Noncognitive Skills, Occupational Attainment, and Relative Wages*

Deborah A. Cobb-Clark
The University of Melbourne
and IZA

Michelle Tan
Australian National University

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Abstract

This paper examines whether men's and women's noncognitive skills influence their occupational attainment and, if so, whether this contributes to the disparity in their relative wages. We find that noncognitive skills have a substantial effect on the probability of employment in many, though not all, occupations in ways that differ by gender. Consequently, men and women with similar noncognitive skills enter occupations at very different rates. Women, however, have lower wages on average not because they work in different occupations than men do, but rather because they earn less than their male colleagues employed in the same occupation. On balance, women's noncognitive skills give them a slight wage advantage. Finally, we find that accounting for the endogeneity of occupational attainment more than halves the proportion of the overall gender wage gap that is unexplained.

Keywords: noncognitve skills, personality, occupation, gender wage gap, decomposition
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1 Introduction

Despite falls in occupational segregation in many countries including the United States (Blau and Kahn, 2000), Canada (Fortin and Huberman, 2002), Britain (Hakim, 1992), and to a lesser extent Australia (Lee and Miller, 2004; Preston and Whitehouse, 2004; Rimmer, 1991), men and women often do very different kinds of work. A large literature investigates the implications of this gender segregation for labour market outcomes. The gender wage gap in particular is often attributed to gender segregation across occupations, industries, or jobs (see for example Blau and Kahn, 2000; Groshen, 1991; Mumford and Smith, 2007). Importantly, because male jobs are generally associated with higher wages, better benefits, and more training opportunities, the concern is that occupational segregation may result in an overall gender wage gap even if there is no wage disparity between men and women employed in the same occupation (Miller, 1994; Preston and Whitehouse, 2004; Robinson, 1998; Woden, 1999). Others, however, argue that occupational segregation may be relatively unimportant for women's wages (see Barón and Cobb-Clark, 2010; Bettio, 2002; Fortin and Huberman, 2002).

The process that leads to occupational segregation is not well understood. For instance, why do men and women work in different jobs? To what extent are gender differences in occupational distributions the result of demand-side factors or the result of differences in men's and women's preferences for certain types of work? How important are noncognitive skills like personality traits, self-efficacy, or interpersonal skills in generating the pattern of employment across occupations?

A small, but growing, economics literature has begun to assess these questions directly. In early work, Andrisani (1977) shows that men with an internal locus of control are employed in better occupations and experience faster occupational advancement. Similarly, Filer (1986) finds that individuals' occupational choices are driven in part by their personality traits (i.e., emotional stability, restraint, objectivity) and preferences (i.e., the things that are most relevant to them in terms of defining personal success). Subsequent work has demonstrated that there seems to be a sensible match between the noncognitive skills of workers and the requirements of specific occupations. Positive core self evaluations (including high self-efficacy), for example, are positively correlated with accepting more challenging jobs (Judge et al., 2000), better job performance (Judge and Bono, 2001), and an ability to translate early advantage into later economic success (Judge and Hurst, 2007). Moreover, women are employed in safer jobs (DeLeire and Levy, 2001; Grazier and Sloane, 2008) or in jobs with low earnings risk (Bonin et al., 2007), which is consistent with the evidence that they are more risk averse than men (see Eckel and Grossman (2008) for a review). Borghans, ter Weel, and Weinberg (2008) find that workers who were more social as youths choose jobs that involve interpersonal interactions specific to instructing or training people, influencing others, and making speeches or presentations. Similarly, Krueger and Schkade (2008) find that gregarious individuals tend to gravitate to the kinds of jobs that involve more social interactions. Finally, noncognitive skills have also been linked to the propensity to work full time (Braakmann, 2009) or in blue collar occupations (Ham et al., 2009).

It is likely that the link between a worker's noncognitive skills and his or her occupational attainment stems in part from the fact that personality traits appear to have labour market returns that are both occupation- and gender-specific (Mueller and Plug, 2006; Nyhus and Pons, 2005). This raises obvious questions regarding the extent to which gender differences in noncognitive skills can account for the disparity in men's and women's relative wages. Recent research investigates this issue and generally concludes that noncognitive skills have a significant, but rather modest, role in explaining the gender wage gap (Braakmann, 2009; Fortin, 2008; Linz and Semykina, 2008; Manning and Swaffield, 2008; Mueller and Plug, 2006; Tan, 2009). These studies, however, analyse the effect of personality on relative wages conditional on the existing occupational distribution, thereby ignoring the effect of men's and women's noncognitive and cognitive skills on their occupational attainment. As Borghans, ter Weel, and Weinberg (2008) argue, however, the failure to account for the effect of various noncognitive skills on occupation-specific wages or in the assignment of people to jobs may underlie the relatively weak effect of noncognitive skills on the gender wage gap.

Our objective is to contribute to this emerging literature by explicitly assessing whether men's and women's noncognitive skills influence the occupations in which they are employed and, if so, whether this contributes to the disparity in men's and women's wages. We are particularly interested in the following questions. Do gender differences in personality (as measured by the Big Five) and locus of control or self–efficacy (as measured by the Pearlin and Schooler (1978) self-efficacy scale) help us understand occupational segregation? How important are noncognitive skills and occupational segregation in explaining the overall gap in men's and women's wages? We address these questions using unique data from the Household, Income, and Labour Dynamics in Australia (HILDA) survey which provides detailed information about noncognitive skills and labour market outcomes for a large, nationally-representative sample of individuals. Unlike much of the previous literature, we do not assume that the existing occupational distribution is exogenous. Rather we adopt an approach suggested by Brown et al. (1980) that allows us to account for the role of gender differences in noncognitive skills, human capital endowments, and demographic characteristics in producing both intra- and inter-occupational gender wage disparity.

We find that noncognitive skills have a substantial effect on the probability of employment in many, though not all, occupations in ways that differ by gender. Consequently, men and women with similar noncognitive skills enter occupations at very different rates. Women, however, have lower wages on average not because they work in different occupations than men do, but rather because they earn less than their male colleagues employed in the same occupation. On balance, our results suggest that women's noncognitive skills give them a slight wage advantage. Finally, we find that accounting for the endogeneity of occupational attainment more than halves the proportion of the overall gender wage gap that is unexplained.

In the next section, we discuss the estimation sample, the extent of occupational segregation, the size of the gender wage gap in Australia, and the noncognitive skills we consider in this analysis. Section 3 provides an overview of the estimation strategy, including the decomposition approach and model of occupational attainment. Our results are presented in Section 4, while our conclusions and suggestions for future research are outlined in Section 5.

2 The HILDA Survey

2.1 The Estimation Sample

The estimation sample is taken from the Household Income and Labour Dynamics in Australia (HILDA) survey which collects panel data from a nationally-representative sample of more than 7,600 Australian households encompassing almost 20,000 individuals aged 15 and older (see Watson, 2009; Woden et al., 2002). The advantage of HILDA data for our purposes is their detailed information about individuals' demographic and human capital characteristics, occupational classification, hours of work, and labour market earnings. In addition, HILDA data provide information about a number of important noncognitive skills. The Pearlin and Schooler (1978) Mastery Scale was administered in waves 3 and 4 providing us with a measure of locus of control (self-efficacy), while individuals responded to a series of personality questions in wave 5 allowing us to utilise a taxonomy of personality known as the Big Five (see Caprara and Cervone, 2000). Finally, the ability to pool data across waves makes our results more robust to particular events affecting the labour market in specific years, improves the precision of our estimates, and reduces concerns about sample selection bias (Barón and Cobb-Clark, 2010).[1]

We use the first six waves of HILDA spanning the years 2001 - 2006 and have necessarily made a number of sample restrictions. In particular, we restrict the sample to include respondents who are aged between 25 and 65 years, are employees (not self–employed) and provide complete information for the variables of interest. In particular, although HILDA respondents enter the estimation sample by meeting the age restriction and being employed at least once between waves 1 and 6, they must also have provided information about their locus of control (in either wave 3 or wave 4) and about their personality (in wave 5). The estimation sample contains 2,587 men and 2,810 women with a total of 21,167 person-year observations.

[1] There are many reasons to assume that there is an individual-specific error component in models of labour market outcomes. Given this, Barón and Cobb-Clark (2010) argue that pooling is potentially useful in reducing sample selection bias because it allows us to observe a larger fraction of the population. In particular, these authors document that, across waves 1 - 6, wave-specific participation rates for HILDA respondents aged 22 to 60 range from 57.6 to 66.2 percent for men and from 48.4 to 54.0 percent for women. However, fully 92.7 percent of men and 82.1 percent of women in this age range are labour market participants in the pooled waves 1 - 6 HILDA sample.

Our dependent variable is the log of hourly wages. For each individual, this is calculated as the ratio of current weekly gross wages and the number of hours usually worked per week in all jobs. The Consumer Price Index (CPI) available from the Australian Bureau of Statistics (2008) is used to deflate wages to 2001 levels.[2] We have excluded from the analysis individuals who report very low (less than $4) or very high (over $90) hourly wage. Sample statistics (means and standard errors) are presented in Appendix Table A1.

2.2 Occupational Segregation and Gender Wage Gaps

We construct 18 occupational categories by combining related 2-digit (sub-major) occupations identified in the second edition Australian Standard Classification of Occupations (Australian Bureau of Statistics, 1997).[3] As our decomposition approach relies on wage regressions run separately by gender and occupation, we strove to maintain as much occupational detail as possible while at the same time ensuring adequate samples of men and women were observed within each occupation. The distribution of Australian men and women across these 18 occupational categories is shown in Figure 1. Occupations are ordered along the x-axis from the occupation employing the smallest proportion of men (advanced clerical) to that employing the largest proportion of men (skilled trades).

[Figure 1 here]

Figure 1 makes it apparent that on average men and women are often employed in different occupations. While less than one percent of men are employed as advanced clerical workers, 16 percent of all men work in the skilled trades. In contrast, six percent of women are advanced clerical workers and less than two percent work as skilled trades persons. Furthermore, women are most likely to be employed in intermediate clerical (15 percent), science, engineering and other professional (14 percent), and education (13 percent) occupations. A standard measure of occupational segregation indicates that 40.9 percent of Australian women would have to

[2] Specifically, we deflate wages using the ratio of the 2001 September quarter CPI to the September quarter CPI in the appropriate year.

[3] See Appendix Table A2. Occupation-specific wages by gender are in Appendix Table A3.

change jobs in order to obtain an occupational distribution that was identical to that of Australian men.[4] This is consistent with Lee and Miller (2004) who also find a high degree of occupational segregation in the Australian labour market.

It is interesting to consider whether women's relative wages are related to the extent to which different occupations are segregated by gender. On average, Australian women have wage rates that are just over 85 percent of those of Australian men. The magnitude of the gender wage gap varies substantially across occupations, however. Figure 2 shows both the mean gender wage gap within each occupation and the fraction of workers in each occupation that are men. Here occupations are ordered along the x-axis by the magnitude of the gender wage gap, from the smallest (other labourers) to the largest (skilled trades).

[**Figure 2 here**]

The results indicate that there is little relationship between the size of the gender wage gap and the extent to which the occupation is integrated. The skilled trades have the highest gender wage gap (24.5 percent) and the highest proportion of male workers (nearly 90 percent). In contrast, more than two-thirds of education professionals and cleaners are women and these occupations have relatively small gender wage gaps (less than 10 percent). At first glance, these results would seem to suggest that there is a positive relationship between the size of the gender wage gap and the extent to which the occupation tends to employ men rather than women. There are many important exceptions to this generalization, however. Advanced clerical workers, for example, face the second largest gender wage gap (24.4 percent), despite that occupation having the highest concentration of women (87 percent). Similarly, the smallest gender wage gap is observed among other labourers even though two thirds of the workers observed in that occupation are men.

[4] We calculate an index of dissimilarity (D) as: $D = 0.5 \sum |p_{jm} - p_{jf}|$ where $j = 1...18$ indexes occupations, p_{jm} and p_{jf} are the proportions of men and women respectively employed in occupation j. In our estimation sample, $D = 0.409$.

2.3 Parameterising Personality and Locus of Control

An individual's personality typically refers to the tendency to exhibit behaviour that distinguishes him or her from someone else. In wave 5, HILDA respondents were asked to use a numeric scale to rate the extent to which 36 separate adjectives describe them.[5] The responses are summarised into a taxonomy of personality traits that has become known as the Big Five. This framework for describing the differences in individuals' personalities has found broad consensus among personality psychologists (Schmitt et al., 2007) and has become the most widely accepted and robust taxonomy of personality traits used to date (King et al., 2005). Each of the five traits are obtained from factor analysis (Borghans, Duckworth, Heckman, and ter Weel, 2008) and psychologists have validated the Big Five in both children and adults, in people across different cultures, and longitudinally (King et al., 2005). Most importantly for our purposes, there is a growing body of evidence that the Big Five dimensions of personality are reliable across gender (Schmitt et al., 2007) and are relatively stable among adults (Caprara and Cervone, 2000).[6]

The Big Five taxonomy differentiates between 1) extroversion, 2) emotional stability, 3) agreeableness, 4) conscientiousness, and 5) openness to experience. Extroversion refers to the degree to which one is sociable, assertive and talkative. Emotional stability is typically described by its opposite, neuroticism, which characterises the extent to which one is worried, insecure, anxious, and angry. Being high on the scale of 'openness to experience' describes those who are imaginative, intellectually curious, and nondogmatic in their attitudes, while agreeableness is associated with being courteous, trusting, cooperative and kind. Finally, conscientiousness captures the degree to which one is dutiful, reliable, thorough, and persevering (Costa and McCrae, 1992; Losoncz, 2007; Schmitt et al., 2007). Measures of these five

[5]Specifically, individuals were asked: "How well do the following words describe you?" Possible responses ranged from 0 ("Does not describe me well at all") to 7 ("Describes me very well"). See Appendix Table A4.

[6]Stability in both correlational patterns and mean levels of trait self–reports suggest that personality may be consistent over time or at least temporally stable (Caprara and Cervone, 2000). This is important because our analysis implictly treats personality and locus of control as time-invariant characteristics. While we cannot rule out the possibility that labour market outcomes also affect measures of noncognitive skills, we investigated this issue by re-estimating our model using only wave 6 data. We find that the intra-occupational component of the wage gap is slightly smaller, while the overall explained component is slightly higher when using only wave 6 data. The substantive conclusions remain unchanged, however.

personality traits are constructed by taking an average score of the relevant trait components. See Appendix Table A4 for details.

Respondents in both waves 3 and 4 were also administered the Pearlin and Schooler (1978) Mastery Scale. The scale consists of seven questions which ask individuals about the extent to which they believe that life events are within their control (rather than the result of external factors) and whether or not they have the ability to solve their problems. People whose external locus of control dominates tend to feel incapable of solving problems and believe that much of what happens is beyond their control. In contrast, people with an internal locus of control see future outcomes as being contingent on their own efforts and feel able to achieve what they want. Psychologists argue that these beliefs are central to an individual's motivation and to the way that he or she makes decisions, takes actions and sets goals. Those with an external locus of control may avoid situations in which they feel unable to cope, preferring instead to take on situations they know they can handle. Conversely, those with an internal locus of control will set higher goals and persist with challenges even when situations become difficult and are more likely to achieve successful outcomes (Strauser et al., 2002). We use responses to the seven items in the Pearlin and Schooler (1978) Mastery Scale to create a single locus of control index (ranging from 7 to 49) with higher scores indicating a more external locus of control and lower scores indicating a more internal locus of control (the index is an average of the scores taken from waves 3 and 4). Details regarding the question wording, response categories, and calculation of the index are presented in Appendix Table A5.

Information about men's and women's noncognitive skills are presented in Table 1. Women report having higher levels of extroversion, agreeableness, emotional stability, and conscientiousness than do men. Men report higher levels of openness to experience. These gender differences are statistically significant, raising the possibility that divergence in men's and women's personalities may affect both occupational attainment and relative wages. At the same time, there is no significant difference in men's and women's locus of control. This implies that locus of control will only affect the gender wage gap if there are gender differences in either 1) the link between occupational attainment and locus of control or 2) occupation-specific wage returns to locus of control.

[Table 1 here]

3 The Estimation Strategy

3.1 Decomposing the Gender Wage Gap

Our interest is in analysing whether differences in men's and women's noncognitive skills can be linked to their occupational segregation and, if so, whether this in turn contributes to the gender wage gap. It is common for researchers analysing the gender wage gap to control for the effects of occupation through the inclusion of a vector of occupational indicator variables in the wage model. This approach, however, makes the strong assumption that the distribution of men's and women's employment across occupations is exogenous. Moreover, using this approach to estimate the extent of labour market discrimination is appropriate only to the extent that gender segregation stems from individuals' unobserved human capital or job preferences rather than from discriminatory factors (see for example, Arulampalam et al., 2007; Miller, 1987). In contrast, we adopt the approach proposed by Brown et al. (1980) which extends the traditional Oaxaca (1973) and Blinder (1973) decomposition to account for the role of gender differences in occupational attainment in producing the overall gap in relative wages.[7]

We begin by modeling occupation-specific wages for men and women as follows:

$$\ln W_{ij}^{m} = X_{ij}^{m}\beta_{j}^{m} + \epsilon_{ij}^{m} \tag{1}$$

$$\ln W_{ij}^{f} = X_{ij}^{f}\beta_{j}^{f} + \epsilon_{ij}^{f}, \tag{2}$$

where i indexes individuals, $j = 1...18$ indexes occupations, and m and f denote men and women respectively. Moreover, $\ln W$ denotes log hourly wages, while X is a vector of demographic characteristics, human capital endowments, and noncognitive skills (the Big Five

[7] This methodology has been used to analyse gender wage gaps in Britain (Miller, 1987), Australia (Kidd, 1993), Kenya and Tanzania (DeBeyer and Knight, 1989), China (Meng and Miller, 1995), Canada (Kidd and Shannon, 1996) and Taiwan (Zveglich and van der Meulen Rodgers, 2004).

personality traits and locus of control index) thought to influence wages. The Big Five personality traits and locus of control index are all standardised to have a zero mean and a standard deviation of one. Finally, $\epsilon \sim N(0, \sigma^2)$, while β_j is a vector of wage returns to be estimated.

A large literature builds on the seminal papers of Oaxaca (1973) and Blinder (1973) in distinguishing between the "explained" and "unexplained" component of the gender wage gap. This decomposition is not unique and the choice of the counterfactual, nondiscriminatory wage structure used in the decomposition inherently depends on assumptions about the nature of discrimination present in the labour market (Elder et al., 2009; Neumark, 1988; Oaxaca and Ransom, 1994). We believe that a model of discrimination against women – rather than favouritism towards men – provides the more interesting counterfactual for our purposes (see Arulampalam et al., 2007; Neumark, 1988).

Consequently, we adopt the following decomposition of the gender gap in mean wages within occupations:

$$\begin{aligned} \overline{lnW}_j^m - \overline{lnW}_j^f &= \overline{X}_j^m \hat{\beta}_j^m - \overline{X}_j^f \hat{\beta}_j^f && (3) \\ &= \overline{X}_j^f (\hat{\beta}_j^m - \hat{\beta}_j^f) + \hat{\beta}_j^m (\overline{X}_j^m - \overline{X}_j^f) && (4) \end{aligned}$$

where $\hat{\beta}$ is the vector of OLS coefficients from a regression of lnW estimated separately by gender and occupation. This decomposition effectively provides an estimate of what women working in occupation j would earn if they retained their own characteristics, but were paid like men working in the same occupation.[8]

Brown et al. (1980) show that the aggregate gender wage gap across all occupations can then be decomposed as follows:

$$\begin{aligned} \overline{lnW}^m - \overline{lnW}^f &= \sum_j P_j^f \overline{X}_j^f (\hat{\beta}_j^m - \hat{\beta}_j^f) + \sum_j P_j^f \hat{\beta}_j^m (\overline{X}_j^m - \overline{X}_j^f) \\ &\quad + \sum_j \overline{lnW}_j^m (P_j^m - \hat{P}_j^f) + \sum_j \overline{lnW}_j^m (\hat{P}_j^f - P_j^f) && (5) \end{aligned}$$

where P_j^m and P_j^f are the proportion of male and female workers employed in occupation

[8]The parallel decomposition based on favouritism towards men is discussed in Section 4.4.

j respectively and $\hat{P}_j^f$ is an estimate of the counterfactual occupational distribution that would result if women retained their own characteristics but entered occupations in the same way as men. The first two terms on the right-hand side weight each occupation-specific gender wage gap by women's actual occupational distribution. The first term captures differences in the wage returns to productivity-related characteristics and is referred to as the unexplained intra–occupation wage differential, while the second is attributable to disparity in the characteristics of men and women employed in occupation j and is referred to as the explained intra–occupation wage differential. The effect of occupational segregation (the inter–occupation component of the wage gap) is captured by the third and fourth right-hand-side terms. Specifically, the third term weights the difference in men's observed occupational distribution and the counterfactual female occupational distribution $\hat{P}_j^f$ by mean male wages. This is the *explained inter-occupational* wage differential which results from the fact that men and women are employed in different occupations in part because they have different characteristics. In contrast, the fourth term captures the *unexplained inter-occupational* wage differential which stems from the change in women's occupational attainment that would result if women retained their own characteristics but began entering occupations at the same rate as equally qualified men.

In order to implement this decomposition, it is necessary to estimate models of occupational attainment and occupation-specific wages. Our model of occupational attainment is discussed in depth in Section 3.2. Our model of occupation-specific wages accounts for individuals' noncognitive skills (Big Five personality traits and locus of control) as well as for their human capital characteristics, in particular labour market experience (years in paid employment, years in current occupation, and years with current employer) and educational attainment (highest level of education). We are fortunate that HILDA provides us with measures of actual, as opposed to potential, experience. However, we also control for a number of demographic characteristics (marital status and presence of children under 14 years old) which the literature suggests are important in explaining gender differences in the effects of measured experience and job mobility. Our model also includes firm size (indicator for firms with less than 100 employees), employee status (indicators for full-time status, supervisor status, permanent employee, and union member), and residence in a high-growth state (Queensland and Western Australia). These measures account for the effects of labour demand on the wages of individual workers employed in specific occupations. Finally, our wage model includes year dummies and an overall constant.

3.2 Modeling Occupational Attainment

We begin with a simple conceptual framework in which occupational attainment arises from the interaction of individuals' preferences for and ability to do certain jobs (i.e., supply-side factors) and employers' hiring decisions (i.e., demand-side factors). On the supply side, job choices are assumed to result from a standard utility maximisation problem in which individuals search for jobs so as to maximise their utility subject to a budget constraint. Utility is a function of individuals' preferences for certain job attributes as well as potential earnings and individuals' choice sets may be constrained by their family structure (e.g., the presence of small children). On the demand side, an employer's willingness to hire an individual with particular productive skills or attributes will be reflected in the wage returns for those skills and attributes. To the extent that preferences for specific job attributes are linked to workers' noncognitive skills, incorporating reliable measures of these skills into a model of occupational attainment is helpful in capturing individuals' selection into occupations. Filer (1986), for example, documents that individuals make occupational choices, in part, on the basis of the things that are relevant to them in terms of defining personal success and that these choices correspond to their personality traits. At the same time, noncognitive skills such as personality and locus of control are dimensions of ability that can be rewarded or penalised in the labour market (see Mueller and Plug, 2006; Nyhus and Pons, 2005). Our estimates of the relationship between noncognitive skills and occupational attainment will reflect both demand- and supply-side effects.

We capture the interaction between these demand- and supply-side factors in a reduced-form multinomial logit model.[9] Specifically, we estimate the probability of individual i being observed in occupation j as follows:

$$P_{ij} = \Pr(O_i = j) = \frac{e^{x_i'\gamma_j}}{\sum_{k=1}^{J} e^{x_i'\gamma_j}} \qquad i = 1, ..., N, \qquad j = 1, ..., J \tag{6}$$

where O_i denotes the occupational classification of individual i, N is the sample size, J is the total number of occupational categories (in our case 18), and x_i is a vector of variables which capture the supply- and demand-side factors leading to individuals' employment in a specific occupation. In particular, x_i includes the Big Five personality traits, our locus of control index, years in paid employment, educational attainment, marital status, the presence of children under the age of 14 years, and measures of an individual's mother's and father's occupational status.[10] As individuals are assumed to choose occupations in part on the basis of aggregate expected future wage returns, the model in equation (6) abstracts from occupation-specific wage differentials across time or geographic location. Therefore, our model of occupational choice includes all of the explanatory variables included in the wage model (see above) with the following exceptions. We drop the period and state dummies which account for variation across time and place in occupation-specific wages. We also exclude a number of employment variables (in particular, years in current occupation, years with current employer, and detailed employment variables) which are useful in understanding wages, but which are likely to be realised only after a decision to enter a specific occupation is made. Similarly, the wage model includes all variables in the occupational attainment model except parents' occupational status which is assumed to affect preferences for, but not the returns to, occupations. The descriptive nature of the decomposition analysis, however, implies that these exclusion restrictions are not necessary for identification.

Estimates from Equation 6 are used to construct two interesting counterfactual occupational distributions. Specifically, coefficients for men are used to predict the occupational

[9] Miller and Volker (1985) compare unordered and ordered probability models of occupational attainment. They conclude that the ordered models are best suited to analysing job hierarchies, while unordered model have an advantage in predicting occupational distributions. Our decomposition analysis requires that we generate a predicted occupational distribution leading us to estimate an unordered model of occupational attainment.

[10] We use the ANU04 occupational status scale, which is based on a wide range of social, economic and demographic indicators thought to underlie the prestige of different occupations (Jones and McMillan, 2001).

distribution that would result if women retained their own characteristics but entered occupations through the same process as men (i.e., $\hat{P}_j^f$). We can also obtain a corresponding counterfactual distribution for men by predicting the proportion of men who would be in occupation j if they faced the same occupational allocation process as women (i.e., $\hat{P}_j^m$). These counterfactual occupational distributions are necessary to estimate the wage decomposition used in this analysis.

4 Results

We begin by considering the implications of our estimates for occupational segregation and the role of noncognitive skills in men's and women's occupational attainment. We then present and discuss the results of the decomposition analysis. Finally, we investigate alternative approaches to modeling occupational attainment.

4.1 Actual and Counterfactual Occupational Distributions

Table 2 compares men's and women's actual occupational distributions with the counterfactual distributions calculated above. If women retained their own characteristics, but entered occupations in the same manner as men, we predict that there would be an increase in the proportion of women working as managers (4.3 percentage points), skilled trades persons (9 percentage points), and intermediate productions workers (11.3 percentage points). Despite these increases, women would remain under-represented in these occupations relative to men. Thus, these are male-dominated occupations partly because of gender differences in those human capital endowments, demographic characteristics, and noncognitive skills underlying occupational attainment.

[Table 2 here]

At the same time, there are cases where gender differences in observed characteristics do not explain gender differences in occupational attainment. For example, we predict that there would be a fall in the proportion of women employed as advanced clerical workers (4.7

percentage points), intermediate sales and service workers (6.7 percentage points), education professionals (6.8 percentage points), and intermediate clerical workers (9 percentage points). Furthermore, the predicted proportions of women in these traditionally female occupations correspond closely to the actual proportion of men observed in these occupations. In other words, this similarity in $\hat{P}_j^f$ and P_j^m indicates that gender differences in individuals' characteristics do not explain why women are more likely to be observed in these occupations.

Finally, we compare the counterfactual male occupational distribution ($\hat{P}_j^m$) to women's actual occupational distribution (P_j^f). If men were employed in occupations through the same process as similarly qualified women, we expect that there would be substantial falls in the proportion of men employed in managerial (4.1 percentage points) and skilled trades (13.3 percentage points) occupations. Despite this, men would still be employed in these occupations in higher proportions than women actually are, indicating that gender differences in characteristics play some role in generating segregation across these occupations. In contrast, the counterfactual proportion of men employed in science, engineering and other associates and intermediate clerical occupations would be similar to the fraction of women employed in these occupations.

Taken together these results indicate that there is no single explanation for segregation in the Australian labour market. In some cases segregation appears to stem from disparity in productivity-related characteristics, while in others there are vast differences in the propensity for men and women with similar skills to be employed in a particular occupation. It is unclear whether the latter results from differences in the preferences of men and women for certain occupations or the hiring behaviour of employers.

4.2 Noncognitive Skills and Occupational Attainment

Selected results (average marginal effects and standard errors) from our estimations of occupational attainment are presented in Table 3 for men and in Table 4 for women. The reported marginal effects represent the estimated effect of a one standard deviation increase in a given personality trait or in the locus of control index on the probability of being employed in a specific occupation.

Men's personality traits are in many cases closely linked to the occupations in which they are employed. Specifically, men who rate themselves as (one standard deviation) more agreeable (i.e., sympathetic, kind, cooperative, and warm) have a 2.8 percentage point lower probability of working as managers and a 2.9 percentage point lower probability of being employed as a business professionals. These effects are substantial given that the proportion of men employed in each of these two occupations is approximately 9.5 percent (see Table 2). A similar increase in agreeableness is linked to a 1.4 percentage point (36.9 percent) increase in the probability that a man works as a science and engineering associate, while men who are more open to experience are significantly more likely to be employed as either business (18.8 percent) or education professionals (32.1 percent). Increased conscientiousness (i.e., being orderly, systematic, efficient, etc.) is associated with a significantly higher probability that men are employed as managers (21.1 percent), but a significantly lower probability that men are employed as educational professionals (24.5 percent) or as factory workers (33.3 percent). Finally, men who rate themselves as more emotionally stable are more likely to have jobs as science and engineering or as business professionals, while with one minor exception, extroversion has no relationship with men's occupational attainment at all.

[Table 3 here]

Men's occupational attainment is also linked to the extent to which they believe that they are able to control life's outcomes. Men who believe that much of what happens in life is outside their control (i.e., have an external locus of control) are 29.5 percent (2.8 percentage points) less likely to be observed working as managers suggesting that those with a more internal locus of control are better able to take on the roles required for directing organisations and supervising staff. Similarly, men are less likely to be education professionals as their locus of control becomes more external. In contrast, men who believe that life's events are largely outside their control are significantly more likely to be employed as cleaners or factory workers than are otherwise similar men. For example, a one standard deviation increase in the extent to which a man has an external locus of control is associated with a 45 percent increase in the probability of being employed as a cleaner and a 19 percent increase in the probability of working as a factory labourer.

These results are consistent with previous evidence that men with an internal locus of control look for more challenging jobs, are employed in better occupations, and move up the job ladder faster (Andrisani, 1977; Borghans, Duckworth, Heckman, and ter Weel, 2008). Moreover, this link between a man's self-efficacy and his job status may also explain in part the wage premium enjoyed by men with a more internal locus of control (for example, Heckman et al., 2006).

Personality traits are also related to the occupational attainment of women, though in ways that differ from men. Interestingly, women's occupational attainment is perhaps most closely related to the extent to which they are open to experience. Women who are 'open to experience' describe themselves as deep, philosophical, creative, intellectual, complex, and imaginative. A one standard deviation increase in openness to experience is associated with an increase of 2.5 percentage points (57 percent) in the predicted probability of women being employed as managers. Being more open to experience is also associated with a significantly higher probability that women are employed as science and engineering, business, and education professionals, but with a significantly lower probability that they are employed as intermediate production workers. Like men, women also have a lower probability of being employed as managers (30 percent) or science and engineering associates (26 percent) as they become more agreeable. Unlike men, women are more likely to be employed as managers and less likely to be employed as intermediate production workers the more extroverted they are.

[Table 4 here]

Finally, women's occupational attainment is not linked to their locus of control. The only exception is that women who have a more external locus of control are somewhat less likely to be employed as science, engineering, or other professionals (1.9 percentage points), however the effect is not particularly large (14.1 percent) and is only marginally significant. In all other cases, there is no significant relationship between a woman's occupation and the extent to which she believes that life's events are under her control. Although not statistically significant, the marginal effects are, by and large, in the same direction as those for men. The lack of a significant role for self-efficacy in women's occupational attainment is interesting in light of previous results that women with an internal locus of control earn more than women with an external locus of control (Grove, 2005; Linz and Semykina, 2008).

Taken together, these results suggest that in many cases, men's and women's noncognitive skills have a substantial effect on their occupational attainment. The nature of this relationship, however, varies by gender, indicating that men and women with similar noncognitive skills enter occupations at different rates. Moreover, an individual's personality and locus of control are unrelated to the probability that he or she is employed in almost half of the occupations we considered suggesting that noncognitive skills may be more relevant in some jobs than others. Still, accounting for noncognitive skills in the estimation of our counterfactual occupational distributions results in more than a five percent change in the proportion of women predicted to be employed in seven out of 18 occupations and a similar change in the proportion of men predicted to be employed in two out of 18 occupations.[11]

4.3 Decomposition Results

The results of the decomposition given in equation 5 are presented in Table 5. We consider two alternative specifications: one excluding (panel A) and one including (panel B) workers' personality traits and locus of control in the set of factors determining occupational attainment and intra-occupational wage rates. Comparison of these two specifications sheds light on the additional effect that noncognitive skills have in explaining the gender wage gap.[12] The results also include bootstrapped standard errors.[13]

[Table 5 here]

[11] Results available upon request.

[12] Many productivity-related characteristics, in particular educational attainment or experience, are likely to be related to noncognitive traits like personality and locus of control (see Borghans, Duckworth, Heckman, and ter Weel, 2008, for example). Thus, noncognitive skills may have both direct (via productivity) and indirect (via education or experience) effects on the gender wage gap. Our analysis provides an estimate of the direct effect.

[13] A bootstrap was implemented by sampling individuals with 215 replications to take into account the interdependency of observations and thus obtain standard errors clustered at the individual level.

The overall gender wage gap is 0.143 log points. The vast majority of this gap (96.6 percent) stems from disparity in the wages of those Australian men and women employed in the same occupation. Less than five percent of the wage gap is attributable to differences in men's and women's occupational attainment.[14] In effect, Australian women earn less on average not because they work in different occupations than men do, but because they earn less than men when employed in the same occupation. Australian women's relative wages would improve only a small amount if they entered occupations in the same proportions as men with the same characteristics. This is particularly striking given the detailed occupational categories we consider, but is consistent with previous research which concludes that, in terms of relative wages, occupational segregation does not substantially disadvantage (and indeed may even advantage) Australian women overall (Barón and Cobb-Clark, 2010; Kee, 2006; Kidd, 1993; Lee and Miller, 2004; Miller, 1987; Rimmer, 1991). Similarly, Bettio (2002) and Fortin (2008) find that, in Canada and Europe, within-occupation wage differentials are also the predominant explanation for the aggregate wage penalty that women face. They argue that women would be better served by policies that promoted advancement up the job ladder within occupations rather than redistribution across occupations towards the male pattern of employment.

Differences in the human capital and demographic characteristics of men and women working within the same occupation explain less than one quarter (23.4 percent) of the disparity in relative wages (see panel A). Moreover, this explained component falls (rather than increases) slightly once we control for noncognitive skills. This indicates that, conditional on their other productivity-related characteristics, women's personality traits and locus of control gives them a slight wage advantage in the Australian labour market (see panel B). In short, accounting for the role of noncognitive skills in driving occupational segregation and wages does not dramatically increase the portion of the overall gender wage gap that can be explained by

[14]The decomposition of the gender wage gap into its aggregate intra- and inter-occupational components is based only on observed gender differences in occupational attainment and occupation-specific wages. Specifically, the intra-occupational component is caluclated by weighting each occupation-specific gender gap by women's occupational distribution. The inter-occupational component weights gender diferences in occupational distributions by men's occupation-specific wages. Because the decomposition into these aggregate components depends only on observed – rather than counterfactual – outcomes it is the same in panels A and B.

differences in Australian men's and women's characteristics.[15] Almost three-quarters of the wage penalty that women face stems from gender differences in the wage returns to human capital, demographic characteristics, and noncognitive skills within occupations. These results are consistent with research on Australian data from the early 1980s which also found that most of the intra-occupational component of the gender wage gap resulted from the unequal wage returns to men's and women's characteristics (Kid 1993). Thus, there appears to be an enduring gap in relative wages within the same detailed occupational classification which remains to be explained. Moreover, this is by far the most important source of the overall gap in women's wages.

Although the inter-occupational component of the gender wage gap is very small, it is completely unexplained by worker characteristics – whether or not we include noncognitive skills in the decomposition analysis. Thus, Australia men and women do not work in different occupations because they have different human capital endowments, demographic characteristics, or noncognitive skills. Rather, occupational segregation occurs because Australian men and women with the same characteristics have very different propensities to enter certain occupations.

4.4 Sensitivity Analysis: Accounting for Occupation

How does the way in which we have modeled occupational attainment affect our conclusions? Does allowing occupational attainment to be endogenous alter our understanding of the gender wage gap? To address these questions we calculate two alternative, but standard, Oaxaca–Blinder decompositions of the overall gender wage gap: first, omitting occupation from the analysis completely and second, including our 18 occupational indicators as exogenous controls. In both cases the wage model also includes our measures of noncognitive skills making these alternative decomposition results comparable to those previously presented in panel B of Table 5. The results of these sensitivity tests are presented in Table 6.

Using a standard Oxaca-Blinder decomposition and ignoring occupation, we find that

[15] This conclusion remains unchanged when we include only non-cognitive skills in the analysis. Specifically, non-cognitive skills have a negative, though small, effect on both the intra-occupational component (-1 percent) and the inter-occupational component (-1 percent) of the gender wage gap. Results available upon request.

the disparity in men's and women's characteristics accounts for 3.8 percent of the gap in relative wages (panel A). Once our 18 occupational dummies are included, however, we find that the explained component of the wage gap becomes negative (29.6 percent) indicating that the pattern of women's employment across occupations serves to substantially reduce the wage penalty they face. This is consistent with recent research using HILDA data and semiparametric decomposition methods (Barón and Cobb-Clark, 2010; Kee, 2006), but differs substantially from the results we obtain when we explicitly model occupational attainment. In particular, 21.3 percent of the total gender wage gap can be explained by differences in characteristics if we account for the endogeneity of employment across occupations (see panel B Table 5).

[Table 6 here]

We also consider how the level of occupational aggregation affects our main results by re-estimating equation 5 using nine one-digit ASCO classifications (see Table 6 panel B). We find that reducing the level of occupational aggregation from 18 to nine occupational categories increases the explained component of the gender wage gap. This is somewhat counterintuitive. However, Kidd and Shannon (1996) also find that there is no clear relationship between the level of occupational aggregation and the proportion of the gap which can be explained suggesting that what may be most important is the structure of job hierarchies within occupational structures (see Bettio, 2002).

Finally, we investigate how our conclusions would change if we assume that labour market discrimination takes the form of favouritism towards men rather than discrimination against women. This leads to a decomposition which rests upon a counterfactual occupational distribution in which men are assumed to enter occupations at the same rate as women with the same characteristics (see Table 6 panel C).[16] We find that the inter-occupational wage differential becomes even larger and can completely account for the overall gender wage gap. The explained component of the gap falls somewhat (from 21.3 to 16.4 percent), but on balance

[16]In effect, we compute the parallel decomposition using $\hat{P}_j^m$ and evaluating differences in occupation-specific wage returns using male characteristics.

a model of favouritism towards men leads to the much the same conclusions as a model of discrimination against women.

Overall, the results of these sensitivity tests indicate that the method one uses to account for occupational attainment has important implications for conclusions regarding the role of men's and women's human capital endowments, demographic characteristics, and noncognitive skills in driving relative wages and the extent to which the gender wage gap is unexplained. Explicitly modeling occupational attainment – as we have done here – substantially increases the proportion of the wage gap that is accounted for by disparity in men's and women's characteristics. Finally, the level of occupational aggregation matters, though in ways that are complex and difficult to summarise, while we find little effect of alternative assumptions regarding the nature of discrimination.

This analysis has been useful in highlighting the sensitivity of our results to alternative methods of accounting for occupation in the decomposition. At the same time, there is also evidence that the effects of occupation are not constant across the wage distribution and that occupational segregation may impose more of a wage penalty on women at the top than at the bottom of the wage distribution. Albrecht et al. (2003), for example, find that the occupational distribution explains more of the gender wage gap among high-wage than low-wage Swedish workers. Barón and Cobb-Clark (2010) find similar results for Australian women in both private- and public-sector employment, while Arulampalam et al. (2007) find the same for some (though not all) European countries. Although we do not present the results here, we investigated this issue by re-estimating our model for women with high versus low educational attainment. Consistent with these studies, we also find that occupational segregation accounts for a larger share of the gender wage gap among highly-educated workers.[17] Thus, it is important to develop methodological approaches that account for both the endogeneity of occupational choice and that allow for differential effects across the wage distribution.

[17] Results available upon request.

5 Conclusions and Directions for Future Research

This paper examines whether men's and women's noncognitive skills are related to the occupations in which they work, and if so, the extent to which this contributes to the wage penalty that women face. Unlike much of the emerging literature that seeks to link noncognitive skills to relative earnings (Braakmann, 2009; Fortin, 2008; Linz and Semykina, 2008; Manning and Swaffield, 2008; Mueller and Plug, 2006; Tan, 2009), we adopt a methodology which explicitly accounts for the role of noncognitive skills in the distribution of men's and women's employment across occupations.

Our results indicate that there is no single explanation for occupational segregation in the Australian labour market. Noncognitive skills do have a substantial effect on the probability of employment in many – though by no means all – of the occupations we consider in ways that differ for men and women. As a consequence, segregation into some occupations results from the vast differences in employment propensities for men and women with similar skills. On balance, however, occupational segregation is not the main driver of the gender wage gap. Australian women earn less on average because they earn less than their male colleagues employed in the same occupation, not because they work in different occupations. Moreover, if anything, Australian women's personality traits and locus of control give them a slight wage advantage. Thus, it does not appear that the relatively small role for noncognitive skills in understanding the gender wage gap stems from a failure to account for the effects of noncognitive skills on job assignment or occupation-specific wage rates as Borghans, ter Weel, and Weinberg (2008) suggest. Finally, our sensitivity tests do indicate, however, that a much larger proportion of the gender wage gap can be explained if occupational attainment is explicitly modeled rather than assumed to be exogenous. This implies that conclusions regarding the source of the gender wage gap rest fundamentally on the method used to account for occupational attainment.

These results advance our understanding of gender wage gaps in many important ways. However, they also leave open a number of puzzles yet to be resolved. Given the degree of segregation in many labour markets, for example, why do inter-occupational wage gaps play so little role in explaining the persistent wage penalty faced by women? Bettio (2002) and Fortin and Huberman (2002) discuss some of the institutional issues regarding this question, however, more work in understanding gender differences in occupational attainment and job assignment within occupations would be useful. In particular, our results document that women are much more likely to enter some and avoid other occupations than are men with the same cognitive and noncognitive skills. To what extent is this the result of differences in either preferences or skills that have we have failed to measure? Recent experimental evidence, for example, suggests that often-observed gender differences in risk-taking or competitive behaviour depend on the specific social context (Booth and Nolan, 2009a,b). Yet we know very little about how risk taking or competition in the workplace influences men's and women's decisions to enter specific occupations. To what extent is gender segregation the result of employers' hiring decisions? Finally, it is important to begin understanding the potential role of noncognitive skills in understanding job ladders within occupations. While occupational segregation appears to play only a minor role in relative wage disparities, the same cannot necessarily be said of job assignment more generally. The most substantial component of the gender wage gap occurs within occupations and remains largely unexplained.

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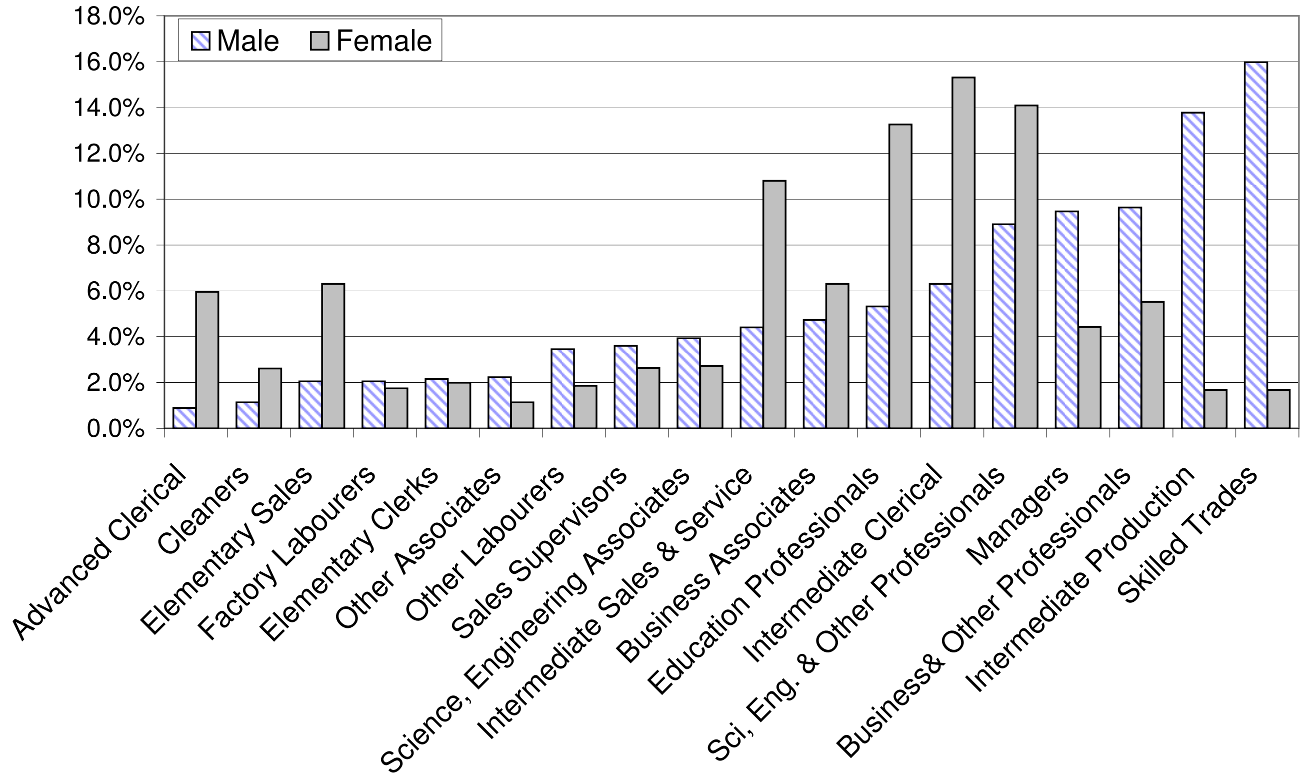
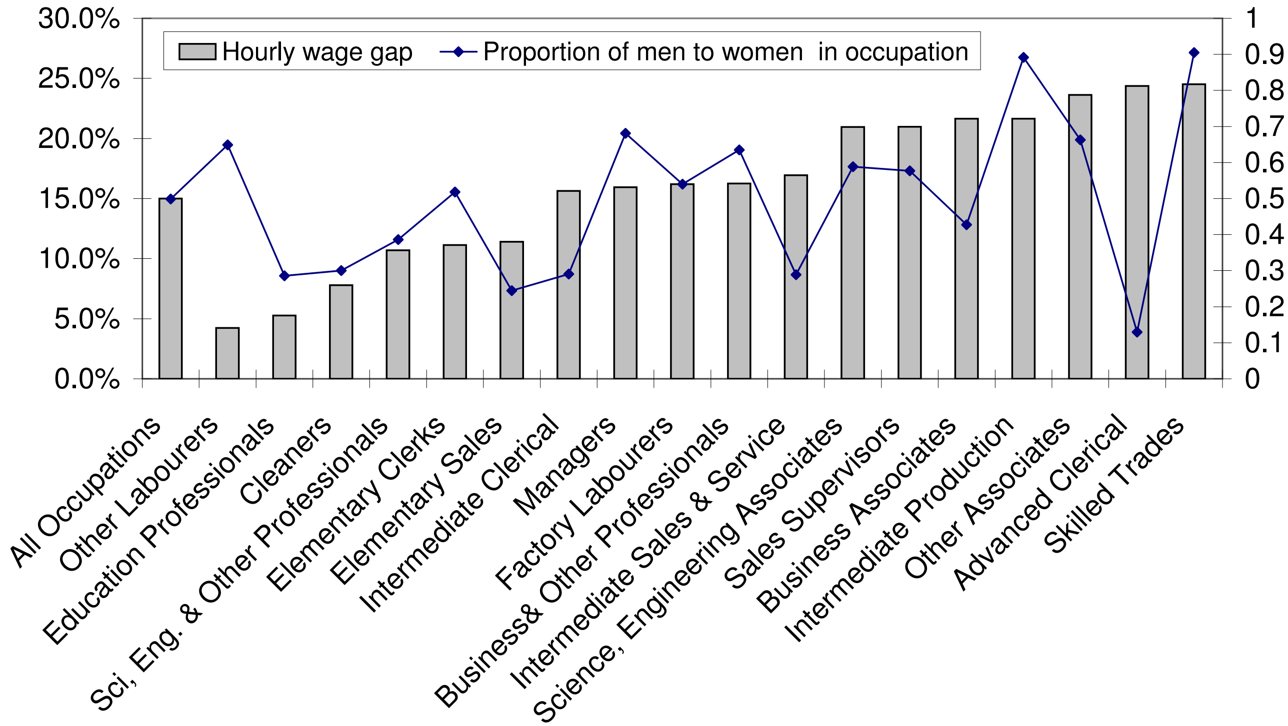
Figure 1: The Occupational Distribution of Workers
(by Gender)



Notes: The sample includes Australian male and female employees aged 25-65 years receiving hourly wages between \$4 and \$90 per hour (expressed in 2001 prices). The occupational classifications are based on the Australian Standard classification of Occupations (ASCO) 2 digit categories. The graph shows the ratio of men to women in each occupation for 2,587 men and 2,810 women in the sample, with a total of 21,167 person–year observations.

Figure 2: Gender Wage Gap and Proportion of Men to Women Across Occupation



Notes: The sample includes Australian male and female employees aged 25-65 years receiving hourly wages between $4 and $90 per hour (expressed in 2001 prices). The occupational classifications are based on the Australian Standard classification of Occupations (ASCO) 2 digit categories. The graph shows the ratio of men to women in each occupation for 2,587 men and 2,810 women in the sample, with a total of 21,167 person–year observations.

Table 1: Noncognitive Skills by Gender

(Means and Standard Deviations)

	Male (N=2,587)		*Female (N=2,810)*		P Values
	Mean	Std. Dev.	Mean	Std. Dev.	
Big Five					
Extroversion	4.24	1.02	4.59	1.12	0.000
Agreeableness	5.15	0.89	5.64	0.80	0.000
Openness to Experience	4.32	1.02	4.22	1.05	0.001
Emotional Stability	5.08	1.06	5.21	1.05	0.000
Conscientiousness	5.03	0.99	5.28	1.00	0.000
Locus of Control	17.89	6.58	17.89	6.78	0.994

Notes: The sample includes Australian male and female employees aged 25-65 receiving hourly wages between $4 and $90 (expressed in 2001 prices). The sample includes 2,587 men and 2,810 women. Two sided p-values are reported, taken from standard t-test performed to test the equality of means between the men and women in the sample.
Source: HILDA waves 1 to 6

Table 2: Actual and Predicted Occupational Distributions

	Women's		Men's	
	Actual	Predicted	Actual	Predicted
	P^{f_j}	$\hat{P}_j^f$	P_j^m	$\hat{P}_j^m$
Managers	4.4	8.7	9.5	5.4
Science, Engineering & Other Professionals	14.1	11.1	8.9	14.0
Science, Engineering Associates	2.7	3.1	3.9	3.6
Skilled Trades	1.7	10.6	16.0	2.7
Advanced Clerical	6.0	1.2	0.9	6.8
Intermediate Sales & Service	10.8	4.1	4.4	9.8
Intermediate Production	1.7	13.0	13.8	1.4
Elementary Clerks	2.0	2.9	2.1	1.5
Business & Other Professionals	5.5	10.1	9.6	5.5
Education Professionals	13.3	6.8	5.3	12.3
Business Associates	6.3	5.7	4.7	7.2
Sales Supervisors	2.6	3.2	3.6	2.8
Other Associates	1.1	2.0	2.2	1.5
Intermediate Clerical	15.3	6.3	6.3	15.3
Elementary Sales	6.3	2.3	2.0	5.6
Cleaners	2.6	2.2	1.1	1.5
Factory Labourers	1.7	1.6	2.1	1.4
Other Labourers	1.9	5.2	3.4	1.7

Source: HILDA waves 1 to 6

Table 3: The Effect of Noncognitive Skills on Men's Occupational Attainment

(Multinomial Logit Average Marginal Effects and Standard Errors)

	Managers	Science, Eng. & Other Prof.	Science, Eng. Associates	Skilled Trades	Advanced Clerical	Intermediate Sales
		Professionals				Service
Extroversion	-0.000	-0.009	-0.000	-0.003	-0.000	0.006
	(0.007)	(0.005)	(0.004)	(0.011)	(0.002)	(0.004)
Agreeableness	-0.028 ***	-0.014 *	0.010 *	-0.017	-0.001	0.003
	(0.008)	(0.006)	(0.004)	(0.012)	(0.002)	(0.004)
Openess to Experience	0.011	0.012 *	0.003	-0.001	-0.000	-0.001
	(0.007)	(0.006)	(0.003)	(0.011)	(0.002)	(0.004)
Emotional Stability	0.007	0.012 *	0.004	0.011	-0.001	-0.001
	(0.008)	(0.006)	(0.004)	(0.013)	(0.002)	(0.004)
Consicientiousness	0.020 **	-0.011	0.003	-0.001	0.003	-0.005
	(0.007)	(0.006)	(0.004)	(0.011)	(0.002)	(0.004)
Locus of Control	-0.028 ***	-0.008	0.001	-0.014	-0.000	-0.001
	(0.008)	(0.006)	(0.004)	(0.013)	(0.002)	(0.004)
	Intermediate Production	**Elementary Clerks**	**Business & Other Prof.**	**Education Professionals**	**Business Associates**	**Sales Supervisor**
			Professionals			
Extroversion	-0.001	-0.004	-0.006	0.002	0.006	0.001
	(0.009)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)
Agreeableness	0.003	0.005	-0.029 ***	0.001	0.001	-0.001
	(0.009)	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)
Openess to Experience	-0.014	-0.004	0.018 **	0.017 **	-0.003	0.001
	(0.009)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
Emotional Stability	0.003	-0.007 *	0.017 *	0.001	-0.003	0.005
	(0.010)	(0.003)	(0.007)	(0.005)	(0.004)	(0.004)
Consicientiousness	-0.009	-0.004	0.004	-0.013 **	0.004	0.006
	(0.009)	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)
Locus of Control	-0.007	0.004	0.002	-0.011 *	0.004	0.001
	(0.010)	(0.004)	(0.007)	(0.006)	(0.004)	(0.004)
	Other Associates	**Intermediate Clerical**	**Elementary Sales**	**Cleaners**	**Factory Labourer**	**Other Labourer**
Extroversion	0.004	-0.008	0.006 *	0.002	0.000	0.000
	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Agreeableness	-0.004	-0.000	0.005	-0.003	-0.003	0.003
	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Openess to Experience	-0.005	-0.007	-0.004	-0.001	-0.004	-0.008 *
	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Emotional Stability	0.002	0.002	0.001	0.001	-0.000	0.002
	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
Consicientiousness	0.001	0.004	0.001	-0.000	-0.007 **	-0.004
	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)
Locus of Control	-0.003	-0.002	0.003	0.005 **	0.004 *	0.006
	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)

Notes: Standard errors in parentheses. The reported marginal effects are *average marginal effects* which reflect the changes in the probability of being observed in an occupation for each observation averaged across the sample.
Source: HILDA waves 1 to 6.

Table 4: The Effect of Noncognitive Skills on Women's Occupational Attainment

(Multinomial Logit: Average Marginal Effects and Standard Errors)

	Managers	Science, Eng. & Other Prof.	Science, Eng. Associates	Skilled Trades	Advanced Clerical	Intermediate Sales
Extroversion	0.012 *	-0.004	0.001	0.001	-0.000	0.001
	(0.005)	(0.007)	(0.003)	(0.003)	(0.005)	(0.006)
Agreeableness	-0.013 *	-0.002	0.007 *	-0.003	-0.004	0.009
	(0.005)	(0.009)	(0.004)	(0.002)	(0.005)	(0.007)
Openess to Experience	0.025 ***	0.021 *	0.002	0.004	0.009	0.009
	(0.006)	(0.009)	(0.003)	(0.003)	(0.005)	(0.007)
Emotional Stability	0.009	0.021 *	-0.000	-0.001	0.005	0.009
	(0.005)	(0.009)	(0.004)	(0.003)	(0.005)	(0.007)
Consicientiousness	-0.004	-0.017 *	0.001	-0.001	0.009	-0.004
	(0.005)	(0.008)	(0.003)	(0.002)	(0.005)	(0.006)
Locus of Control	-0.006	-0.019 *	0.004	-0.001	-0.004	0.009
	(0.006)	(0.009)	(0.004)	(0.003)	(0.005)	(0.007)
	Intermediate Production	Elementary Clerks	Business & Other Prof.	Education Professionals	Business Associates	Sales Supervisor
Extroversion	-0.005 *	0.002	-0.004	0.004	-0.002	0.005
	(0.002)	(0.003)	(0.004)	(0.008)	(0.004)	(0.002)
Agreeableness	-0.001	0.001	-0.009	0.000	-0.005	-0.001
	(0.002)	(0.004)	(0.005)	(0.009)	(0.004)	(0.003)
Openess to Experience	-0.007 **	-0.004	0.012 **	0.024 **	-0.000	0.004
	(0.002)	(0.003)	(0.004)	(0.009)	(0.005)	(0.003)
Emotional Stability	-0.001	0.007 *	0.011 *	0.014	0.001	-0.004
	(0.002)	(0.003)	(0.005)	(0.010)	(0.005)	(0.003)
Consicientiousness	-0.001	-0.001	-0.003	0.004	0.007	0.004
	(0.002)	(0.002)	(0.005)	(0.009)	(0.004)	(0.003)
Locus of Control	-0.002	0.004	-0.000	-0.015	-0.004	0.000
	(0.003)	(0.003)	(0.005)	(0.009)	(0.005)	(0.003)
	Other Associates	Intermediate Clerical	Elementary Sales	Cleaners	Factory Labourer	Other Labourer
Extroversion	-0.001	-0.010	0.009 *	0.002	-0.005	-0.001
	(0.002)	(0.008)	(0.004)	(0.002)	(0.002)	(0.002)
Agreeableness	-0.004 *	0.011	0.008	-0.001	-0.003	-0.002
	(0.002)	(0.009)	(0.005)	(0.004)	(0.003)	(0.003)
Openess to Experience	-0.004	0.007	-0.003	-0.001	0.005	-0.004
	(0.002)	(0.009)	(0.005)	(0.003)	(0.003)	(0.003)
Emotional Stability	0.000	0.015	-0.007	-0.001	0.000	-0.002
	(0.002)	(0.009)	(0.005)	(0.003)	(0.002)	(0.003)
Consicientiousness	0.003	0.002	0.001	-0.002	-0.005	-0.001
	(0.002)	(0.008)	(0.005)	(0.003)	(0.003)	(0.002)
Locus of Control	-0.003	0.011	0.003	0.005	0.001	-0.001
	(0.002)	(0.009)	(0.005)	(0.003)	(0.003)	(0.003)

Notes: Standard errors in parentheses. The reported marginal effects are *average marginal effects* which reflect the changes in the probability of being observed in an occupation for each observation averaged across the sample.
Source: HILDA waves 1 to 6.

Table 5: Decomposition Results: Components of Gender Wage Gap

	PANEL A without noncognitive skills			PANEL B including noncognitive skills		
	Wage Gap	Std. Error	% of Total Gap	Wage Gap	Std. Error	% of Total Gap
Intra–Occupational						
Unexplained Component						
$\sum_j P_j^f \overline{X}_j^f (\hat{\beta}_j^m - \hat{\beta}_j^f)$	0.105	0.017	73.22%	0.107	0.020	74.91%
Explained Component						
$\sum_j P_j^f \hat{\beta}_j^m (\overline{X}_j^m - \overline{X}_j^f)$	0.033	0.018	23.37 %	0.031	0.020	21.68 %
Total	0.138		96.59 %	0.138		96.59 %
Inter–Occupational						
Explained Component						
$\sum_j \overline{lnW}_j^m (P_j^m - \hat{P}_j^f)$	-0.001	0.004	-0.54 %	-0.001	0.004	-0.41 %
Unexplained Component						
$\sum_j \overline{lnW}_j^m (\hat{P}_j^f - P_j^f)$	0.006	0.007	3.95 %	0.005	0.007	3.82 %
Total	0.005		3.41 %	0.005		3.41 %
TOTAL Unexplained Gap	0.110	0.018	77.17 %	0.113	0.021	78.73 %
TOTAL Explained Gap	0.033	0.018	22.83 %	0.030	0.020	21.27 %
TOTAL Gap	0.143	0.008		0.143	0.009	

Notes: The sample includes Australian male and female employees aged 25-65 receiving hourly wages between \$4 and \$90 (expressed in 2001 prices). The table reports bootstrapped standard errors with 214 replications for the specification in Panel A and 224 replications for the specification in Panel B. Standard errors are clustered at the individual level with 2,587 men and 2,810 women in the sample (21,167 person–year observations). The inter-occupational explained component reported in Panel A and B appear identical because of rounding, however actual values are -0.0008 and -0.0006 respectively.
Source: HILDA, waves 1 to 6.

Table 6: Sensitivity Analysis

	PANEL A:					
	Standard Oaxaca Decomposition					
	Explained Component		Unexplained Component		Total	
Aggregate Gap						
i) excluding occupation	0.005	3.8%	0.138	96.2%	0.143	100.0%
ii) including occupation	-0.042	-29.6%	0.185	129.6%	0.143	100.0%
	PANEL B:					
	Main Decomposition with 9 Occupational Categories					
	Explained Component		Unexplained Component		Total	
Intra-occupation	0.047	32.9%	0.102	71.5%	0.149	104.4%
Inter-occupation	-0.004	-2.5%	-0.003	-1.9%	-0.006	-4.4%
	0.044	30.4%	0.1	69.6%	0.143	100.0%
	PANEL C:					
	Alternative Decomposition with 18 Occupational Categories					
	Explained Component		Unexplained Component		Total	
Intra-occupation	0.014	9.9%	0.161	112.6%	0.175	122.5%
Inter-occupation	0.009	6.5%	-0.041	-29.0%	-0.032	-22.5%
	0.023	16.4%	0.12	83.6%	0.143	100.0%

Notes:

Panel A: The Standard Oaxaca Decomposition employs the Oaxaca–Blinder model which estimates differences in log hourly wage of men and women as $\overline{lnW}^m - \overline{lnW}^f = (\alpha^m - \hat{\alpha}^f) + \overline{X}^f(\hat{\beta}^m - \hat{\beta}^f) + \hat{\beta}^m(\overline{X}^m - \overline{X}^f)$; the full set of controls, without occupation, is used to estimate the model i); and model ii) is estimated with 18 occupational categories.

Panel B: This specification uses the main decomposition methodology, the full set of explanatory variables and is aggregated across nine ASCO 1 digit categories.

Panel C: The alternative counterfactual specification uses the main decomposition methodology and the full set of explanatory variables; 18 occupational categories; and uses a counterfactual male occupational distribution based on the counterfactual that the men are treated like women.

Table A1: Summary Statistics - Employed Australians Aged 25 to 65 Years

(by Gender)

	Male (N=10,560)		Female (N=10,607)	
	Mean	Std. Dev.	Mean	Std. Dev.
Wages (AUD)				
Hourly Wage	22.88	23.10	19.46	8.26
Log Hourly Wage	3.04	25.62	2.89	0.38
Employment Details (%)				
Full-Time	0.91	0.29	0.53	0.50
Supervisory Duties	0.58	0.49	0.45	0.50
Permanent Employee	0.81	0.40	0.69	0.46
Labour Market Experience				
Years in paid employment	23.26	10.70	19.85	9.38
Occupation Tenure	10.83	9.91	9.57	9.25
Tenure with Current Employer	8.23	8.65	6.80	7.19
Highest Level of Education (%)				
University	0.28	0.45	0.34	0.47
Diploma	0.41	0.49	0.26	0.44
Demographic				
Age	41.74	9.90	41.90	9.59
Married or Defacto (%)	0.78	0.42	0.72	0.45
Resident Children aged 0 -14 (%)	0.40	0.49	0.40	0.49
Australian Born (%)	0.78	0.41	0.79	0.41
Fathers ANU4 score	41.17	23.13	42.68	23.10
Mothers ANU4 score	28.44	25.18	30.72	25.62
High Growth States (%)	0.31	0.46	0.30	0.46
Other Employment Details (%)				
Firm has under 100 employees	0.55	0.50	0.59	0.49
Union member	0.36	0.48	0.34	0.47

Notes: The sample includes Australian male and female employees aged 25-65 receiving hourly wages between \$4 and \$90 per hour (expressed in 2001 prices). Reported wages were deflated using the ratio of the 2001 September quarter CPI to the September quarter CPI of the appropriate year. The sample includes 2,587 men and 2,810 women, with a total of 21,167 person–year observations
Source: HILDA waves 1 to 6

Table A2: Occupational Categories Used in the Analysis

Index	Occupation Categories	*Comprised of ASCO 2 Digit Occupation Catergories*	
1	Managers	11	Generalist Managers
		12	Specialist Managers
2	Science, Engineering & Other Professionals	21	Science, Building and Engineering Professionals
		23	Health Professionals
		25	Social, Arts and Miscellaneous Professionals
3	Science, Engineering Associates	31	Science, Engineering and Related Associate Professionals
		34	Health and Welfare Associate Professionals
4	Skilled Trades	41	Mechanical and Fabrication Engineering Tradespersons
		42	Automotive Tradespersons
		43	Electrical and Electronics Tradespersons
		44	Construction Tradespersons
		45	Food Tradespersons
		46	Skilled Agricultural and Horticultural Workers
		49	Other Tradespersons and Related Workers
5	Advanced Clerical	51	Secretaries and Personal Assistants
		59	Other Advanced Clerical and Service Workers
6	Intermediate Sales & Service	62	Intermediate Sales and Related Workers
		63	Intermediate Service Workers
7	Intermediate Production	71	Intermediate Plant Operators
		72	Intermediate Machine Operators
		73	Road and Rail Transport Drivers
		79	Other Intermediate Production and Transport Workers
8	Elementary Clerks	81	Elementary Clerks
		83	Elementary Service Workers
22	Business Professionals	22	Business and Information Professionals
24	Education Professionals	24	Education Professionals
32	Business Associates	32	Business and Administration Associate Professionals
33	Sales Supervisors	33	Managing Supervisors (Sales and Service)
39	Other Associates	39	Other Associate Professionals
61	Intermediate Clerical	61	Intermediate Clerical Workers
82	Elementary Sales	82	Elementary Sales Workers
91	Cleaners	91	Cleaners
92	Factory Labourers	92	Factory Labourers
99	Other labourers	99	Other Labourers and Related Workers

This table provides the details of the Australian Standard classification of Occupations (ASCO) 2 digit categories which correspond to the 18 occupation categories used in the analysis.

Table A3: Mean Hourly Wage Across Occupations and Gender

	All		Male		Female	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Managers	29.39	0.32	30.97	0.41	26.03	0.46
Science Engineering and Other Professionals	25.44	0.22	27.23	0.43	24.32	0.23
Science and Engineering Associates	22.06	0.34	24.14	0.45	19.08	0.44
Skilled Trades	19.64	0.17	20.11	0.17	15.18	0.49
Advanced Clerical	19.41	0.33	24.64	1.52	18.64	0.29
Intermediate Sales and Service	16.16	0.15	18.38	0.31	15.26	0.17
Intermediate Production	18.74	0.20	19.19	0.22	15.04	0.38
Elementary Clerks	16.86	0.31	17.82	0.49	15.84	0.37
Business Professionals	27.25	0.27	28.97	0.36	24.26	0.37
Education Professionals	23.72	0.20	24.64	0.37	23.34	0.23
Business Assoicates	22.95	0.28	26.19	0.50	20.52	0.29
Sales Supervisors	18.26	0.31	20.04	0.47	15.84	0.30
Other Associates	23.28	0.40	25.29	0.47	19.31	0.57
Intermediate Clerical	17.92	0.13	20.15	0.29	17.00	0.14
Elementary Sales	15.10	0.16	16.52	0.46	14.64	0.16
Cleaners	14.44	0.37	15.27	0.78	14.08	0.40
Factory Labourers	15.92	0.31	17.21	0.36	14.42	0.50
Other Labourers	15.40	0.27	15.63	0.31	14.97	0.54

Notes: The sample includes Australian male and female employees aged 25-65 receiving hourly wages between $4 and $90 (expressed in 2001 prices).

Table A4: The Big Five Dimensions of Personality

Dimension	Correlated Trait Adjective
Extroversion	Talkative
	Bashful (reversed)
	Quiet (reversed)
	Shy (reversed)
	Lively
	Extroverted
Agreeableness	Sympathetic
	Kindness
	Co-operative
	Warmth
Conscientiousness	Orderly
	Systematic
	Inefficient (reversed)
	Sloppy (reversed)
	Disorganised (reversed)
	Efficient
Emotional Stability	Envy (reversed)
	Moody (reversed)
	Touchy (reversed)
	Jealous (reversed)
	Temperamental (reversed)
	Fretful(reversed)
Openness to Experience	Deep
	Philosophical
	Creative
	Intellectual
	Complex
	Imaginative

This table provides a summary of the trait descriptions used to calculate the five personality dimensions provided in HILDA. Each dimension is measured on a scale of 1 to 7, the higher the score the more the trait describes a person

Table A5: Pearlin and Schooler (1978) Mastery Scale

Question: Please indicate how strongly do you agree or disagree with each the following statements?	Score
I have little control over the things that happen to me	1–7
There is no way I can solve some of the problems I have	1–7
There is little I can do to change many of the important things in my life	1–7
I often feel helpless in dealing with the problems of life	1–7
Sometimes I feel that I am being pushed around in life	1–7
What happens to me in the future mostly depends on me	1-7 **
I can do just about anything I set my mind to do	1–7 **

Notes: This table provides a summary of the scores used to calculate the locus of control index used in the analysis. Each score is measured on a scale of 1 to 7, the higher the score the more the respondent agrees with the statement. A single (7–49) index is created from these seven questions, with the higher the score the more the individual feels that events in life are outside of their capacity and their control (externals), the lower the score the more the individual feels that events in their life are determined by their own actions and ability (internals). ** Indicates that the scores have been reversed for these measures in order to calculate the index.