The relationship between immigration to Australia and the labour market outcomes of Australian-born workers

Robert Breunig[*], Nathan Deutscher and Hang Thi To

Australian National University

11 December 2016

Abstract

We examine the relationship between immigration to Australia and the labour market outcomes of Australian-born workers. We use immigrant supply changes in skill groups—defined by education and experience—to identify the impact of immigration on the labour market. We find that immigration flows into those skill groups that have the highest earnings and lowest unemployment. Once we control for the impact of experience and education on labour market outcomes, we find almost no evidence that immigration harms the labour market outcomes of those born in Australia.

Keywords: immigration; Australia; native labour market outcomes

JEL Codes: J21,J31,J61,F22

[*] We gratefully acknowledge financial support from the Productivity Commission in preparing this manuscript. We appreciate the comments of two anonymous referees which have helped us to improve the paper. None of the views expressed in the paper should be attributed to anyone except the authors. All errors are those of the authors.
Corresponding author: robert.breunig@anu.edu.au

1. Introduction

The impact of immigration on Australian-born workers, particularly on their wages and their employment prospects, is an important economic question. It sheds light on the functioning of the labour market and provides information about the costs and benefits of migration. It provides some insight as to whether current policy settings regarding immigrant intake have effects on Australian-born workers.

Immigration is also an important political issue, with growing anti-immigrant settlement worldwide (see Dunt (2016)). Opposition to immigration, and its effects on workers in Australia, appears to have been at least partly responsible for the recent Senate success of the One Nation party (Walker (2016)).

In this paper, we look carefully at the data to see if we can discern an effect of immigration on the labour market outcomes of those born in Australia and those who have lived in Australia for over five years.

A standard competitive labour market model suggests that immigration should have a negative impact on native wages. An influx of immigrants shifts the supply curve to the right, depressing wages. This simple theoretical model, however, may fail to capture a variety of other economic phenomena that may offset the negative wage effect.

One possibility is that the immigrant influx is part of a demand shift in the overall economy. The demand shift would have the effect of raising wages and could dominate the supply shift, resulting in higher wages for all. Another possibility is that immigrants may fill roles that would otherwise be unfilled (e.g. mine workers, nurses or fruit-pickers) and the presence of these workers actually lifts the productivity (and wages) of native workers in related employment. The supply of capital, the characteristics of the new workers and the structure of technology will all matter in determining the overall effect of immigration on wages.

Congruent with this muddy theoretical picture, the literature paints a very mixed picture of the effect of immigration on labour market outcomes. Early literature in the United States pointed towards very small effects of immigration on natives (Friedberg and Hunt (1995) and Smith and Edmonston (1997)). Using a novel approach that moved away from geographical identification and more towards skill-based identification, Borjas (2003) finds that the employment opportunities of natives have been harmed by immigration. More recently, Ottaviano and Peri (2012) and Manacorda, Manning and Wadsworth (2012), extending and refining Borjas' work, find evidence for varying effects across population subgroups in the US and UK respectively, with at times positive effects for native workers as a whole sitting alongside negative effects for less educated natives and past migrants.

The above papers differ in their assumptions about the changing nature of capital, the definition and size of skill groups and the substitutability of different types of labour. Varying these assumptions appears to have a significant impact on the measured effects of immigrants on labour market outcomes.

In this paper, we employ the approach of Borjas (2003). We divide the national labour market into skill groups based upon education and experience. We examine whether changes in the fraction of immigrants in skill groups are associated with labour market outcomes for those born in Australia, after controlling for other factors. There are two main advantages of our approach. First, it is data-driven and asks a simple correlation question in a non-parametric way. Second, it allows for geographic mobility in labour markets, which is ruled out in approaches that use the spatial distribution of immigrants for identification.

Our contribution to the international literature is two-fold. First, we apply this new identification strategy to Australia data. It is useful to have non-US, empirical evidence to advance our understanding of the effects of immigration internationally. Secondly, the points-based Australian immigration system is different from the relatively more open and uncontrolled immigration into the US and UK. Previous studies have focused on these two countries. Seeing if results differ gives us some insight into the effect of different immigration policies on labour market outcomes of natives.

We define immigrants as anyone born outside of Australia and focus on the labour market outcomes of the Australian-born. We also consider the relationship between outcomes for incumbents (those born in Australia plus those who migrated to Australia more than five years previously) and recent (less than five years in Australia) migrants. We examine a variety of outcomes: weekly earnings, annual earnings, hourly wage, weekly hours worked, labour force participation and employment.

We use three different data sets for our analysis. First, we use the Australian Bureau of Statistics series of Surveys of Income and Housing to estimate the number of migrants and non-migrants in each skill group. We use the same data to measure the labour market outcomes of the Australian-born. Second, we match census data to the Household, Income and Labour Dynamics in Australia (HILDA) survey. In this case we use HILDA to estimate many of the labour market outcomes of the Australian-born but use complete census data to determine the number of migrants and non-migrants in different skill groups. Results across both sets of data are quite similar.

We find strong evidence of immigrant selection. That is, immigration flows into skill groups where wages and employment are high. We find almost no evidence that outcomes for those born in Australia have been harmed by immigration. If anything, there is some evidence that immigration has a small positive association with outcomes for the Australian-born.

In the next section, we discuss the definition of skill groups and the methodology that we use. In section 3, we present the data. Empirical results are in section 4. As is the case with all empirical work, the results are subject to certain caveats and these are discussed in detail in section 5. We also discuss our results in relation to immigration policy and labour markets and provide some conclusions in this last section.

2. Methodology and related Australian literature

Our analysis examines the effect of immigration on labour market outcomes of Australian-born workers using the national labour market approach (e.g. Borjas, 2003, 2006). In our implementation of this approach, individuals are classified into five distinct educational groups: high school dropouts (persons whose highest level of education was year 11 or below); high-school graduates (persons whose highest level of education was year 12); diploma graduates without year 12 education (persons who obtained a certificate or a diploma but did not complete year 12); diploma graduates after completing year 12 (persons who obtained a certificate or a diploma after having completed year 12); university graduates (persons whose highest education was either a undergraduate or post-graduate degree, or a graduate or diploma certificate).

Individuals are also classified into eight experience groups based on the number of years that have elapsed since the person completed school.[1] We assume that the age of entry into the labour market is 17 for a typical high school dropout; 19 for a typical high-school graduate, 19 for a typical diploma graduate without year 12 education, 21 for a diploma graduate after completing year 12, and 23 for a typical university graduate. The work experience is then given by the age of the individual minus the age at which the individual entered the labour market. We restrict our analysis to people who have between 1 and 40 years of experience and aggregate the data into eight experience groups with five-year experience intervals such as 1 to 5 years of experience, 6 to 10 years of experience, and so on.

The individual data is aggregated into different education-experience cells. For each of these cells, the share of immigrants in the population is given by:

$$p_{ijt} = \frac{M_{ijt}}{M_{ijt} + N_{ijt}}$$

where M_{ijt} is the number of immigrants in cell (i, j, t), and N_{ijt} is the number of Australia-born individuals in cell (i, j, t). We estimate the following specification:

$$y_{ijt} = \theta p_{ijt} + s_i + x_j + \pi_t + (s_i \times x_j) + (s_i \times \pi_t) + \left(x_j \times \pi_t\right) + \varepsilon_{ijt} \qquad (1)$$

where y_{ijt} is the mean value of a particular labour market outcome for Australia-born workers in cell (i, j, t); s_i is a vector of dummy variables for education groups (i=1 to 5); x_j is a vector of dummy variables for experience groups (j=1 to 8); π_t is vector of dummy variables for time (5 time periods for the SIH data and 3 time periods for the matched HILDA / census data); ε_{ijt} is a normally distributed random error.

[1] In essence, we measure potential experience. This will be different for people of the same age depending upon the age at which they finished their schooling/education. We refer to this as experience throughout.

The model includes time dummies to account for changes in the macroeconomic environment that affect all groups. Dummies for education and experience and their interaction account for supply and demand factors specific to each skill group that determine the overall level of labour market outcomes for that group. Interacting education and experience with time dummies allows the profile of groups to evolve differently over time.

Identification in the model comes from changes within skill groups over time. Differences in the *changes* in the proportion of immigrants within cells are related to differential changes in labour market outcomes. The approach is non-parametric in the sense that we are allowing the data to relate changes in immigration to changes in labour market outcomes without imposing any structural restrictions on this relationship. (We do not estimate a wage equation, for example.) There is no need to control for other characteristics such as average occupation or industry within a cell since these effects and their evolution over time are perfectly captured by the fixed effects and the interactions.

One previous Australian paper used this approach. Bond and Gaston (2011) used the first five waves of the HILDA data to assess p imact on weekly earnings and hours worked of Australian-born workers. They found that immigrant share has a positive relationship with Australian-born workers' earnings and hours worked.

The implementation of Bond and Gaston (2011) is flawed, however, because they used HILDA for both the outcome data and the immigrant share data. It is inappropriate to use HILDA to estimate population-level shares of migrants and non-migrants. HILDA is a panel with an initial sample chosen in 2001. This sample is followed in time with new sample members joining through marriage and birth. As such, there is almost no inflow of migrants into the sample; see Figure 4 of Watson (2012).[2] During the period of Bond and Gaston's (2011) study, the change in the share of immigrants in the HILDA sample is driven by two factors: differential sample attrition of migrants and non-migrants and a small number of migrants who join the sample because they partner with a continuing sample member.[3]

Sinning and Vorell (2012) investigate attitudes towards, and the effects of, immigration on the labour market and crime in Australia. They use data from the 1996, 2001 and 2006 Censuses and crime statistics to estimate the effect of immigration on median income, unemployment and crime rates at various levels of aggregation (including functional economic regions that account for economic interactions between regions and large-scale Census regions). They find no statistically significant effect of immigration; similar to what we find when we consider the geographic approach below in section 4.2. The geographic approach, which has been used extensively in the economic migration literature (e.g. Altonji and Card, 1991; Hunt, 1992; Card, 2001, 2005), has come under increasing attack since Borjas (2003). The approach assumes that geographic labour markets are fixed and distinct. Yet, we know that there are important movements of both firms and workers that tend to equalize economic conditions across cities and regions. In Australia, this trend is strongly seen in a shift of innovative activity and employment from Victoria and New South Wales to Queensland and Western Australia during the time of our data window.

[2] HILDA added a top-up sample in 2011 (wave 11) which picked up many new immigrants but going forward from 2011, the same problem arises.

[3] Migrants, particularly from non-English speaking countries, attrited at a slightly higher rate than non-migrants during these five waves. See Table 8.24 in Summerfield et al. (2012). This is the variation that drives the results in Bond and Gason (2011).

Our approach allows for a national-level labour market. We assume fixed and distinct labour markets defined by skill groups (rather than by sub-national geographic areas). Workers are assumed to be unable to change the skill group in which they supply labour in response to prices.[4] Furthermore, workers in different skills groups are assumed to be imperfect substitutes for one another. Given that skill groups are defined in terms of experience and education levels that are not able to be altered by workers, this assumption seems less problematic than strict geographical segregation. Mobility across occupations, industries and regions does not affect identification. The restriction that workers compete in skill groups defined by education and experience is an important one and is discussed further in sections 4.1 and 5. We contrast our empirical results with the geographic approach in section 4.2

3. Data

Our analysis is grouped into two parts. In the first part, we use data drawn from the Survey of Income and Housing in Australia (SIH) conducted by the Australian Bureau of Statistics (ABS). We use data from five biennial surveys from 2003 to 2012. The survey collects information from usual residents of private dwellings in urban and rural areas of Australia, covering about 98% of all people living in Australia. Residents in non-private dwellings such as hotels, boarding schools, boarding houses and institutions are excluded.

In the second part of our analysis, we use data drawn from waves 1, 6 and 11 of HILDA combined with data from the Australian Census of Population and Housing (Census). The HILDA survey is an annual, household-based panel study that collects information on

[4] This assumption implies that once in Australia, immigrants can not select into a different education-experience group than the one into which their education and experience places them. It does not rule out immigrant selectivity in the sense that more skilled immigrants may be more likely to immigrate to Australia or that immigrants flow at a higher ate into high wage education-experience groups than they do into low wage education-experience groups.

respondents' economic and demographic characteristics. The wave 1 HILDA survey was conducted in 2001 and covered 13,969 from 7,682 households. The survey has grown slightly over time as all individual sample members and their children are followed. The sample was replenished in wave 11 with a top-up sample of 4,009 people added in the survey.

The Australian Population and Housing Censuses provide information on the number of people in each part of Australia, what they do and how they live. The data record the details of all people (including visitors) who spend the night in each dwelling on Census Night. Immigrants are included in the census provided that they intend to stay in Australia for at least one year. The data thus excludes those who intend to stay in Australia for less than one year.[5] Census data contains information on topics such as age, gender, education, birthplace and employment status of all people in Australia on Census Night.[6]

In the first part of our analysis, we estimate the model of equation (1) using SIH data for five financial years 2003-2004, 2005-2006, 2007-2008, 2009-2010, 2011-2012. We only use data from 2003 onwards. Survey years prior to 2003-04 group education in broader categories that are different than those used in 2003-04 and onwards. This makes it impossible for us to extend our chosen skill group definitions further back in time than 2003.

We estimate the model for six different dependent variables relating to the labour market outcomes of Australian-born workers: annual earnings from wage and salary, weekly earnings from wage and salary, log hourly wage rate, weekly hours worked, the labour force

[5] We thank Jenny Dobak of the Australian Bureau of Statistics (ABS) for clarifying this.
[6] We use the entire census data to construct the fraction of immigrants in each skill group. For 2006 and 2011, this data is available online through ABS table builder. For 2001, the data was constructed for us by the ABS and provided through the Productivity Commission. We thank Meredith Baker and Troy Podbury of the Productivity Commission and Steve Gelsi and Dominique O'Dea of the ABS for their assistance in procuring the data. We also thank Sharron Turner at ANU for her assistance in helping us to access ABS data.

participation rate and the unemployment. The key explanatory variable of interest, the share of immigrants in each education/experience cell, is also extracted from the SIH as the survey samples, properly weighted, are representative cross-sections in each year.

In the second part, we estimate equation (1) using HILDA data from waves 1, 6 and 11 combined with complete Census data for 2001, 2006 and 2011. The explanatory variable of interest, the share of immigrants in each skill group, is extracted from Census data. For the labour market outcomes we use the Census data for the unemployment rate and the labour force participation rate of Australian-born workers. Data for weekly hours worked, weekly and annual earnings (i.e. labour income) and hourly wage rates are extracted from HILDA data as Census data do not provide individual earnings in continuous values. The necessity of using immigrant share from Census data comes from the fact that the share of immigrants in HILDA is not an appropriate indicator for the changing immigrant share in Australia over time, as discussed above.

Descriptive statistics, from the SIH, of the main variables used in the analysis are provided in Figures 1 to 6.[7] Figure 1 presents the migrant share for each education-experience cell, grouped by education category. For young people, migrant shares are relatively higher in groups with university education compared to groups without university education. This reflects the shift towards a higher skill requirement in Australian immigration policy in recent years as well as strong labour market demand in Australia for highly educated people.

Figure 2 presents the mean values of annual earnings of Australian-born workers by education and experience, grouped by education category. With the same experience, annual earnings are

[7] HILDA and the Census provide a similar impression and are available from the authors upon request.

higher for people with higher educational attainment. Annual earnings increase faster for the young. The effect of experience is smaller after 20 years of experience. For all groups we see the usual inverted U-shape earnings/experience profile.

Figures 3 and 4 show the mean annual earnings of Australian born workers by education and experience, respectively. We see very strong returns to university education and again an inverted U-shape experience/earnings profile. Figures 5 and 6 present the unemployment rate of Australian born workers by education and experience groups. The Figures show that the unemployment rate decreases with the level of education and with experience; the exception is slightly higher unemployment for those in the highest experience group.

Figures 7 and 8 show the distribution of changes over time in the key variable p_{ijt} in the two data sets—SIH and Census. The model is identified from these changes and the key empirical question is: are changes in the share of immigrants in total workers statistically related to labour market outcomes of Australian-born workers over the sample period? We can see that in both data sets, the changes in the share of migrants is centered around zero and is fairly small. However, we do observe both positive and negative changes.

In the Census, we find that the average proportional change in migrant share (pooling across the two time periods) is 0.0022. The minimum is -0.07 and the maximum is 0.10. In the SIH, the average is slightly negative (-0.0049), the minimum is -0.13 and the maximum change is 0.18. The migrant share changes calculated from the SIH have a slightly higher variance than those calculated from the Census. In general, across both data sets, the larger changes are for the most highly educated groups who saw positive increases in the share of immigrants over time. The two groups with certificates (year 12 and no year 12) saw the largest decreases in immigrant share.

Our data is somewhat shorter in time span and contains slightly fewer annual observations than typically found in the international literature. Borjas (2003, 2006) uses decennial census data from 1960 through 2000. Ottaviano and Peri (2012) use basically the same data as Borjas (2006). They also use annual CPS data for the period 1962-2006. Manacorda et al. (2012) use the annual UK Labour Force Survey and General Household Survey from mid 1970s to mid 2000s. UK and US data have larger populations to work with, so might be expected to be better placed to detect small effects than we are, all else being equal.

4. Empirical results

We estimate models of the labour market outcomes of Australian-born workers (annual and weekly earnings, weekly hours worked, hourly wage rate, labour force participation, and unemployment rate) against the share of migrants with different specifications: (i) models that include only the time dummy variables, (ii) models controlling for all dummy variables including dummies for education groups, for experience groups, and dummies for time but without any interaction terms; (iii) models controlling for education, experience, time and the interactions between dummy variables that allow for changing skill premia over time.

We present weighted regressions using the weights defined as the number of Australian-born in each education-experience cell for whom the relevant outcome variable is defined. That is, we weight labour force participation regressions by the native population, unemployment regressions by the native labour force, and hours and earnings regressions by the number of natives employed. We also present unweighted estimates for comparison. In all of our models, we present standard errors that control for clustering on education-experience cells to allow for serial correlation in the estimates.

Unweighted results give equal weight to each education-experience cell even when the number of individuals in each of those cells is very different. The correlation that we estimate between immigration flows and labour market outcomes is essentially a conditional mean. Weighting this conditional mean by the number of Australian-born in each cell gives more importance to those cells with more individuals in the labour market. We prefer the weighted estimated because they come closer to a population average across all labour market participants in the same way that a weighted mean based upon sub-group means from different sized sub-groups would be closer to the population average than an unweighted average of sub-group means. Note that weighting does not overcome model mis-specification. Weighting will not produce a population weighted average causal parameter if the different sub-groups have different values for θ.

Summary results from SIH data are presented in Tables 1 and 3 and results from HILDA wage and earnings data matched to census data for immigrant shares by experience/education cells are reported in Tables 2 and 4. We only present estimates of the value of the key parameter, θ. Full regression results with control variables are available from the authors.

Table 1 presents the results for the full sample from the SIH. In the first row, we estimate a model that includes only time dummies and no controls for education or experience. Row two presents results where we add the controls for education and experience levels, but no interactions between the two. Row three presents the results when we add the full set of skill controls including interactions between education and experience and interactions with time which allow skill premia to vary across time. Unweighted estimates are provided in row four for comparison. The weighted estimates with a full set of shift and interaction dummies (row three) are our preferred model throughout.

If we do not control for levels of education, experience and the interactions between those variables, we find that there is a positive relationship (and statistically significant) between immigration and wages (measured as yearly earnings, weekly earnings or hourly wage) in the sense that more immigration is correlated with higher wages. Immigration is also correlated with higher labour force participation and lower unemployment.

If we control for experience, education, time dummies and the interactions between these dummy variables, we find little statistical relationship between immigration and wages or other labour market outcomes (participation or unemployment). There does appear to be some small positive association between immigration and the participation rate.

The positive association is quite small. If the share of immigrants goes up by 5 percentage points (from say 20% to 25%), this is associated with a 2.6 percentage point increase in the participation rate.[8] Recall from Figure 9 that the typical changes are very small—on the order of one percentage point.

The results for the HILDA/Census data are quite similar—see Table 2. We find a strong association between Australian-born labour market outcomes and immigrant shares when we do not control for different returns to experience and education. Once we include a full set of dummies, these associations disappear. We find no statistically significant associations.

[8] This can be worked out as $\Delta y_{ijt} = \hat{\theta}\Delta p_{ijt}$.

Overall, the results show strong evidence for migrant selection. The first row of the table shows that migrants come from overseas into those skill groups that have the highest earnings and the best employment opportunities. Once we account for the differential returns to experience and education, we find no evidence across the sample that immigration is associated with worse outcomes for Australian-born workers. In the SIH data, immigrants appear to bring small positive outcomes to Australian-born workers in terms of hours worked and participation rate. In all cases, these associations are small in size and only significant at the 10 per cent level.

We re-estimate the models, splitting the sample by male/female. (See Tables 3 and 4 for SIH and HILDA/Census, respectively.) The patterns that we observe in Tables 1 and 2 are repeated for all of our models. These full results are available from the authors upon request.

For men, in both data sets, we find no statistically significant association between immigration and labour market outcomes. In SIH, we find positive associations between immigration and hours and participation in the female sub-sample. Using the Census data, we find a positive association between immigration and the unemployment rate for women. More immigration seems related to more unemployment. This is significant at the 5 per cent level, but very small and only for females. If the share of immigrants goes up by 5 percentage points, the unemployment rate for females increases by about 0.6 percentage points. Note that we only find this relationship in the Census data. The coefficient for females in the SIH data is actually negative, although not statistically significant.

The model of equation (1) imposes a constant response parameter, θ, across all experience and education groups.[9] If the labour market outcomes of different types of workers have different responses to immigration, the assumption of a constant response parameter would be incorrect. To test this hypothesis, at least somewhat, we estimate the model for a sub-population of people with experience less than or equal to 15 years. We again estimate models where we pool across all individuals as well as separately by male and female.

The results are broadly consistent with what we find in the main sample. For the SIH (see Table 3) the only statistically significant relationship that we find is for female unemployment. If the share of immigrants goes up by 5 percentage points, this is associated with a drop in the unemployment rate for females of about 0.9 percentage points. In the combined HILDA / Census data (see Table 4).

Throughout this paper so far, we have compared immigrants (as those born outside Australia) to those born in Australia. But Australia has a very large stock of immigrants who, while born outside of Australia, have lived in Australia for a long time. To check if our results are driven by how we classify individuals, we re-estimate the model comparing `incumbents' to `recent immigrants'. We define incumbents as those born in Australia plus those who have migrated to Australia more than five years previously. `Recent immigrants' are now defined as those who migrated to Australia within the last five years.

We estimate the labour market outcomes of incumbents as a function of the share of recent immigrants in overall population. Weights are now defined based upon the number of

[9] Given the large number of fixed effects in the model, it is not possible to estimate a model with a parameter that varies by skill group.

incumbents rather than the number of Australian-born. We only estimate models using the Census / HILDA data. In the SIH, we do not have precise enough information about year of arrival in Australia to distinguish between incumbents and recent arrivals. Results for the full sample are provided in Table 5[10].

The only statistically significant effect we find is a positive association between the participation rate and immigration. If the share of recent immigrants goes up by 5 percentage points, this is associated with an increase in labour force participation of incumbents of about 1.4 percentage points. When we compare Tables 2 and 5, it appears that the effect of selection is much stronger when we compare Australian-born to all immigrants than when we compare incumbents to recent immigrants. We also split the samples by male and female. For males, none of the coefficients are statistically significant. For females, we find a positive relationship between recent immigration and incumbents' weekly hours.[11]

Overall, across all of these estimates, our results indicate that immigration is higher into those skill groups (defined by education and experience) that have higher wages and better labour market prospects. This is consistent with immigrants coming to Australia with knowledge of where returns are high and is also consistent with selective migration policies. Once we control for this selection into skill groups by immigrants, there is very little evidence of any negative labour market effects on those born in Australia resulting from immigration.

4.1 Are immigrants and Australian-born workers in same skill groups comparable?

[10] If we redefine incumbents as those who have been in Australia for 10 years or more the results are substantively the same as what is shown in Table 5.

[11] These results are available from the authors.

A key element of our model is the assumption that migrants and Australian-born workers compete within the same education/experience cells (skill groups). It could be that experience and education obtained outside of Australia has a lower value in the local labour market and that in fact migrants are competing with Australians at lower levels of experience and education. This would mean that we have mis-classified some individuals as competing in one skill group when they should actually be in another, lower skill group.

First, it is important to note that mis-classification by itself poses no threat to our identification strategy. We identify the effects in the model from changes in the share of migrants. Mis-classification poses no problem unless the degree of mis-classification is also changing over time.

Nonetheless, it is important to see if immigrants and Australian-born individuals within skill group cells look similar. In Table 6, we present the three most common occupations for migrants and natives by education and 10-year experience groupings. The two groups look very similar, particularly where levels of education are highest. If we think of anecdotes where overseas-trained doctors are driving taxis in Australia, this might be the group for whom we would worry the most about mis-classification. Yet, the top three occupations are the same and in the same order for both immigrants and Australian-born. Australian-born individuals with higher education are between 6 and 15 percentage points more likely to be professionals than comparable immigrants, so there is some evidence for higher occupational status for the highly educated if they are Australian-born. However, within our sample there is not evidence of large-scale occupational downgrading by migrants.

In Tables 7 and 8, we present the Duncan index of dissimilarity comparing native and migrant occupational distributions (at the one digit level) holding either education (Table 7) or experience (Table 8) constant. This index captures the proportion of either group that would need to change occupations to make the two distributions equal. The more similar the occupational distributions, the smaller the index. We have highlighted the smallest values in each row and column.

The results are comforting. Within education groups, less experienced migrants look most similar to less experienced natives. However, highly experienced migrants look more similar to moderately experienced natives, so there may be some discount placed on overseas experience. Within experience groups, migrants almost always look most similar to natives with the same education.

We reproduced Tables 7 and 8 splitting the immigrants by source country into English-speaking/Anglosphere (UK, Ireland, New Zealand, Canada, US) and all others. For the Anglosphere migrants, we find much more similarity in occupation than what is shown in Tables 7 and 8 and no discount for overseas experience. The results for the non-Anglosphere immigrants look very similar to Tables 7 and 8 and the discount, if any, for overseas experience appears to be concentrated within that group.

We also reproduced Tables 7 and 8 for 2006. It does appear that similarity is growing over time in the data. If we compare the most similar pairs within education-experience cells, 13 pairs became more similar from 2006 to 2011 and 6 pairs became less similar (one stayed the same). This was the case when we held experience constant and when we held education constant. The differences were not large.[12]

As a final check on our classification of skill groups, we re-estimate all of the models with fewer education-experience cells. Some authors have argued that wider skill groups are better as the assumption of no competition across skill groups is more likely to hold when skill groups

[12] These alternative/expanded versions of Tables 7 and 8 are available from the authors upon request.

are more broadly defined. We re-estimate all the models using 12 groups—3 educational groups (high school dropout; university graduates; all others) and 4 experience groups defined by 10 year groupings.[13]

The results are quite similar to what we have already presented.[14] For the SIH data, the only significant associations are a positive relationship between hours and immigration and a negative relationship between unemployment and immigration when we pool male and female together. The coefficients are 11.8 and -0.08 and are just significant at the 10% level. When we split the sample by male and female we find no statistically significant coefficients.

For the combined HILDA/Census data, we only find a statistically significant association between immigrants and the participation rate. The coefficient in the pooled sample is 0.40. We find a statistically significant estimate of 0.252 for males. We find no effect for females.

Interestingly, we find stronger effects when we consider broad skill groupings for incumbents, but the results are mixed. (See Table 9.) We find a negative association between incumbent wages and the fraction of recent immigrants. We find statistically significant associations between immigration and weekly hours and participation. The fraction of recent immigrants is significant at the 5% level for participation, but only at the 10% level for wages and weekly hours. The wage and hours effects are fairly strong. If the share of recent immigrants goes up by 1 percentage point, this is associated with a drop in wages of 2.6 per cent, an increase in weekly hours of 32 minutes and an increase in the participation rate of one-half of one percentage point.

[13] Looking at Figure 3, the middle 3 educational categories which we have combined together have very similar average earnings.

[14] For this reason we only discuss the results and do not present full tables. These are available from the authors upon request.

When we split the sample by sex, see Table 9, we again find mixed results. For males we find a positive association between recent migration and the participation rate but also a positive association with the unemployment rate. The wage and hours effects from the pooled sample are concentrated amongst female workers.

It is important to note that the negative wage effect is very fragile and driven by one skill group: degree holders with 1-10 years of experience. If we add a dummy variable for that group (or drop them from the analysis), the coefficient on immigrant share in the wage regression becomes positive, 0.5376, but insignificant. Between 2001 and 2011, this group of individuals had lower wage growth than expected and this could plausibly be for other reasons such as the Global Financial Crisis or the mining boom.

A priori, it is difficult to say whether the more narrow skill groups or the broader skill groups provide better estimates. Comparing Table 2 to Table 9, we can see that the standard errors are two to three times larger when we use the broader groups and the incumbent sample. The broader groups will provide more imprecise estimates and potentially more volatile estimates since we are estimating on a much smaller effective sample size. The wider groups will give biased estimates if skill groups are too narrowly defined and if there is leakage and competition across skill groups. As others in the literature have pointed out, the results do depend upon the definition of skill groups.

4.2 Identification through geographic differences in migration patterns

In the literature, studies have used the spatial approach to estimate the labour market impact of immigration. This approach assumes that geographical regions are discrete labour markets and thus comparisons are made across local labour markets to find the impact of immigration. As discussed above, one of the limitations of this methodology is that identification is based on an assumption of no geographical labour mobility. We apply this approach to see how our results using the skill-based groups differ from the geographical approach.

Following Altonji and Card (1991), we regress geographic area averages of the labour market outcome variables for Australian-born and incumbent groups against measures of the immigrant fraction in the area and a variety of controls for the characteristics of each area. Geographic areas are based on the Australian Standard Geographical Classification and have a minimum population size of 250,000 persons. Specifically, we estimate weekly earnings, yearly income, hourly wage, number of hours work per week, unemployment rate and labour force participation of Australian-born workers and incumbents between 18-64 years old against the share of immigrants in each area, proportion of Australian born workers/incumbents having university education in the area, average age of Australian-born/incumbents in the area, average years of experience in current occupation of Australian-born workers/incumbents, and total population in the area. In the models for both male and female respondents, we also include proportion of male in the area as an explanatory variable for labour market outcomes.

Geographic areas in Census 2001 match geographic areas in Census 2006 but do not match geographical classifications used in Census 2011 and HILDA. We thus use two approaches. For 2011 data, we estimate OLS regressions of the models. For 2001 and 2006 data, we estimate both pooled OLS regressions and instrumental variable regressions where we use the immigrant fraction in 2001 as an instrument for the immigrant fraction in 2006.

The results are found in Tables 10 and 11 where we present the coefficient on the immigrant share variable.[15] We find more evidence for a positive relationship between immigration and outcomes than we do for the skills-based approach. Looking at the OLS results from Wave 11

[15] Detailed regression results are available from the authors.

of HILDA combined with 2011 census data in Table 10, we see positive, but not quite statistically significant associations with earnings and wages in the full sample. When we split by male/female, we see strong positive and statistically significant relationships with wages and earnings for females. For males, we find a small positive association with the unemployment rate (which we also find in the full sample).

For the combined census data from 2001 and 2006, the only statistically significant result is a negative relationship with the unemployment rate (immigration increasing is associated with unemployment decreasing) for females. This disappears when we use IV. The IV results are all small and statistically insignificant.

Our results are consistent with Borjas (2003) who finds either zero or small negative effects of immigration on native labour market outcomes using the geographical approach. These effects get smaller (the negative effects become larger) when he uses the skills-based approach. Comparing the 2011 OLS results in Table 10 to our preferred results from the skills-based approach, we find positive associations which become zero when we use the skills-based approach.

Overall, we find many statistically insignificant results in both cases but the evidence for no effect of immigration is stronger in the skills-based approach. We prefer these latter results for the theoretical reasons discussed above.

5. Discussion and conclusion

In this paper we use a simple and data driven approach to address whether labour market outcomes of Australian-born workers are related to patterns of migration. We construct skill groups which are defined by education and years of (potential) experience. We look at whether changes in the share of immigrants in these cells over time is related to changing labour market outcomes for the Australian-born. We control for a variety of fixed effects as well as macro-economic conditions and we allow the return to skills to vary over time.

Overall, we find little evidence that the labour market outcomes of Australian-born workers are negatively related to immigration. If anything, when we consider narrowly defined skill groups and compare the Australian-born to all immigrants, there is some evidence for small positive associations. However, these associations are only just statistically significant, so the evidence is scant. Our results are consistent across two very different data sets.

We do find some negative effects of recent migrants (those who arrived in Australia in the last five years) on employment and wage of incumbents (Australian-born and immigrants who have resided in Australia for more than five years) when we consider very broadly defined skill groups. However, we also find positive associations between recent migration and weekly hours and labour force participation of incumbents.

The approach that we use has an advantage over approaches that use the uneven geographical spread of immigrants to identify the impact of immigration on labour market outcomes. In those approaches, geographical labour markets are assumed to be distinct and movement between labour markets which might be driven by differences in employment opportunities and wages are ruled out. In Australia, this looks like a very bad assumption given the large flows of workers from one state to another which we observed during the mining boom which took place during our data period, 2001-2011.

The disadvantage of our approach is that we assume that each skill group is a distinct pool of labour. Specifically, we assume that the arrival of immigrants in one skill group is not causing Australian-born workers to move to competing in another skill group. Given that skill groups are defined on relatively immutable categories, education and potential experience, this seems less problematic than the geographical assumption. When we examined this assumption, we find great occupational similarity between migrants and Australian-born within the skill groups that we have defined.

We make no assumptions about the structure of production or the demand side of the labour market. The effects that we estimate combine influences within competing labour market groups and cross-group effects. If the relative price of labour goes up for one skill group, there are multiple ways that purchasers of labour can react. They can use less labour and more capital; or they could use more of some other type of imperfectly substitutable labour. Our approach allows for this but does not separately identify these effects.

Our results show less evidence of a negative effect of immigration on native workers than similar studies on the US or the UK, which are discussed in the introduction. This could be because of Australian immigration policies which have been more selective than in the US or the UK. Or, it could be that immigrants interact with different labour market institutions in different countries. Collective bargaining agreements are much more important in Australia than in the US and the UK. Table A in the Appendix summarises important changes to Australia's migration policy prior to and during our sample period.

Since the 1970s, Australia has been operating migration programmes that are selective on the basis of skills. Overall, the balance of skilled to non-skilled migrants has shifted markedly to the former with migrants having higher qualifications and greater English language ability than in the past. There is a close association between skills and productivity such that today Australia's migrants are likely to be more productive on arrival in Australia than in the past.

A number of studies (e.g. Antecol et al. 2003 and Cobb-Clark 2000) show that migrants entering under skilled programmes differ systematically from those entering under family reunification programmes, with the former having higher skills and better labour market performance once in Australia. Australia's skilled migration selection processes deliver superior employment outcomes for migrants than would accrue if would-be migrants were chosen at random (Cully, 2011.)

In the US and in the UK, the influx of immigrants at lower skill levels has been more important than in Australia. Our results could be driven by this difference with wage competition at higher skill levels being fundamentally different than wage competition at lower skill levels. The data does not allow us to convincingly sort out these different factors.

Our results are dependent both upon the immigration policies in place during the period 2001-2012 and the overall economic conditions. As we are estimating over a period of very robust economic growth, it is perhaps not surprising that we find very little negative impact of immigration. It could be that in periods of slow growth or contraction there are negative effects, but we would not be able to identify these in our data. Given that our approach is non-parametric and data-driven, our results are dependent upon policy settings. The results do not give any insight into how different policies might affect the relationship between immigration and labour market outcomes of Australian-born workers.

One reason why we may fail to find statistically significant results is that the amount of variation in immigrant shares in our data is pretty small. Recalling Figures 9 and 10, most of the skill groups show little or no change in the proportion of immigrants over time. A longer time window and more variability in immigration would assist in identification, but we do not currently have either of these things.

Our data does not account for short-term migrants. They are absent in the census data by construction. In the SIH, they would only be counted if they were living in private dwellings. This means that 457 visa holders (see Table A) are unlikely to be having a large impact on our results. If short-term migrants are living in hostels or non-private dwellings, they will not be in our data. Our intuition is that, while this group may be important for certain low-skill jobs in the economy, the overall results are not substantially impacted by their absence.

Throughout, we have discussed changes in the percentage of migrants in skill groups as being related to in-flows of migration. But, they can also be related to outflows. Immigrant shares in skill groups can drop if Australian-born workers are out-migrating even in the absence of any change in immigration. Our intuition, again, is that this is not an important determinant of the results. Out-migration has been important in highly skilled groups in Australia, but less so during the economic boom of the 2000s. For most groups, in-migration dominates out-migration and it is this effect that we are mostly capturing.

Despite these caveats, the paper provides important new information about the relationship between immigration and the labour market outcomes of Australian-born workers. If there were strong negative effects, the approach used here should reveal at least some of those effects. The fact that we find almost no negative effects means that, at least at the level of the overall economy and the vast majority of workers, immigration is not a major factor in the conditions of Australian workers.

References

Altonji, J.G. and D. Card (1991). The effects of immigration on the labor market outcomes of less skilled natives. In: J.M. Abowd and R.B. Freeman (ed) *Immigration, trade, and the labor market.* Chicago and London: The University of Chicago Press

Antecol, H., Cobb-Clark, D.A. and Trejo, S.J. (2003) Immigration policy and the skills of immigrants to Australia, Canada and the United States, *Journal of Human Resources*, 38(1) 192–221.

Bond, M., and Gaston, N. 2011. The impact of Immigration on Australian-born workers: An assessment using the National Labour Market Approach. Economics Papers 30(3): 400-413

Borjas, G. J. 2003. The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *The Quarterly Journal of Economics*, *118*(4), 1335-1374.

Borjas, G. J. 2006. Native Internal Migration and the Labor Market Impact of Immigration. *Journal of Human Resources*, *41*(2), 221-258.

Card, D., 2001. Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration, Journal of Labor Economics, 19(1), 22-64.

Card, D., 2005. Is the New Immigration Really So Bad? The Economic Journal, 115, F300-F323.

Cobb-Clark, D.A. (2000) Do Selection Criteria Make a Difference? Visa Category and the Labour Market Status of Immigrants to Australia, *Economic Record*, 76(232) 15-31.

Cully, M. (2011) How much do migrants account for the unexpected rise in the labour force participation rate in Australia over the past decade? Paper prepared for the *2011 Australian Conference of Economists* www.immi.gov.au/media/publications/research/_pdf/migrants-account-unexpected-rise-labour-force-rate-aus-2000-2010.pdf (accessed 22 May 2015)

Duncan, O. B. and Duncan, B. 1955. Residential Distribution and Occupational Segregation. *American Journal of Sociology*, *60*(5), 493-503.

Dunt, I. 2016. It's a Brexit world: Tide of anti-immigrant sentiment sweeps globe. *Politics.co.uk*. http://www.politics.co.uk/news/2016/08/11/it-s-a-brexit-world-tide-of-anti-immigrant-sentiment-sweeps

Friedberg, R. M., and Hunt, J. 1995. The Impact of Immigrants on Host Country Wages, Employment and Growth. *The Journal of Economic Perspectives*, 23-44.

Hunt, J. 1992. The Impact of the 1962 Repatriates from Algeria on the French Labor Market. *Industrial and Labor Relations Review*, 45(3), 556-572.

Manacorda, M., Manning, A., and Wadsworth, J. 2012. The Impact of Immigration on the Structure of Wages: Theory and Evidence from Britain. *Journal of the European Economic Association*, *10*(1), 120-151.

Ottaviano, G. I., and Peri, G. 2012. Rethinking the Effect of Immigration on Wages. *Journal of the European Economic Association*, *10*(1), 152-197.

Productivity Commission (2010). *Population and Migration: Understanding the Numbers*. Productivity Commission Research Paper, December 2010. Canberra: Commonwealth Government of Australia.

Sinning, M. and Vorell, M. 2012. There Goes the Neighborhood? People's Attitudes and the Effects of Immigration to Australia, unpublished working paper available from authors.

Smith, J. P., & Edmonston, B. (Eds.). 1997. *The new Americans: Economic, demographic, and fiscal effects of immigration*. National Academies Press.

Summerfield, M. , Freidin, S., Hahn, M., Ittak, P., Li, N., Macalalad, Watson, N., Wilkins, R., Wooden, M. 2012. 'HILDA User Manual–Release 11', Melbourne Institute of Applied Economic and Social Research.

Walker, J. 2016. Federal Election 2016: One Nation's Hanson puts band back together. *The Australian.* 9 July 2016. http://www.theaustralian.com.au/news/inquirer/one-nations-pauline-hanson-puts-the-band-back-together/news-story/d198687f849fe3466286f1b9836d0d41

Watson, N. 2012. Longitudinal and Cross-sectional Weighting Methodology for the HILDA Survey. HILDA Project Technical Paper Series No. 2/12, December 2012. Melbourne Institute of Applied Economic and Social Research.

Figure 1: Migrant share by Education and Experience: SIH

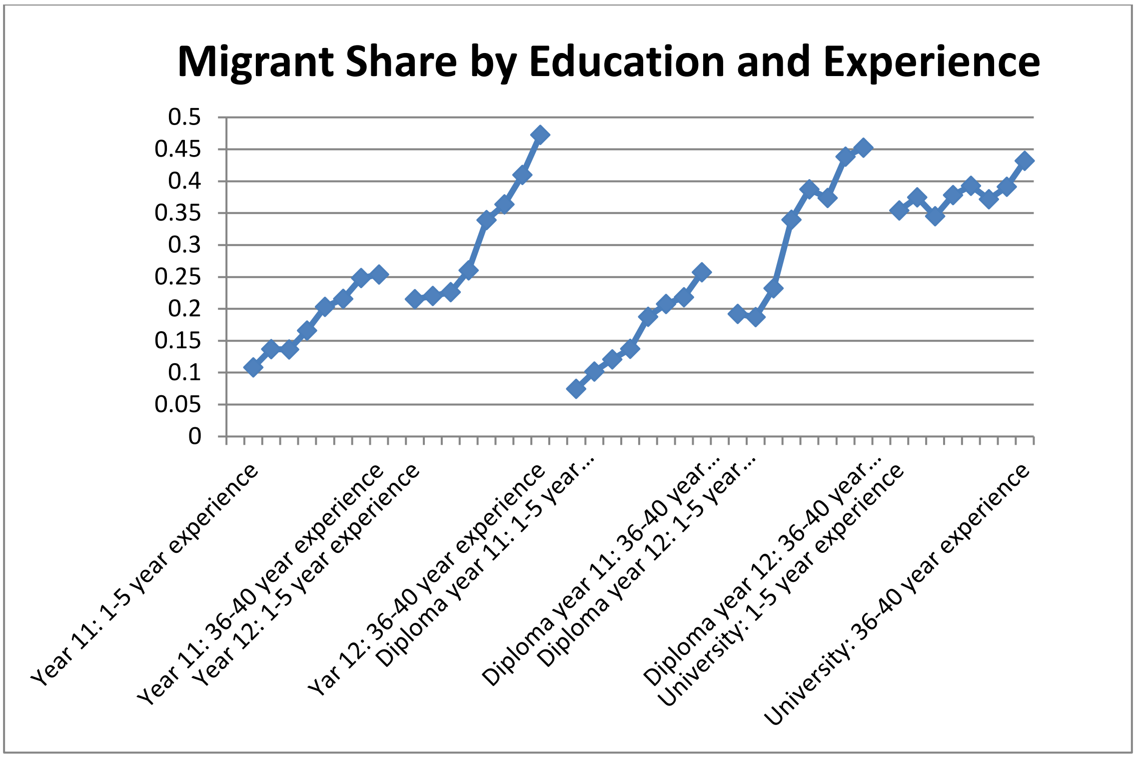

Figure 2: Annual earnings of Australian born workers by education and experience: SIH

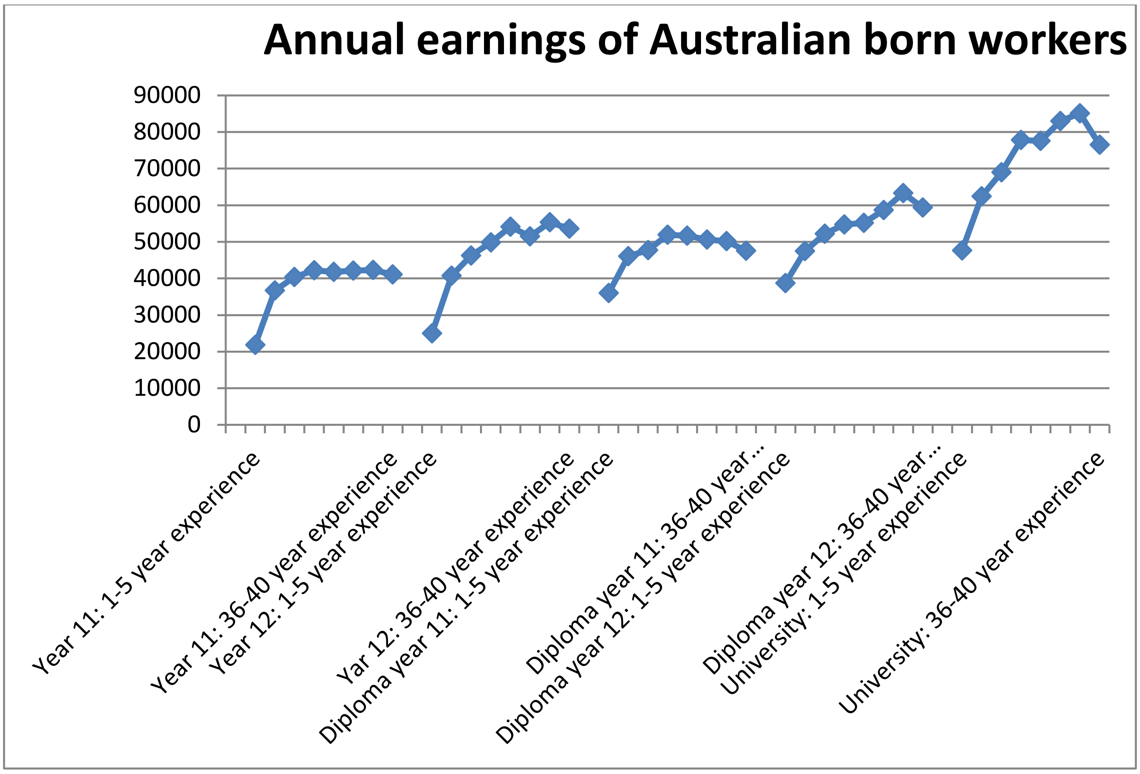

Figure 3: Annual earnings of Australian born workers by education groups

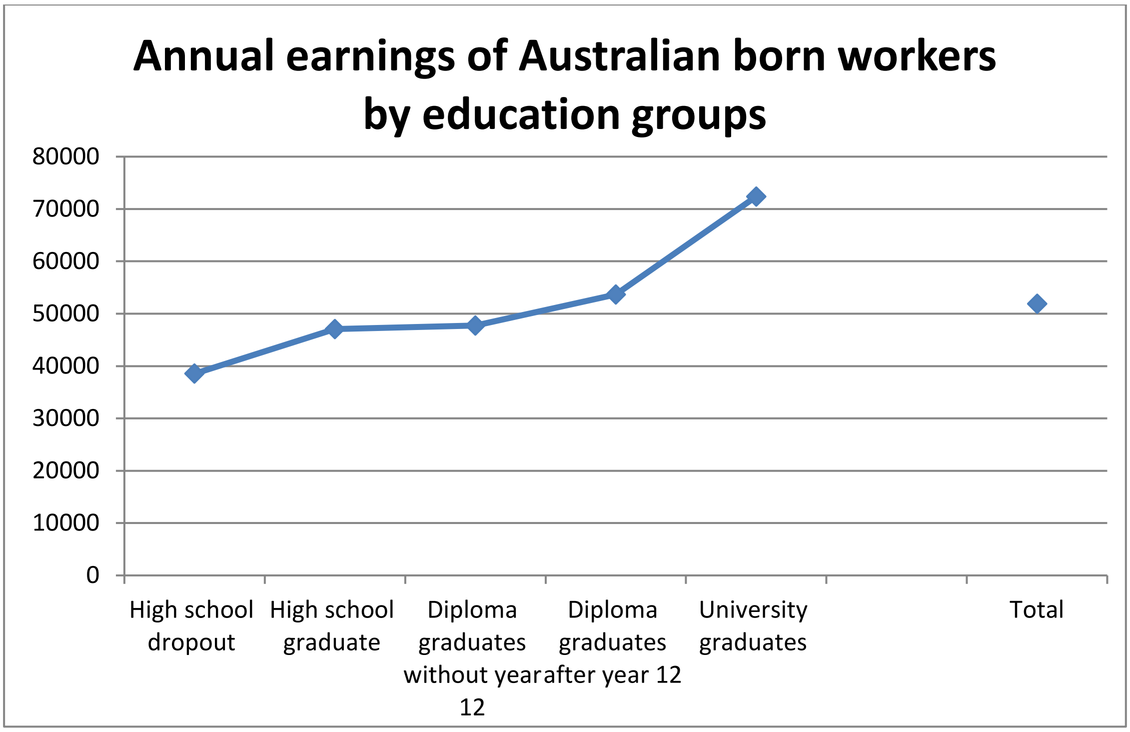

Figure 4: Annual earnings of Australian born workers by experience groups

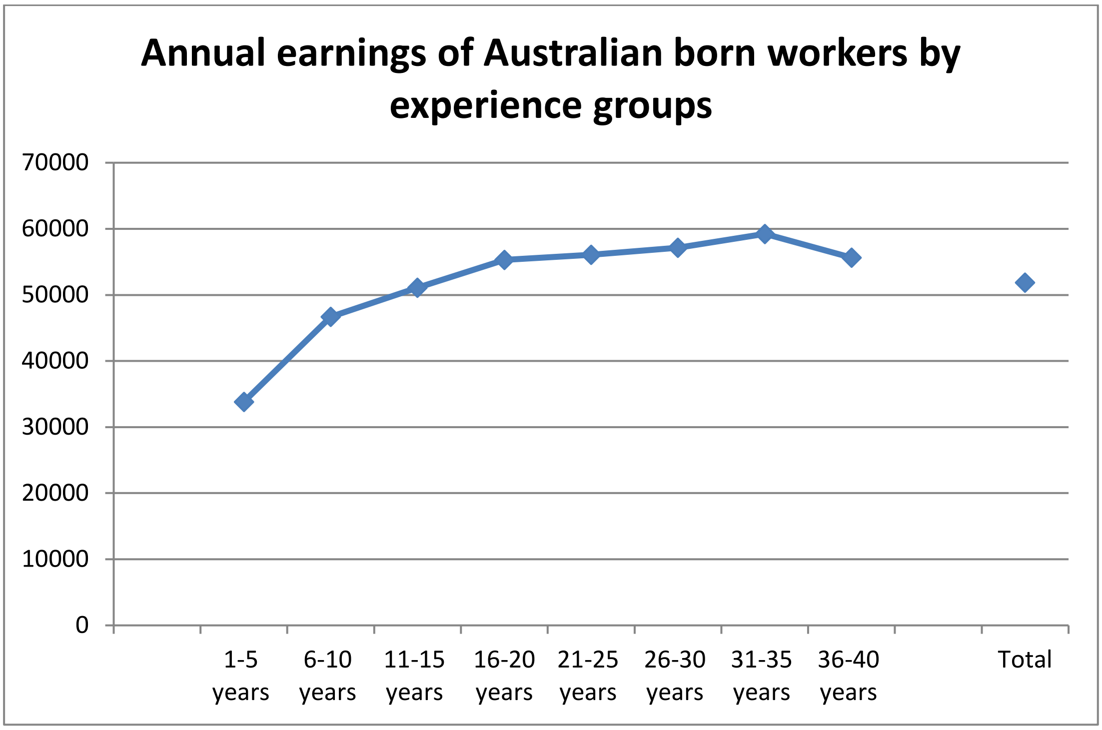

Figure 5: Unemployment rate of Australian born workers by education groups

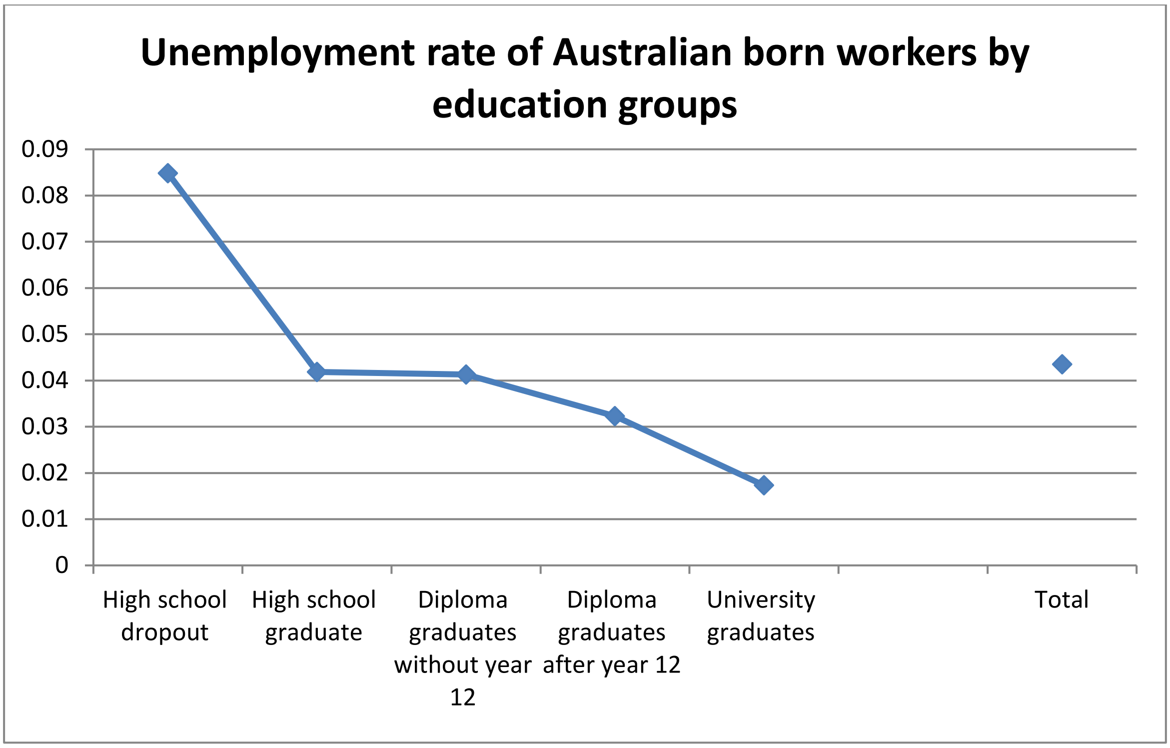

Figure 6: Unemployment rate of Australian born workers by experience groups

Figure 7: Distribution of migrant share changes between periods: SIH data

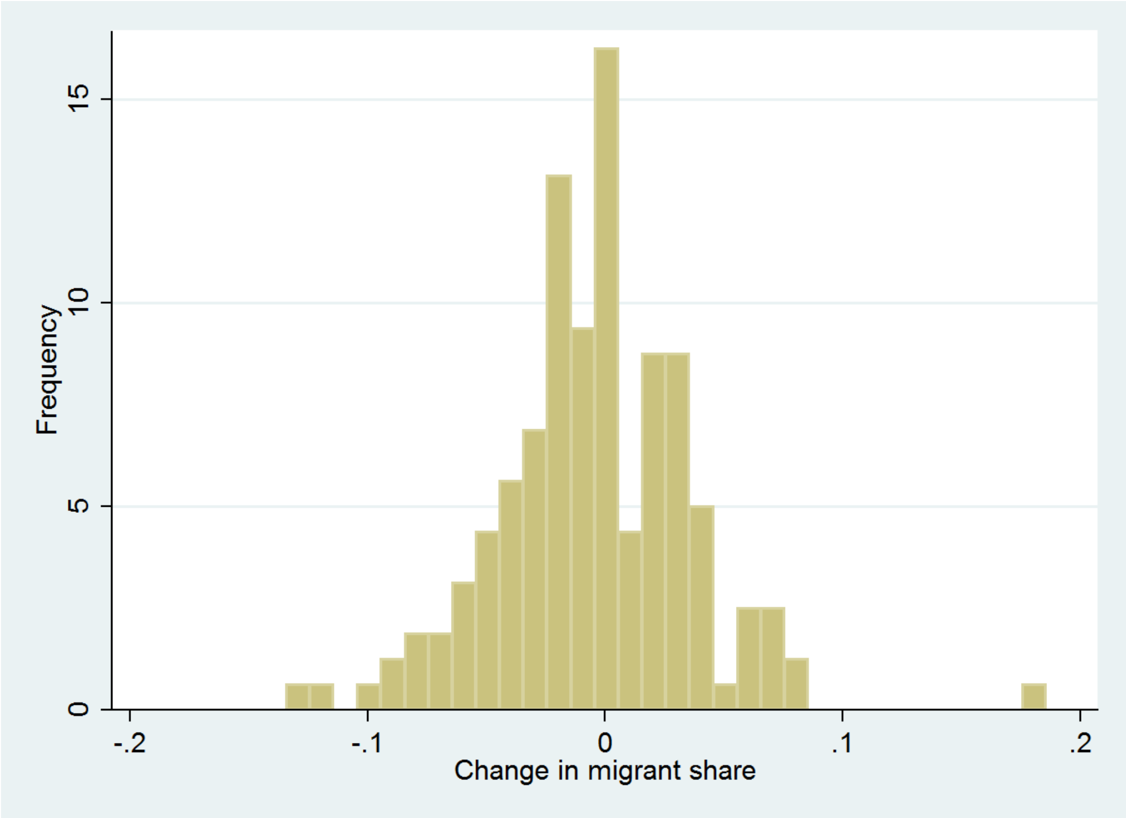

Figure 8: Distribution of migrant share changes between periods: Census data

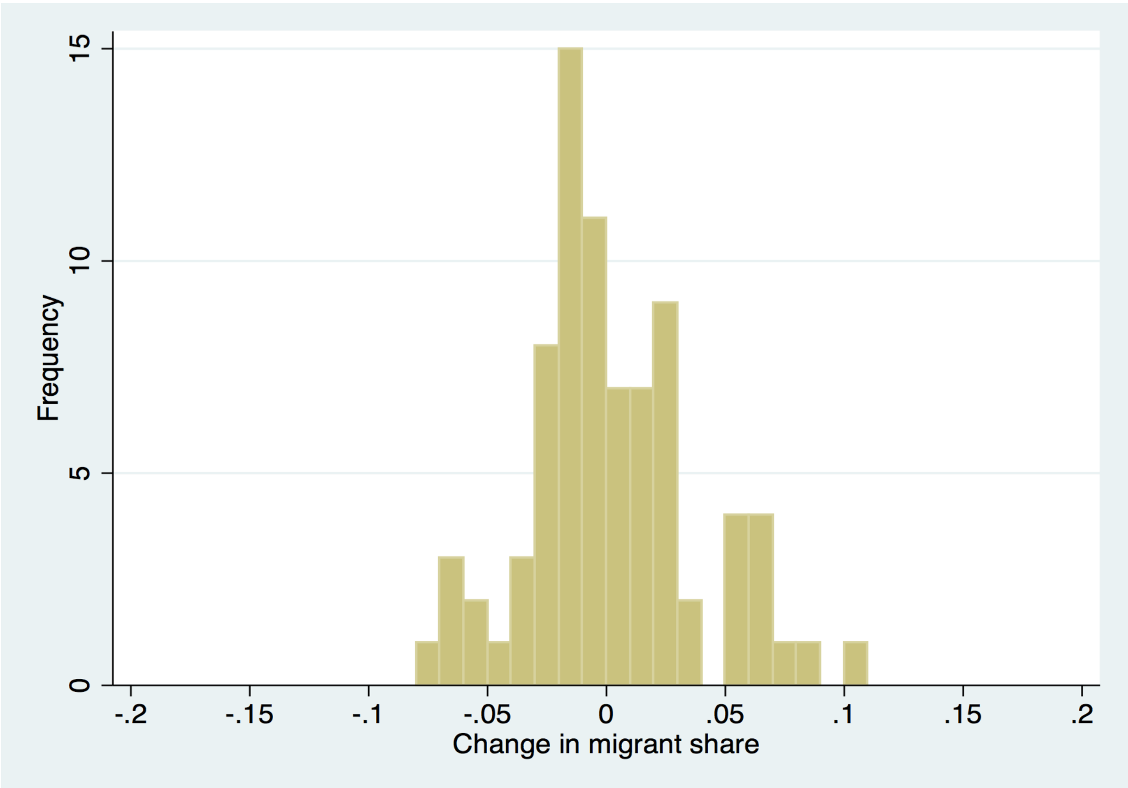

Table 1: Estimated values of θ from equation (1): SIH, full sample

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	1.879***	1.650***	1.510***	7.480**	0.240*	-0.205***
	(0.360)	(0.301)	(0.231)	(2.991)	(0.120)	(0.055)
Weighted, dummies but no interactions						
θ	-0.090	-0.086	-0.144**	0.089	0.108	-0.017
	(0.143)	(0.135)	(0.068)	(3.124)	(0.111)	(0.053)
Weighted, all dummies						
θ	0.175	0.021	-0.077	6.983	0.525**	-0.021
	(0.154)	(0.169)	(0.205)	(4.190)	(0.250)	(0.043)
Unweighted, all dummies						
θ	.388**	0.179	0.035	8.549*	.464**	-0.035
	(0.177)	(0.186)	(0.196)	(4.662)	(0.207)	(0.04)

Note: *,**,*** indicate statistical significance at the 10%, 5%, and 1% significance level respectively.

Table 2: Estimated values of θ from equation (1): HILDA and Census, full sample

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate†	Unemployment rate†
Weighted, time dummies only						
θ	2.016***	1.821***	1.686***	4.682	0.241**	-0.244***
	(0.404)	(0.337)	(0.245)	(4.193)	(0.119)	(0.066)
Weighted, dummies but no interactions						
θ	0.210	0.455***	0.243*	6.315	-0.007	-0.015
	(0.185)	(0.154)	(0.130)	(6.010)	(0.089)	(0.058)
Weighted, all dummies						
θ	0.267	0.752	0.612	11.349	0.074	0.076
	(0.666)	(0.607)	(0.413)	(14.997)	(0.081)	(0.047)
Unweighted, all dummies						
θ	-0.061	0.534	0.622	13.922	0.034	0.061
	(0.714)	(0.634)	(0.476)	(14.987)	(0.071)	(0.038)

Note: *,**,*** indicate statistical significance at the 10%, 5%, and 1% significance level respectively.
†Calculated from Census; otherwise calculated from HILDA

Table 3: Estimated values of θ from equation (1): SIH, selected sub-samples

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
male only						
θ	0.064	0.064	0.068	-0.848	0.131	-0.037
	(0.164)	(0.181)	(0.196)	(3.226)	(0.101)	(0.051)
female only						
θ	0.155	0.153	-0.029	8.112*	0.209*	-0.039
	(0.184)	(0.170)	(0.203)	(4.803)	(0.104)	(0.050)
all individuals with 15 years of experience or less						
θ	0.247	-0.082	-0.254	3.465	0.175	-0.098
	(0.332)	(0.445)	(0.406)	(9.117)	(0.207)	(0.094)
males with 15 years of experience or less						
θ	0.298	0.240	0.359	-5.202	-0.049	0.033
	(0.222)	(0.278)	(0.398)	(3.885)	(0.106)	(0.087)
females with 15 years of experience or less						
θ	0.071	-0.122	-0.038	7.417	0.100	-0.189*
	(0.348)	(0.354)	(0.586)	(7.253)	(0.160)	(0.099)

Models include full set of time dummies, education and experience fixed effects and full set of interactions

Note: *,**,*** indicate statistical significance at the 10%, 5%, and 1% significance level respectively.

Table 4: Estimated values of θ from equation (1): HILDA and Census, selected subsamples

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
male only						
θ	0.792	1.213	1.166	16.878	0.009	0.037
	(0.814)	(0.832)	(0.704)	(16.506)	(0.053)	(0.039)
female only						
θ	-1.105	-0.486	-0.673	8.443	-0.033	0.112**
	(0.784)	(0.747)	(0.531)	(18.539)	(0.092)	(0.050)
all individuals with 15 years of experience or less						
θ	0.038	0.593	0.230	-4.133	0.180*	0.167
	(0.432)	(0.504)	(0.694)	(24.168)	(0.096)	(0.110)
males with 15 years of experience or less						
θ	0.335	0.975	1.020	5.704	0.059	0.083
	(0.841)	(0.809)	(0.735)	(26.580)	(0.076)	(0.079)
females with 15 years of experience or less						
θ	-0.691	-0.370	-0.773	-7.373	-0.002	0.256*
	(1.295)	(1.259)	(0.840)	(32.681)	(0.101)	(0.134)

Models include full set of time dummies, education and experience fixed effects and full set of interactions

Note: *,**,*** indicate statistical significance at the 10%, 5%, and 1% significance level respectively.

Table 5: Estimated values of *θ* from equation (1): HILDA and Census, full sample (incumbents compared to recent immigrants)

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate†	Unemployment rate†
Weighted, time dummies only						
θ	0.142	0.529	0.564	-0.411	0.915***	-0.116
	(1.260)	(1.116)	(0.813)	(14.295)	(0.235)	(0.079)
Weighted, dummies but no interactions						
θ	0.211	0.141	-0.028	9.603	0.298**	-0.434***
	(0.316)	(0.296)	(0.287)	(12.951)	(0.132)	(0.125)
Weighted, all dummies						
θ	0.437	0.519	-0.516	35.527	0.287**	0.101
	(1.108)	(1.024)	(0.654)	(31.419)	(0.135)	(0.095)
Unweighted, all dummies						
θ	-0.224	-0.049	-0.647	26.260	0.280*	0.111
	(1.220)	(1.181)	(0.917)	(32.177)	(0.146)	(0.084)

Note: *,**,*** indicate statistical significance at the 10%, 5%, and 1% significance level respectively

†Calculated from Census; otherwise calculated from HILDA

Table 6: Three most common occupations by skill group and migrant / Australian-born status

Calculated from 2011 Census data

	Education	Experience	Top 3 professions (and fraction of workers in occupation)					
Migrants	Dropout	1-10 years	Labourers	0.285	Trades	0.191	Machinery	0.139
	Dropout	11-20 years	Labourers	0.276	Machinery	0.185	Trades	0.160
	Dropout	21-30 years	Labourers	0.235	Machinery	0.171	Clerical	0.154
	Dropout	31-40 years	Labourers	0.233	Clerical	0.178	Machinery	0.160
	Y12	1-10 years	Sales	0.216	Community	0.183	Labourers	0.175
	Y12	11-20 years	Clerical	0.174	Labourers	0.169	Trades	0.119
	Y12	21-30 years	Clerical	0.202	Labourers	0.155	Managers	0.149
	Y12	31-40 years	Clerical	0.203	Labourers	0.172	Managers	0.153
	Cert w/o Y12	1-10 years	Trades	0.410	Community	0.140	Labourers	0.121
	Cert w/o Y12	11-20 years	Trades	0.374	Community	0.125	Clerical	0.102
	Cert w/o Y12	21-30 years	Trades	0.323	Community	0.136	Managers	0.124
	Cert w/o Y12	31-40 years	Trades	0.310	Community	0.133	Managers	0.125
	Cert w Y12	1-10 years	Trades	0.256	Community	0.178	Labourers	0.126
	Cert w Y12	11-20 years	Trades	0.254	Professionals	0.152	Clerical	0.150
	Cert w Y12	21-30 years	Trades	0.226	Professionals	0.169	Clerical	0.152
	Cert w Y12	31-40 years	Trades	0.213	Professionals	0.185	Clerical	0.150
	Degree	1-10 years	Professionals	0.511	Clerical	0.139	Managers	0.094
	Degree	11-20 years	Professionals	0.537	Managers	0.166	Clerical	0.117
	Degree	21-30 years	Professionals	0.528	Managers	0.189	Clerical	0.110
	Degree	31-40 years	Professionals	0.554	Managers	0.177	Clerical	0.105

Table 6 (continued): Three most common occupations by skill group and migrant / Australian-born status

Calculated from 2011 Census data

Natives	Dropout	1-10 years	Trades	0.249	Labourers	0.229	Sales	0.155
	Dropout	11-20 years	Labourers	0.220	Machinery	0.192	Clerical	0.141
	Dropout	21-30 years	Clerical	0.211	Labourers	0.182	Machinery	0.163
	Dropout	31-40 years	Clerical	0.239	Labourers	0.177	Machinery	0.151
	Y12	1-10 years	Sales	0.255	Community	0.174	Clerical	0.162
	Y12	11-20 years	Clerical	0.249	Managers	0.160	Sales	0.130
	Y12	21-30 years	Clerical	0.294	Managers	0.191	Sales	0.115
	Y12	31-40 years	Clerical	0.293	Managers	0.213	Professionals	0.107
	Cert w/o Y12	1-10 years	Trades	0.482	Community	0.105	Clerical	0.094
	Cert w/o Y12	11-20 years	Trades	0.386	Managers	0.116	Clerical	0.108
	Cert w/o Y12	21-30 years	Trades	0.310	Managers	0.146	Clerical	0.132
	Cert w/o Y12	31-40 years	Trades	0.282	Managers	0.143	Clerical	0.139
	Cert w Y12	1-10 years	Trades	0.288	Clerical	0.175	Community	0.168
	Cert w Y12	11-20 years	Trades	0.247	Clerical	0.186	Managers	0.147
	Cert w Y12	21-30 years	Professionals	0.209	Clerical	0.179	Managers	0.175
	Cert w Y12	31-40 years	Professionals	0.283	Managers	0.180	Clerical	0.161
	Degree	1-10 years	Professionals	0.655	Managers	0.112	Clerical	0.101
	Degree	11-20 years	Professionals	0.601	Managers	0.199	Clerical	0.096
	Degree	21-30 years	Professionals	0.621	Managers	0.212	Clerical	0.083
	Degree	31-40 years	Professionals	0.643	Managers	0.198	Clerical	0.077

Table 7: Duncan index of dis-similarity for Australian-born and immigrant workers calculated from 2011 Census data (holding education constant)

Education-experience of native groups	Experience of corresponding immigrant group			
	1-10 years	11-20 years	21-30 years	31-40 years
High school dropouts				
1-10 years	0.097	0.182	0.197	0.209
11-20 years	0.173	0.097	0.040	0.063
21-30 years	0.240	0.195	0.107	0.081
31-40 years	0.261	0.225	0.137	0.108
Year 12				
1-10 years	0.099	0.244	0.266	0.282
11-20 years	0.271	0.148	0.104	0.121
21-30 years	0.332	0.209	0.169	0.188
31-40 years	0.354	0.222	0.183	0.197
Certificate (w/o Year 12)				
1-10 years	0.082	0.122	0.175	0.186
11-20 years	0.108	0.057	0.080	0.091
21-30 years	0.172	0.094	0.041	0.035
31-40 years	0.195	0.119	0.056	0.040
Certificate (w Year 12)				
1-10 years	0.114	0.132	0.168	0.199
11-20 years	0.198	0.080	0.078	0.101
21-30 years	0.294	0.150	0.108	0.105
31-40 years	0.355	0.211	0.163	0.146
Degree				
1-10 years	0.161	0.122	0.138	0.116
11-20 years	0.195	0.096	0.083	0.069
21-30 years	0.228	0.130	0.116	0.102
31-40 years	0.236	0.138	0.124	0.110

Numbers in table indicate the proportion of individuals who would have to change occupation to make the occupational distribution identical for two groups.

Table 8: Duncan index of dis-similarity for Australian-born and immigrant workers calculated from 2011 Census data (holding experience constant)

Education-experience of native groups	Education of corresponding immigrant group				
	High school dropout	Year 12	Certificate (w/o Year 12)	Certificate (w Year 12)	Degree
1-10 years					
High school dropout	0.097	0.252	0.246	0.200	0.585
Year 12	0.324	0.099	0.305	0.187	0.488
Certificate (w/o Year 12)	0.328	0.399	0.082	0.227	0.550
Certificate (w Year 12)	0.353	0.280	0.220	0.114	0.427
Degree	0.711	0.640	0.668	0.622	0.161
11-20 years					
High school dropout	0.097	0.155	0.346	0.332	0.568
Year 12	0.345	0.148	0.331	0.270	0.441
Certificate (w/o Year 12)	0.315	0.275	0.057	0.175	0.537
Certificate (w Year 12)	0.387	0.223	0.225	0.080	0.422
Degree	0.685	0.566	0.632	0.536	0.096
21-30 years					
High school dropout	0.107	0.112	0.349	0.346	0.556
Year 12	0.324	0.169	0.325	0.275	0.421
Certificate (w/o Year 12)	0.319	0.241	0.041	0.119	0.492
Certificate (w Year 12)	0.374	0.258	0.242	0.108	0.333
Degree	0.696	0.594	0.623	0.524	0.116
31-40 years					
High school dropout	0.108	0.096	0.354	0.346	0.564
Year 12	0.304	0.197	0.324	0.275	0.447
Certificate (w/o Year 12)	0.324	0.252	0.040	0.103	0.493
Certificate (w Year 12)	0.388	0.306	0.283	0.146	0.271
Degree	0.703	0.614	0.622	0.512	0.110

Numbers in table indicate the proportion of individuals who would have to change occupation to make the occupational distribution identical for two groups.

Table 9: Estimated values of θ from equation (1): HILDA and Census (incumbents compared to recent immigrants)
Broad experience groups and education categories (3 education categories and 4 experience categories)

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate†	Unemployment rate†
All incumbents						
θ	0.618	0.307	-2.587*	53.607*	0.580**	0.257
	(1.104)	(1.082)	(1.243)	(29.675)	(0.235)	(0.153)
Male only						
θ	0.430	0.371	-0.266	33.002	0.366*	0.306**
	(1.944)	(2.170)	(1.596)	(50.258)	(0.186)	(0.120)
Female only						
θ	1.226	0.444	-5.471***	91.568***	0.440	0.130
	(1.999)	(1.815)	(1.452)	(24.716)	(0.338)	(0.340)

Models include full set of time dummies, education and experience fixed effects and full set of interactions

Note: *,**,*** indicate statistical significance at the 10%, 5%, and 1% significance level respectively

†Calculated from Census; otherwise calculated from HILDA

Table 10: Effects of migrant share on Australian-born workers, identification through geographical variation

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
2011 Full Sample (OLS estimation) Census and HILDA	0.253 (0.185)	0.210 (0.193)	0.264 (0.202)	0.044 (2.678)	-0.023 (0.036)	0.028** (0.012)
2011 males (OLS estimation) Census and HILDA	0.065 (0.099)	0.058 (0.103)	0.041 (0.096)	0.495 (1.210)	-0.015 (0.015)	0.010** (0.005)
2011 males (OLS estimation) Census and HILDA	0.545*** (0.174)	0.519*** (0.157)	0.441*** (0.156)	3.020 (3.404)	0.015 (0.037)	0.006 (0.012)

Table 11: Effects of migrant share on Australian-born workers, identification through geographical variation

Variable	Unemployment rate (OLS)	Participation rate (OLS)	Unemployment rate (IV)	Participation rate (IV)
2001 and 2006 full sample Census data only	-.087 (.099)	.008 (.104)	-.0112 (.024)	-.065 (.048)
2001 and 2006 males Census data only	.049 (.134)	-.100 (.102)	0.007 (0.032)	-0.032 (0.047)
2001 and 2006 females Census data only	-.238** (.098)	.073 (.169)	-0.027 (0.018)	-0.059 (0.054)

Table A: Selected changes to Australia's migration policy

Year	*Action*
1973	Trans-Tasman Travel Arrangement between Australia and New Zealand introduced
1977	First tailored Humanitarian Program commenced operation
1996	Temporary Business (long stay) 457 visas introduced
1999	Migration Occupations in Demand (MODL) introduced
2001	Australian-educated overseas students made eligible for permanent residence
2003	Increase in points awarded for Australian honours, masters and PhD degrees
2004	MODL expanded to include accountants and a number of trade occupations
2005	Trade Skills Training Visa introduced
2006	Increase in base level of English proficiency required
2008	'Demand-driven' model for permanent skilled migration introduced Introduction of Critical Skills List (CSL) for independent skilled visa applicants
2009	Changes to CSL to focus it on health, medical, engineering and IT professionals
2010	MODL revoked and a Skilled Occupation List introduced Certain occupations (catering and hairdressing) removed
2011	Enterprise Migration Agreements introduced Revised points list
2012	SkillSelect introduced
2013	Business Innovation and Investment Programme introduced Significant Investor Visa introduced
2014	Designated Area Migration Agreements introduced

(Edited and updated from Productivity Commission (2010), Table 4.2, page 27 which details *Selected changes to Australia's immigration policy from 1973 - 2010.*)