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Native-migrant wage differential across occupations: Evidence from Australia

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ABSTRACT

We investigate wage differential by migrant status across white-collar and blue-collar occupations in Australia. Migrants are observed to have a higher wage; this difference, however, does not exist once we control for covariates. The unconditional wage differential varies over wage distribution as well as by occupation. Significant wage differentials are found above the median: positive for white-collar workers and negative for blue-collar workers. Using recently developed decomposition methods based on Firpo, Fortin, and Lemieux (2009) we decompose wage differentials across their distribution. Overall, the wage advantage of migrants reflects their superior labour market characteristics, and in particular, their levels of education. We find that English language proficiency plays an important role in wage differences among immigrants from non-English speaking countries.

INTRODUCTION

The assimilation of immigrants in the labour market is an important measure of success both for the immigrants and for the receiving country. Immigrants typically earn lower wages than natives, although recent evidence points to improving labour market outcomes for immigrants in Australia. One out of every four people currently living in Australia was born abroad. Immigration policies increasingly aim to select immigrants with favourable labour market characteristics. In Australia, since the 1970s, the immigration policy increasingly specified an explicit set of criteria targeting age, skills (in terms of education, occupation and experience) and language proficiency. Recent years have seen an increased influx of immigrants from non-English-speaking countries in Africa as well as in South and Eastern Asia. The policies that determine the selection of immigrants have evolved over time to favour those who are young, more qualified and experienced, more fluent in English, and who possess the skills that are in demand among employers (Guven and Islam, 2015). Skilled migrants formed about 20 percent of the total immigration intake during the early 1990s, rising to about 65 per cent by 2010. However, support for immigration, and the determination of its appropriate magnitude, is the subject of continuing public debate. That concern is not restricted to Australia but lies at the heart of the debate about immigration in many countries – including most European nations, the US and Canada (Bauer et al., 2000; Scheve and Slaughter, 2001; Simon and Sikich, 2007).

The emphasis on skills in admitting immigrants should be reflected in a reduction in the migrant wage disadvantage in the labour market, particularly in white collared occupations. However, recent evidence suggests that there is no reduction in the wage gap. Despite a similar focus on skilled migration policy in Canada, Green and Worswick (2012) document the poor labour market

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outcomes of recent cohort of immigrants. Clarke and Skuterud (2012) find that immigrants in Australia face a smaller employment and earnings disadvantage than immigrants in Canada. New Zealand is another country with a points-based skilled migration policy. Stillman and Maré (2009) find that immigrant men in New Zealand face a relative wage disadvantage. In a review of the skilled migration policy, Tani (2014) points out that while such a system succeeds in selecting economically desirable migrants, it cannot prevent poor labour market outcomes for immigrants. Hence, understanding the extent and drivers of immigrants' success in Australia is important to assess whether this experience can be replicated in other countries.

In this article, we investigate the extent of the earnings differences among different groups of migrant and native workers in Australia. The total earnings gap between native and migrant workers in Australia was previously investigated by Chiswick and Miller (1985), Beggs and Chapman (1988) and McDonald and Worswick (1999), among others. More recent studies have focused on comparative analysis: Miller and Neo (2003) compared earnings gaps in Australia and the USA, while Antecol et al. (2003) compared native–migrant earnings across Australia, Canada and the USA. The common findings can be summarised as follows: (i) migrants in Australia earn less than their native counterparts; (ii) the earnings disadvantage faced by migrants in Australia is small, especially relative to Canada and USA[1] (iii) while there is evidence of labour market assimilation, with migrant earnings increasing with the number of years spent in Australia, the catch-up is slow. Chiswick et al. (2005) find similar assimilation pattern in terms of occupational ladders. In a recent study, Clarke and Skuterud (2012) compared the economic performances of migrants in Canada and Australia over the period 1986 to 2006. They found that the better labour market conditions in Australia, together with the difference in the source country of migrants, led to a smaller migrant disadvantage than in Canada.

This article differs from existing studies in that we examine the wage differences by occupational sectors and over the entire distribution. Migrants differ by gender, culture and language, education and training, vocational skill and in terms of many other attributes. These characteristics may influence their entry into the labour market of the host country, their performance in the various submarkets, and also their wages and employment. In recognition of that heterogeneity, we examine whether the individual characteristics or returns to the characteristics contribute to reducing the wage differences. We use the method based on the Recentered Influence Function (RIF) projections developed by Firpo et al. (2007, 2009). The RIF method generates *unconditional* quantile estimates, while the commonly used Quantile Regression (QR) gives *conditional* quantile estimates. Using the RIF unconditional quantile estimates, we decompose the wage gap between migrants and native-born in each occupation at different points of the wage distribution. This enables us to explore the contributions of differences in labour characteristics and differences in labour market returns to the observed gap, over the entire distribution – not just at the means. These decompositions are important for an understanding of the effects and limitations of the policy settings. Immigration policies can influence the composition of immigrant populations by selecting individuals with favourable labour market characteristics, but returns from these characteristics are determined through complex interactions of the economic and structural aspects of local labour market institutions.

This article contributes to our understanding of the native–migrant wage differential in Australia in the following ways. We account for the occupational differences between white-collar workers and blue-collar workers. We focus on skilled and unskilled workers separately considering that Australian immigration policy has become increasingly focused on migrant skill (Islam and Fausten, 2008). We examine the contribution of covariates to the explained and unexplained wage gap across the entire distribution. We then explore whether the country of origin still matters and find significant wage disparity between migrants from English speaking countries (ESB) and non-English speaking countries (NESB). We examine the role of English language proficiency in explaining the wage gap among migrants from Non English Speaking countries (NESB). Language proficiency affects both economic and social outcomes of immigrants (see, for example, Chiswick and Miller, 1995). Strong language skills determine the occupations that immigrants could look for, and perform in the labour market.

We find that migrants in Australia earn higher wages than natives, overall, although this wage differential varies along the wage distribution, across occupations and countries of origin. Where wage advantages for migrant workers exist, this primarily reflects migrants having higher education levels than natives. When compared with *similarly qualified* native workers, migrants receive lower wages, and thus, lower returns on education. Looking at wage differentials between migrants by origin countries, we find that proficiency in English explains a significant part of the wage gap. It is to be noted that our results are not causal. The results do not provide any suggestions of what would happen if a migrant chooses certain occupations. We rather provide evidence of potential sources of differences in wages across occupations between two groups of workers. The results will provide suggestive evidence of the effectiveness of Australia's current immigration policy, which is based on a well-defined set of observed skills.

DATA

We use data from waves 1 to 11 of the Household Income and Labour Dynamics in Australia (HILDA) survey, a longitudinal survey of Australian households. The survey commenced in 2001, and about 15,127 individuals aged 15 and over from 7,683 households are interviewed annually. Immigrants comprise 22 per cent of the HILDA sample, compared with their share (26%) of Australia's total population in 2008 (Australian Bureau of Statistics (2010). We restrict our sample to persons aged 20 to 65 years, in order to minimize the impact of labour market entries and exits. We also check the sensitivity of estimations by restricting the sample to 24-59 years in the analysis. Migrants are defined based on their country of birth: those born overseas are classified as migrants and Australian-born individuals are classified as natives. In order to capture the wage gap across occupations, workers are divided into two groups: managers and professionals are grouped together under the heading of white collar workers, while blue collar workers consist of technicians and trades workers, community and personal service workers, clerical and administrative workers, sales workers, machinery operators and drivers, and labourers[2] .

Descriptive statistics and the differences between natives and migrants, along with the significance of such differences using the *t*-test, are reported in Table 1. Natives and migrants differ in terms of their labour market characteristics. On average, migrants are older, more experienced, and more likely to be married than natives. In contrast to widely held perceptions, migrants earn higher weekly wages than natives, and work fewer hours per week, on average. Considering unconditional hourly wages, taking into account weekly wages and hours worked, migrants still maintain a wage advantage over natives. Education plays an important role in determining wages. Across the population, migrants are better qualified than natives, a higher proportion of migrants hold either a graduate or postgraduate qualification compared to natives and a lower proportion of migrants did not complete Year 12. Unconditional wages differ across occupations. The means reported in Table 1 indicate that there are small, but significant, differences between the occupational distributions of native and migrant workers[3] . Compared with natives, a higher proportion of migrants are in white-collar occupations and a lower proportion in blue-collar occupations. These results are in line with the skilled immigration policy of Australia, which targets foreign workers with superior observable attributes for potential success in the labour market.

Apart from the skills and individual characteristics such as age, migrants' labour market dynamics are influenced by the time spent in the host country (years since migration). Skills acquired in the home country may need to be augmented in the host country and migrants need time to adjust

TABLE 1

DESCRIPTIVE STATISTICS

Variable	Natives Mean	Natives Std Dev	Migrants Mean	Migrants Std Dev	Difference
Age	42.305	(18.508)	49.363	(16.996)	−7.058***
Female	0.528	(0.499)	0.522	(0.499)	0.006**
Married	0.594	(0.491)	0.706	(0.455)	−0.112***
Experience	25.609	(18.485)	31.347	(17.123)	−5.739***
Log weekly wage	6.453	(0.893)	6.614	(0.797)	−0.162***
Weekly hours	23.986	(21.753)	21.576	(21.647)	2.409***
Log hourly wage	3.007	(0.574)	3.105	(0.576)	−0.098***
Education					
Postgraduate	0.026	(0.159)	0.056	(0.231)	−0.030***
Bachelor degree/diploma	0.239	(0.426)	0.304	(0.460)	−0.065***
Vocational certificates	0.215	(0.411)	0.197	(0.398)	0.018***
Year 12	0.149	(0.357)	0.159	(0.366)	−0.010***
Year 11 and below	0.370	(0.483)	0.282	(0.450)	0.088***
Occupation					
Blue Collar	0.649	(0.477)	0.594	(0.491)	0.055***
White Collar	0.351	(0.002)	0.406	(0.491)	−0.05***

Notes: The last column reports the difference between natives and migrants, with superscripts denoting the significance of a *t*-test of the differences. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

to the host country labour market conditions and institutions. Figure 1A shows the occupational distribution of migrants by years since migration. The proportion of migrants in blue-collar occupations is higher in the initial years of arrival and declines as migrants spend more time in the host country. Thus, migrants might initially start in relatively unskilled jobs and move to more skilled jobs as they become familiar with the host country's labour market. Figure 1B documents similar adjustment process in terms of migrant earnings. Earnings display an inverted U shaped pattern. Earnings increase with years since migration as migrants adjust to the host country labour market by building networks and acquiring skills and knowledge complementary to the local labour market. This effect starts to level off and decline after 30 years in the host country. In our regression, we use age and experience which account for years since migration in Australia.

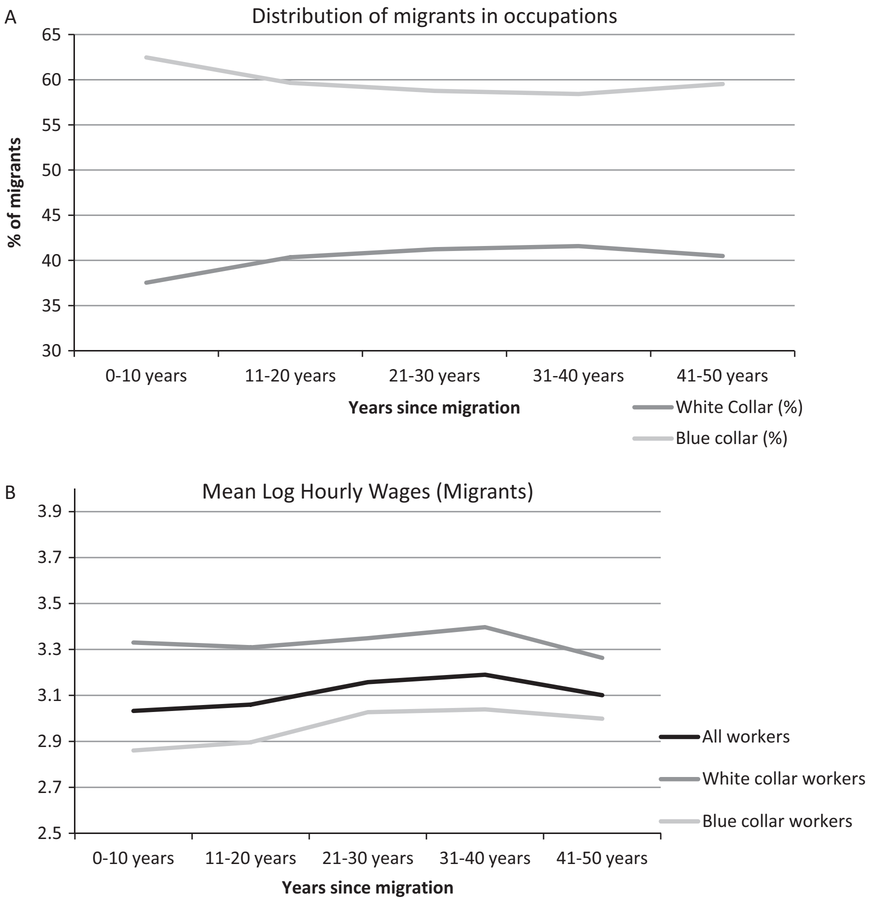
Kernel density estimates for logged hourly wages are plotted in Figure 2 to illustrate the wage distributions of native and migrants in the two occupational groups. Consistent with the mean differences noted above, there is no evidence of a migrant disadvantage in the wage distributions.

This initial finding raises further questions about potential wage differences conditional on characteristics. Further, it is of interest to explore the differences along the wage distribution and to investigate whether migrant characteristics are driving wage equality in the market and the role, if any, of returns to the characteristics.

EMPIRICAL STRATEGY

To examine the wage gap between migrants and natives, we ran random effects Generalized Least Squares (GLS) regressions of the natural logarithm of each individual's hourly wage on a migrant indicator dummy, controlling for gender, age, household size, year of observation and geographical location[4] . The results from this regression can be interpreted as capturing the magnitude of the mean unconditional wage gap between migrants and natives.

FIGURE 1
YEARS SINCE MIGRATION AND MIGRANT WORKERS



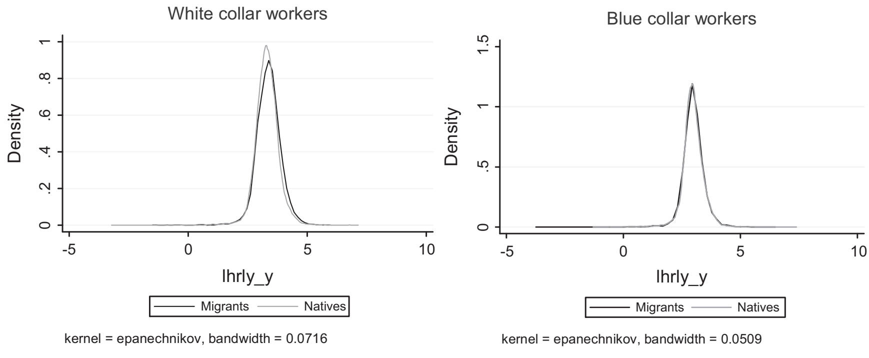
The estimation equation is

$$\ln w_i = X_i' \beta_1 + M_i \beta_2 + \varepsilon_i \tag{1}$$

where a subscript i refers to an individual, X is a vector of the characteristics detailed above, β_1 is the corresponding vector of coefficients, M is a migrant dummy variable which is equal to one for migrant, and β_2 measures the wage differential between migrants and natives. Because we have multiple observations for each individual, we cluster standard errors at the person level[5] .

We divide the sample into distinct occupational categories. The occupations are divided into two main categories: white-collar workers (consisting of managers and professionals) and blue-collar workers (consisting of the remaining occupational groups). One concern regarding classifying individuals based on occupation is the selection into occupation. Hence, one needs to address the endogeneity of occupation. In the absence of credible instruments, we use control variable approach to address such endogeneity. Selection of migrants into occupational groups may be driven by a host of factors such as language fluency, credential recognition, transferability of their human capital

FIGURE 2
HOURLY WAGES (KERNEL DENSITY ESTIMATES)



and role of networks. We control for a number of observable characteristics that determine success in the labour market. We particularly investigate the role played by the country of origin and language fluency. In order to address the potential selection based on unobservable characteristics, we control for ability of individuals. However, it is still possible that migrants face additional barriers to work in certain occupations. We expect that characteristics such as language skills, education and the ability of the individual are important sources of differences between migrant and native-born individual's selection into different occupations. If there is a negative selection, such that high-skilled migrants are selecting the low-skilled occupation because of additional barriers in the labour market for foreign-born workers, then our results provide a lower limit to what would actually happen in the absence of any barriers based on the nativity status of an individual in the Australian labour market. Note, however, that we here compare migrants and native-born. If the unobserved attributes that could drive their different choices of occupation are not significantly different between immigrants and native-born, then our results hold. To the extent that immigrants and native-born differ in unobservable traits that determine the selection into different occupations, our results will be biased.

We consider a separate analysis of each occupational group, which allows a comparison of wage differentials as well as of the contributions of characteristics such as education, by skill levels. Education plays an important role in determining labour market earnings, so we also include a vector of variables for education. However, completed education might be a "noisy" and ethnically biased measure of individuals' academic skill, given the variation in the quality of schooling across countries of origin and between migrants and natives. Therefore, the results are likely to understate the actual importance of differences in academic skill. In addition, the educational level of an individual can vary depending on her/his ability. Many studies in the context of the USA use Armed Forces Qualification Test (AFQT) test scores to measure academic skills or ability. In one such study, Neal and Johnson (1996) show that family background variables such as parental education can explain a significant fraction of AFQT scores. In the absence of any direct measure of cognitive ability, we use parental background as a proxy. We control for both father's and mother's education, in addition to the individual's own education, in order to capture the role of innate ability and academic skills. Parental education is also likely to be a key determinant of educational achievement. For example, Chen (2009) found a significant effect of parental education on children's academic achievements, with the father's and mother's educations having different impacts depending on the gender and ability of the children. In the context of immigrants, Card et al. (2000) and Guven and Islam (2015) found a significant intergenerational transmission of level of education and wages. Blau et al. (2013) found that the father's education can have a strong effect on the education, fertility and labour supply of second generation female immigrants in the USA. We therefore include controls in this study for both mother's and father's education, in order to account for the underlying abilities and skills of an individual, which may be inherited, transmitted or developed through family channels.

Next, we examine the gap across the entire wage distribution. To account for the fact that the distribution of observable characteristics may be very different across immigrants and natives, as well as across occupation types, we use the decomposition method proposed by Firpo et al. (2007, 2009) (hereafter referred to as the FFL method). This decomposition method is similar in nature to a standard Oaxaca-Blinder decomposition. However, it has the advantage that it allows us to consider the ways in which various characteristics of immigrants and natives affect the distribution of wages at points other than the mean. The method, built on earlier work by DiNardo et al. (1996), provides estimates of the effect of each individual covariate at different parts of the wage distribution. While conditional quintile regressions go beyond the decomposition at the mean, the FFL approach enables unconditional estimates across quantiles, thus capturing the dispersions both 'within' and 'between' groups.

The standard Oaxaca-Blinder decomposition starts with an OLS regression, then decomposes the mean differentials. Following parallel steps, the FFL decomposition starts with the following re-centred influence function (RIF_i) for observation w_i, such that

$$RIF_i = q(\tau) + \frac{[1(w_i \geq q(\tau)) - (1-\tau)]}{f(q(\tau))} \tag{2}$$

where f() is the density and 1() indicates whether the observed wage is at or above the quantile q(τ). Regressing the RIF_i on characteristics X_i and the migrant dummy as discussed for equation (1) leads to an estimate of $\hat{\beta}$, which represent the estimated partial effects using an unconditional quantile, the marginal effects of the explanatory variables.

The decompositions involve estimating separate RIF regressions for migrant, native and counterfactual wage distributions at chosen quantiles, and performing the usual Blinder-Oaxaca decomposition of each part of the wage gap into differences due to characteristics (the composition effect) and differences in returns (the structure effect). The first stage involves constructing a counterfactual wage distribution that immigrants would have obtained had they received the same returns to their labour market characteristics as native-born population. Thus, the differences between the actual distribution of the native-born and the counterfactual distribution are attributable to the different characteristics of natives and immigrants (i.e. the "composition effect"), and the differences between immigrants' actual distribution and the counterfactual represent the unexplained migrant earnings gap (i.e. the "structure effect"). In the second stage, composition and wage structure effects are further divided by the separate contribution of each covariate to any distributional statistic of interest, as opposed to just the mean, as in the Oaxaca-Blinder decomposition. This allows us to identify the specific characteristics, differentiated across natives and immigrants, which lead to the nativity earnings gap. The advantages of the RIF method are twofold: first, *unconditional* quantiles are usually of real interest in economic applications; second, this approach allows one to estimate the marginal effects of explanatory variables on the targeted *unconditional* quantiles.

ESTIMATION RESULTS

Results: random effect GLS

Table 2 reports the random effect GLS estimates for all workers. Consistent with the earlier discussion of the unconditional wage gap, migrant earnings are higher than native earnings when we do

TABLE 2

RANDOM EFFECT GLS REGRESSIONS FOR ALL WORKERS

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.044***	0.010	−0.029***	−0.028***
	(0.009)	(0.008)	(0.008)	(0.009)
Age		0.046***	0.041***	0.044***
		(0.002)	(0.002)	(0.002)
Female		−0.123***	−0.138***	−0.133***
		(0.007)	(0.006)	(0.007)
Postgraduate			0.430***	0.392***
			(0.015)	(0.016)
Bachelor degree/diploma			0.293***	0.265***
			(0.009)	(0.011)
Vocational certificates			0.089***	0.077***
			(0.009)	(0.011)
Year 12			0.121***	0.101***
			(0.011)	(0.013)
Household size		−0.004**	−0.001	−0.002
		(0.002)	(0.002)	(0.002)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents' schooling	No	No	No	Yes
Observations	67,050	67,050	67,050	55,897
Number of individuals	14,541	14,541	14,541	11,016

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

not control for any demographic variables (column 1). The results suggest the role of favourable characteristics of migrant workers: the wage advantage becomes insignificant once we control for age, and negative when we control for education. Contrary to our expectation, controlling for ability as proxied by parental education does not have any significant effect on the results. The control variables are of the expected signs: wages increase with age, are lower for female workers, and increase with education levels. As reported in Table 3 for white-collar occupations, returns to education are positive, with greater returns to a postgraduate qualification. Interestingly, these can also be observed for blue-collar occupations. The results underline the comparatively better education profile of migrant workers. Analysing the wage differences by occupational groups (Table 3 for white-collar and Table 4 for blue-collar workers) provides further insights into this finding. Controlling for individual characteristics, we observe no significant differences between migrants and natives within white-collar occupations (Table 3). However, migrants earn significantly less than their native counterparts within blue-collar occupations (Table 4). They earn about 3 per cent less than the native-born workers in blue-collar occupation. The results remain robust adding parental education as control. Consistent with white-collar workers, we see female workers earn about 13 per cent less than their male counterparts in blue-collar occupations.

The migrant wage advantage primarily reflects migrants' higher education levels. However, a migrant with the same educational level as a native worker earns less in both white-collar and blue-collar occupations, though the difference is not statistically significant for white-collar workers. While we cannot draw any definitive conclusions, the results indicate that parental education (or an individual's ability) plays a role, to some extent, for migrant workers in white-collar occupations. Column 4 in Table 3 shows that the coefficient becomes more negative when we control for ability (parental education). However, the difference between the coefficients of the migrant variable in columns 3 and 4 is not statistically significant, and therefore the results are only suggestive. On the

TABLE 3

RANDOM EFFECT GLS REGRESSIONS FOR WHITE COLLAR WORKERS

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.065***	0.024*	−0.004	−0.006
	(0.01)	(0.012)	(0.012)	(0.013)
Age		0.053***	0.051***	0.052***
		(0.003)	(0.003)	(0.003)
Female		−0.105***	−0.124***	−0.127***
		(0.010)	(0.010)	(0.011)
Postgraduate			0.361***	0.323***
			(0.022)	(0.025)
Bachelor degree/diploma			0.295***	0.264***
			(0.019)	(0.021)
Vocational certificates			0.064***	0.043*
			(0.021)	(0.023)
Year 12			0.185***	0.156***
			(0.023)	(0.026)
Household size		−0.001	0.001	0.000
		(0.00282)	(0.003)	(0.003)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents' schooling	No	No	No	Yes
Observations	24,941	24,941	24,941	22,310
Number of individuals	6,440	6,440	6,440	5,377

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TABLE 4

RANDOM EFFECT GLS REGRESSIONS FOR BLUE COLLAR WORKERS

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.019**	−0.004	−0.029***	−0.029***
	(0.009)	(0.009)	(0.009)	(0.010)
Age		0.035***	0.033***	0.036***
		(0.002)	(0.002)	(0.002)
Female		−0.131***	−0.133***	−0.127***
		(0.007)	(0.007)	(0.008)
Postgraduate			0.353***	0.349***
			(0.028)	(0.031)
Bachelor degree/diploma			0.176***	0.160***
			(0.011)	(0.012)
Vocational certificates			0.084***	0.076***
			(0.009)	(0.011)
Year 12			0.074***	0.062***
			(0.011)	(0.012)
Household size		−0.004**	−0.002	−0.004*
		(0.002)	(0.002)	(0.002)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents' schooling	No	No	No	Yes
Observations	42,070	42,070	42,070	33,558
Number of individuals	11,186	11,186	11,186	8,305

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

other hand, controlling for parental education does not have any effect on the estimate of migrant dummy in the blue-collar occupations (comparing columns 3 and 4 of Table 4). As mentioned earlier, we perform robustness checks in terms of our sample selection by restricting the sample to 24-59 years of age and by analysing males and females separately, and the results are consistent[6] .

Further disaggregation of blue collar occupations (reported in Appendix table 1-A1, A2 and A3) shows that, accounting for characteristics, migrants have a significant wage advantage only at the lowest end of the occupation scale. Thus, the overall, statistically significant disadvantage observed for blue collar workers in Table 4 seems to stem from the middle level, semi-skilled occupational categories such service and sales workers (Table A2 in the appendix).

Differences across migrant countries of origin are well documented in the Australian literature. The top panel in Table 5 reports the results by origin countries, disaggregating migrants into those originating from English-speaking countries (ESB) and those from non-English-speaking countries (NESB). Regardless of their occupation, ESB migrants earn higher wages and NESB migrants earn lower wages than their native counterparts, leading to about a 10 per cent wage gap between ESB and NESB migrants. This finding is the latest addition to the literature on the well-documented difference between these two migrant groups. Various studies have discussed the possible effects of different characteristics in explaining the labour market disadvantage of NESB migrants, particularly the effect of English language proficiency. Chiswick and Miller (1995) and Dustmann and Fabbri (2003) documented the link between language and earnings; however, there has been little empirical evaluation of the factors which contribute to the ESB–NESB wage differential. One reason for this could be the lack of data. Ideally, a further disaggregation of migrants by origin countries and a richer dataset on migrants would enable us to differentiate between the effects of migrant characteristics, origin country institutions and language in determining Australian labour market outcomes. Unfortunately, this is hampered by the lack of availability of data which are suitable for empirical analysis. However, the questions on language in HILDA allow us to shed further light on the wage disadvantage of NESB migrants by including English language proficiency explicitly.

TABLE 5

RANDOM EFFECT GLS REGRESSIONS BY COUNTRY OF ORIGIN

Log Hourly Wages	All workers	White Collar	Blue Collar
ESB	0.028**	0.034*	0.013
	(0.013)	(0.017)	(0.015)
NESB	−0.078***	−0.048***	−0.065***
	(0.012)	(0.018)	(0.013)
Observations	55,897	22,310	33,558
No of individuals	11,016	5,377	8,305
NESB workers			
English	0.082***	0.102***	0.062***
	(0.014)	(0.032)	(0.015)
Observations	3,911	1,501	2,408
No of individuals	1,016	452	722
Control for year	Yes	Yes	Yes
Control for state	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes

Notes: The table reports coefficients from random effect GLS. The regressions include controls for age, age squared, gender, education level, household size, year, state and parents' schooling. Standard errors clustered at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The second panel of Table 5 reports the estimates for the sample of NESB migrants, including English language proficiency (*english*) as an independent variable. The variable is constructed from individuals' self-reported English speaking ability, increasing from 0 (not well at all) to 3 (very well). The question was only asked of migrants who reported speaking a language other than English at home, and hence, the sample is restricted to NESB migrants. The reported mean value of *english* is 2.327, with 55 per cent reporting that they speak well or very well. English language proficiency has a significant positive effect on wages. A one-unit increase in English ability leads to a 10 per cent increase in wages for white collar workers, while the corresponding increase for blue collar workers is 6 per cent. Given that ESB migrants are expected to speak English very well, our results suggest that the level of proficiency in English explains almost all of the wage differences between ESB and NESB migrants. For NESB migrants, English language ability can also be considered as a proxy for unobserved ability and productivity (omitted variable problem). Thus, the coefficient of English language skills could reflect the effect of both language and unobserved ability, and thus, the observed magnitude of the English coefficient could be interpreted as the gross effects of language skills in Australia.

Note that, while language skills can explain the observed differences in wages between ESB and NESB migrant workers, we cannot rule out an explanation based on stereotyping, such as possible discrimination between native-born and migrant workers, or between NESB and ESB migrants. The decomposition analysis presented below sheds further light on the presence of such factors.

Although we account for occupational setting and attempt to control for ability through parental education, migrant disadvantage can be influenced by the nature of employment within industries. Since the distribution of migrant and native employment differs across industries, we address this issue by including industries as additional controls in our estimations. The results are reported in Table A4 in the appendix. Overall, the results suggest that our previous findings are robust to accounting for industries.

Results: RIF regression

The results from RIF regressions are tabulated in Table 6. All estimations include a full set of control variables. The migrant–native wage difference varies along the distribution and across the two occupational classifications. In white-collar occupations, migrants have both lower wages (below the median) and higher wages (above the median). A 2 per cent wage disadvantage is observed at the 25^{th} percentile, while at the 75^{th} percentile, migrants have a 2 per cent wage advantage over their native-born counterparts. The regression results are the opposite for blue collar occupations: above the median migrants earn lower wages; specifically, at the 75^{th} percentile of the wage distribution, blue-collar immigrants in Australia receive 3 per cent lower wages than native workers.

Results: FFL decomposition

We further decompose the observed wage differential into the composition effect and the wage structure effect (Table 7). The first row of the table reports the difference between the log of hourly wages of migrants and native-born workers at different quantiles, with positive values reflecting higher migrant wages. (The wage differential is calculated as (exp(log points difference) $-$ 1) $\times$ 100). The wage difference in favour of migrants increases over the quantiles but there are differences across occupations. While white-collar migrants have 4 per cent higher wages at the 10^{th} percentile, increasing to almost 13 per cent at the 90^{th} percentile, blue-collar workers have, at most, 3 per cent higher wages than their native counterparts.

The composition effect captures the contribution of characteristics to the overall wage differential. The positive sign of the composition effect (tabulated in the second panel in Table 7) indicates

TABLE 6

RE-CENTRED WAGE REGRESSIONS

Log Hourly Wages	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
All workers					
Migrant	−0.009	−0.009*	−0.028***	−0.033***	−0.006
	(0.007)	(0.005)	(0.005)	(0.006)	(0.010)
Observations	55,897	55,897	55,897	55,897	55,897
R-squared	0.077	0.165	0.221	0.196	0.109
White Collar Workers					
Migrant	0.001	−0.019**	0.004	0.021**	0.048***
	(0.012)	(0.008)	(0.008)	(0.009)	(0.016)
Observations	22,310	22,310	22,310	22,310	22,310
R-squared	0.087	0.164	0.208	0.167	0.086
Blue Collar Workers					
Migrant	−0.002	0.004	−0.002	−0.031***	−0.074***
	(0.009)	(0.006)	(0.005)	(0.008)	(0.012)
Observations	33,558	33,558	33,558	33,558	33,558
R-squared	0.059	0.138	0.165	0.139	0.080
Control for year	Yes	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficients from random effect GLS. The regressions include controls for age, age squared, gender, education level, household size, year, state and parents' schooling. The standard errors are clustered at the individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

that the migrant wage advantage arises as a result of migrant workers' better labour market characteristics. The age and gender profile of immigrants works in their favour. Again, education is an important contributor to the migrant wage advantage. In particular, postgraduate degrees contribute significantly to migrant wages in white-collar occupations. For blue-collar workers as well, postgraduate and graduate education contributes to higher migrant wages (except at the 90th quantile).

Overall, the wage structure effect is negative, indicating that if natives received the same returns to their characteristics as migrant workers, their wages would be lower, particularly at the 50th and 75th quantiles. However, we do not find a persistent negative effect when looking at the results by occupation. Given the focus on skills in the migration and labour markets, the returns to education are of particular interest. Regardless of their occupation and education level, we find that migrants receive lower returns to their education. Again, the only exception is for the blue-collar workers at the top of the wage distribution.

DISCUSSION OF RESULTS

Given that the aim of the article is to analyse native–migrant wage differentials, our empirical estimates reflect labour market outcomes for employed workers. Thus, they are conditional on participation and unemployment. However, we note that natives and migrants differ in terms of their probabilities of participation and employment. Migrants have higher probabilities of unemployment: 3.6 per cent of migrants are unemployed, compared to 3 per cent of natives. In addition, 24.7 per cent of migrants do not participate in the labour force, compared to 19.5 per cent of natives. If these differences in labour force participation are driven mainly by migrants with low returns in the labour market, then our estimates underestimate the extent of the underlying migrant wage disadvantage.

TABLE 7

FFL DECOMPOSITION OF THE MIGRANT–NATIVE WAGE GAP

	All Workers					White Collar Workers					Blue Collar Workers				
Log Hourly Wages	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)	Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)
Difference (Migrant–Native)	0.021	0.033	0.037	0.050	0.093	0.041	0.050	0.081	0.090	0.127	0.001	0.018	0.024	0.007	0.030
CompositionEffect	0.024	0.040	0.072	0.091	0.097	0.051	0.066	0.069	0.076	0.088	−0.003	0.007	0.024	0.044	−0.024
Age	0.145	0.135	0.162	0.164	0.107	0.174	0.179	0.168	0.132	0.096	0.137	0.105	0.118	0.141	−0.103
Female	0.000	0.000	0.001	0.001	0.001	0.003	0.004	0.006	0.008	0.012	−0.001	−0.002	−0.003	−0.004	0.006
postgraduate	0.011	0.015	0.023	0.030	0.030	0.032	0.030	0.025	0.024	0.024	0.003	0.004	0.006	0.012	−0.006
Bachelor degree/ diploma	0.016	0.019	0.026	0.027	0.022	−0.007	−0.005	−0.004	−0.003	−0.003	0.010	0.011	0.016	0.023	−0.017
Vocational certifi-cates	−0.007	−0.006	−0.007	−0.005	−0.002	−0.004	−0.003	−0.001	0.000	0.001	−0.005	−0.005	−0.006	−0.008	0.004
Year 12	0.000	0.000	0.000	0.000	0.000	−0.001	−0.001	−0.001	−0.001	−0.001	0.000	0.001	0.001	0.001	0.000
Structure Effect	−0.003	−0.007	−0.036	−0.041	−0.004	−0.011	−0.017	0.012	0.014	0.038	0.003	0.011	0.000	−0.036	0.054
Age	−0.373	−0.285	−0.430	−0.379	0.452	0.077	0.096	−0.510	0.044	0.759	−0.523	−0.245	−0.552	−0.577	0.413
Female	−0.009	−0.007	0.010	0.018	0.006	−0.013	0.011	0.020	0.016	0.023	−0.005	−0.008	0.005	0.016	−0.006
Postgraduate	−0.007	−0.007	−0.010	−0.011	−0.009	−0.060	−0.027	−0.016	−0.014	−0.010	−0.001	−0.001	−0.003	−0.011	0.006
Bachelor degree/ diploma	−0.023	−0.023	−0.030	−0.014	0.003	−0.180	−0.053	−0.020	−0.008	0.003	−0.008	−0.006	−0.018	−0.033	0.020
Vocational certifi-cates	−0.011	−0.010	−0.020	−0.016	−0.012	−0.020	−0.016	−0.010	−0.004	−0.004	−0.011	−0.009	−0.015	−0.026	0.018
Year 12	−0.011	−0.011	−0.015	−0.011	−0.007	−0.017	−0.016	−0.008	−0.001	−0.003	−0.009	−0.006	−0.012	−0.017	0.019

Notes: Base Category: year (wave 1), father's education (did not complete primary school), mother's education (did not complete primary school), state (NSW). Controls for parents' education include a separate set of dummies for different levels of schooling (e.g., no education, primary school, secondary school, bachelor degree, etc.). Estimations include age squared and household size as controls.

The issue of migrant selection may arise even before migrants enter the Australian labour market; that is, immigrants may self-select to join the labour market in countries which are booming (Friedberg and Hunt, 1995), and where their skills are in demand. As noted by Borjas (1987), immigrants are probably not a random subset of the source countries' workforces. We would expect those who immigrate to have higher expected levels of earnings in Australia than in their country of origin, and vice versa for those who do not immigrate. Skilled migrants in particular move across international boundaries to exploit the economic opportunities that are accessible to them. It is also likely that the Australian government bases its immigration policy on past immigration rates and/or domestic labour market conditions. Our results also point to a positive selection of migrants on unobservables.

We find that education explains the migrant wage advantage in white collar jobs; controlling for education and parental background, there are no significant differences between native and migrant workers. In blue-collar occupations, however, migrants have lower wages after accounting for education and ability. Bjerk (2007) shows that such a pattern of wage gap across occupations is consistent with both preference-based and statistical discrimination. Preference-based discrimination is likely to persist in blue-collar occupations but not in white-collar occupations. The importance of skills for productivity in white-collar occupations results in much higher costs for firms in this sector that exercise discriminatory preferences. The direct link between skills and productivity is weaker in the blue-collar sector, and hence, the cost of engaging in discrimination is lower. Further, given this importance of skills in white-collar jobs, these firms are likely to spend more resources in gauging worker productivity directly, instead of merely using migrant status as a signal. Hence, it is likely that lower wages due to statistical discrimination will not be observed in white-collar jobs, but will continue to prevail in blue-collar jobs. Apart from discrimination, these differences in wage gap between the two sectors can arise from an omitted variables bias and measurement errors. The negative coefficient on the migrant variable may be due to unobserved characteristics correlated with migrant status. However, we observe that the coefficient differs across occupations within white- and blue-collar occupations. As was pointed out by Bjerk (2007), omitted variables in such cases tend to exhibit differential distributions by worker type (native/migrant) and/or occupational group (white-collar/blue-collar).

While we do find evidence of lower returns to education for migrants, we do not find any systematic negative structural effects across occupations within white-collar and blue-collar occupations. Given the results underlining the importance of language proficiency, lower returns on education may reflect the differences in the language of instruction and the quality of the institutions at which the education was obtained. There could also be additional factors that inhibit the transfer of skills between countries, and migrants could face disadvantages in dimensions other than wages, such as problems of over-skilling, and even of securing employment in the first instance.

CONCLUSION

We investigate the migrant–native wage gap in two important dimensions, between white collar and blue collar occupations and along the wage distribution. Furthermore, we employ the recent advances in the decomposition literature to explore the contributions of characteristics and returns to characteristics to the overall wage differential. Our results show that migrants in Australia have a wage advantage relative to natives, which reflects their more favourable labour market characteristics. The wage differential varies by occupation and over the wage distribution. White-collar migrants experience a positive wage differential at the higher end of the wage distribution, while blue-collar migrants have a negative wage differential at the higher end.

The analysis underlines the importance of education in determining the migrant wage advantage. All estimations, as well as the decomposition analysis, indicate that the higher wages are a reflection of migrants' better education profile. However, migrants receive lower returns on their education. We confirm that the wage differential varies by the country of origin. Our results also highlight the role of English language proficiency in explaining ESB–NESB wage differences. Australia's migration policy is aimed at the selection of migrants with better labour market characteristics, in terms of age, education and language requirements, which contribute towards better labour market outcomes for migrants.

One limitation of our study is that we use HILDA survey data, which commenced in 2001. Immigration policy in Australia has changed significantly since the late 1990s. Skilled migration has been the main component of the migration programme in the last two decades. Competition to migrate to Australia has increased significantly. Hence, the most recent migrants could have better English language proficiency and other attributes than those we observed in HILDA survey. In the context of Australia, Guven and Islam (2015) show that English language proficiency increases earnings and improves the chance of getting a job. It is to be noted that a large proportion of the skilled immigrants come with their spouse- many of whom are not skilled, although they are classified as 'skilled'. Still today more than one-third of migrants come under the family migration scheme or on humanitarian or employer-sponsored visa schemes. Moreover, the criteria for English language proficiency differ across skill occupations. The Skill stream of Australia's permanent migration programme provides for over 60 skilled visa subclasses, each with their own characteristics and criteria. A vast majority of these migrants come from non-English speaking countries in Asia. Although these migrants need to go through IELTS or similar language assessment tools, causal observations suggest that a vast majority of them cannot speak English as fluently as native speakers.

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NOTES

1. For example, Miller and Neo (2003) found that, in Australia, migrants earn 12 per cent less than native workers, compared to a 24 per cent gap faced by migrants in the USA.
2. We further estimate the model separately for each sub-category of blue-collar occupations. However, sample size for migrants becomes small with further occupational disaggregation.
3. See Parasnis (2006) for a detailed analysis of migrant segregation in the Australian labour market.
4. See for example Bjerk (2007) for the use of GLS method in a similar context. Bjerk examines the Black–White wage inequality across occupational sectors in the United States.
5. We also cluster standard errors at both the person and survey-year level, since we have repeated person-data. The results are robust to what we present here.
6. Results of these estimations are available from the authors.

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APPENDIX

TABLE A1

RANDOM EFFECT GLS REGRESSIONS FOR BLUE- COLLAR WORKERS (TECHNICIANS AND TRADES WORKERS)

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.061***	0.012	0.017	−0.010
	(0.013)	(0.019)	(0.019)	(0.019)
Age		0.061**	0.146***	0.173***
		(0.029)	(0.029)	(0.027)
Female		−0.229***	−0.205***	−0.199***
		(0.012)	(0.008)	(0.011)
Experience		−0.034***	−0.120***	−0.143***
		(0.011)	(0.012)	(0.015)
Postgraduate (edu1)			−0.501***	−0.618***
			(0.048)	(0.086)
Bachelor degree/diploma (edu2)			−0.274***	−0.391***
			(0.028)	(0.073)
Vocational certificates (edu3)			0.057**	0.019
			(0.025)	(0.038)
Household size		0.004	0.004	0.004
		(0.004)	(0.004)	(0.003)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents schooling	No	No	No	Yes
Observations	8,189	7,219	7,219	5,728
Number of individuals	2,739	2,352	2,352	1,763

Notes: The table reports coefficients from random effect GLS. Regressions also include square of age and experience variables. Robust standard errors in parentheses. Standard errors clustered at the state level. ***$p<0.01$, **$p<0.05$, *$p<0.1$

TABLE A2

RANDOM EFFECT GLS REGRESSIONS FOR BLUE-COLLAR WORKERS (COMMUNITY AND PERSONAL SERVICE WORKERS, CLERICAL AND ADMINISTRATIVE WORKERS, SALES WORKERS)

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.040***	−0.056***	−0.056***	−0.057***
	(0.010)	(0.010)	(0.010)	(0.009)
Age		0.103***	0.160***	0.152***
		(0.009)	(0.005)	(0.007)
Female		−0.121***	−0.119***	−0.109***
		(0.004)	(0.004)	(0.006)
Experience		−0.055***	−0.119***	−0.107***
		(0.005)	(0.003)	(0.004)
Postgraduate (edu1)			−0.315***	−0.225***
			(0.032)	(0.047)
Bachelor degree/diploma (edu2)			−0.300***	−0.242***
			(0.026)	(0.016)
Vocational certificates (edu3)			−0.070***	−0.050***
			(0.013)	(0.018)
Household size		−0.006***	−0.005***	−0.007***
		(0.001)	(0.001)	(0.002)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents schooling	No	No	No	Yes
Observations	27,107	20,539	20,539	16,914
Number of individuals	8,239	6,417	6,417	5,008

Notes: The table reports coefficients from random effect GLS. Regressions also include square of age and experience variables. Robust standard errors in parentheses. Standard errors clustered at the state level. ***$p<0.01$, **$p<0.05$, *$p<0.1$

TABLE A3

RANDOM EFFECT GLS REGRESSIONS FOR BLUE COLLAR WORKERS (MACHINERY OPERATORS AND DRIVERS, LABOURERS)

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.057***	0.044***	0.050***	0.061***
	(0.010)	(0.016)	(0.019)	(0.012)
Age		0.066***	0.228***	0.294***
		(0.015)	(0.046)	(0.061)
Female		−0.190***	−0.184***	−0.156***
		(0.016)	(0.016)	(0.015)
Experience		−0.028***	−0.197***	−0.256***
		(0.008)	(0.047)	(0.063)
Postgraduate (edu1)			−1.078***	−1.278***
			(0.392)	(0.376)
Bachelor degree/diploma (edu2)			−0.712***	−0.928***
			(0.213)	(0.264)
Vocational certificates (edu3)			−0.134**	−0.191***
			(0.058)	(0.067)
Household size		−0.009***	−0.009***	−0.016***
		(0.002)	(0.002)	(0.005)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents schooling	No	No	No	Yes
Observations	11,038	9,136	9,136	6,383
Number of individuals	3,812	3,086	3,086	2,019

Notes: The table reports coefficients from random effect GLS. Regressions also include square of age and experience variables. Robust standard errors in parentheses. Standard errors clustered at the state level. ***p<0.01, **p<0.05, *p<0.1

TABLE A4

RANDOM EFFECT GLS REGRESSIONS: CONTROLLING FOR INDUSTRIES

Log Hourly Wages	All Workers	White Collar	Blue Collar
Migrant	−0.025***	−0.011	−0.023**
	(0.009)	(0.013)	(0.010)
Age	0.040***	0.050***	0.032***
	(0.002)	(0.003)	(0.002)
Female	−0.123***	−0.127***	−0.100***
	(0.007)	(0.011)	(0.008)
Postgraduate	0.381***	0.304***	0.335***
	(0.016)	(0.025)	(0.031)
Bachelor degree/diploma	0.251***	0.241***	0.154***
	(0.012)	(0.022)	(0.012)
Vocational certificates	0.072***	0.039*	0.072***
	(0.010)	(0.023)	(0.010)
Year 12	0.102***	0.145***	0.064***
	(0.012)	(0.026)	(0.012)
Household size	−0.001	0.001	−0.003
	(0.002)	(0.003)	(0.002)
Control for year	Yes	Yes	Yes
Control for state	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes
Control for industries	Yes	Yes	Yes
Observations	55,584	22,170	33,389
Number of individuals	10,981	5,357	8,278

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.