model overcomes the limitation of existing analysis using cross tabulations in predicting an individual's labour market outcome.

Our model can also be used to study the effect across industries of changes in these characteristics. In this regard, it can also serve as a tool with which to probe the impacts on individual industries of, for example, an ageing population or a population that is becoming better educated.

1.3 Modelling data

The paper uses HILDA (Release 4.1, which was the latest release available when this project commenced) to estimate the association between selected socio-demographic characteristics and the probability of an individual's particular labour market outcome. The phrase 'labour market outcome' is a broad term that defines a person as falling within the mutually exclusive states of being employed in any of the 17 one-digit ANZSIC industries, unemployed or not in the labour force.

There were 12 408 individuals in the dataset and, after excluding observations with missing data, a subset of HILDA with a total of 10 468 individuals was used in the model estimation. We could have interpolated missing observations or created dummy variables for missing values to account for these omitted observations. However, each method has limitations, so we opted to exclude missing observations from the modelling work. For further details on the missing values, the data used in the modelling exercise and their distribution across various labour market outcomes, see Appendix A.

The complete HILDA dataset is described in detail in Appendix B, which sets out and describes the profile of Australian industries by various socio-demographic factors. These profiles can differ significantly between industries.

2 Modelling labour market outcomes

The thrust of this paper is to quantify the association between an individual's key socio-demographic characteristics and probabilities of various labour market outcomes, and to make a quantitative assessment of impacts on the probabilities on labour market outcomes of changes in one or a few characteristics. For example, we seek to estimate the impact of changes in levels of educational achievement on the probabilities of being employed across different industries.

2.1 The modelling methodology

To identify the impact, *ceteris paribus*, of each characteristic, we needed to estimate a multivariate econometric model in which an individual's socio-demographic characteristics of interest formed at least part of the 'explanatory' variables.

We adopt a multinomial logit model (Wooldridge 2002)[4] and assign non-zero probabilities to every individual for all 19 labour market outcomes. Such a model enables us to make unbiased predictions of the probabilities for all individuals. At the same time, it can also predict the probabilities for hypothetical individuals with arbitrary characteristics considered.

An implication of the model is that the probabilities of each labour market outcome can be uniquely determined by the socio-demographic and employment characteristics included, assuming labour demand and supply have reached equilibrium.

It is important to emphasise that, because of the cross-section nature of the data, it was not possible to formally establish causality between the likelihood of various labour market outcomes and the socio-demographic and employment characteristics of an individual[5]. While there may be some strong priors in this regard, it has not been possible to statistically test them. As a result, this research seeks only to establish the significance of association between the explanatory variables and the probability of an individual experiencing a certain labour market outcome.

2.2 Variables in the model

The dependant variables being modelled are the probability of being in any one of the 19 labour market outcomes. For any given set of explanatory variables, which describe the characteristics of individuals, the model estimates 19 probability values which, together, sum to unity.

[4] A more correct approach would be to construct a nested logit model to relax the Independence from Irrelevant Alternatives (IIA) assumption underpinning a multinomial logit model, as some industries may be correlated with each other. However, extensive nested logit modelling based on some viable nested structures seems to indicate that there is not sufficient evidence to argue for adopting a more advanced model than multinomial logit.

[5] Although HILDA is available as panel data spanning multiple waves, Wave 4 is only a snapshot of HILDA without a dynamic structure. Likely future work, by including panel data, may be able to examine causality.

There are 15 broad explanatory variables included in the model:

- age;
- marital status;
- country of birth;
- indigenous status;
- gender;
- age of youngest child living in the residence, indicating the age of children under care;
- remoteness, indicating the regional nature of the person's residence;
- socio-economic index of residence, indicating the relative socio-economic advantage/ disadvantage of the person's post code of residence;
- state/territory of residence;
- education level;
- current enrolment for study, indicating the person's status as a student;
- health condition—whether the person has a long-term health condition;
- social functioning ability—whether the person has good social skills;
- length of employment; and
- unemployment duration.

All of the explanatory variables except for age, employment and unemployment duration are classified as categorical—non-continuous with a finite number of discrete values. The age squared variable is created to address the non-linearity associated with age. With an increase in age, the probability of the majority of the 19 labour market outcomes is expected to rise. However, after some time, the probability does not continue to rise further but drops, giving an inverted-U shape to the age variable. The age squared term is included to take care of this non-linearity in the relationship.

Employment history variables such as the length of employment and unemployment are included because the former is related to experience and hence likely to influence labour market outcomes, and the latter might have an adverse effect on employment prospects. The education variable, 'highest level of educational attainment', has seven categories, starting from year 11 or below including certificate I/II, followed by: year 12; certificate III/IV; diploma; bachelor degree; graduate diploma; and masters or PhD.

Having children is expected to affect labour market outcomes; moreover, the age of the youngest child may have greater measureable impact. For example, given the mother's

traditional role as the primary carer for young children, it is likely that a high proportion of these mothers would be in the not in the labour force category. Also, mothers with a younger child who are in the workforce are more likely to be employed in industries that have a higher proportion of part-timers and offer flexible work arrangements. However, it is not generally expected that a similar impact would apply to males. To investigate how employment prospects are affected by the presence of a young child in a family, and also how these effects vary from males to females, an interaction term between gender and the age of the youngest child under care was created. It results in ten categories: male/female with no child, male/female with four different ages for the youngest child under care, 0–4, 5–14, 15–24 and 25 or more.

As employment depends on the availability of the person to take up the job, a study variable is included to give proxy for availability. A person studying full-time may look for jobs in industries that tend to hire part-timers on a flexible basis. Part-time study may be correlated with a certain type of employment. For example, instances of tradesmen or professionals gaining higher education and/or additional skills to improve career prospects occur frequently in some industries.

There are three location-of-residence variables included in the model: remoteness, relative socio-economic position, and state or territory of residence. These variables may be important for determining labour market outcomes. For example, all other things being equal, employment near where one already resides may be preferred to having to relocate.

Remoteness of living area is likely to be more commonly associated with some labour market outcomes (e.g., employment in mining) than others. The classifications of the remoteness variable are: major city, inner region, outer region, remote, and very remote.

Labour market outcomes are also expected to be associated with the relative socio-economic index of the regions of residence. An area with relative prosperity may be expected to offer more jobs and more highly paid jobs than a relatively poor area. Our model has accordingly included a socio-economic index from HILDA that arranges the areas of residence in a decile distribution, ranked by a region's relative economic advantage, generating ten categories.

The states and territories variable is included in the model mainly to address the stratification issue. As the modelling procedure used unweighted survey data, it was appropriate to include all stratification variables in the model. HILDA includes the strata variables 'states and territories'. The model includes it as one of the explanatory variables.

The five remaining categorical variables: marital status, country of birth—English or non-English speaking country, indigenous status or not, problematic health condition or not, and social functioning score—perfect or not, are binary in nature. They each take the value 'one' when an individual is, respectively, married or in a *de facto* relationship, born in a non-English

speaking country, has indigenous status, has no long-term health condition and has perfect social functioning score.

In order to provide an understanding of the data used in modelling and their distribution, average values for some of the explanatory variables for the dataset used in the econometric model are shown in Table A.3 in Appendix A. The average for a binary variable is its mean, and can be interpreted as the proportion of observations for which that particular variable takes the value 'one'. For example, the mean for the variable 'marital status' is 0.67, which means that 67 per cent of individuals in the sample are either married or in a *de facto* relationship. The average for a particular class of a category variable is the frequency of that class. For example, the category variable education has 7 levels, and the average value of 0.36 attached to year 11 or below education level indicates that 36 per cent of the sample population possess an educational qualification of year 11 or below.

2.3 Model estimates

Estimates for all explanatory variables using the multinomial logit model of 19 labour market outcomes have been obtained using Stata software (Stata 2007). Two alternative multinomial models were also constructed for comparison. One is estimated for three employment outcomes only (not in the labour force, unemployed and employed). The other was estimated for the subset of those employed (in the 17 industries). Predicted probabilities did not differ noticeably from those shown in Table 3.2 or reported elsewhere in the paper.

The model was estimated for 18 outcomes only, as the 19th outcome was set as the reference outcome, and the probability associated with the reference outcome was derived indirectly from the estimated probabilities of all other outcomes. The unemployed outcome has been selected as the reference outcome, but the choice was arbitrarily made. Choosing a different reference outcome would produce different coefficient values, but it would not alter the probability values reported throughout the paper. A total of 846 coefficients (47 coefficients for each of the 18 labour market outcomes, excluding the constant terms) were estimated from 10 486 observations. Appendix B provides an overall picture of statistical significance of estimated parameters across labour market outcomes and variables.

3 Analysis of Individual socio-demographic characteristics and labour market outcomes

3.1 Labour market outcome probabilities of representative individuals

Coefficient values, obtained from estimating the multinomial logit model described in the last section, can be used to estimate the probability of each of the 19 labour market outcomes for an individual with any particular socio-demographic characteristics. For example, we seek to estimate the probability of being unemployed (or any of the other 18 outcomes) for a male of a certain age with a certain level of educational qualification and other socio-demographic characteristics.

For the analysis for this paper, we have identified two groups of representative individuals, referred as 'stylised' males and 'stylised' females. These stylised males and females are characterised by chosen socio-demographic and employment settings outlined in Table 3.1. The choice of the settings is in a majority of cases dictated by the mode, instead of mean, values of the characteristics. Analysis of labour market outcomes of a 'mean' person, when most explanatory variables are discrete, can only be hypothetical. In contrast, stylised males and females are much closer to reality, and so studying them would provide more insights than is possible using mean values. For example, stylised persons are set to come from NSW which represents 30 per cent of the sample, live in major cities (61 per cent of the sample), are married (67 per cent of the sample) and born in English speaking countries (89 per cent of the sample). These modal values are shown in Table A.3 in Appendix A, which reports variable descriptions with their respective averages, as referred to in the previous section. Although persons with no children under care is the majority group in the sample, we chose our stylised persons to have children under care, primarily to study the complex interactions of working and caring for children.

Table 3.1: Characteristics of 'stylised' males and females

Characteristics	Male	Female
Age	40	40
Marital status	Married or *de facto*	Married or *de facto*
Country of birth	English speaking country	English speaking country
Indigenous status	Non indigenous	Non indigenous
Age of the youngest child under care	5–14	5–14
Remoteness of living area	Major city	Major city
Socio-economic index of living area	3rd decile	3rd decile
State and Territory	NSW	NSW
Highest level of education	Certificate III/IV	Year 11 or below
Current enrolment for study	Not enrolled	Not enrolled
Health condition	No long-term health condition	No long-term health condition
Social functioning ability	Perfect social functioning score	Perfect social functioning score
Duration of unemployment (years)	1.218	0.703
Duration of employment (years)	20.325	16.823

Columns 2 and 4 in Table 3.2 below reports the labour market outcome probabilities estimated for stylised males and females. Probability values of being employed (which is an aggregation of probabilities associated with all 17 industries of employment), unemployed and not in the labour force added together equate to one. Subtracting from unity the probability value associated with not in the labour force gives an indication of probability of workforce participation.

As the table suggests, stylised males and stylised females clearly face different prospects regarding labour force status as well as industry of employment. Compared to females, the probability of workforce participation is larger for stylised males by almost 15 percentage points. Also, stylised males are on average 17 percentage points more likely to be employed than their stylised female counterparts. On the other hand, a stylised female faces, by more than an additional two percentage points, the likelihood of being unemployed compared to a stylised male.

While employed, stylised females have better prospects in some industries than their counterpart males, and vice versa. Compared to males, the likelihood of females being employed in retail trade, property and business services, education and health and community services is much larger. On the other hand, stylised males have much better chances in electricity, gas and water, construction, transport and storage and manufacturing than their female counterparts.

Table 3.2: Probability of labour market outcomes for stylised males and females, both married and single

Labour market outcome	Predicted Probabilities			
	Male		Female	
	Married	Single	Married	Single
Not in the labour force	0.0268	0.0276	0.1750	0.1762
Unemployed	0.0055	0.0104	0.0256	0.0471
Employed (*sum of the 17 industries*	0.9677	0.9621	0.7994	0.7767
-Agriculture	0.0067	0.0055	0.0066	0.0053
-Mining	0.0066	0.0050	0.0000	0.0000
-Manufacturing	0.1743	0.1885	0.0764	0.0808
-Electricity gas & water supply	0.0035	0.0020	0.0004	0.0002
-Construction	0.2249	0.2235	0.0416	0.0405
-Wholesale trade	0.0685	0.0580	0.0496	0.0411
-Retail trade	0.0793	0.0831	0.1539	0.1580
-Accommodation, cafes & restaurants	0.0361	0.0421	0.0429	0.0490
-Transport and storage	0.0958	0.1064	0.0406	0.0441
-Communication services	0.0380	0.0252	0.0224	0.0146
-Finance and Insurance	0.0436	0.0351	0.0462	0.0364
-Property and business services	0.0350	0.0300	0.0676	0.0567
-Government admin & defence	0.0297	0.0279	0.0172	0.0158
-Education	0.0239	0.0232	0.0750	0.0710
-Health and community services	0.0371	0.0388	0.1207	0.1237
-Cultural and recreational services	0.0085	0.0091	0.0090	0.0095
-Personal and other services	0.0562	0.0586	0.0293	0.0299
SUM	1.0000	1.0000	1.0000	1.0000

3.2 Marginal probabilities and impact analysis

We use the concept of marginal probability to identify the impact, *ceteris paribus*, of each characteristic on the labour market outcome probabilities. Marginal probability can be defined as the change in the probability of a certain outcome when an explanatory variable changes its value. For example, we estimate the impact of marital status on being unemployed for a stylised male. To do this, we first estimate the probability of a stylised male (married) being unemployed, i.e., 0.0055 (see Column 2 in Table 3.2). We then estimate the probability of the

same outcome for a single male, keeping all other socio-demographic characteristics unchanged, which is 0.0104 (see Column 3 in Table 3.2). The difference between the two probability values (0.0049) quantifies the impact of marital status (married to single) on probability of a stylised male being unemployed, everything else remaining the same.

Marginal probabilities can also be estimated for a set of variables. The difference in the predicted probabilities reported in Column 2 and Column 4 in Table 3.2 shows the impact of gender and education as the stylised male is different from a stylised female not only by gender but by education too. Throughout the paper we have used the concept of marginal probability values estimated for one or a set of variables.

In the next section, we discuss the impact of several socio-demographic characteristics on the probabilities of several labour market outcomes. Our primary focus is on age, gender, marital status and age of children, educational attainment and English speaking ability[6]. While we are primarily interested in predicting the impact on the industry of employment, we also discuss the impact on total workforce participation, unemployment and employment. The impact on the latter two outcomes can be read directly from the marginal probability values associated with being unemployed and employed respectively. The impact on workforce participation is obtained by subtracting the marginal probability of not being in the labour force from unity, as mentioned earlier. Since probability values associated with being employed, unemployed and not in the labour force sum to one, we generally report any two of the aggregate outcomes.

3.2.1 Impact of socio-demographic characteristics on aggregate workforce participation, unemployment and employment

3.2.1.1 Age and gender

In order to find the impact of ageing, we estimated labour market outcomes probabilities for stylised males and females by varying the 'age' variable, with other characteristics remaining the same. In this particular exercise, to avoid mixing up our findings with the impact of having children, we modified our concept of stylised males and females by giving them no children.

Figure 3.1 reports probability values associated with being employed and not being in the labour force for both a stylised male and a female but without children under care, for ages 16 to 78[7]. For isolating the gender impact only, we have set education level for both stylised

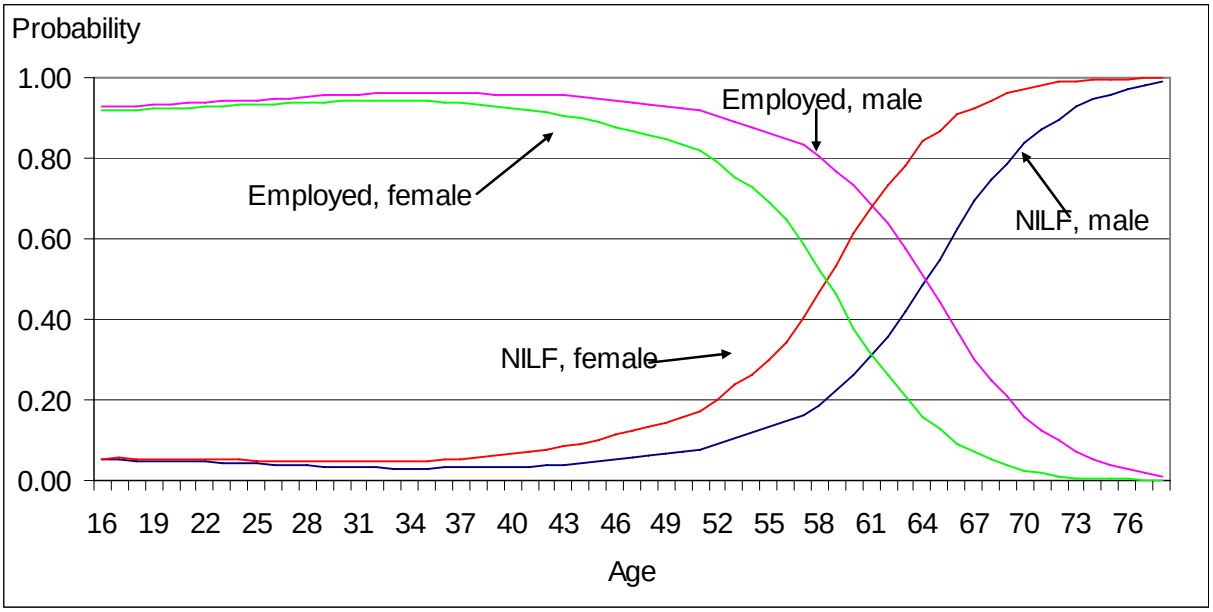
[6] The marginal probabilities estimated for all labour market outcomes for any/all of the explanatory variables are available on request.

[7] Generally, a five-period moving average has been used to smooth out `anomalies' that would otherwise appear so that attention can be focused on the trend. The anomalies arise because the employment and unemployment duration variables have to be adjusted with age. It would not be sensible, for example, to have a young female, aged 25, with the employment and unemployment duration values set for stylised females aged 40. Unfortunately,

males and females at the same level–certificate III/IV. Our results suggest that labour market outcomes are affected differently by age and gender. While there is a general propensity of employment prospects to rise first with age and then decline, there is a clear indication that these propensities are influenced by gender. Males are more likely to be employed than females at any age.

The gender impact, which can be read off as the vertical distance between male and female probability values for a particular outcome, is noticeable around the 20s and becomes critical around age 40 onward until the late 50's or early 60's. This is when the male and female probabilities begin to converge, once more men retire. This gender gap in employment probability is largely accounted for by lower labour force participation by females rather than by their much higher unemployment rate. Figure 3.1 shows that the probability gap of employment between men and women mirrors the probability gap of not being in the labour force.

Figure 3.1: Probabilities of being employed and not in the labour force for stylised males without children under care and their female counterparts



3.2.1.2 Age of children under care

The propensity of women with young children to exit the labour force (at least temporarily) is dependent on the age of their children. In order to understand the impact of this variable on women's workforce participation and employment, we looked at a stylised female's marginal probabilities associated with different age brackets of children under care, in reference to

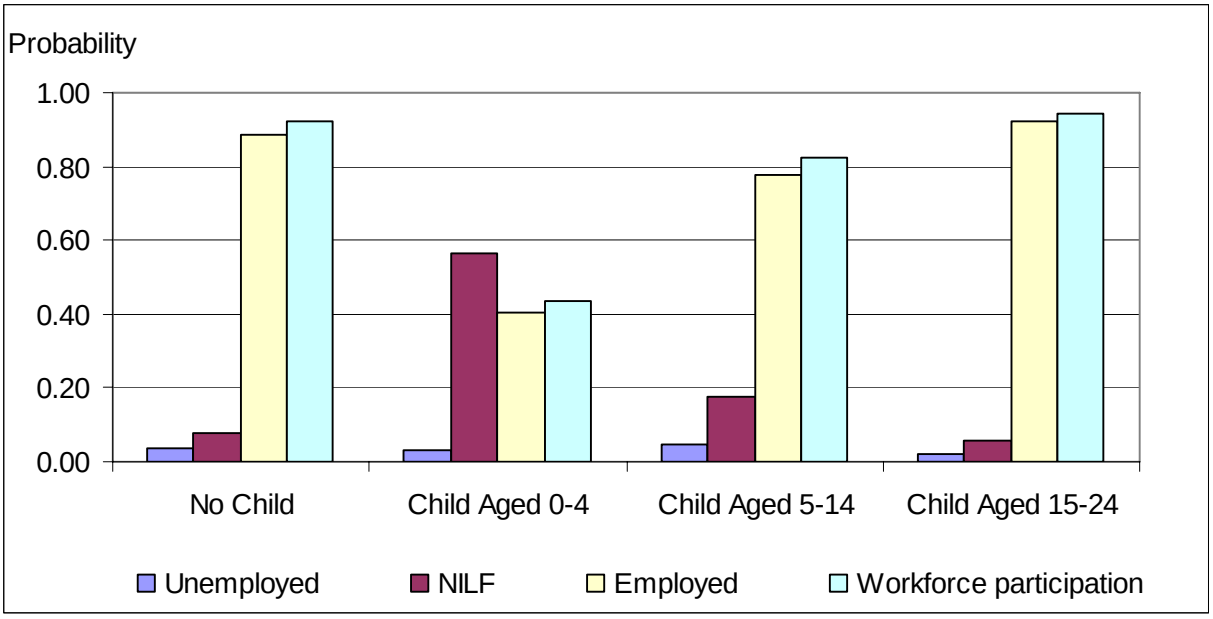
discrete adjustments give rise to noisy plots. The 'jaggedness' that would appear without smoothing is an artefact of keeping the two variables adjusted to age in a discrete way.

marital status.

As anticipated, the age of the youngest child under care is a quite important determinant of a mother's labour market outcomes. As Figure 3.2 shows, women's workforce participation probability drops dramatically (almost 50 per cent) when they start caring for very young children of 0 to 4 years. The situation starts to improve with the increase in the age of children, but does not recover completely to the pre-children situation until the children are 15 to 24 years old.

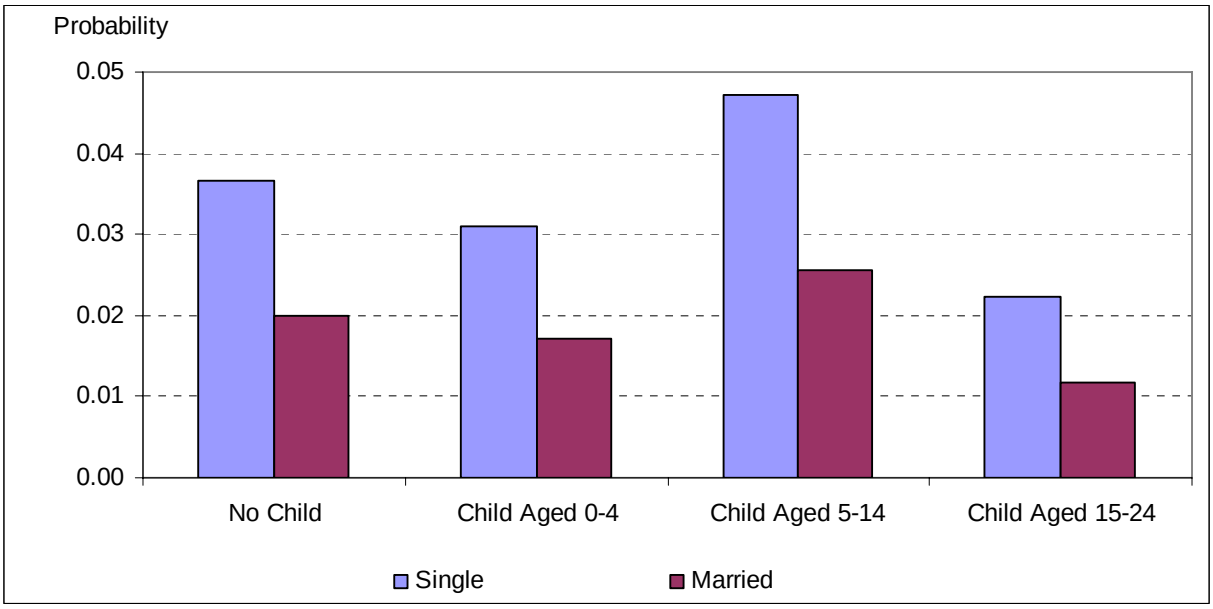
The probability of being employed is almost the same for women with no children and women with children over 15 years of age. As in the case of workforce participation, employment probability is lowest for mothers of pre-school aged children, and it rises as the age of child under care rises.

Figure 3.2: Aggregate labour market outcomes for females by age of youngest child under care



We found slight divergences in the absolute predicted probability values for married and single women across various child caring situations. But the difference becomes noticeable only for unemployment probabilities when proportionate changes are considered. The unemployment probability almost doubles for single mothers compared to married or partnered mothers across the board (as shown in Figure 3.3).

Figure 3.3: Unemployment probability for females by marital status and age of youngest child under care



Our results find that having children has relatively little impact on men in terms of probabilities of workforce participation, being employed or unemployed.

3.2.1.3 Education, English skill and aggregate employment probabilities

In this section, we investigate the impact of educational attainment and English skill on the probabilities of labour market outcomes, referenced to stylised males and females. As mentioned earlier, we used the variable country of birth (English speaking countries or not) as a proxy for English skill. It is assumed that a person born in an English speaking country has better English skills than a person born in a non-English speaking country. For the discussion that follows, better English skill and born in an English speaking country are synonymous. The same applies for lesser English skill and born in a non-English speaking country.

3.2.1.4 Education level

Figures 3.4 and 3.5 chart probability values associated with not being in the labour force and being employed at different levels of educational attainment for stylised males and stylised females. The difference in histogram bar heights between any two education levels indicates the magnitude of the impact of attaining a higher level compared to a lower level of education. Together, these two charts show that:

- higher education impacts positively on the likelihood of employment and workforce participation for both males and females (except for certificate III/IV), but the relative impact is weaker for men.

- the employment prospects of a female increase by more than 6 percentage points when the highest education level of masters and PhD (compared to year 11 or below) is attained. For a male, the increase is much less—only 2.5 percentage points.
- the impact of higher education is stronger when the prospect of workforce participation is considered. A stylised female's prospect of entering the workforce increases by 14 percentage points when the highest education level of masters and PhD (compared to year 11 or below) is attained, whereas for a stylised male the increase is only 1.7 percentage points.

Figure 3.4: Probability of not being in the labour force for stylised males and females by education level

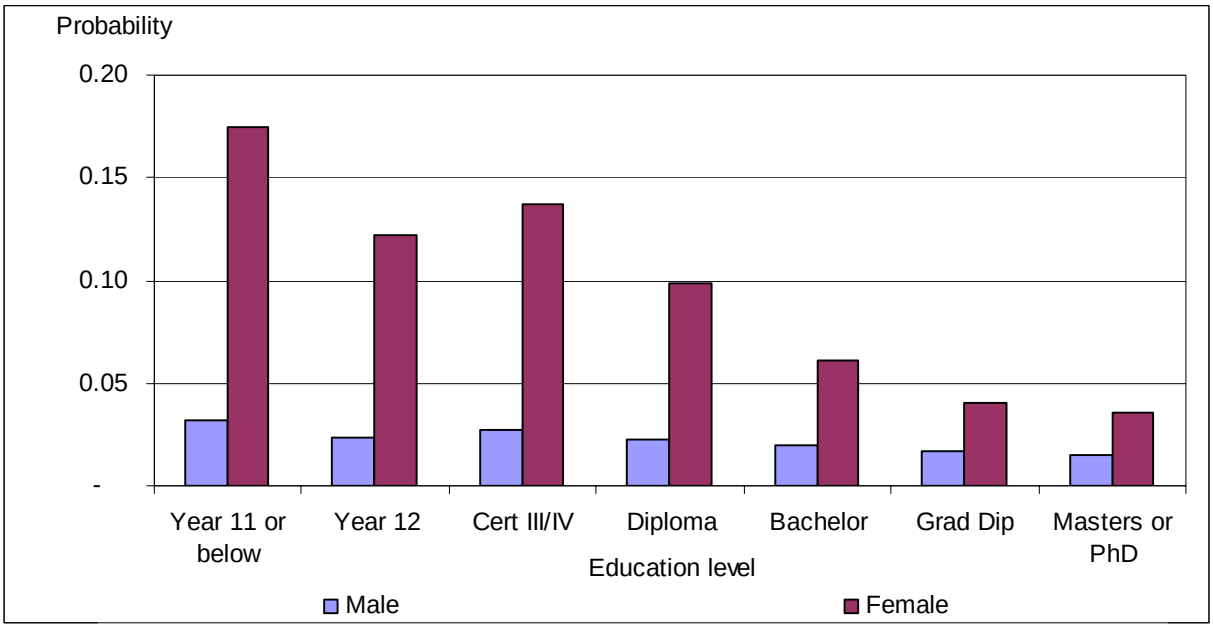
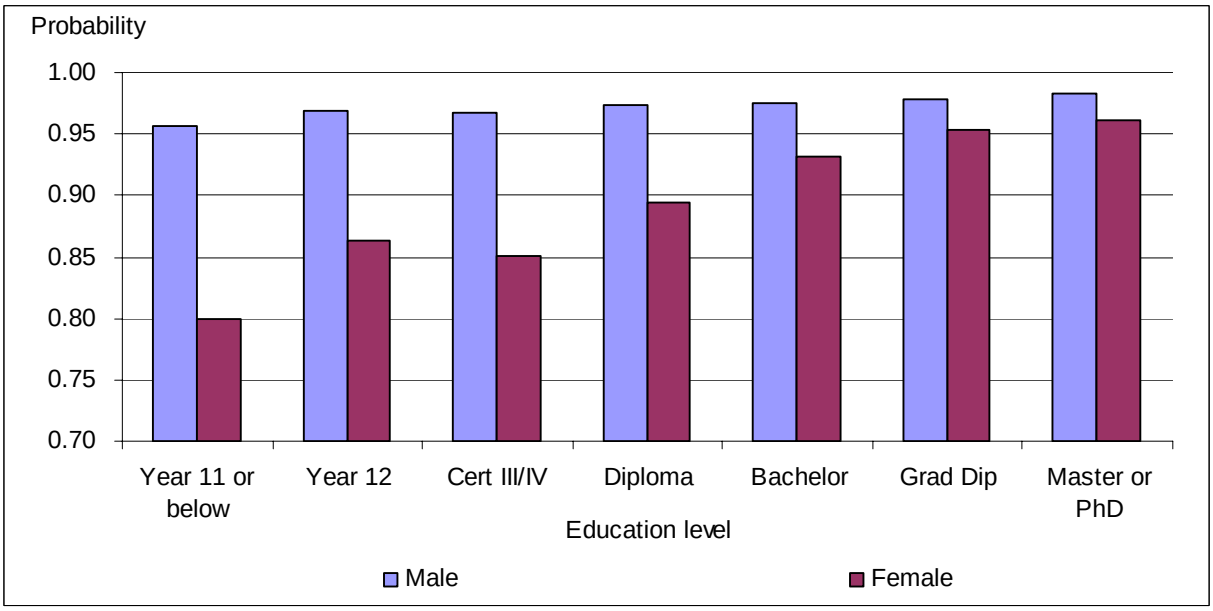


Figure 3.5: Employment probability for stylised males and females by education level



3.2.1.5 English skills

At each education level, individuals with lower English speaking skills (that is, born in a non-English speaking country) have a lesser chance of being employed than those with better English speaking skills (born in an English speaking country). But the differences for males are much smaller than for females—males with lesser English skill have one percentage point

less chance of being employed than other males while similar categories of females have about four percentage points less chance than other females.

3.2.2 Impact of socio-demographic characteristics on industry of employment

In this section, we take the analysis a step further to explore the industry effects of socio-demographic characteristics. The characteristics chosen are the same as used in the previous section—age, gender, age of children under care, education level and English skill. Marital status is dropped as this variable did not have a noticeable impact on aggregate employment prospects. For the sake of clarity of presentation, we report on selected industries, although a detailed estimate for all one-digit ANZSIC industries is available on request. Our analysis reveals significant divergence in industry employment outcomes and socio-economic status.

3.2.2.1 Age and gender

To examine the association between age, gender and age of child under care with employment probability, six top industries are selected separately for men and women, ranked by employment shares of male and female employees respectively. The industries selected for impact assessment of these variables on males are: manufacturing, construction, retail trade, accommodation, cafes and restaurants, transport and storage, and property and business services. For females, they are: manufacturing, retail trade, accommodation, cafes and restaurants, health and community services, education, and property and business services.

Figure 3.6 shows the probability of employment for males in the selected industries. These males have the same characteristics as stylised males, except that they have no children under care. This exception is made to allow for examining the impact of the age spread over a broader range. The age range relevant for a stylised male with a 4–15 year old child under care cannot be generally expected to start before 30, which is much shorter than the age range considered here (starting from age 16).

As the figure shows, employment probability exhibits quite different age profiles across the industries. The major characteristic of Figure 3.6 is the inverse relationship between age and employment probability in construction, retail and accommodation, cafes and restaurants. In contrast, parabolic shapes of the probability age profiles are seen in manufacturing and transport and storage, with probability peaks occurring at ages around 38 and 50 respectively. Among them, the transport and storage sector appears to have a relatively pronounced probability peak. It appears that age has very little impact on employment in the property and business services industry.

Figure 3.6: Probability of employment by selected industry for stylised males but without any child under care

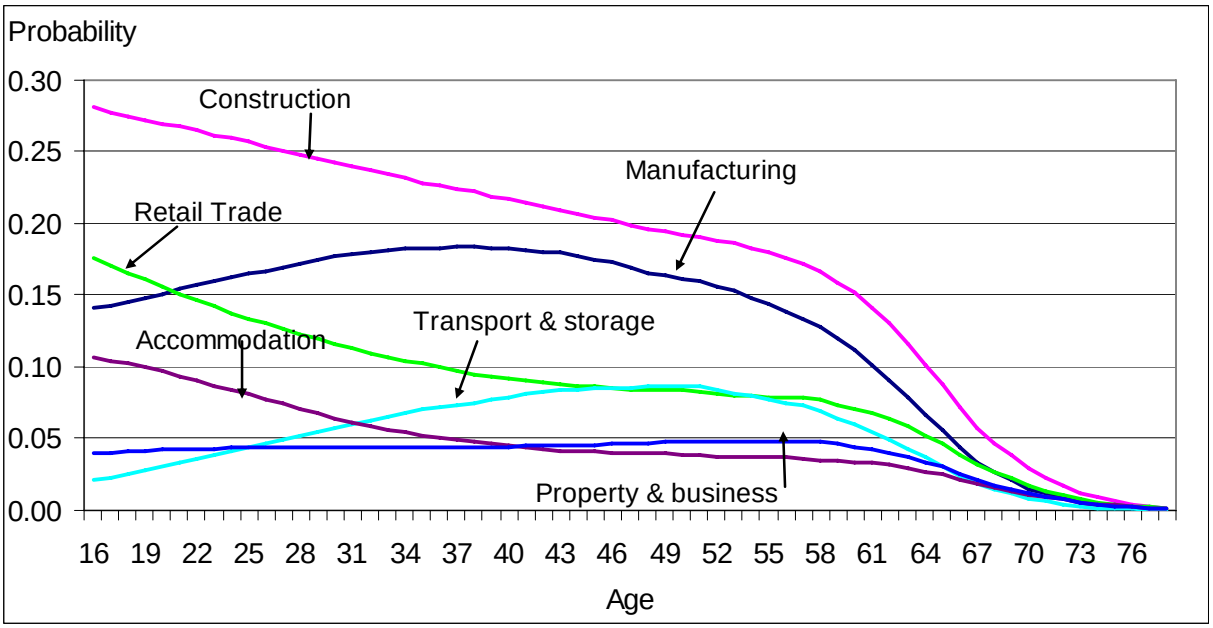
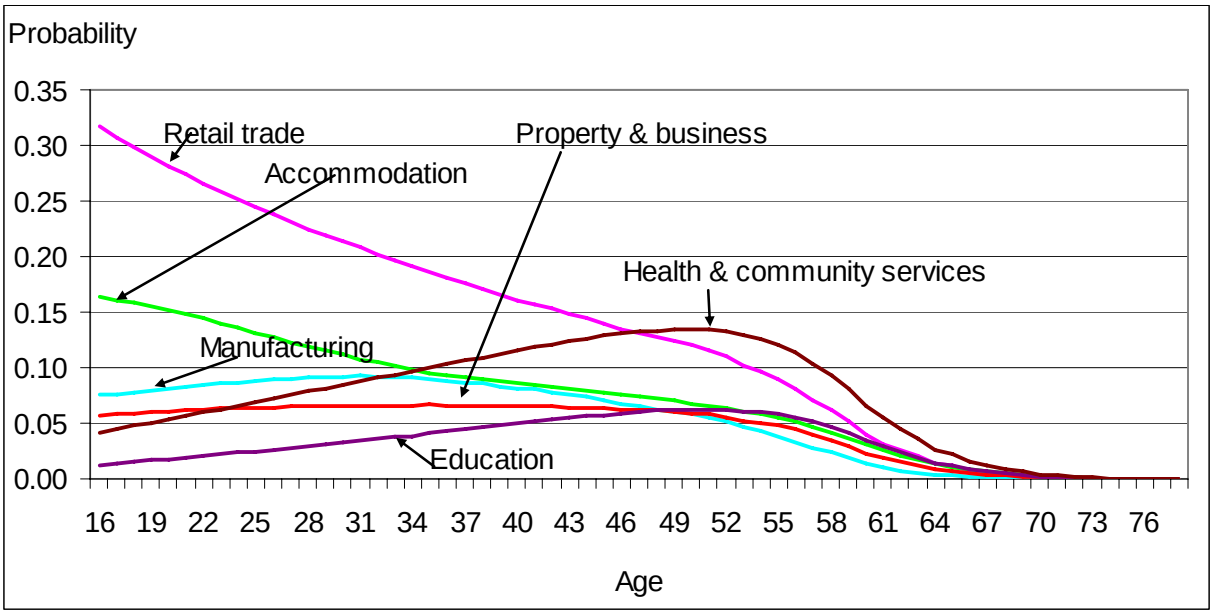


Figure 3.7 is a similar plot for stylised females with no children under care. Retail trade and accommodation, cafes and restaurants exhibit a continuously declining probability profile with age for females, with the other four exhibiting a parabolic shape. While the peaks of probabilities for employment in manufacturing and property and business are around age 30, peaks for health and community services and education are not reached before age 50.

There is a right skewness in the probability of employment for women specifically in the health and community services sector, characterised by a rapid probability decline once the peak age is exceeded, reflecting the traditional early female retirement age as supported by data in Figure C.4 in Appendix C.

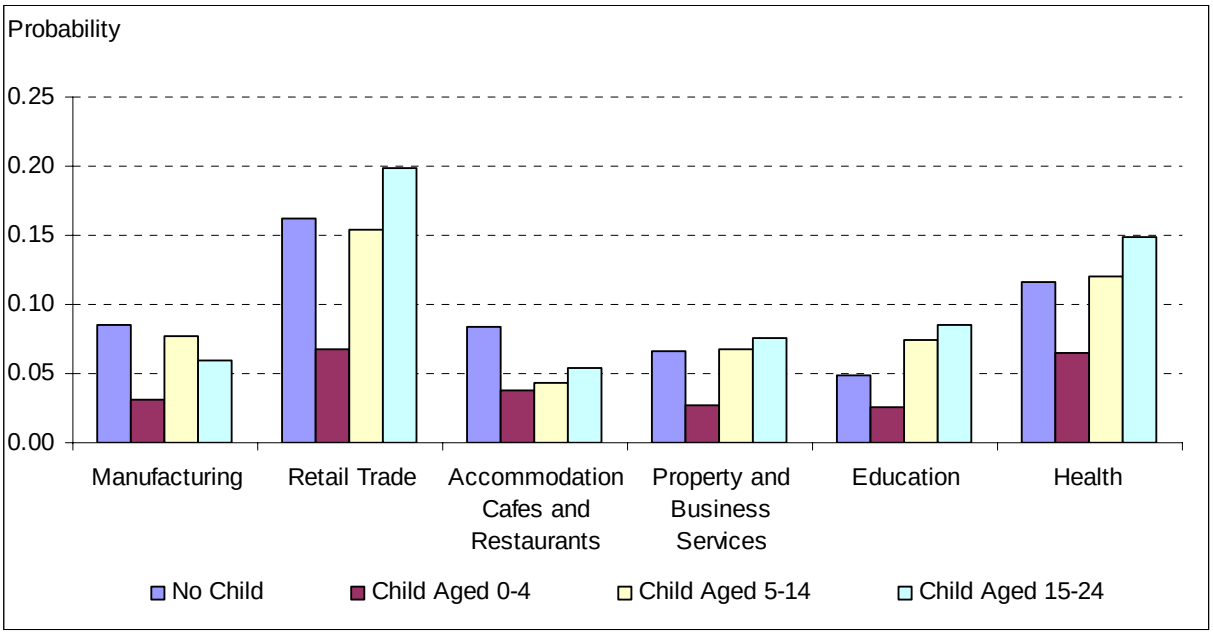
Figure 3.7: Probability of employment in selected industries for stylised females but without any child under care



3.2.2.2 Age of children under care

The marginal impact of age of children under care on female employment prospects varies across industries. In order to examine this, we present in Figure 3.8 the probability values for stylised females with children of various age groups in six industries. There is little detectable difference in aggregate employment probability between married and single women across all ages of children under care (discussed in section 3.2.1.2) on the impact of children's age on industry employment probabilities for females. We therefore consider only married/partnered women.

Figure 3.8: Employment probability for stylised females in selected industries by the age of youngest child under care



From Figure 3.8 we can see that there is a consistent drop in probability of employment in all industries once a female shifts from a 'no child caring' status to a status of caring for a 0–4 year old. Her employment probability increases in every industry once the child grows into the second age bracket of 5–14 years, but the rise in probability in absolute value terms is highly divergent by industry. The employment probability continues to increase for the mother as the child gets older in all industries except in manufacturing. Retail trade offers the highest chance of employment to females irrespective of their child caring status and age of child under care, followed by health and community services.

The sensitivity of employment probability to industry by age of child under care is underpinned by the diverse jobs offered by different industries, some of which are suitable to females with different working hour needs. Figure 3.8 above demonstrates that once the age of the youngest child under care exceeds the 0–4 year range, the employment probabilities in health, education and property and business services services actually exceed that for a female without a child. This may be reflective of greater flexibility of working hours in these industries. A similar outcome is observed for retail, but only once the youngest child is in the 15–24 age category, by then the propensity for mothers to remain at home in a child minding capacity has significantly diminished.

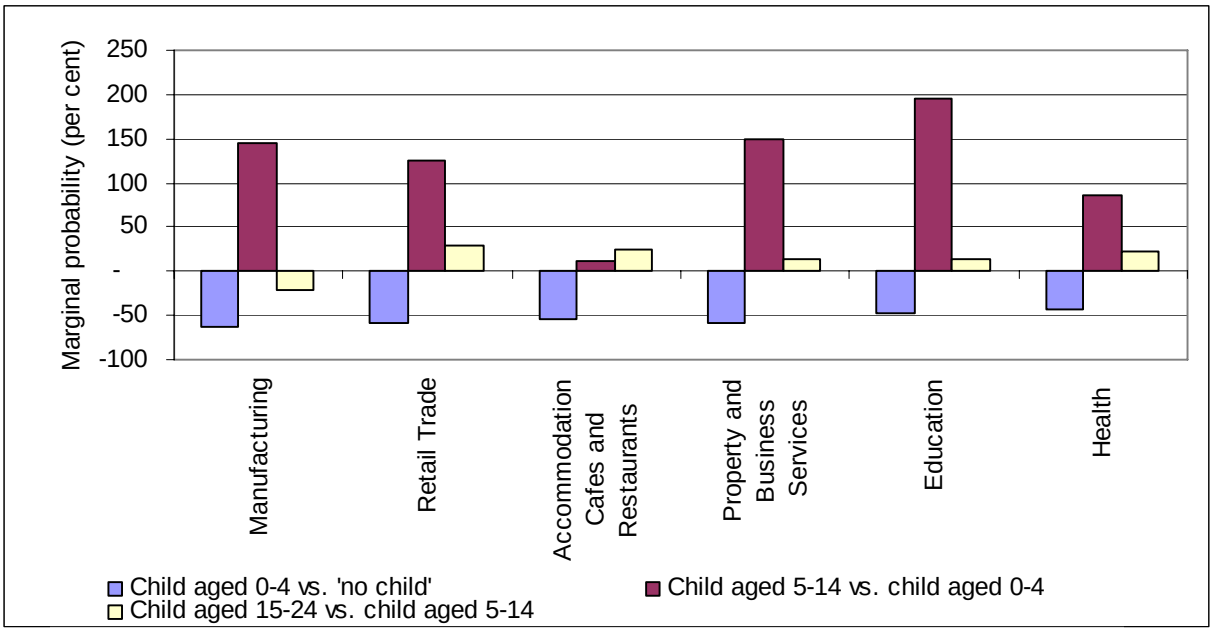
In contrast to the absolute probability values shown above, Figure 3.9 presents marginal probabilities, which quantify the impact on mothers' employment prospects occasioned by changes in the age of child under care. For example, the figure indicates that the probability of employment in education drops by 50 per cent when a female undertakes the care of pre-school

aged child compared to a 'no child' situation. Similarly, the probability of employment in property and business services increases by 150 per cent when the child under care moves from 0–4 years group to the next higher group of 5–14 years.

Although it is theoretically possible to calculate the impact of all changes, for the purposes of this paper we only chart changes in probabilities between two adjacent cases. Specifically:

- having a child of 0–4 years old compared to a 'no child under care' situation;
- having a child of 5–14 years old compared to having a child of 0–4 years; and
- having a child of 15–24 years old compared to having a child of 5–14 years.

Figure 3.9: Marginal employment probability with changes in age of child under care for stylised females in selected industries



The impact on female employment of having a child to care for compared to a 'not caring for a child' is most felt in manufacturing and property and business services, and least by health and community services. The impact on employment prospects is positive for all industries once a child reaches the age between 5 and 14, and the impact is most noticeable in education. The impact of caring for a child 15 years or older compared to a child of 5–14 years of age is positive for all industries except manufacturing. The impact is almost of similar size on retail trade, accommodation, cafes and restaurants and health, and is more than the impact on employment probabilities in education and property and business services.

Another feature of the chart is that the proportionate fall in the employment probability between no child and child 0–4 years is less for accommodation, cafes and restaurants than for

retail, manufacturing and property and business services. This may reflect the influence of a higher proportion of non-standard hours and a higher proportion of part-time opportunities in accommodation, cafes and restaurants than in the other sectors, with these times of working better suited to sharing of child caring duties between these women and their partners. Note that among the industries examined above, education and health appear to be the most flexible sectors for females with children aged 0 to 4 years.

3.2.2.3 Education and English skill by industry of employment

Educational attainment clearly influences chances of being employed in a particular industry. In this section, we closely examine the relationship between industry employment probability and educational level for both males and females with varying English language skills.

By analysing the employment probabilities of stylised males and females, born in English and non-English speaking countries, we gain insights on male and female industry employment probabilities, including:

- For males with education at bachelor level or above, the four most employable industries are: manufacturing, finance and insurance, property and business services, and education. Together they account for more than 50 per cent of the male aggregate employment probability, education industry alone contributing the major share. This observation is valid irrespective of English skill level.
- For similar females, there are three such industries, together contributing to between 60 and 85 per cent of aggregate female employment probability. They are, in order of importance, education, health and community services, and property and business services.
- The most employable industry for males with education up to year 12 is manufacturing, and no difference in the pattern is noticeable between males of varying English skill levels.
- For males with lesser English skill, manufacturing continues to offer the best chance up to a bachelor education level. But for males with better English skills, the construction industry offers the best chance of employment once a trade certificate (certificate III/IV) is obtained.
- For females with education up to year 12, it is the retail trade industry which offers the best chance of employment, irrespective of their English skill levels.
- Once these females obtain a trade certificate, their best prospect of employment lies in the health and community services industry.

Tables 3.3 and 3.4 present marginal probabilities of the impact of higher education and better English language skills on industry employment. The marginal probabilities are proportionate changes in probability of employment in an industry when a higher educational level is attained, compared to the base case education level of year 11 or below. A total of ten industries (five each for males and females) provide a representative overview. Each industry

was placed into one of three broad groups:

- those with consistently positive impacts at all levels of higher education, comprising industries such as education, government administration and defence, health and community services, and cultural and recreational services;
- those with consistently negative impacts at all levels of higher education, comprising agriculture, manufacturing, retail and transport and storage industries; and
- those with mixed impacts, comprising the remaining industries.

To report our results we selected the education industry from the first group and manufacturing from the second. Among the industries with mixed outcomes, we selected different sets for males and females. Mining, construction and personal and other services were selected to examine the impact of educational attainment on male employment prospects. To examine the impact for females, personal and other services industry was selected along with accommodation, cafes and restaurants and property and business services.

Table 3.3: Impact on male probability of employment due to higher educational attainment (compared to year 11 or below)

Stylised males born in English speaking countries						
	Per cent					
Industry	**Year 12**	**Certificate III/IV**	**Diploma**	**Bachelor**	**Grad Dip**	**Masters/ PhD**
Education	40	30	330	706	1519	1770
Manufacturing	-6	-3	-22	-22	-58	-38
Mining	12	27	-18	59	18	0
Construction	-31	47	-26	-64	-82	-86
Personal and other services	37	101	129	7	10	-28
Stylised males born in non-English speaking countries						
	Per cent					
Industry	**Year 12**	**Certificate III/IV**	**Diploma**	**Bachelor**	**Grad Dip**	**Masters/ PhD**
Education	46	32	386	840	2075	2404
Manufacturing	-2	-1	-12	-9	-44	-17
Mining	17	29	-7	86	59	34
Construction	-28	50	-16	-58	-76	-81
Personal and other services	42	105	159	25	48	-3

Table 3.4: Impact on female probability of employment due to higher educational attainment (compared to year 11 or below)

Stylised females born in English speaking countries						
	Per cent					
Industry	**Year 12**	**Certificate III/IV**	**Diploma**	**Bachelor**	**Grad Dip**	**Masters/ PhD**
Education	34	22	242	370	610	713
Manufacturing	-10	-9	-38	-55	-82	-73
Accom cafes & restaurants	-7	4	-41	-78	-82	-96
Property and business services	20	-24	37	64	9	-16
Personal and other services	30	89	82	-37	-52	-69
Stylised females born in non-English speaking countries						
	Per cent					
Industry	**Year 12**	**Certificate III/IV**	**Diploma**	**Bachelor**	**Grad Dip**	**Masters/ PhD**
Education	44	30	326	534	998	1214
Manufacturing	-4	-3	-23	-39	-72	-56
Accom cafes & restaurants	0	11	-26	-70	-73	-93
Property and business services	29	-19	71	122	68	36
Personal and other services	40	101	127	-16	-25	-49

Table 3.3 shows that the prospect of finding a job in education is positive at all levels of higher education for all males and females and it becomes increasingly positive once a person obtains a diploma and beyond. According to our modelling results, higher education impacts more on male employment prospects than those of females and, among males, it is the males born in non-English speaking countries who appear to benefit more from higher education to get a job in the education industry.

Conversely, higher education at all levels impacts negatively on job prospects in manufacturing for all males and females, although males born in non-English speaking countries seem to be least affected. The negative impact of higher education on obtaining a job in manufacturing is not surprising given that, as Figure B.9 in appendix B indicates, a relatively small proportion of employees (about 13 per cent) in manufacturing have a higher education at bachelor or above, and 50 per cent of its employees have education at the level of year 12 or below.

Among the industries with mixed impact, construction for males and accommodation, cafes and restaurants for females exhibit the same pattern. Both of these industries appear to offer a positive job prospect when a trade certificate is obtained, with a negative impact for all other educational attainments. Level of English skill does not appear to make any difference in the outcome.

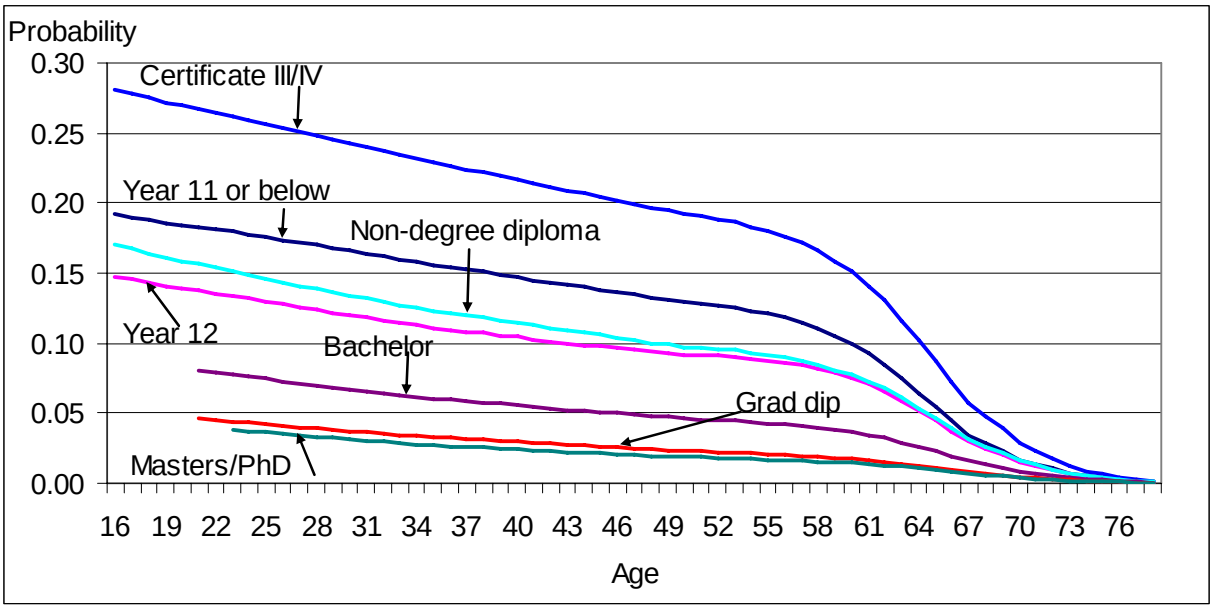
For employment in personal and other services, the impact of higher education is positive but

only up to a certain level. For males, a higher education beyond a graduate diploma is associated with a negative impact for employment in this industry; and for females, the negative impact starts earlier, at a bachelor level. The effects, however, are skewed towards being more positive for people born in non-English speaking countries.

Mining is another industry producing mixed results. Employment prospects in this industry are highest when a bachelor degree is obtained. For females, property and business services offer the highest chance of employment for a bachelor degree.

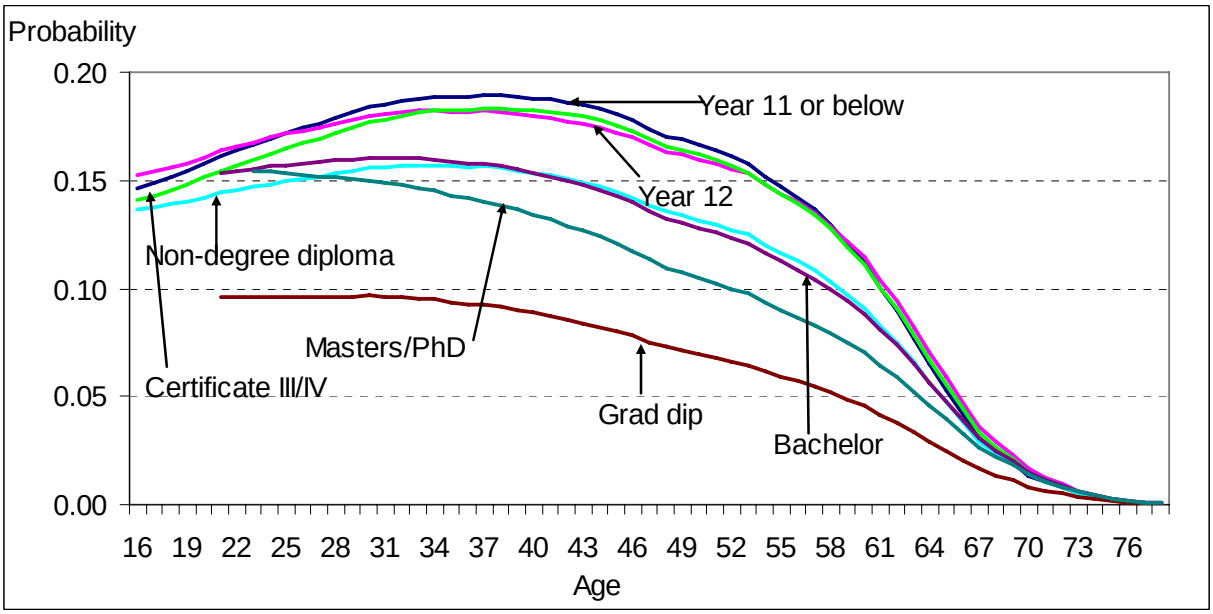
The above discussion highlights the impact of educational attainment on the probability of employment in various industries. Estimated probabilities are for an individual at a certain age. We next examine the impact of educational attainment on employment probabilities across the length of an individual's working age for the construction industry We find that the declining effect on aggregate employment probability with age, as observed earlier in Figure 3.1, is spread widely for various levels of education, until a steep reduction in probability of employment near the retirement age, especially for those with a lower educational level (Figure 3.10).

Figure 3.10: Probability of being employed in the construction industry for males by education level



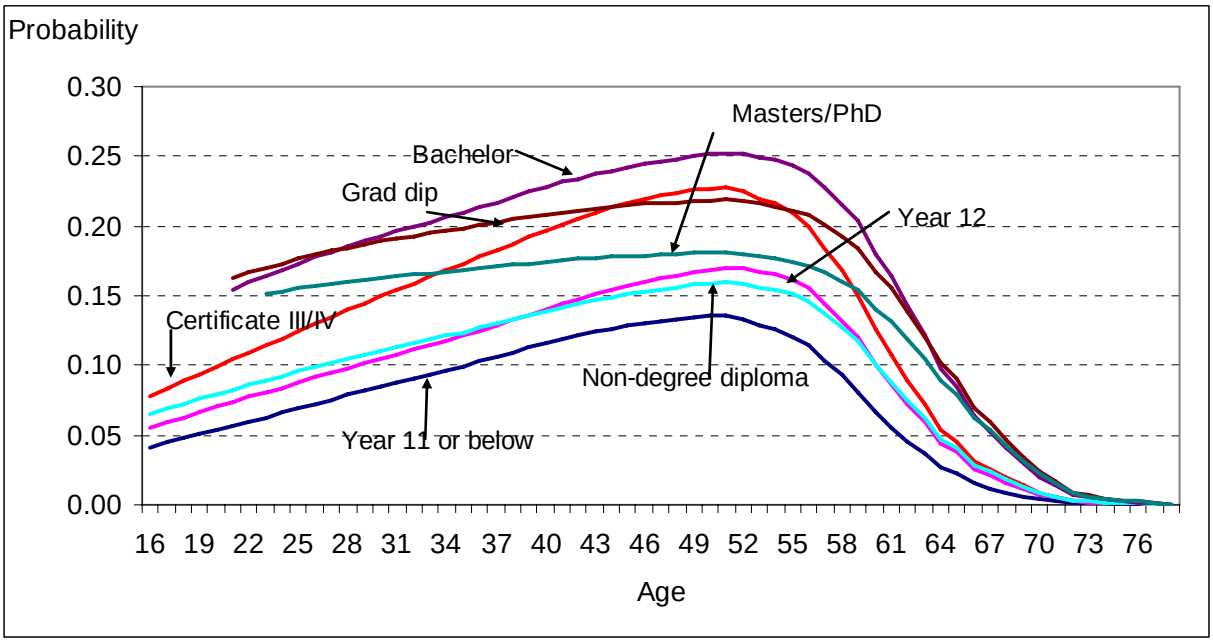
In contrast manufacturing employment probability (Figure 3.11) initially rises with age for those having educational levels below graduate diploma. Unlike the range evident for the construction industry, education levels are clustered at the three lowest levels.

Figure 3.11: Probability of being employed in the manufacturing industry for males by education level



There is, however, an interesting twist when the impact of education in health is considered across all possible ages of a stylised female (Figure 3.12). The probability of being employed in health is higher with higher levels of education for all ages. However, there is a change in the relative position of these educational levels, which was not observed in the other two industries presented above. Although a graduate diploma initially offers a better chance of employment in health, between 45 to 54 years of age certificate III/IV offers higher probability in the industry. A masters or a PhD degree has lower probability relative to certificate III/IV even at an earlier age of 34. The situation is reversed only in late 50s.

Figure 3.12: Probability of being employed in the health and community services industry for females by education level



4 Concluding comments

The aim of this paper has been to highlight the role of key socio-demographic characteristics in labour force and industry employment outcomes in Australia so as to inform policy. Previous studies have identified demographic change as a key factor influencing labour participation and the structure of the labour force across industries. They also have highlighted how labour force characteristics are associated with forms of employment. However, they have not focused directly on industry effects.

In an attempt to fill this gap, we present results of multivariate econometric modelling of the relationship between an individual's socio-demographic characteristics and the probability of being in one of 19 labour market outcomes: employed in any of the 17 one-digit ANZSIC industry sectors, unemployed, or not in the labour force. The econometrics is very complex; there are 18 equations in the model—each equation has 47 separate coefficients to be estimated (846 different coefficients in all). A framework for reducing output complexity is accomplished through creating stylised socio-demographic profiles of a male and female, which allows the model to serve as a tool with which to probe the impacts across industries of changes in ageing, education and age of children by gender.

The operational question we ask is: what is the impact of a change in a social-demographic variable x (holding all other variables fixed) on all 19 different employment outcome probabilities? For example varying gender draws out interesting results. Males and females face different employment prospects in different industries. Moreover, the likelihood of females being employed in retail trade, property and business services, education and health

and community services is much larger than their male counterpart. On the other hand, males have much better chances in electricity, gas and water, construction, transport and storage and manufacturing.

Changing the age of dependent children also brings to light interesting findings. We discover that the age of the child under care is an important determinant of a mother's labour market outcome probabilities. Women's workforce participation probability nearly falls to half when they start caring for pre-school aged children. The probability generally starts to rise with the rise in the age of the child. Moreover, in absolute value terms, this rise varies dramatically by industry. Among the industries reported, the rise of a woman's employment prospect as the child under her care grows older is highest in retail trade, followed by health and community services. The sensitivity of employment probability to industry by age of the child under care may be reflective of greater flexibility of working hours in these industries.

Education is another important variable we analyse. The impact of higher education varies across industries and by gender. Some industries show positive impacts consistently at each level of higher education. Similarly, some industries show consistently negative impacts, and some industries show mixed outcomes.

The results presented here provide a glimpse into the linkages between labour market outcomes and socio-demographic characteristics. They facilitate a better appreciation of the large divergence of heterogeneous outcomes across industries as well as important insights into labour market participation for women returning to work after child bearing. These findings could be used to inform policy in education and training so that programs could be more effectively tailored to accommodate these differences across industries.

However, the work only scratches the surface of what is possible. There are 15 variables with many possible settings (e.g. different educational attainment levels) for 17 industries so there is much potential for further exploration using this modelling infrastructure. There are many more insights that could be gained relevant across government agencies including the Departments of Education, Employment and Workplace Relations, Health and Human Services and Families, Housing, Community Services, and Indigenous Affairs. We hope that other government research areas will pursue this approach.

The model can also be used to study the effect across different industries of changes in, for example, worker age. In this regard it becomes a tool with which to gauge the impacts of an ageing population. Information from other studies can be used to help create worker profiles that are representative of growing numbers of workers over time. Moreover, studies that provide information on future consumption patterns consequent upon an ageing population (see Giesecke, J and G A Meagher 2008) will give an indication of which industries will be experiencing demand growth and which will be experiencing falls. Together with this information, our modelling results may facilitate a better understanding of how specific

industries may need to adjust to accommodate changing employment patterns.

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APPENDIX A

A. Data

This appendix provides descriptive information on the confidentialised unit record HILDA data used in our modelling (HILDA Release 4.1, which was the latest release available when this project commenced).[8] HILDA is a household-based panel study which began in 2001. Interviews are conducted annually with all adult members of each household, and the survey collects information about economic and subjective well-being, labour market dynamics and family dynamics.

The households in the survey were selected using a multi-staged approach. The list of 1996 Census Collection Districts (CDs) formed the area-based frame from which a specific number of CDs were selected. The frame of CDs was stratified by State, and within the five largest States in terms of population, by metropolitan and non-metropolitan regions.

The panel members are followed over time and each year is termed as a wave. Wave 4, which provides the database of the current study, consists of 6 743 households and 12 408 individuals. Observations with missing data fields were excluded from the econometric modelling. After such an exclusion, a subset of HILDA was obtained with a total of 10 468 individuals (observations). Table A.1 shows the data fields or variables with missing values.

Table A.1: Missing values in HILDA[9]

Variables	Number missing	Per cent missing
Education	4	0.0
Indigenous status	3	0.0
Social functioning	1025	8.3
Unemployment length	863	7.0
Employment length	1015	8.2

The samples were disaggregated into three main categories—not in the labour force, the unemployed and the employed. The category not in the labour force includes individuals aged 15 or over who are neither employed nor unemployed and also not looking for a job. Individuals in this category typically include women with young children, individuals with a

[8] Use of HILDA Release 4.1 (Wave 4) also seemed reasonable in that observations are not too far removed from the original sampling conducted in Wave 1 (2001). New waves potentially suffer from relatively more selection bias and it becomes more difficult to generalise about the Australian population.
[9] There is an overlap of missing values among different fields.

long-term health condition or retirees. Those unemployed refer to persons aged 15 years and over who were not employed during the reference week, and had actively looked for full-time or part-time work at any time in the four weeks up to the end of the reference week and were available for work in the reference week, or were waiting to start a new job within four weeks from the end of the reference week and could have started in the reference week if the job had then been available. The employed group contains those employed in any of the 17 one-digit ANZSIC classification, which is an exhaustive list of all Australian industry sectors.

Table A.2 provides the number of observations and proportion counts for all 19 labour market outcomes for both the full and subset data sample.

Table A.2: Labour force outcome categories

Cat.	**Label**	**Full sample**		**Sub sample**	
		Number of observations	Proportion (%)	Number of observations	Proportion (%)
1	Not in the labour force	4 173	33.63	3 525	33.67
2	Unemployed	413	3.33	285	2.72
3	Agriculture	389	3.14	334	3.19
4	Mining	109	0.88	93	0.89
5	Manufacturing	823	6.63	711	6.79
6	Electricity gas & water	62	0.50	58	0.55
7	Construction	555	4.47	476	4.55
8	Wholesale trade	273	2.20	235	2.24
9	Retail trade	1 074	8.66	737	7.04
10	Accom. cafes & restaurants	380	3.06	279	2.67
11	Transport & storage	303	2.44	272	2.6
12	Communication services	145	1.17	133	1.27
13	Finance & insurance	280	2.26	253	2.42
14	Property & business services	841	6.78	722	6.9
15	Government admin & defence	412	3.32	376	3.59
16	Education	745	6.00	693	6.62
17	Health & community services	934	7.53	848	8.1
18	Cultural & recreational services	214	1.72	181	1.73
19	Personal & other services	282	2.27	257	2.46
	Total	**12 408**	**100**	**10 468**	**100**

Although each labour market outcome category set out in Table A.2 contains sufficient number of observations for the estimation of the model, industries such as electricity gas and water, and to a lesser extent mining do so with very few degrees of freedom.

Table A.3 provides average values of variables used in the model.

Table A.3: Variable definition and description of the model

Variable	Averages
Demographic characteristics	
Age – age as at 30 June 2004	46.40
Age – age squared term	2439.28
Marital status – Married or de facto	0.67
Country of birth – born in non-English speaking country	0.11
Indigenous status – indigenous	0.02
Gender and youngest residential child's age – Male with no child*	0.30
Gender and youngest residential child's age – Male with 0-4 y.o.	0.06
Gender and youngest residential child's age – Male with 5-14 y.o.	0.07
Gender and youngest residential child's age – Male with 15-24 y.o.	0.03
Gender and youngest residential child's age – Male with 25 y.o. and over	0.01
Gender and youngest residential child's age – Female with no child	0.30
Gender and youngest residential child's age – Female with 0-4 y.o.	0.07
Gender and youngest residential child's age – Female with 5-14 y.o.	0.10
Gender and youngest residential child's age – Female with 15-24 y.o.	0.05
Gender and youngest residential child's age – Female with 25 y.o. and over	0.02
Geographic characteristics	
Remoteness of living area – major city*	0.61
Remoteness of living area – inner region	0.25
Remoteness of living area – outer region	0.12
Remoteness of living area – remote area	0.02
Remoteness of living area – very remote area	0.00
Socio-economic index of living area – lowest decile*	0.11
Socio-economic index of living area – 2nd decile	0.10
Socio-economic index of living area – 3rd decile	0.12
Socio-economic index of living area – 4th decile	0.11
Socio-economic index of living area – 5th decile	0.09
Socio-economic index of living area – 6th decile	0.09
Socio-economic index of living area – 7th decile	0.09
Socio-economic index of living area – 8th decile	0.09
Socio-economic index of living area – 9th decile	0.11
Socio-economic index of living area – highest decile	0.08
State and Territory – NSW*	0.30
State and Territory – VIC	0.25
State and Territory – QLD	0.20
State and Territory – SA	0.10
State and Territory – WA	0.10
State and Territory – TAS	0.03
State and Territory – NT	0.01

Variable	Averages
State and Territory – ACT	0.02
Education	
Highest level of education – Year 11 or below including certificate I/II*	0.36
Highest level of education – Year 12	0.14
Highest level of education – Certificate III/IV	0.20
Highest level of education – Diploma	0.09
Highest level of education – Bachelor degree	0.13
Highest level of education – Grad Diploma or Grad Certificate	0.05
Highest level of education – Master or PhD	0.03
Current enrolment for study – Not enrolled*	0.84
Current enrolment for study – part-time study	0.09
Current enrolment for study – full-time study	0.07
Health condition	
Health condition – has long-term health condition	0.27
Social functioning ability – has perfect social functioning score	0.50
Employment history	
Duration of unemployment	0.59
Duration of employment	21.57

* indicates reference category of variable for econometric model

APPENDIX B

A broad overview of statistical significance of the estimated coefficients

A total of 272 coefficients (or more than 32 per cent) is found statistically significant at the 5 per cent level, implying with 95 per cent certainty that they are different from zero. Another 53 variables (6 per cent of the total) are statistically significant at the 10 per cent level. Some of the other highlights are:

- Industries with close to or more than 50 per cent of their coefficients significant (at 5 or 10 per cent) are:
  - finance and business;
  - manufacturing;
  - government administration and defence; and
  - education and health.
- At the other end of the spectrum, only 23 per cent of retail coefficients are statistically significant.
- Marital status and unemployment length are the only two variables whose coefficient values are all significant at the 5 per cent level.
- Variables such as social functioning, employment length, full-time and part-time study are significant for most industries at the 5 per cent level.
- Age is statistically significant for a majority of the outcomes; its squared term is significant for all except two.
- Education is also significant for most of the outcomes. For a majority of service industries, education is statistically highly significant. However, for construction, wholesale, transport, and accommodation, cafes and restaurants, education levels beyond diploma are not significant.
- 'Country of birth' is generally significant, except in manufacturing, electricity gas and water, retail, accommodation, cafes and restaurants and communications.
- Having children displays very different significance levels across gender.
  - For males, the association between having children and/or age of the children and the prospect of employment in any industry is rarely statistically significant.
  - For females, the association is generally statistically significant, and the incidence of significance is more common in situations where children are of younger age groups.

APPENDIX C

C. Demographic and socio-demographic profiles of major Australian industries

This section provides an overview of the current demographic profiles of Australian industries, based on weighted data in HILDA. Industries included in the study are exhaustive of all Australian industries defined at the one-digit ANZSIC level. In some cases, to provide further insights, the analysis extends to the two-digit level for manufacturing. The socio-demographic profiles of the workforce differ across industries, sometimes significantly, with the result that various effective industry responses to maintain and/or expand the existing level of labour input might well be quite different.

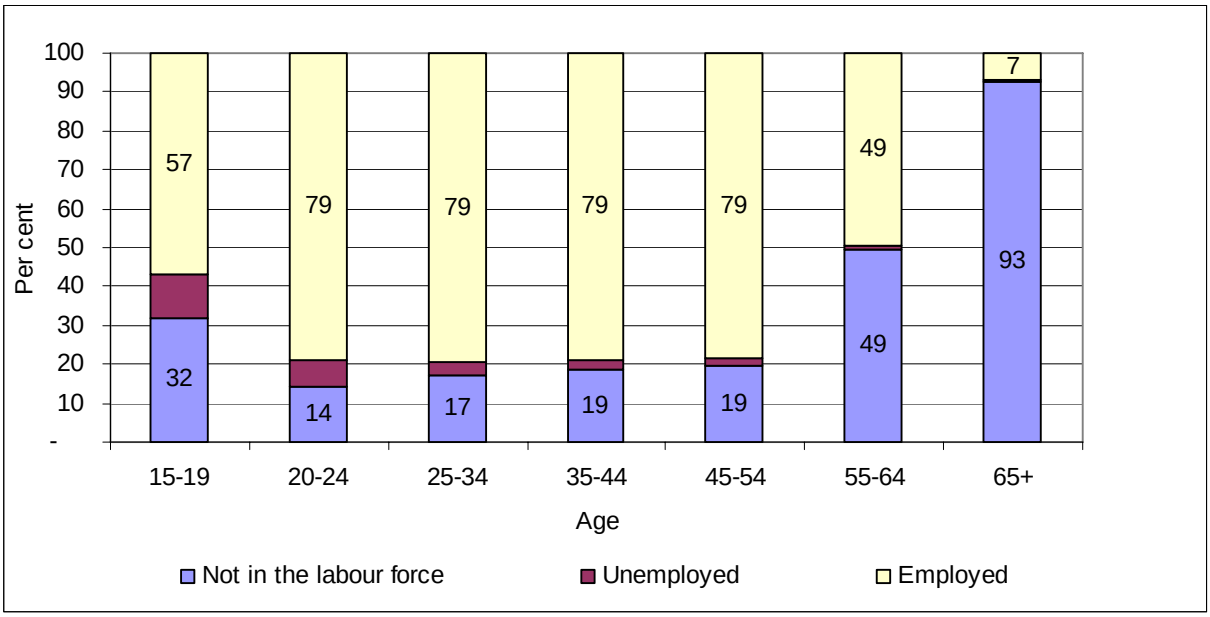
The socio-demographic profiles analysed below are: age, gender, age of the youngest children under care, marital status, educational attainment, study enrolment status and English skill.

C.1 Age profile of Australian industries

The age profile of employed individuals varies quite considerably across industries, reflecting several factors including different requirements in relation to physical ability, educational attainment and previous employment experience. Employment experience and skill tend to increase with age, which in turn raises the individual's employability in some industries more than in others. On the other hand, with ageing, physical ability begins to decline after a certain peak age, which may make individuals in older age cohorts less attractive to industries involving physically demanding work. Further, industries which require higher levels of educational attainment are generally less suited to younger people with as yet insufficient education, skill and experience.

Figure C.1 illustrates the relationship between age and total labour market outcomes of those not in the labour force, unemployed and employed. The proportion of unemployed is the largest in the age category 15–19 years, and the proportion declines with age. Both employed and not in the labour force categories display a U shape relation with age.

Figure C.1: Proportion of unemployed, employed and not in the labour force by age category



Figures C.2 and C.3 illustrate the relationship between age and industry of employment. There is a relatively high proportion of younger workers in the retail trade and accommodation, cafes and restaurants industries. To a lesser extent, this is also true of cultural and recreational services industries, especially compared with agriculture and electricity, gas and water. Of the manufacturing industries, TCF (textiles, clothing and footwear) have the highest proportion of older workers (45 years and older).

Figure C.2: Age profile and industry of employment: all industries

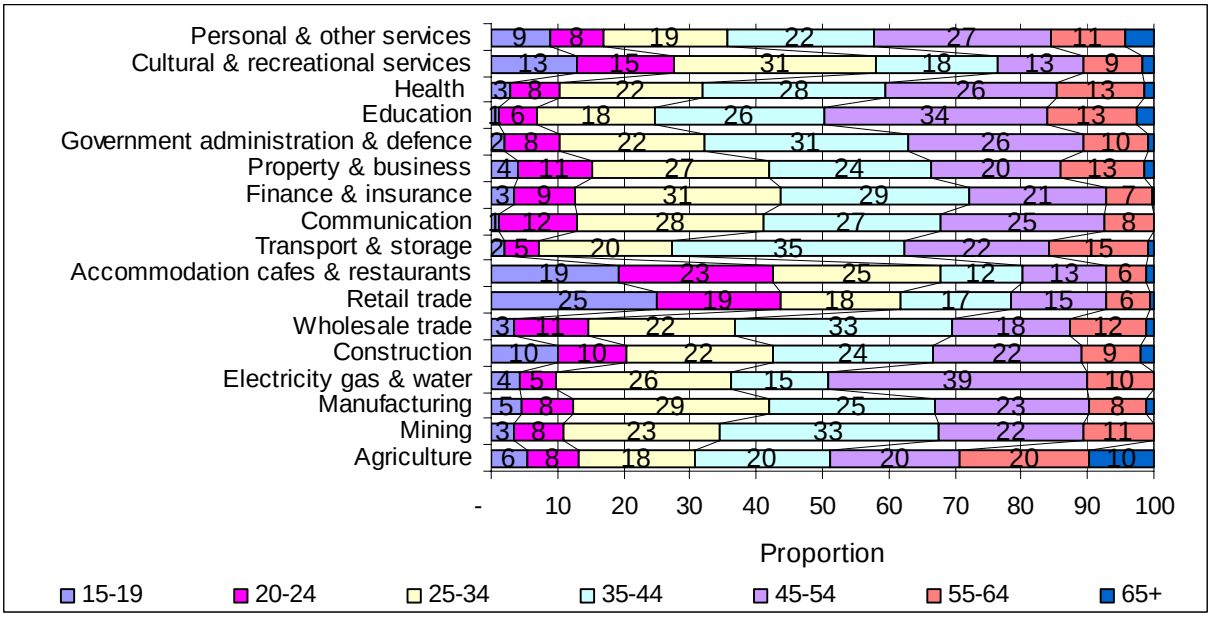
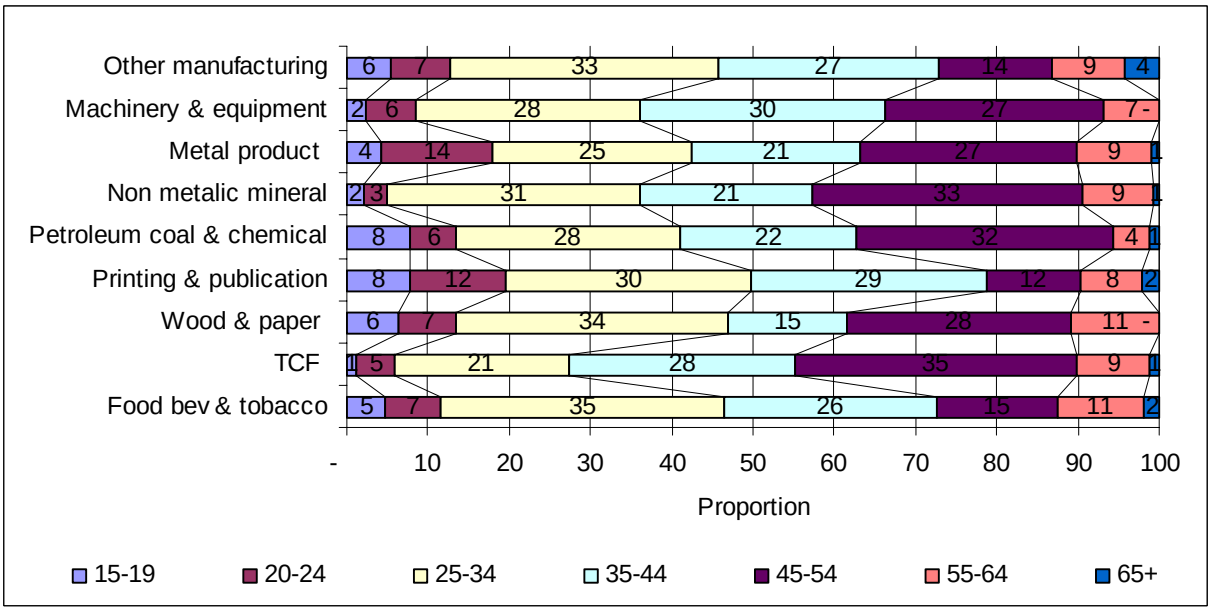


Figure C.3: Age profile and industry of employment: manufacturing



A relatively younger age profile (up to 34 years old) also exists in construction, finance and insurance, manufacturing, and property and business services. Within manufacturing, the age cohort of workers up to 34 years of age is the largest in the printing and publication, wood and paper, TCF, and other manufacturing industries, together accounting for 44 per cent of the manufacturing workforce.

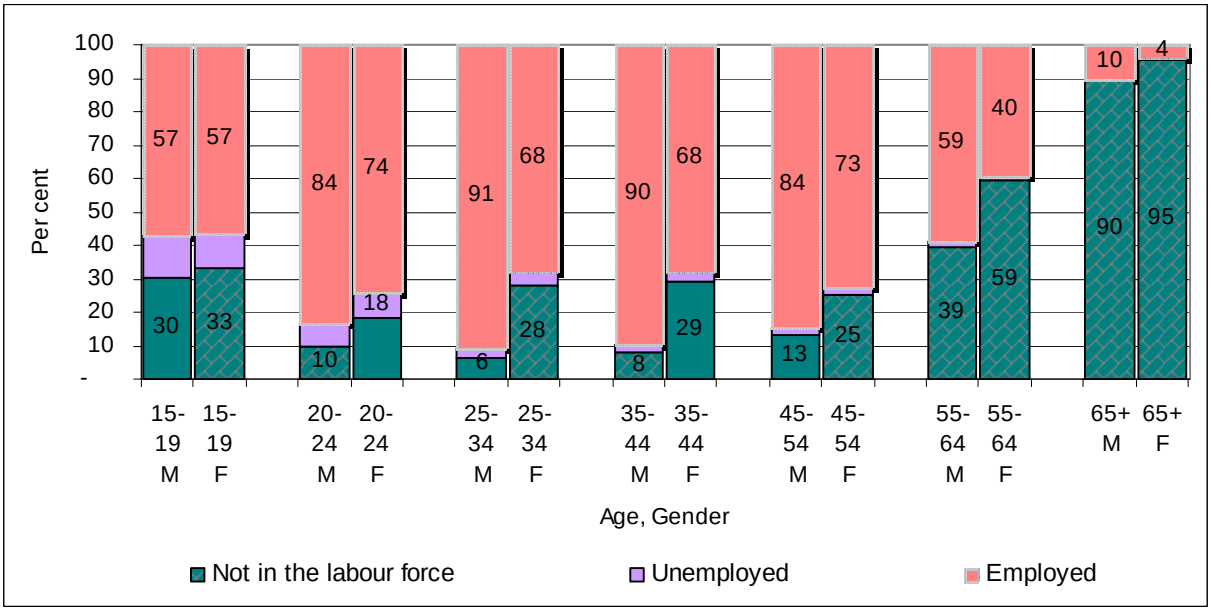
At the other end of the age profile, agriculture, education and electricity gas and water each has about 50 per cent of its workers over 45 years of age. Agriculture also has the highest

proportion of workers aged between 55–64, and 65 and above.

C.2 Age and gender

The labour force outcomes across age cohort illustrated in Figure C.1 are somewhat different when disaggregated by gender, as demonstrated in Figure C.4.

Figure C.4: Proportion of unemployed, employed and not in the labour force by gender and age

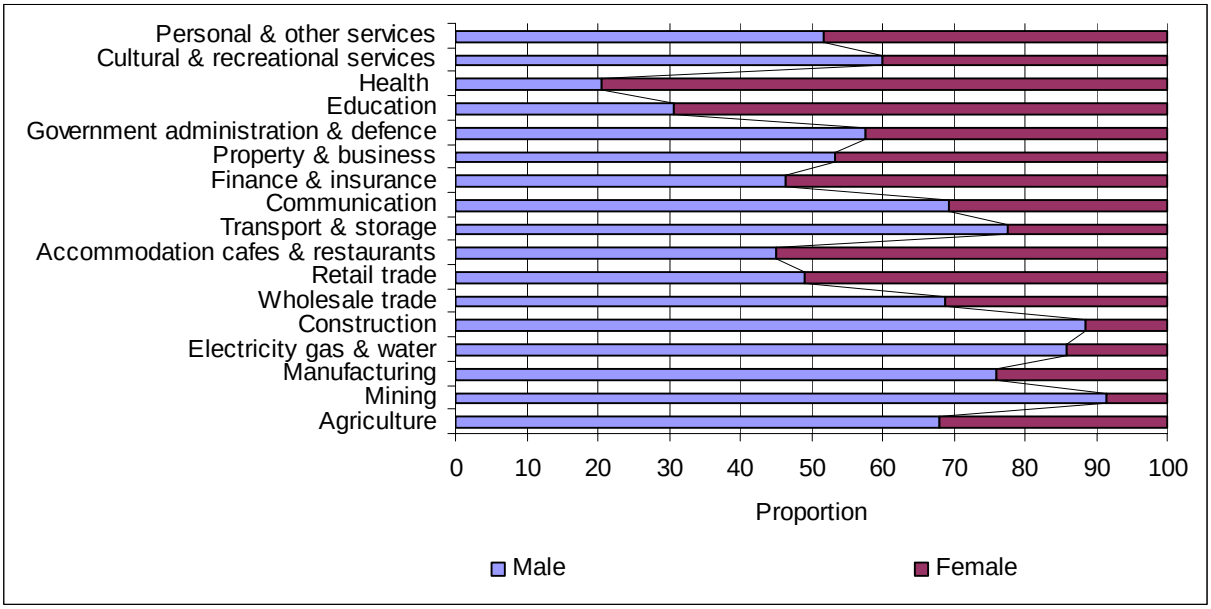


Proportion employed is same for both males and females in the youngest age cohort, but the gender discrepancy becomes noticeable in the subsequent years. In these years a gender difference in employment proportion is almost the same as the gender difference in the proportion of not in the labour force. This implies that a decline in labour force participation by females rather than an increase in the rate of female unemployment accounts for the gender differences in employment rates. While the relatively higher proportion of not in the labour force category in the younger age cohorts may reflect the impact of children on female labour force participation, the higher proportion of this category in 55 and beyond age bracket is primarily due to the propensity for females to retire earlier.

C.3 Gender and industry of employment

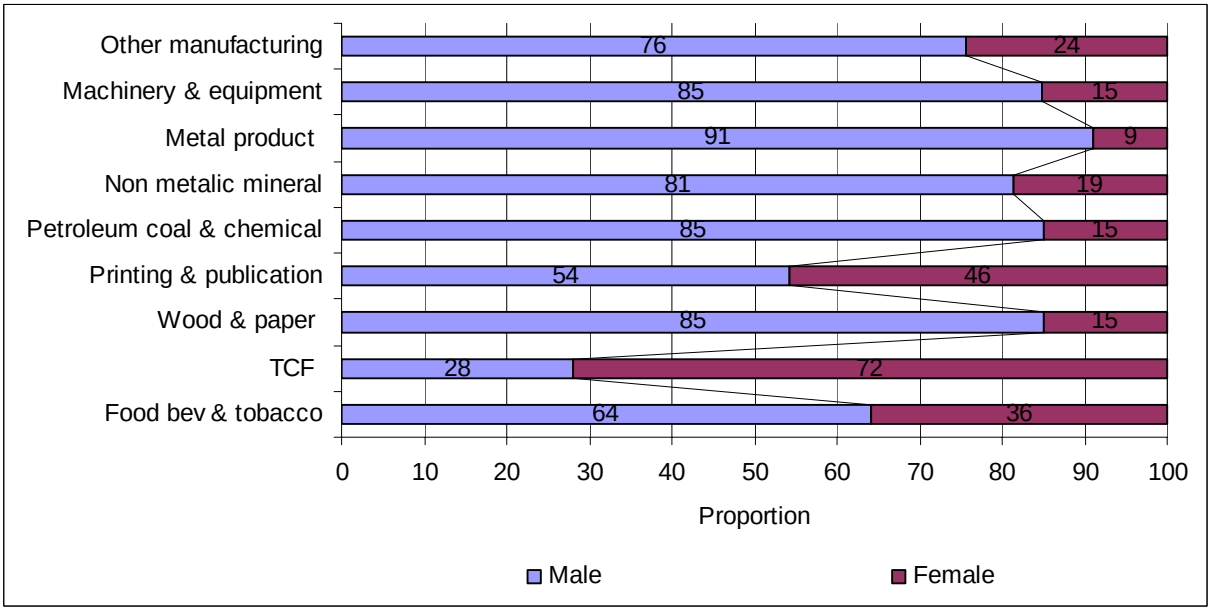
Disaggregating industry employment data by gender shows a distinct pattern dictated by gender (Figure C.5). A higher proportion of males is employed in mining, electricity gas and water, and construction, while more females are employed in health and education industries.

Figure C.5: Gender and industry of employment



Within manufacturing, there is a considerably higher proportion of females than males in the TCF industry (Figure C.6). On the other hand, industries such as machinery and equipment, metal product, petroleum coal and chemical, and wood and paper products are overwhelmingly represented by male workers.

Figure C.6: Gender and industry of employment in manufacturing



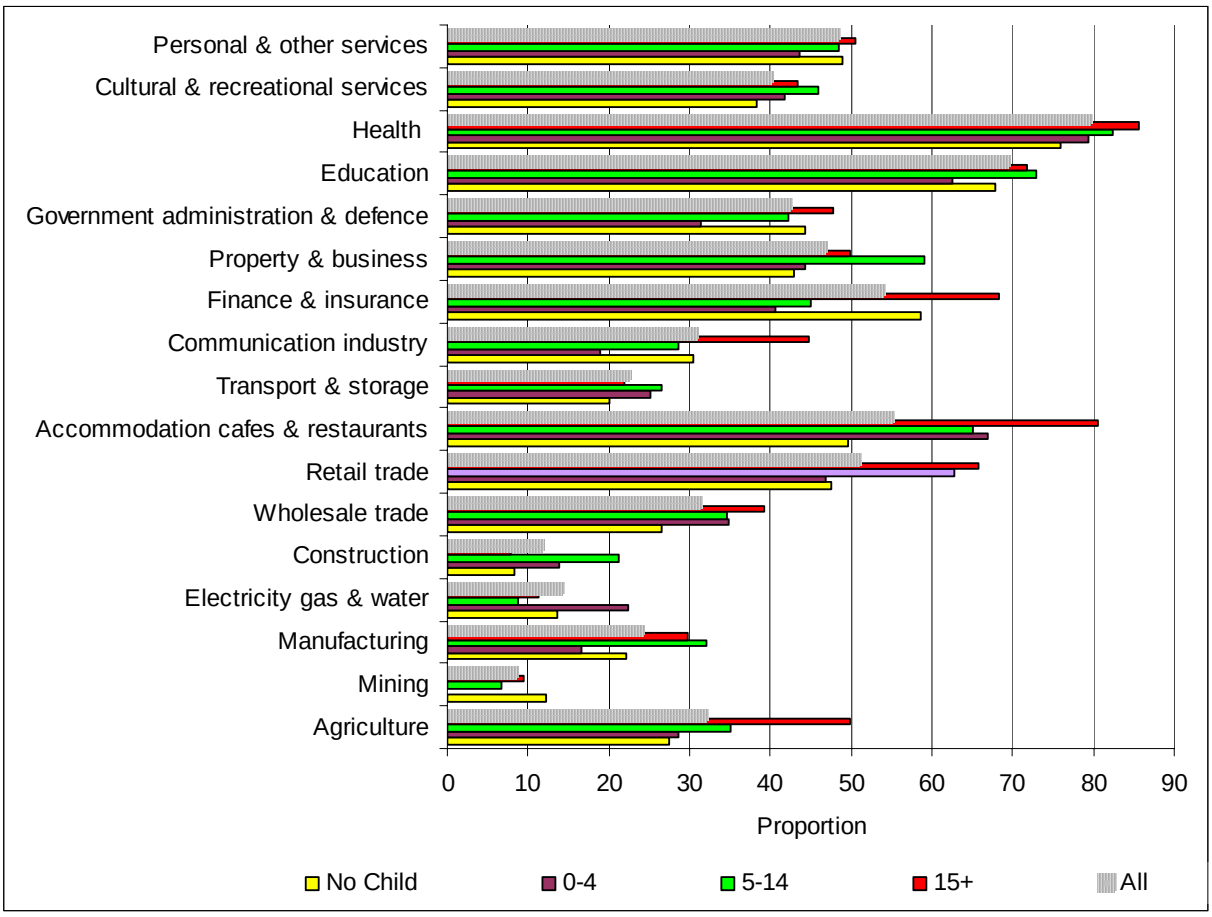
C.4 Age of children under care

The gender proportion within an industry varies with age of children under care. Figure C.7 displays the proportion of females in each industry, disaggregated by the age of the youngest

child, compared to the industry average female proportion. The figure shows that, in the finance and insurance industry, females on average account for 54 per cent of employment; but only 40 per cent of its employees who have pre school age children under care are females.

In the category of workers with children of 15 years or over under care, the ratio of women employees is higher than industry average. This observation is true for all industries except electricity, gas and water and transport and storage, where on average only 15 per cent of employees are females.

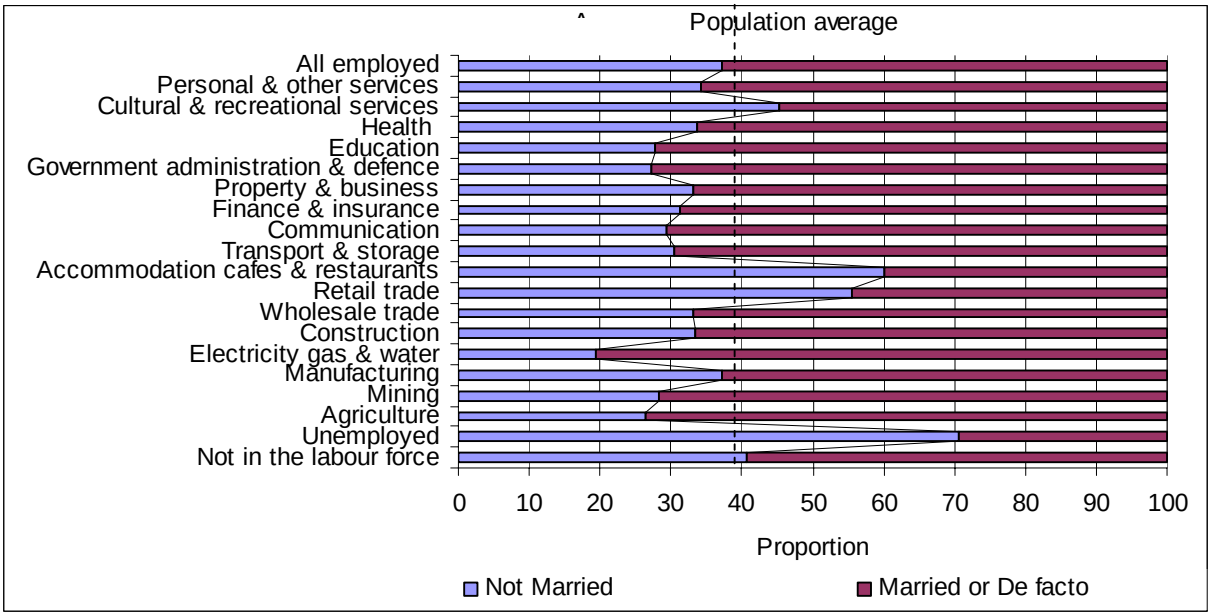
Figure C.7: Children's age and industry of employment for females



C.5 Marital status and labour market outcome

Figure C.8 depicts the employment proportion by marital status against all 19 labour market outcomes. Among all industries, electricity gas and water has the highest proportion of married employees, closely followed by agriculture, education, government administration and mining. On the other side of the spectrum are accommodation, cafes and restaurants and retail industries. The lower incidence of being married in these industries may be partly due to prevalence of younger age workers.

Figure C.8: Marital status and labour market outcome



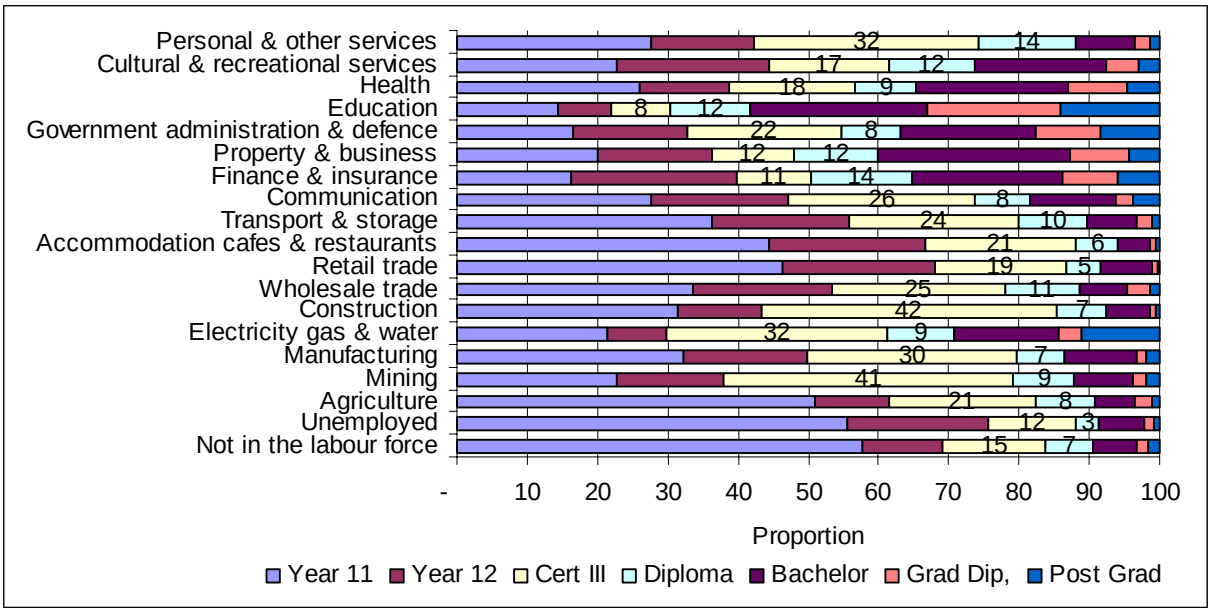
C.6 Education

Being a major determinant of skill acquisition, education is widely expected to influence overall employability as well as employment prospects across industries. As industries have divergent skill requirements, not every industry looks for workers with high educational qualifications. Some industries require specialised skills, which are only acquired through undertaking special courses. These may not be offered by university education. In HILDA, every individual's highest educational qualification is recorded, and in this study we have grouped them into seven categories: year 11 or below, year 12, certificate III/IV, diploma, bachelor, graduate diploma and post-graduate degree. While education level up to year 12 provides a general skill, specialised intermediate level trade skills are attained through undertaking trade courses offered at the certificate III/IV and diploma levels, and research and higher level professional skills are gained through graduate and post-graduate courses.

Figure C.9 illustrates the relationship between highest level of education and labour market

outcomes. It mirrors our prior understanding of the 'gateway' industries, with 46 per cent of retail and 44 per cent of accommodation, cafes and restaurants industry workers having the highest education of year 11 or below. Education up to year 11 or below is most common among those in the not in the labour force category (58 percent) followed by those unemployed (56 percent).

Figure C.9: Highest education level, industry of employment or other labour market outcome



With regards to traditional trades—certificate III/IV and diploma—construction and mining industries appear to be hiring a large proportion of their workers with these levels of qualifications. Approximately 50 per cent of their workers have either a certificate III /IV or diploma, highlighting that traditional trade skills may be in high demand in these two industries. The 46 per cent of workers in personal and other services with certificate III/IV and diploma are likely to include hair dressers and other related occupations. The two other industries with relatively more employees with certificate III/IV and diploma, are electricity gas and water and manufacturing (41 and 37 per cent respectively).

For the highest level of qualification of bachelors or above, the education industry has the highest proportion (58 per cent). This is then followed by property and business services, government, finance and insurance, and health, each having 35 to 40 per cent of its workforce holding a bachelor or above. Electricity gas and water is second only to education for having the highest proportion of post graduate qualifications.

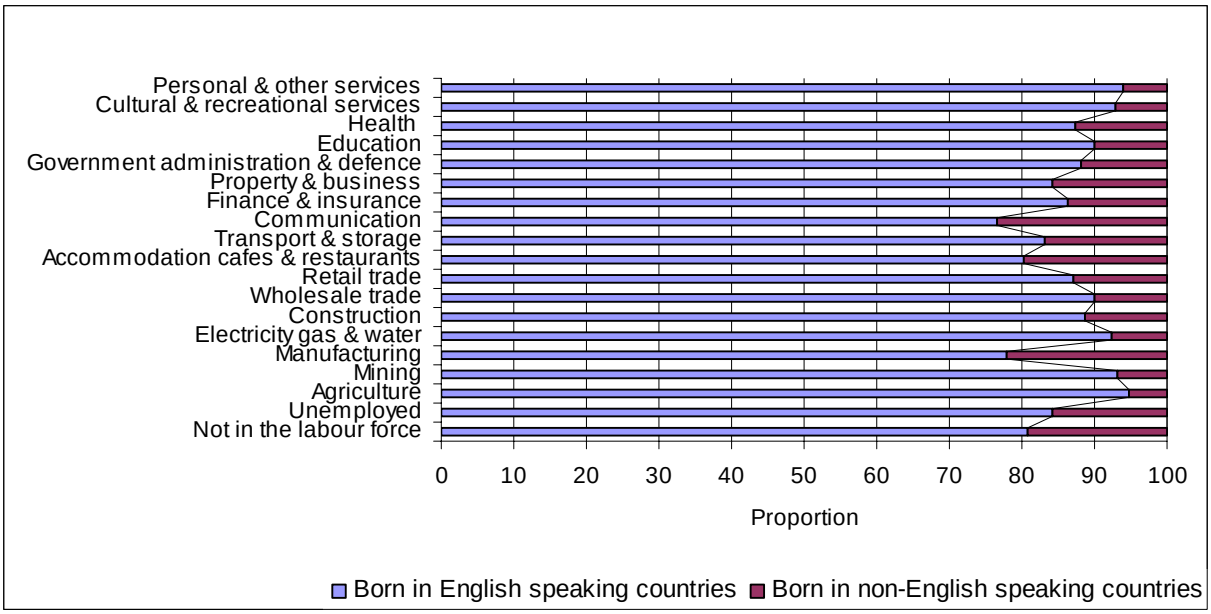
Nevertheless, as expected, low levels of education are prevalent among workers in the ‘gateway’ industries, and in the unemployed and not in the labour force categories.

C.7 Country of birth

Another important determinant of Australian labour market outcome is the ability to communicate in English. HILDA contains information on individual's assessed English language ability and reports these as a score. Since it was respondents' own appraisals, we did not consider it very reliable. Instead, we use birth in an English speaking country as a proxy for a person's English language skill. However, the proxy has limitations, not only for those with English speaking parents born in a non-English speaking country, but also for very young migrants. It is also arguable that country of birth can reflect cultural issues that could also impact on labour market outcomes.

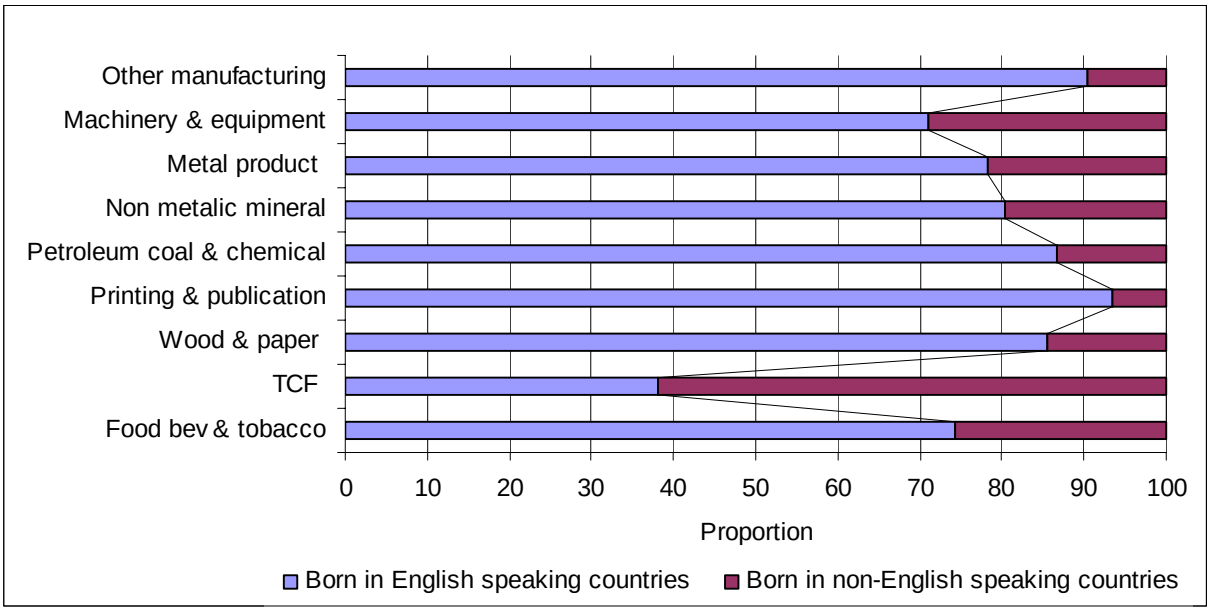
Communication, manufacturing, accommodation, cafes and restaurants and transport and storage industries have the highest proportion of workers born in a non-English speaking background (Figure C.10). The reverse is true for agriculture, mining, cultural and recreational services and personal services industries.

Figure C.10: Country of birth and labour market outcome



The relatively higher proportion of manufacturing workers born in a non-English speaking country (22 per cent) is partly explained by the high incidence of these workers in some of its component industries, TCF, food beverage & tobacco, machinery & equipment and metal product industries. They altogether account for 61 per cent of the manufacturing workforce, and have a relatively higher proportion of workers born in a non-English speaking country, as illustrated by Figure C.11.

Figure C.11: Country of birth and employment in manufacturing industries



Sixty-two per cent of TCF workers are born in non-English speaking countries, followed by 29 per cent in machinery and equipment, 26 per cent in food beverages and tobacco and 22 per cent in metal product. On the other hand, printing and publication and other manufacturing are overwhelmingly represented by workers born in English speaking countries.