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The immigrant wage gap and assimilation in Australia: the impact of unobserved heterogeneity

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Abstract

Immigrants to Australia are selected on observable characteristics. They may also differ from natives on unobservable characteristics such as ambition or motivation. Controlling for unobserved heterogeneity, we find a wage gap for immigrant men from English-speaking backgrounds, in contrast with previous research. Controlling for unobserved heterogeneity also seems important for finding cohort effects. Immigrants that arrived before 1976 faced a larger wage gap compared to native-born Australians than subsequent cohorts. Confirming other research, we find wage gaps for immigrant men and women from non-English speaking backgrounds. All immigrants experience wage assimilation as time spent in Australia increases.

JEL Codes: J31, J61

Keywords : immigrants; wage gap; assimilation; Australia; cohort effects

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1 Introduction

Australia is a land of immigrants, with over 25% of the population born overseas and net population growth heavily driven by migration (ABS, 2011). In 2010 Australia had the third highest proportion of overseas born residents in the world (ABS, 2011). It is unsurprising then that immigration is a key policy issue in Australia and extensively researched in academic literature.

The experience of immigrants to Australia is thus of interest in its own right but is also of interest in relation to the experiences of Canada and the U.S., with which it shares some characteristics. Australia is similar to Canada with its emphasis on skilled migration; in both countries skilled migrants are admitted on the basis of a points test (see Lester and Richardson, 2004). Relative to the U.S., Cobb-Clark et al. (2001) report that a larger proportion of immigrants enter Australia and Canada as skilled migrants. There are important differences between the experiences of Australia, Canada and the U.S. as well. Australia receives a greater proportion of its immigrants from outside Europe, America and Asia than did Canada or the U.S. Lester and Richardson (2004) report that recent migrants to Australia have better labour market outcomes than Canadian migrants. Antecol et al. (2003) and Antecol et al. (2006) find that wage assimilation of immigrants differs between the US, Canada and Australia.

Although a number of studies have explored the wage gap and assimilation of immigrants (e.g. Haig, 1980, Chiswick and Miller, 1985, McDonald and Worswick, 1999), no study of Australia has used panel data to control for unobserved individual heterogeneity which could bias results. Immigrants may differ from native-born Australians in unobservable characteristics, and immigrants arriving at different points in time and under differing policy regimes may also differ from one another in unobservable individual effects. If these unobservable effects are not accounted for, they can lead to an omitted variable problem, potentially biasing estimates.

We estimate wage equations using the Hausman-Taylor estimator (Hausman and Taylor, 1981), which allows estimation of time-invariant included variables such as immigrant status whilst controlling for unobserved individual heterogeneity. Our results confirm that controlling for unobserved individual effects changes the estimated wage gap and the assimilation profile. Using panel data from the Household Income and Labour Dynamics in Australia (HILDA) survey, we find that immigrant women as a whole face no wage gap upon entry, whereas immigrant men earn significantly less than comparable native-born Australians upon entry. The immigrant wage gap upon entry for men is larger than previously found and assimilation is slower than previously found. In contrast to previous research, we find that immigrant men from English-speaking countries face a similar wage gap on arrival to those from non-English speaking countries, but they assimilate much faster.

When immigrants are split into separate arrival cohorts, the wage gap and assimilation profiles differ between cohorts. This may be interpreted as changes in cohort quality over time or may be due to changes in Australian immigration policy and economic conditions affecting the selectivity of immigrants to Australia.

2 Assimilation and unobserved heterogeneity

A large body of literature has examined the labour market adjustment of immigrants to Australia and the factors affecting their earnings and earnings assimilation. Most studies have utilised some form of cross-sectional data and the standard human capital function modified for immigrant adjustment as used by Chiswick (1978). Haig (1980) and Chiswick and Miller (1985) were among the first to look at earnings differentials between native-born Australians and immigrants. Chiswick and Miller (1985) use microdata from the 1981 Australian Census and find that male immigrants have seven percent lower incomes than comparable native born men, but find no earnings disadvantage for second generation migrants. They find that immigrants have lower returns on their home country education and work experience than native born men, and immigrants from non-English speaking countries are affected by this more than immigrants from English-speaking countries. In general most Australian studies find that migrants from Non-English speaking countries earn less than their Australian counterparts, but those from English-speaking countries have similar outcomes to the native-born (Preston, 2001, p108). A few studies have even found that migrants from some English speaking countries earn more than comparable Australian-born workers (Chapman and Mulvey, 1986, Langford, 1995).

Other cross-sectional research has sought to explain the reasons behind immigrant–native born earnings differentials. International transferability of human capital (Chiswick and Miller, 2010, Chapman and Iredale, 1993, Beggs and Chapman, 1991), English language fluency (Chiswick and Miller, 1995), labour market conditions in Australia at the time of migration (McDonald and Worswick, 1999) and age at migration (Wilkins,2003), to mention a few, may explain the immigrant earnings or wage gap. Chiswick and Miller (1985) find that immigrants' income increases with duration of residence, but McDonald and Worswick (1999) find that the wage gap for immigrants from non-English speaking backgrounds does not decrease with time spent in Australia, indicating little or no earnings assimilation.

Second generation migrants have also received considerable attention in the Australian literature. Chiswick and Miller's (1985) find no wage gap for second and third generation immigrants. Doiron and Guttmann (2009) find that the wealth disadvantage faced by immigrants is not mirrored by the second generation. Using HILDA data, Messinis (2009) shows that second generation immigrants from non-English speaking backgrounds do not face the wage disadvantage experienced by first generation migrants but second generation migrants from English speaking backgrounds earn less than otherwise comparable Australians. This may be due to differences in unobserved ability or motivation between second generation migrants from English-speaking and non-English speaking backgrounds.

The majority of the literature in Australia has utilised cross-sectional data. This may create biased estimates of the assimilation process if there is selective out-migration, or if individuals arriving at different points in time differ in unobserved human capital characteristics. Borjas (1989) and Lubotsky (2007) both find that selective out-migration of lower quality immigrants has overstated the wage progress and assimilation of immigrants to the United States in previous studies using cross-sectional data. Cobb-Clark (2003) states in her paper that unobserved individual heterogeneity may be present 'as changes in the state of the Australian labour market and the generosity of Australian income support policy would have directly affected returns to migration, altering the selectivity of the immigrant stream.'

Borjas (1985) demonstrates that unobserved heterogeneity among immigrant cohorts can bias estimates of years since migration on relative wage outcomes of immigrants and the native-born. The effect of years since migration on earnings is biased upwards if new immigrants are more able than immigrants that have arrived before them. Beggs and Chapman (1988) find evidence of cohort effects for immigrants to Australia from non-English speaking backgrounds, but not for immigrants from English speaking backgrounds. In a later study, however, McDonald and Worswick (1999) find no evidence that unobserved cohort quality of immigrants has changed over time or that immigrant assimilation is affected by macro-economic conditions such as recessions. Their study uses pooled cross-sectional data from the Australian Bureau of Statistics Income Distribution Surveys for the years 1982, 1986 and 1990. The data however, does not provide consistent and comparable year of arrival information between surveys and arrival cohort variables differ across the surveys, which could have affected their results. They also state in their conclusion that 'the lack of variation in macroeconomic conditions across the surveys is likely to make identification of macroeconomic effects on earnings difficult.'

Panel data can be used to control for unobserved individual heterogeneity (Baltagi, 2005) and selective out-migration (Borjas, 1989; Lubotsky, 2007). To the best of our knowledge the only Australian study that uses longitudinal data to estimate immigrant earnings is Chiswick, Lee and Miller (2005). They make use of data from the Longitudinal Survey of Immigrants to Australia Panel 1 (LSIA) and find that wage equation estimates for immigrants in the cross-section are similar to those utilising longitudinal data, but the data does not allow them to calculate wage gaps or assimilation profiles. The LSIA has several limitations as pointed out by Beenstock, Chiswick and Patel (2010) and Cobb-Clark (2001). Its duration is short--immigrants are followed for only three and one half years after migration. Sample size is quite small and it does not include a comparison group of native-born individuals.

Several international studies have used panel data to control for unobserved individual heterogeneity in order to get consistent estimates of assimilation and entry effects for immigrants. Hum and Simpson (2004) estimate immigrant earnings using the Hausman-Taylor estimator (Hausman and Taylor, 1981) to control for unobserved individual heterogeneity. They find that immigrant earnings assimilation in Canada may be much slower than previously thought, once panel data is used to account for unobservable individual effects such as motivation. Fertig and Schurer

(2007) find a similar result using panel data for Germany. In the case of the US, Hu (2000) finds little or no immigrant assimilation once longitudinal data is used. Lubotsky (2007) shows that studies utilising repeated cross-sections or synthetic cohorts in the US have overstated the assimilation and wage growth of immigrants. Using longitudinal earnings records from 1951 to 1997 for the US, he found that immigrant earnings growth was considerably slower than had been predicted using repeated cross-sections.

Hum and Simpson (2004) use the Hausman Taylor estimator as we do in this paper to control for unobserved individual effects. The Hausman Taylor estimator has been applied to other labour market research; Garcia-Mainar and Montuenga-Gomez (2005) uses the Hausman Taylor estimator to estimate returns to education in Spain and Portugal and Chowdury and Nickell (1985) estimate earnings equations by treating several factors as endogenous using the Hausman Taylor estimator

Against this background, the contribution of our paper is to study the assimilation experience of Australian immigrants using panel data and accounting for the role of unobserved heterogeneity. Australia provides an excellent example for our analysis as it is one of the traditional immigration countries and immigrants to Australia are relatively skilled, partly because they are selected based on observed characteristics. This makes the Australian immigration experience very different from immigration to the US or Europe. Observed characteristics may be correlated with unobserved characteristics and thus taking these into account in understanding the experience of Australian immigrants is important. Our results are similar to Lubotsky's (2007) for the U.S. in that we find that previous research which failed to account for unobserved heterogeneity understates the wage gap and overstates assimilation.

3 Data

The data used is derived from the first nine waves (2001 – 2009) of the Household, Income and Labour Dynamics in Australia Survey (HILDA). Wooden and Watson (2007) provide a detailed overview of HILDA. The survey is a nationally representative longitudinal survey based on Australian households. It began in 2001 and approximately 7,000 households and 13,000 individuals have responded in every wave.[2] The HILDA survey provides detailed information on an individual's family history, education, employment details and income. For any panel survey, attrition is a major issue. Generally attrition rates, for the HILDA survey, have moderated over time although response rates among immigrants from non-English speaking backgrounds have been particularly low (Wooden and Watson, 2007). They show that response rates for the HILDA survey are in line with other major panel surveys, such as the British Household Panel Survey (BHPS).

We use HILDA data to create two analysis sub-samples. The first sample pools the observations over all nine waves to create a pooled cross-section. The pooled cross-section sample is used to estimate a baseline model for comparison with our panel results and with previous studies. The second sample uses the HILDA data as an unbalanced panel over nine waves to estimate the fixed effects, random effects and Hausman-Taylor panel data estimators. In both the panel and pooled cross-section, we consider men and women separately.

Our sample is restricted to men and women aged between 24 and 59 years of age, to exclude those facing decisions about full-time study or retirement. In addition, full time students are excluded even if they reported being employed. We also exclude individuals who are self-employed or working in a family business. This is a standard exclusion that most studies on immigrant wages impose. Individuals who refused to disclose their country of origin or their year of arrival to Australia or those who report working positive hours but have missing or zero hourly wages are excluded. Those who reported working more than 60 hours or less than 5 hours a week are also excluded to minimize measurement error in hourly wage[3]. Finally those with missing or incomplete work experience information are excluded. We exclude individuals who are retired or have stopped working due to illness, injury or disability. The exclusions listed above are common to both analysis sub-samples.

For the panel sample we also exclude all individuals who are not employed. A small number of individuals[4] in our panel sample acquired greater amounts of education with time. In these cases we assign an education level to them based on an average

[2] See Melbourne Institute of Applied Economic and Social Research (2010) for more details.
[3] Our substantive results are not influenced by this exclusion based on working hours which affects less than one per cent of the sample.
[4] Less than 5% of the sample of men and 7% of the sample of women.

of their education level during the panel. This was done in order to make education level time-invariant for all individuals. Most studies report education as a time-invariant variable and without this our results would be based upon the within variation for only a small number of individuals who acquire more education whilst working full-time. The number of observations by wave for the panel is reported in Table 1. Means and standard deviations of key variables for individuals in wave 5 of the panel sample are provided in Table 2.

[Table 1 about here]

For the pooled cross-section, we drop observations if the partner has incomplete wage or employment information, or if the partner is self-employed. Those with missing work experience information are also dropped. Sample statistics are similar to the panel sample in Table 2 and are available upon request from the authors.

[Table 2 about here]

We now discuss the definition of key variables[5]. Hourly wage is defined as the gross weekly salary of the individual from all jobs divided by the total number of hours worked in that week. Immigrant is a dummy variable which is equal to 1 if the individual is born outside of Australia. English-speaking background (ESB) is equal to 1 if an immigrant is from the United Kingdom (UK), New Zealand, Canada, USA, Ireland or South Africa; all other immigrants are defined has having a non-English speaking background (NESB). Second generation migrant is a dummy variable equal to 1 if an individual is born in Australia but has at least one parent who was born overseas. Partnered status includes both marriages and de-facto relationships.

The percentage of immigrants is approximately 22%, less than the official estimate that immigrants comprise approximately 25% of the population according to the 2006 census (ABS, 2009). The lower figure in our sample is mostly due to under-representation of immigrants (see Wooden and Watson (2007)) and also partly due to the age exclusions we impose. In the panel estimates, we only consider employed individuals which may also have an effect on the percentage of immigrants in our analysis sample. Approximately 27% of the men are second generation

[5] Full details of construction of other variables are available from the authors.

migrants, close to the ABS estimate that 26% of Australians have at least one parent who was born overseas (ABS, 2009). For women, approximately 24% are second generation migrants. As can be seen in Table 2, both male and female immigrants earn more on average than their Australian counterparts. This is not surprising since immigrants in the sample are better educated, older, have greater work experience and mainly stay in cities or urban areas. Native-born Australians, on the other hand, are more likely to be in paid employment than immigrants; this is especially so for women. Immigrants are much more likely to live in a city than native-born Australians, with about 80% of immigrants living in cities in both samples. The figure for native-born Australians is much lower, with about 61% living in cities.

4 Empirical Strategy

4.1 Hausman Taylor Estimator

Hausman and Taylor (1981) - hereafter HT - formulated an instrumental variable estimator for panel data that controls for possible correlation between included variables and unobserved individual effects. The standard fixed effects estimator can control for unobservable individual effects but it does not allow estimation of any included time-invariant variables. The HT estimator allows estimation of included time-invariant variables, provided that the number of included exogenous variables that are varying over both individuals and time are greater than the number of included endogenous variables that are time invariant. Another advantage of the HT estimator is that external instruments are not required; instruments are derived from within the model. HT also show that, under some circumstances, the estimator improves efficiency relative to standard fixed effects.

In describing the HT estimator, we will follow the approach of Breusch, Mizon and Schmidt (1989) - hereafter BMS - and use the same notation and formulation. The model for individual *i* is

(1) $$y_{it} = X_{it}'\beta + Z_i'\gamma + \alpha_i + \epsilon_{it} \ .$$

X_{it} represent variables which vary over both individuals and time whereas Z_i represents observed variables that are time invariant, but vary over individuals. Immigrant status, which is the focus of this paper, is contained in Z_i. α_i represents the unobserved, time-invariant individual effect. X and Z (the variables stacked in a matrix in the usual way) are also partitioned into:

$$X = (X_1, X_2), \qquad Z = (Z_1, Z_2),$$

Such that X_1 and Z_1 are asymptotically uncorrelated with α_i but X_2 and Z_2 are asymptotically correlated with α_i. The dimensions of the partitions are:

$$X\ is\ TN \times k\ hence\ \ X_1\ is\ TN \times k_1\ and\ X_2 is\ TN \times k_2\ \ such\ that\ k = k_1 + k_2$$

$$Z\ is\ TN \times g\ hence\ \ Z_1\ is\ TN \times g_1\ and\ Z_2 is\ TN \times g_2\ \ such\ that\ g = g_1 + g_2$$

We use balanced panel notation for simplicity. The extension to unbalanced panel, which we use in our application, is straightforward. Following HT and BMS, We define projections that will be us ed to derive the HT estimator. Define P_A as the orthogonal projection onto the column space of a matrix A.

$P_A = A(A'A)^{-1}A$ provided A is of full column rank

$$Q_A = I - P_A$$

Let V be a $NT \times N$ matrix of ones such that:

$P_v y_{it} = \frac{1}{T}\sum_{i=1}^{n} y_{it} = \overline{y_\iota}$ and $P_v Z = Z$

$Q_v y_{it} = y_{it} - \frac{1}{T}\sum_{i=1}^{n} y_{it} = y_{it} - \overline{y_\iota}$ and $Q_v Z = 0$

Also note that:

$\theta^2 = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + T\sigma_\alpha^2}$ and;

$cov(\alpha + \epsilon) = \sigma_\epsilon^2 \Omega$ where $\Omega^{-1} = Q_v + \theta^2 P_v\ \ and\ \ \Omega^{-\frac{1}{2}} = Q_v + \theta P_v$

The HT estimator uses these projections. Transform (1) by $\Omega^{-\frac{1}{2}}$:

$$\Omega^{-\frac{1}{2}} y = \Omega^{-\frac{1}{2}} X\beta + \Omega^{-\frac{1}{2}} Z\gamma + \Omega^{-\frac{1}{2}} (\alpha + \epsilon)$$

The resulting error terms now have a scalar covariance matrix, as proved in HT. We can then then perform IV with $A = (Q_v, X_1, Z_1)$:

(3) $$P_A\Omega^{-\frac{1}{2}}\,y = P_A\Omega^{-\frac{1}{2}}\,X\beta + P_A\Omega^{-\frac{1}{2}}\,Z\gamma + P_A\Omega^{-\frac{1}{2}}\,(\alpha + \epsilon)$$

BMS show that the IV of (3) using instruments $A = (Q_v, X_1, Z_1)$ is equivalent to using either B or C as instruments with B and C defined as:

$$B = (Q_v X_1, Q_v X_2, X_1, Z_1)$$

$$C = (Q_v X_1, Q_v X_2, P_v X_1, Z_1)$$

The order condition for the existence of the HT estimator is $k_1 \geq g_2$, hence the number of included time-varying variables that are uncorrelated with the unobservable individual effects has to be greater than or equal to the included time-invariant variables that are correlated with the individual effects.

Amemiya and MaCurdy (1986) - hereafter AM - and BMS both propose estimators that are more efficient than the HT estimator but impose stronger exogeneity assumptions, see Baltagi (2005, p127). Cornwell and Rupert (1988) confirm that AM and BMS estimators are more efficient than the HT estimator in their analysis of returns to schooling, but their results are disputed by Baltagi and K hanti-Akom (1990). The AM and HT estimators have been found to produce similar estimates (e.g., Hum and Simpson, 2004). Implementing AM and BMS in unbalanced panels requires additional assumptions to deal with missing observations and individual spells which do not start at the same time period. AM and BMS also impose stronger exogeneity assumptions than the HT estimator. Our unbalanced panel and the weaker exogeneity assumptions required motivate our choice of the HT estimator.

4.2 Panel Model Specification

We estimate three wage equations each for men and women, all of which use the natural log of hourly wage as the dependent variable. Table 3 presents the variables that are used in the first wage equation. The second wage equation splits immigrants into those from English speaking backgrounds (ESB) and those from non-English speaking backgrounds (NESB). ESB and NESB migrants are allowed to have different assimilation profiles. Lastly, we estimate a wage equation that has dummies for different arrival cohorts of immigrants. We estimate wage equations for men and women separately, as returns to human capital and labour market outcomes generally vary between men and women (Preston (2001), p102).

Table 3: List of variables included in panel regressions

The dependent variable is the natural log of hourly wage	
	Variable
Time Varying Exogenous:	
	(Age/100)^2
	Partnered
	Years since migration / 100
	(Years since migration / 100)^2
	Four geographical location dummies are included:
	1. City
	2. Inner regional
	3. Outer regional
	4. Remote Australia
	Wave dummies are included for all nine waves
Time Varying Endogenous:	
	Experience/100
	(Experience/100)^2
Time Invariant Exogenous:	
	Indigenous
Time Invariant Endogenous:	
	Immigrant
	Tertiary
	Certificate
	Year 12

Many authors have estimated separate wage equations for the native-born and immigrants to allow for differing rates of return to education, experience, age etc. between the two groups (Beggs and Chapman, 1988, Chiswick and Miller 1985). We test this assumption by estimating a random effects model with interaction terms for the included variables and immigrant status[6]. Testing the interaction terms using the HT estimator is impossible since the number of endogenous variables increases with the inclusion of the interaction terms while there is no change in the number of available instruments. Hence, we have used the random effects model to test the significance of the interaction terms most of which are insignificant. For the sample of men, the only interaction term that is significant is the Wave 2 time dummy

[6] These results are available from the authors.

variable[7]. This could indicate a true year effect or it could be a product of some data feature such as wage imputation for wave 2. The interaction term for wave 2 and immigrant status is included in all the panel regressions for men. Apart from the wave 2 variable, we find no evidence that other variables including year dummies affect immigrants and the native-born differently. McDonald and Worswick (1999) find the same. In the sample of women, returns to work experience and its square appear to vary between immigrants and the native-born. Interaction terms for experience and its square with immigrant status are included in all panel regressions for women. It is important to note that the included interaction terms will affect the interpretation of the coefficient of the immigrant dummy variable in all models. Interaction terms will need to be taken into account when interpreting the immigrant wage gap and assimilation effects.

Deciding which of the included variables are endogenous is of particular importance, as specifying the wrong instruments will lead to inconsistent and biased results for the HT estimator. Baltagi, Bresson and Pirotte (2003) provide a testing procedure, using the Hausman test (Hausman, 1978), to determine the suitability of the HT estimator. They suggest a first Hausman test to distinguish between the random effects model and the fixed effects model. If the random effects model is rejected then a second Hausman test is carried out contrasting the HT estimator and the fixed effects model. The fixed effects model provides a suitable benchmark to test the exogeneity assumptions of the HT estimator. Hence, the choice of endogenous variables for the HT estimator can be tested using a Hausman test for the HT estimator versus fixed effects. Hum and Simpson (2004), in their study of immigrants in Canada, use experience and its square, education, immigrant status, weeks worked and language as potentially correlated with the individual effects. We use experience, experience squared, the education dummies and immigrant status as potentially correlated with the individual effects. This is a subset of the instruments used by Hum and Simpson (2004). Intuitively it seems obvious that these variables would be correlated with the individual effects. When we think of unobservable individual effects we often think of ability and motivation both of which would affect the education level of an individual. More motivated individuals are also likely to have greater work experience. Willis (1985) provides an extensive account

[7] Dropping wave 2 data or dropping wave 1 and wave 2 data has no effect on the reported results.

of how ability bias may affect estimates of the returns to education and experience[8]. Immigrants are likely to differ from native-born individuals in both ability and motivation; it is also possible that immigrants arriving at different points in time also differ from one another in unobservable characteristics.

4.3 Instruments for time-invariant endogenous variables

Weak instruments can cause problems for any instrumental variable method. Statistically insignificant estimates and large standard errors for the time-invariant endogenous variables are obtained when using the HT estimator with weak instruments (Stata Corporation, 2009). In Table 4, we present the F-stat for the regression of each of the included endogenous variables on the time-varying exogenous variables[9] that will be used to construct the instruments.

Table 4: F-Stats from the regression of each the variables on the time-varying exogenous variables

	Men	Women
Variable	**F-Stat**	**F-Stat**
Immigrant	9797.10	10840.38
Tertiary	58.92	45.25
Certificate	15.75	9.44
Year 12	23.87	15.19

Staiger and Stock (1997) suggest that an F-stat less than 10 is problematic and an F-stat below 5 is a sign of extreme finite sample bias. An F-stat of less than 10 is an indication that the instruments are weak and will not perform well in finite samples.[10] All the F-stats presented in Table 4 are greater than 10 except for the F-stat for `Certificate' in the sample of women. The Certificate and Year 12 variables for both men and women are only slightly correlated with the instruments and this may lead to imprecise estimates for their coefficients. From the F-stats and correlations the instruments used for the remaining endogenous variables appear adequate and the time-varying endogenous variables are mean differenced to remove any unobserved individual effects. Hence, the coefficient estimates for other included variables

[8] See also Garcia-Mainar and Montuenga-Gomez (2005).
[9] Table 3 provides a list of the time-varying exogenous variables used.
[10] Stock and Yogo (2005) provide tests and critical values which improve upon this `rule of thumb', but only for the case where the number of included endogenous variables is 2 or less.

should not be affected by any inconsistency in the estimates of the non time-varying education variables. As our aim is to evaluate the immigrant wage gap and not the returns to education, this problem is left as a possible extension to this paper. It could be solved by finding other instruments for education.

5 Results

5.1 Results from pooled cross-section

Table 5 presents coefficient estimates for the pooled regression using the Heckman sample selection model (Heckman, 1979). We refer to this as the `baseline model'. Two wage equations are estimated using the pooled panel data for both men and women. The sample selection correction term is significant in all regressions and since previous Australian studies using cross-sectional data report estimates from a Heckman selection model, we do the same for comparability. Note that we do not control for selection in the panel data models which follow, so OLS is perhaps a more appropriate benchmark model. The results from OLS are very similar to what is presented here. The pooled regressions impose common returns to characteristics for both immigrants and the native-born. As mentioned in the model section, this restriction is tested in the panel models and interaction terms that are significant are included. For simplicity, this is ignored in the baseline model.

[Table 5 about here]

There are two main reasons why we estimate this baseline model. Firstly, it allows us to compare our results to previous studies that use cross-sectional or synthetic cohort data. Secondly, the baseline model acts as a benchmark for the HT estimates which we present in section 5.2. The baseline model provides similar results to previous studies on immigrant wages using cross-sectional or synthetic cohort data. This is not surprising since unobserved individual effects are not controlled for in the baseline model.

The first regression (1) contains a single immigrant dummy variable and the assimilation profile of all immigrants is assumed to be the same. This provides an aggregate measure of the wage disadvantage of immigrants. The estimates of the entry and assimilation effects are statistically significant for both men and women. Both male and female immigrants earn approximately 10%[11] less upon arrival than

[11] $\ln y = \beta x + \epsilon$ where x is a dummy variable. The effects of x on y is $e^{\beta} - 1$ (Halvorsen and Palmqvist, 1980).

similar native-born Australians. Female immigrants assimilate faster than male immigrants. In the second regression (2) immigrants are separated into two broad groups: immigrants from English-speaking backgrounds (ESB) and immigrants from non-English speaking backgrounds (NESB). Separate assimilation profiles are included for ESB and NESB immigrants. ESB immigrants, both men and women, do not face a wage disadvantage and have similar outcomes to native-born Australians. The estimate of the entry effect for ESB immigrants is positive but statistically insignificant, consistent with McDonald and Worswick (1999) and Chiswick and Miller (1985). Male and female NESB migrants, on the other hand, face a statistically significant and similar wage disadvantage on arrival. Our results suggest that immigrant men from a NESB experience slow wage assimilation as also found by Chiswick and Miller(1985) and Beggs and Chapman (1988).

Figure 1: Wage assimilation of immigrants from non-English speaking background (NESB): estimates from pooled cross-section

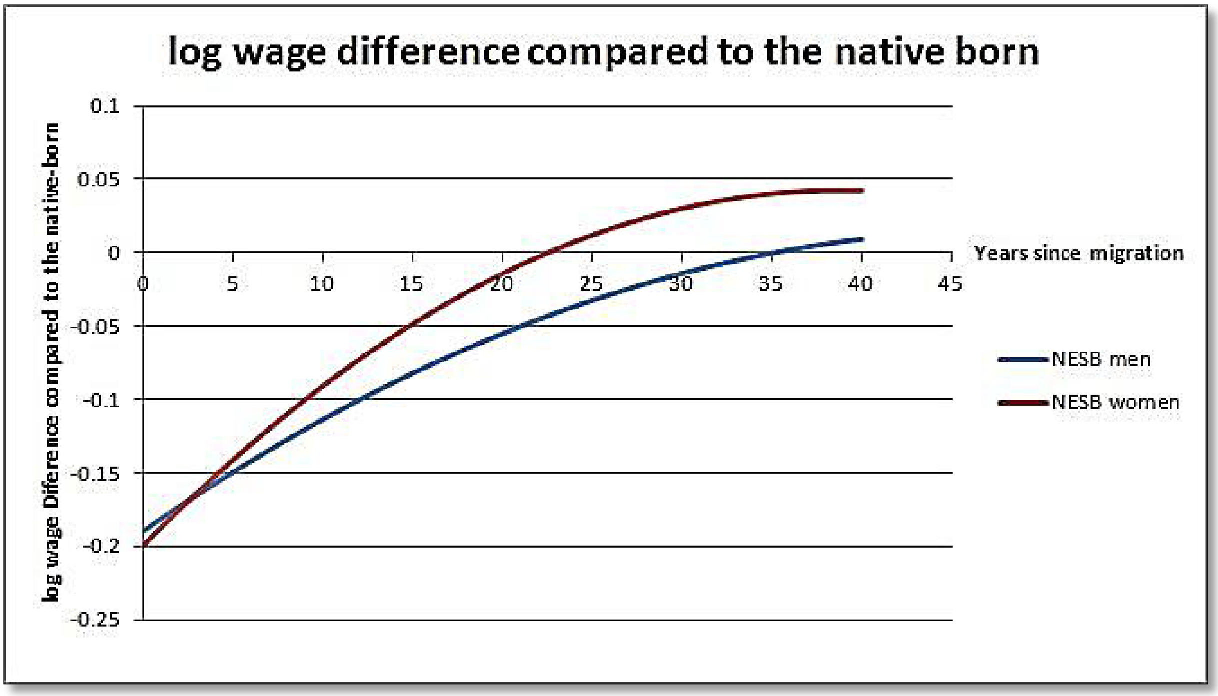


Figure 1 illustrates the assimilation profiles for NESB men and women. Immigrant women from NESB assimilate more rapidly, achieving wage parity after about 22 years in Australia, whereas it takes men 35 years. The estimated assimilation profile of immigrant men from NESB means that many of them will not achieve wage parity with the native-born during their working lives.

These results are broadly consistent with previous research in Australia on immigrant wages that do not take into account unobserved individual effects. Next, we present estimates using the HT estimator that takes advantage of the panel nature of the data to control for unobservable individual effects.

5.2 Results from panel estimators

5.2.1 All Immigrants

Table 6 presents results for the fixed effects, random effects and HT estimates of the wage equation with a single immigrant dummy variable. All immigrants are assumed to have the same rate of wage assimilation. Returns to included variables are allowed to vary based upon the specification tests described in section 4.2 above. According to the random effects estimates, immigrant men earn 12% less than similar native-born Australians in their first year in Australia. Wage assimilation is not rapid but occurs within 20 years of arrival. The random effects estimates for women are more complicated to interpret. Although the immigrant dummy variable is statistically insignificant and quite small, immigrant women receive lower returns to work experience than native-born women. Applying a Hausman Test for random effects versus fixed effects rejects the random effects model for both men and women; in the absence of model mis-specification this result is generally interpreted as rejecting the assumption that the unobserved effects are uncorrelated with the included variables.

[Table 6 about here]

Since unobservable individual effects are present, we turn to the HT estimator as a way to control for these unobservable effects. Using the Hausman test, we reject the fixed effects estimators for both men and women in favour of the HT estimator. Of course, the Hausman test procedure is known to be sensitive to general model mis-specification and the results should be taken with some caution. Nonetheless, this provides at least some evidence that the HT estimator controls for unobservable individual effects in the wage equations and employs acceptable exogeneity assumptions.

The HT estimates imply a larger entry effect of 18% for immigrant men. Wage assimilation is also much slower than in the random effects model, with immigrant men achieving wage parity with similar native-born men after 20 years. Both the coefficients of years since migration and its square are statistically significant for men in our sample. The HT estimate for the coefficient of tertiary education is quite high and statistically significant but it is not precisely measured. Comparable Australian studies that have controlled for unobservable individual heterogeneity using panel data are not available to contrast the size of the tertiary variable, but García-Mainar and Montuenga-Gómez (2005) obtained similarly large estimates for returns to education in Spain and Portugal using the HT estimator. For women, the HT estimates for the coefficients of the interaction terms of immigrant status with experience are statistically insignificant (p-value is 0.19 for joint significant). The coefficients of the immigrant and assimilation effects are also jointly insignificant (p-value is 0.37 for joint significance). After controlling for unobserved individual heterogeneity, immigrant women as a whole do not face any wage disadvantage when compared to similar native-born women.[12] This is an interesting result especially considering that immigrant men face a significant wage disadvantage. This result may be driven by selection. Here, we only consider those who choose to work and the proportion of immigrant women who work is slightly lower than in the native-born population. It is likely that immigrant women self-select into work on the basis of favourable characteristics, such as high levels of education or motivation.

5.2.2 Immigrants from English-speaking and non-English speaking backgrounds

Estimates for ESB and NESB immigrants are presented in Table 7. As before, the Hausman test rejects the random effects model when compared to fixed effects, and rejects fixed effects when tested against the HT estimates for both men and women. After controlling for unobserved individual heterogeneity, both ESB and NESB immigrant men face an entry effect. Previous studies using cross-sectional or synthetic cohort data have concluded that ESB immigrants do not face any entry effects (Chiswick and Miller 1985, McDonald and Worswick, 1999). Their results may have been biased since unobservable individual heterogeneity was not taken

[12] Jointly the coefficients of immigrant, immi*(experience /100), immi*(experience/100)^2, Years since migration/100 and (years since migration/100)^2 are also statistically insignificant (*p-value* 0.12).

into account. Immigrant men from ESB face a smaller entry effect than those from NESB, consistent with previous findings. Figure 2 illustrates the assimilation profiles for ESB and NESB men. We find evidence of wage assimilation for both ESB and NESB immigrant men. ESB men assimilate much faster than NESB men, which is not surprising given their English language skills are usually better and their skills are usually more transferable to the Australian labour market.

We find no entry effect for immigrant women from ESB. The coefficient on ESB and years since migration variables are small and statistically insignificant (p-value is 0.7584 for joint significance). On the other hand, immigrant women from NESB face a small wage gap on entry with rapid assimilation; but the effect is not precisely measured. The wage gap experienced by NESB immigrant women which is not shared by ESB women may be due to many NESB women migrants arriving as spouses rather than as a primary skilled migrant or because their human capital characteristics such as education are less readily transferable to Australia. Wage assimilation for NESB immigrant women with time spent in Australia is shown in Figure 3. NESB immigrant women assimilate much faster than immigrant men from either ESB or NESB. Again, these results should be interpreted with some caution as we only consider those women who choose to work. As discussed above, these women are positively selected from the population of women immigrants and these estimates should not be applied to non-working immigrant women.

[Table 7 about here]

A limitation of using HILDA data is that information on visa type is not available. Using visa information, we could have disaggregated immigrants further by entry category. This would have allowed us to analyse the labour market performance of immigrant groups who arrive with different visas and under different circumstances. Although disaggregating immigrants allows us to further analyse the wage gap it could lead to small samples for certain groups making estimates unreliable.

**Figure 2: Wage assimilation of immigrant men:
Estimates from Hausman-Taylor panel regression model**

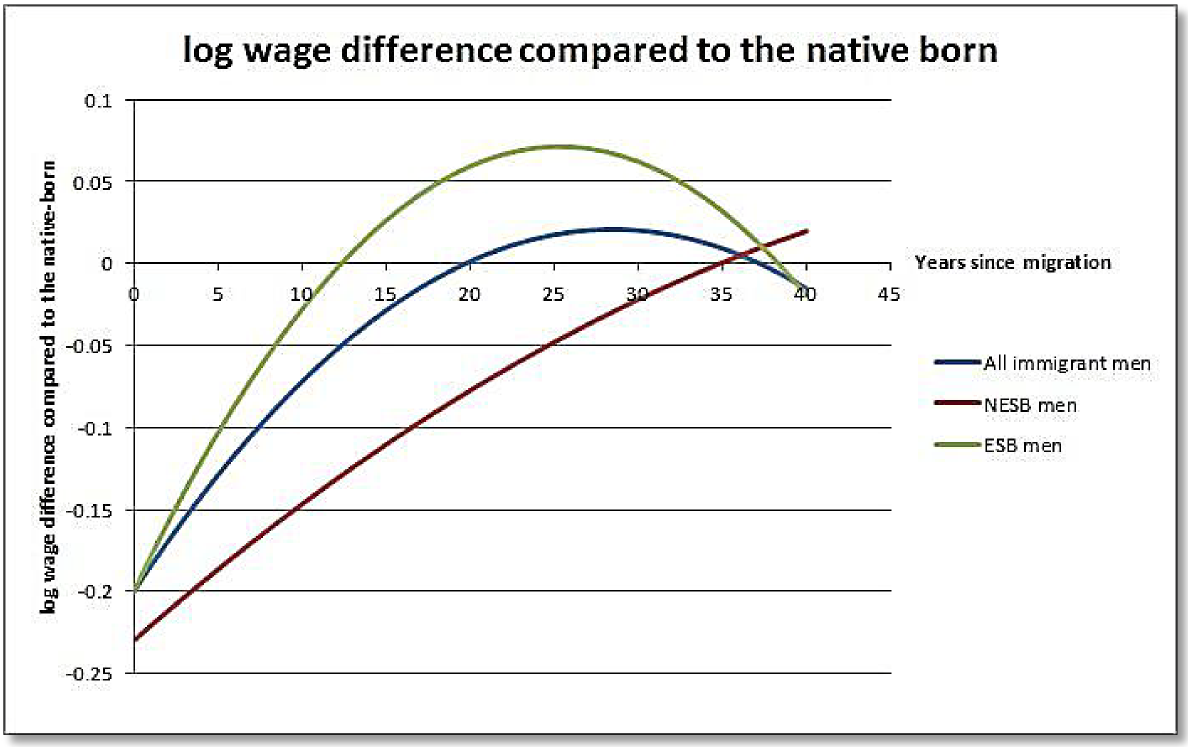
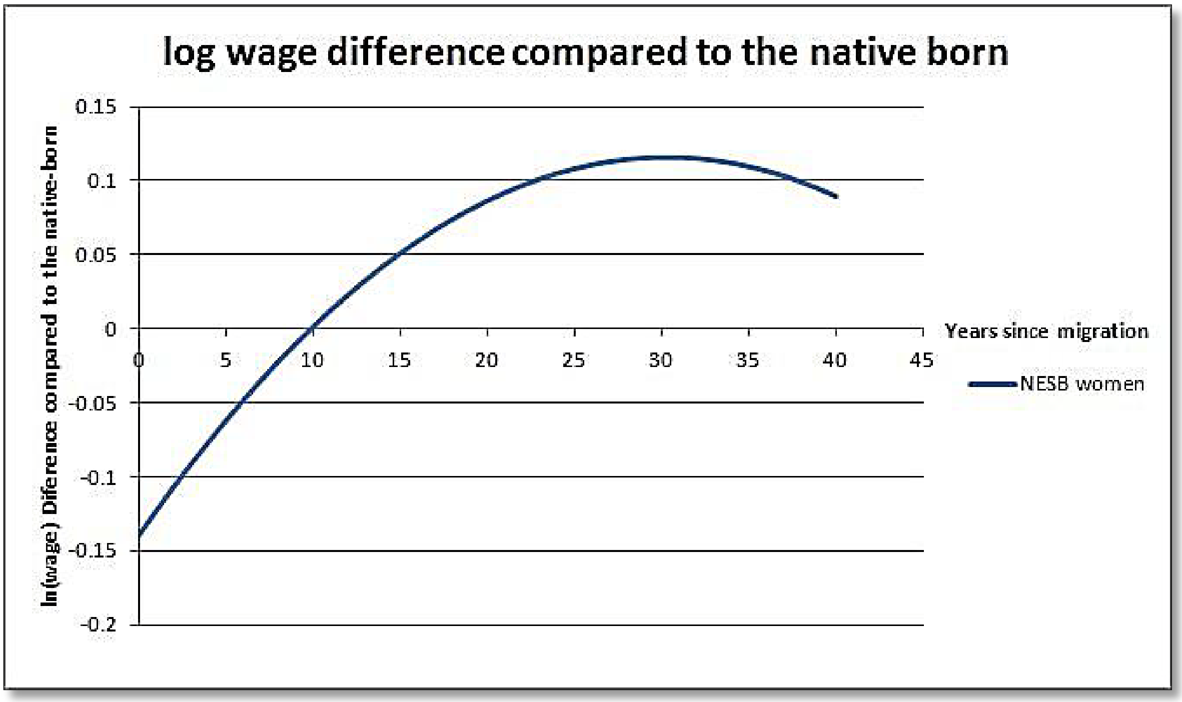


Figure 3: Wage assimilation of non-English speaking backgroun immigrant women: Estimates from Hausman-Taylor panel regression model



5.2.3 Cohort Effects

We re-estimate our panel data models allowing for different effects for different cohorts of immigrants. We consider three cohorts: immigrants who arrive prior to 1976, immigrants who arrived between 1976 and 1995 and immigrants who have arrived since 1995. We will refer to these cohorts as Cohort 1, Cohort 2 and Cohort 3 respectively. Similar cohort definitions are used in Doiron and Guttmann (2009). Each arrival cohort is allowed to have different initial wage gaps and separate assimilation profiles.

Australian immigration policy has undergone many changes since the 1970s, placing greater emphasis on skilled migrants, being more racially equitable and accepting immigrants from any country provided they meet certain skills or humanitarian criteria. The Australian labour market has also undergone changes during this period and this could have an impact on the selectivity of migrants to Australia by affecting the potential returns to migration. As shown in Table 8, immigrants that arrived later are better educated and from more diverse backgrounds than earlier immigrants. The majority of immigrants in Cohort 1 are from ESB as expected given the white Australia policy, which was in force before the 1970s.

[Table 8 about here]

Table 9 presents results for the wage equations with cohort dummy variables.[13] Unlike previous studies (McDonald and Worswick, 1999, Miller and Neo, 2003), we find evidence that cohort effects are present for both men and women, with immigrants who arrive later having a much smaller wage gap upon entry compared to earlier cohorts. Immigrants who arrived before 1976 experience the largest wage penalty. Immigrant men in Cohort 1 earn 64% less than similar native-born Australians and immigrant women in Cohort 1 earn 71% less than similar native-born Australians. Successive cohorts are better off, facing a much smaller entry effect as compared to Cohort 1. This is not surprising given that Australia's immigration policy is now more geared towards skilled immigrants than it was in 1970s. Another argument is that the Australian labour market has become more regulated since the

[13] As above, returns to experience are allowed to vary for immigrant and non-immigrant women but we find that the interaction terms in the HT estimates are jointly insignificant. Dropping these interaction terms does not change the fundamental conclusions.

1980s, offering immigrants protection against lower wages. Miller and Neo (2003) state in their paper that award wages and unionisation in Australia may be responsible for higher immigrant wages. Selectivity of immigrants is another possible explanation. The changing economic conditions in Australia from the 1970s to now would have affected the relative returns to migration and affected the selectivity of immigrants. Both internal and external factors affect the decisions of potential migrants to migrate to Australia over other countries (Cobb-Clark and Connolly, 1997). If the Australian economy out-performs its western counterparts, then immigrants may view Australia as a more lucrative migration destination.

[Table 9 about here]

Although we find the presence of cohort effects, it is in general difficult to separate out exogenous changes in cohort quality from policy-induced effects.

6 Discussion and Conclusions

In this paper we have attempted to improve our understanding of the immigrant wage gap and immigrant wage assimilation in Australia by estimating a model which uses panel data to control for unobserved differences between migrants and non-migrants. Most of our results are consistent with the previous Australian literature.

We find two novel results. First, we find that once we control for unobserved effects, the immigrant wage gap for all immigrant men is larger. Importantly, there now appears to be a wage gap between male immigrants from English-speaking backgrounds and native-born Australians. Other studies have failed to find such a gap. This result is not surprising if unobserved characteristics are positively correlated with observed characteristics. Since Australia's immigrants are selected on observable characteristics such as education it is not surprising that there is positive selection on unobservables such as ability and motivation as well.

Our second novel result is the finding of cohort effects. In particular, we find that more recent cohorts of immigrants appear to have smaller wage gaps than those from previous cohorts. The progressively better labour market performance of immigrants that arrive in later cohorts may be due to changes in Australian immigration policy that favours skilled migrants. It may also be due to the increased selectivity of immigrants. Economic and labour market conditions in Australia may be affecting the potential returns to migration and making Australia a more lucrative country to migrate to than in the past. Controlling for unobserved heterogeneity appears to be important in identifying these cohort effects.

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Table 1: Sample Size by Wave

		Wave								
		1	2	3	4	5	6	7	8	9
Men	Immigrants	677	593	564	524	521	520	480	448	443
	Native-Born	1,951	1,950	1,867	1,848	1,873	1,915	1,871	1,899	1,940
	n	2,628	2,543	2,431	2,372	2,394	2,435	2,351	2,347	2,383
Women	Immigrants	624	557	534	505	516	523	505	477	466
	Native-Born	1,960	1,877	1,880	1,829	1,894	1,932	1,928	1,918	1,891
	n	2,584	2,434	2,414	2,334	2,410	2,455	2,433	2,395	2,357

Table 2: Key variables: Panel Sample Wave 5 Mean and Standard Deviations

	Men		Women	
Sub Group	**Native-Born**	**Immigrants**	**Native-Born**	**Immigrants**
Observations	1,873	521	1,894	516
Hourly Wage	25.8174 (14.5082)	26.8774 (13.4391)	22.0316 (12.4402)	23.3303 (11.9809)
Age	39.6514 (9.5286)	42.8868 (9.6131)	40.5100 (9.4699)	42.7752 (9.1422)
Experience	21.2617 (10.2697)	23.0133 (10.4649)	18.7623 (9.2186)	20.4334 (9.7251)
Partnered	0.7421	0.8023	0.7122	0.7597
Years since migration	N/A	23.0422 (12.9650)	N/A	24.4690 (13.4826)
Indigenous	0.0166	N/A	0.0206	N/A
Second Generation Migrant	0.2670	N/A	0.2381	N/A
English speaking background	N/A	0.5086	N/A	0.4651
Non-English speaking background	N/A	0.4914	N/A	0.5349
City	0.6295	0.8042	0.6151	0.7907
Inner regional	0.2515	0.1305	0.2582	0.1453
Outer regional	0.1009	0.0480	0.1040	0.0543
Remote	0.0133	0.0154	0.0169	0.0078
Very remote	0.0048	0.0019	0.0058	0.0019
Bachelor’s or higher	0.2637	0.3704	0.3310	0.4031
Certificate	0.4196	0.3436	0.2841	0.2442
Year12	0.1201	0.1267	0.1309	0.1783
Year 11 or less	0.1965	0.1593	0.2540	0.1744

Note: only standard deviations of continuous variables are shown in brackets

Table 5: Baseline model: Heckman sample selection model for log hourly wage on immigrant status

	Men		Women	
Variable	(1)	(2)	(1)	(2)
ESB		0.01		0.01
		(0.031)		(0.032)
NESB		-0.19***		-0.20***
		(0.029)		(0.028)
NESB*(Years since migration/100)		0.85***		1.25***
		(0.269)		(0.244)
NESB*(Years since migration/100)^2		-0.88*		-1.61***
		(0.527)		(0.451)
ESB*(Years since migration/100)		0.07		0.11
		(0.259)		(0.267)
ESB*(Years since migration/100)^2		-0.16		-0.05
		(0.494)		(0.503)
Immigrant	-0.10***		-0.11***	
	(0.021)		(0.021)	
Years since migration/100	0.50***		0.78***	
	(0.188)		(0.180)	
(Years since migration/100)^2	-0.56		-0.96***	
	(0.363)		(0.337)	
Lambda	-0.26***	-0.25***	0.05***	0.05***
	(0.033)	(0.033)	(0.017)	(0.017)

Notes: (i) Results for the full set of included variables is available from the author upon request (ii) standard errors in parentheses (iii) *** p<0.01, ** p<0.05, * p<0.1

Table 6: Fixed effects, random effects and HT(IV) estimates of log hourly wage on immigrant status

Variable	Men			Women		
	Fixed Effects	Random Effects	HT(IV)	Fixed Effects	Random Effects	HT(IV)
(Age/100)^2	-2.94**	-1.66***	-4.05***	-3.44***	-0.62***	-2.87***
	(1.310)	(0.218)	(0.809)	(0.877)	(0.108)	(0.565)
Experience/100	5.68***	3.19***	4.82***	3.67***	2.66***	3.99***
	(1.006)	(0.183)	(0.507)	(0.864)	(0.190)	(0.398)
(Experience/100)^2	-2.34*	-2.76***	-1.33	-1.14	-3.99***	-1.75**
	(1.293)	(0.382)	(0.846)	(1.001)	(0.441)	(0.749)
Immi*(Experience/100)				-1.83	-1.25***	-0.84
				(1.650)	(0.387)	(0.773)
Immi*(Experience/100)^2				2.32	2.41***	2.35*
				(1.468)	(0.908)	(1.354)
Partnered	0.01	0.04***	0.01	0.01	0.03***	0.01*
	(0.009)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
Immigrant		-0.13***	-0.20**		-0.03	-0.07
		(0.031)	(0.100)		(0.039)	(0.081)
Years since migration/100	1.51***	1.02***	1.55***	1.71	0.97***	0.88
	(0.405)	(0.246)	(0.357)	(1.410)	(0.246)	(0.578)
(Years since migration/100)^2	-2.81***	-1.56***	-2.72***	-1.05	-1.08**	-1.31*
	(0.743)	(0.473)	(0.650)	(0.827)	(0.457)	(0.751)
Indigenous		0.00	0.13		0.02	0.08
		(0.046)	(0.235)		(0.039)	(0.073)
Tertiary		0.48***	1.42***		0.38***	0.40**
		(0.018)	(0.461)		(0.014)	(0.177)
Certificate		0.14***	0.57		0.09***	-0.12
		(0.015)	(0.993)		(0.014)	(0.375)
Year 12		0.15***	0.67		0.10***	0.14
		(0.021)	(1.437)		(0.017)	(0.608)
Immi*wave2	-0.05***	-0.04***	-0.05***			
	(0.015)	(0.014)	(0.013)			
Constant	2.34***	2.38***	1.94***	2.73***	2.36***	2.51***
	(0.283)	(0.057)	(0.721)	(0.208)	(0.064)	(0.275)
Hausman test		144.84	1.52		50.48	5.85
(*p*-value)		(0.0000)	(1.0000)		(0.0002)	(0.9991)

Notes: (i) Wave dummies and location variables were also included. Results for the full set of included variables is available from the author upon request (ii) for men interaction terms were included for wave 2 and immigrant status (iii) for women interaction terms were included for experience and its square and immigrant status (iv) standard errors in parentheses (v)*** p<0.01, ** p<0.05, * p<0.1

Table 7: Fixed effects, random effects and HT(IV) estimates of wage equations with ESB and NESB immigrant dummy variables

Variable	Men			Women		
	Fixed Effects	Random Effects	HT(IV)	Fixed Effects	Random Effects	HT(IV)
(Age/100)^2	-2.90**	-1.59***	-4.21***	-3.45***	-0.60***	-2.92***
	(1.314)	(0.219)	(0.758)	(0.877)	(0.108)	(0.569)
Experience/100	5.70***	3.14***	4.73***	3.66***	2.65***	4.00***
	(1.006)	(0.184)	(0.431)	(0.864)	(0.190)	(0.404)
(Experience/100)^2	-2.37*	-2.78***	-1.19	-1.13	-4.00***	-1.71**
	(1.297)	(0.382)	(0.807)	(1.000)	(0.440)	(0.748)
Immi*(Experience/100)				-1.83	-1.44***	-0.96
				(1.651)	(0.389)	(0.774)
Immi*(Experience/100)^2				2.37	2.79***	2.44*
				(1.472)	(0.911)	(1.353)
Partnered	0.01	0.04***	0.01	0.01	0.03***	0.01
	(0.009)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
NESB		-0.19***	-0.23**		-0.12***	-0.14
		(0.041)	(0.114)		(0.044)	(0.093)
ESB		-0.05	-0.20*		0.14***	0.07
		(0.044)	(0.105)		(0.053)	(0.111)
NESB*(Years since	0.85	1.04***	0.90*	2.48*	1.71***	1.69**
migration /100)	(0.542)	(0.346)	(0.482)	(1.454)	(0.324)	(0.678)
NESB*(Years since	-0.84	-1.13*	-0.69	-3.14***	-2.21***	-2.79***
migration /100)^2	(1.078)	(0.683)	(0.943)	(1.112)	(0.597)	(0.960)
ESB*(Years since	2.11***	0.88**	2.14***	0.71	0.01	-0.10
migration /100)	(0.568)	(0.343)	(0.506)	(1.495)	(0.359)	(0.723)
ESB*(Years since	-4.40***	-1.80***	-4.22***	1.06	0.37	0.58
migration /100)^2	(1.017)	(0.650)	(0.894)	(1.162)	(0.685)	(1.055)
Indigenous		0.00	0.13		0.02	0.08
		(0.046)	(0.178)		(0.039)	(0.075)
Tertiary		0.48***	1.36***		0.38***	0.39**
		(0.018)	(0.342)		(0.014)	(0.182)
Certificate		0.14***	0.31		0.09***	-0.15
		(0.015)	(0.673)		(0.014)	(0.386)
Year 12		0.14***	0.28		0.10***	0.09
		(0.021)	(0.949)		(0.017)	(0.624)
Immi*wave2	-0.05***	-0.04***	-0.05***			
	(0.015)	(0.014)	(0.013)			
Constant	2.34***	2.38***	2.14***	2.74***	2.36***	2.53***
	(0.283)	(0.057)	(0.481)	(0.208)	(0.064)	(0.282)
Hausman Test		156.14	2.19		56.40	7.85
(*p*-value)		(0.0000)	(1.0000)		(0.0001)	(0.9975)

Notes: (i) Wave dummies and location variables were also included. Results for the full set of included variables is available from the author upon request (ii) for men interaction terms were included for wave 2 and immigrant status (iii) for women interaction terms were included for experience and its square and immigrant status (iv) standard errors in parentheses (v)*** p<0.01, ** p<0.05, * p<0.1

Table 8: Variable means and standard deviations by arrival cohorts of immigrants

	Immigrant Men			Immigrant Women		
	Cohort 1	**Cohort 2**	**Cohort 3**	**Cohort 1**	**Cohort 2**	**Cohort 3**
Wage	27.5145	26.6889	26.8976	24.1536	23.8105	22.4274
	(15.4509)	(14.7536)	(16.1974)	(15.8322)	(13.8286)	(10.2445)
Age	46.9566	41.0000	36.1066	47.3282	41.1483	35.3567
	(8.0341)	(9.4775)	(8.0799)	(7.6617)	(8.6957)	(7.7188)
Experience	28.4107	20.6043	15.2916	24.7636	18.7569	12.9967
	(9.1662)	(9.8596)	(8.4821)	(8.7464)	(8.9980)	(8.0272)
Years since migration	37.3309	18.1303	5.7365	38.5129	18.5772	5.5190
	(7.2986)	(5.4693)	(3.1546)	(7.2045)	(5.5409)	(3.0579)
Tertiary	0.2757	0.4038	0.4939	0.2966	0.4263	0.5161
Certificate	0.3971	0.3171	0.2598	0.2731	0.2456	0.2646
Year 12	0.1134	0.1342	0.1385	0.1624	0.1952	0.1418
Year 11	0.2138	0.1449	0.1078	0.2679	0.1329	0.0775
English speaking background	0.5936	0.4483	0.4583	0.5852	0.3934	0.4284
non-English speaking background	0.4064	0.5517	0.5417	0.4148	0.6066	0.5716
Sample size	1,614	2,340	816	1,743	2,280	684

Notes: (i) Standard deviations are in parenthesis. Standard deviations are not provided for dummy variables (ii) Definition of arrival cohorts are: cohort01 arrived before 1976, cohort02 arrived between 1976 and 1995 and cohort03 arrived after 1995.

Table 9: Fixed effects, random effects and HT(IV) estimates of wage equations with immigrant cohort effects

	Men			Women		
VARIABLES	Fixed Effects	Random Effects	HT(IV)	Fixed Effects	Random Effects	HT(IV)
(Age/100)^2	-2.77**	-3.04***	-3.85***	-3.44***	-0.61***	-2.86***
	(1.313)	(0.799)	(0.806)	(0.877)	(0.108)	(0.558)
Experience/100	5.69***	2.60***	4.83***	3.67***	2.66***	4.05***
	(1.007)	(0.355)	(0.503)	(0.864)	(0.190)	(0.412)
(Experience/100)^2	-2.40*	-1.63**	-1.42*	-1.14	-3.99***	-1.77**
	(1.294)	(0.714)	(0.843)	(1.000)	(0.441)	(0.744)
Immi*(Experience/100)				-2.13	-1.31***	-1.31
				(1.652)	(0.390)	(0.799)
Immi*(Experience/100)^2				2.55*	2.51***	2.70**
				(1.483)	(0.915)	(1.353)
Partnered	0.01	0.04***	0.01	0.01	0.03***	0.01*
	(0.009)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
Cohort01		-0.60**	-1.03***		-0.93***	-1.24***
		(0.289)	(0.319)		(0.295)	(0.347)
Cohort02		-0.25***	-0.30**		-0.12	-0.15
		(0.080)	(0.139)		(0.089)	(0.113)
Cohort03		-0.12***	-0.17		-0.08	-0.09
		(0.044)	(0.176)		(0.053)	(0.092)
C01*(Years since	6.13***	3.40**	6.04***	7.57***	5.48***	7.06***
migration/100)	(1.781)	(1.504)	(1.578)	(2.357)	(1.516)	(1.851)
C01*(Years since	-8.55***	-4.47**	-8.35***	-7.94***	-6.51***	-8.54***
migration/100)^2	(2.365)	(1.922)	(2.089)	(2.500)	(1.905)	(2.255)
C02*(Years since	2.51***	2.45***	2.58***	3.27*	2.17**	2.49**
migration/100)	(0.959)	(0.850)	(0.851)	(1.696)	(0.904)	(1.043)
C02*(Years since	-6.30**	-5.93***	-6.32***	-5.48**	-4.55*	-5.53**
migration/100)^2	(2.532)	(2.276)	(2.247)	(2.649)	(2.373)	(2.446)
C03*(Years since	0.66	0.31	0.66	5.30**	3.81**	4.61***
migration/100)	(1.390)	(1.291)	(1.234)	(2.267)	(1.511)	(1.737)
C03*(Years since	4.35	7.36	4.54	-29.60**	-24.48**	-29.74**
migration/100)^2	(10.640)	(10.078)	(9.448)	(13.675)	(12.000)	(12.621)
Indigenous		-0.00	0.13		0.02	0.07
		(0.046)	(0.246)		(0.039)	(0.074)
Tertiary		0.48***	1.47***		0.38***	0.40**
		(0.018)	(0.480)		(0.014)	(0.179)
Certificate		0.14***	0.71		0.09***	-0.09
		(0.015)	(1.024)		(0.014)	(0.373)
Year 12		0.15***	1.05		0.11***	0.14
		(0.021)	(1.360)		(0.017)	(0.576)
Immi * wave2	-0.05***	-0.04***	-0.05***			
	(0.015)	(0.014)	(0.013)			
Constant	2.25***	2.20***	1.79**	2.63***	2.36***	2.50***
	(0.285)	(0.118)	(0.725)	(0.210)	(0.064)	(0.273)
Hausman Test		126.91	1.28		50.78	5.86
p-value		0.0000	1.0000		0.0003	0.9999

Notes: (i) Wave dummies and location variables were also included. Results for the full set of included variables is available from the author upon request (ii) for men interaction terms were included for wave 2 and immigrant status (iii) for women interaction terms were included for experience and its square and immigrant status (iv) standard errors in parentheses (v)*** p<0.01, ** p<0.05, * p<0.1