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

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Foreword

The Commission contracted Professor Robert Breunig and his team (Nathan Deutscher and Dr Hang Thi To) from the Crawford School of Public Policy at the Australian National University to provide an independent economic analysis of immigrants' impacts on labour market outcomes of incumbents in Australia. This technical supplement presents their preliminary paper. Their final paper will be published with the final report of the inquiry in March 2016.

The Commission welcomes comments and feedback on this draft paper.

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

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Preliminary

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 no evidence that immigration harms the labour market outcomes of those born in Australia.

1 Introduction

The impact of immigration on Australian-born workers, particularly on their wages and their employment prospects, is a question that can provoke heated and emotional debate. Anecdote and visceral impressions can easily dominate either side of the public conversation. 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.

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.

These 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 up 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 Australian-born labour market outcomes, after controlling for environmental 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. Secondly, it allows for geographic equalization in labour markets, which is ruled out in approaches that identify the impact of immigration by the spatial distribution of immigrants.

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. In one set of analysis 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. In a second set of analysis, we match census data to the Household, Income and Labour Dynamics in Australia (HILDA) survey. In this case we use HILDA to estimate 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 are high and unemployment is low. We find no evidence that outcomes for those born in Australia have been harmed by immigration. If anything, there is some evidence that immigration has had a small positive effect on 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.

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 total workers 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 workers in cell (i, j, t). We estimate the following specification:

[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.

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

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.

The model includes time dummies to account for changes in the macroeconomic environment that affect all groups. By including dummies for education and experience and their interaction, we account for the supply and demand factors specific to each skill group that determine the overall level of labour market outcomes for that skill group. Interacting education and experience with time dummies allows the profile of skill 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 only the HILDA data to assess the effects of immigration on weekly earnings and weekly hours worked of Australian-born workers. They found that immigrant share has a positive effects on Australian-born workers' earnings and weekly hours worked. Their approach is flawed however because they used HILDA for both the outcome data and the immigrant share data.

Since HILDA is a panel with an initial sample chosen in 2001, there is no inflow of migrants into the sample. 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 (or join the HILDA sample through one of the other following rules of the data). Immigrant flows can not be captured in any meaningful sense through this panel data set.

Sinning and Vorell (2011) investigate both attitudes towards the effects of immigration on the labour market and crime, and the actual effects themselves. To do the latter they estimate the effect of immigration on SLA median income and unemployment and LGA crime rates. They use data from 1996, 2001 and 2006 Censuses and crime statistics. To address selection issues, they instrument immigration stock in a period with a counterfactual immigration stock created under the assumption that new immigrants settle according to the last-period distribution of immigrants. The second stage regressions include regional controls such as median age, population size, educational and occupational distributions and region and time fixed-effects. In neither of these preferred models is the immigration coefficient statistically significant, however, their instrument is weak, with a first stage F-statistic below 10 when both period and time fixed effects are included, clouding the interpretation of these results.

The geographic approach of Sinning and Vorell (2011) (and many others) 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, see Bakhtiari and Breunig (2015).

Our approach allows for a national-level labour market but assumes no substitutability across skill groups. Essentially, we assume fixed and distinct labour markets defined by skill groups (rather than by sub-national geographic regions as in the geographic approach). Workers and firms are assumed unable to change the skill group in which they supply or demand labour in response to prices. Given skill groups are defined broadly and in terms of experience and education levels that are not able to be altered by workers, and mobility across occupations, industries and regions is still permitted, this assumption seems less problematic than strict geographical segregation. It is an important restriction and one discussed further in section 5.

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. Private dwellings are houses, flats, home units, caravans, garages, tents and other structures that were used as places of residence at the time of interview. Long-stay caravan parks are also included. These are distinct from non-private dwellings, such as hotels, boarding schools, boarding houses and institutions, whose residents are excluded. The SIH contains a wide range of information on demographic and economic characteristics of individuals and households.

In the second part of our analysis, we use data drawn from the Household, Income and Labour Dynamics in Australia (HILDA) combined with data from the Australian Census of Population and Housing.

The HILDA survey is a household-based panel study that collects information on respondents' economic and demographic characteristics. The wave 1 HILDA survey was conducted in 2001 and has been conducted annually since. The vast majority of data was collected through face-to-face interviews and a small fraction of the data was collected through telephone interviews. 13,969 people were interviewed in wave one 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 census data thus excludes those who intend to stay in Australia for less than one year.[2] Census data contains information in related topics such as age, gender, education, birthplace, employment status of all people in Australia on Census Night.[3]

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 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 are representative cross-sections in each year.

In the second part, we estimate the model of equation (1) using HILDA data combined with Census data for three years 2001, 2006 and 2011. The explanatory variable of interest, the share of immigrants in each skill group, is extracted from Census data. For the dependent variables relating to 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 from HILDA data is not an appropriate indicator for immigrant share in Australia over time because the same sample of respondents is followed over time in the survey. The hours worked and income data from HILDA can be reasonably assumed to be representative for the matching cohort of Australian-born in the Census.

[2] We thank Jenny Dobak of the Australian Bureau of Statistics (ABS) for clarifying this.

[3] We use the entire census data to construct our estimates of the fraction of immigrants in each skill group. For 2006 and 2011, this data is available online through the ABS table builder product. 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.

Descriptive statistics, from the SIH, of the main variables used in the analysis are provided in Figures 1 to 6. Figure 1 presents the migrant share for each education-experience cell. The Figure shows that 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. With the same experience, annual earnings are 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.

Figure 7 presents migrant share by education and experience from the Census data and Figure 8 shows annual earnings by education and experience from HILDA. The overall impression provided by the two data sets is quite similar.

Figures 9 and 10 show the distribution of changes over time in the key variable p_{ijt} in the two data sets—Census and SIH. 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.

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 .10. In the SIH, the average is slightly negative (-0.0049), the minimum is -0.13 and the maximum change is 0.18. 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.

4 Empirical results

We estimate models of the labour market outcomes of Australian-born workers (including annual earnings, 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) model controlling for education, experience, time and the interactions between dummy variables that allow for changing skill premium over time.

We present weighted regressions using the weights defined as the number of Australian-born workers or the number of incumbents in each education-experience cell. This gives larger influence to those skill groups with more workers, which is an appropriate way to reflect the underlying uncertainty in how closely mean cell values reflect underlying population means. 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.

The results from SIH data are presented in Tables 1 to 6 and results from HILDA data for wages matched to census data for immigrant shares by experience/education cells are reported in Tables 7 to 12.

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 interaction between education and experience and interactions with time which allow skill premium to vary across time. Unweighted estimates are provided in row 4 for comparison. The weighted estimates with a full set of shift and interaction dummies are our preferred model.

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

The effects are very small and only significant at the 10 per cent level. If the share of immigrants goes up by 5 percentage points (from say 20% to 25%), this is associated with an increase in weekly working time of about 20 minutes. Tables 1 and 2 present information on the between-period changes in immigrant share for both data sets. While there are some large changes, on average, the changes are very small—on the order of one percentage point.

The results for the HILDA/Census data are quite similar—see Table 7. 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 mostly disappear. We do find a small, statistically significant relationship between immigrant share on the unemployment rate. If the share of immigrants goes up by 5 percentage points, this is associated with a 0.4 percentage point increase in the unemployment rate. In contrast, there is a positive relationship between immigration on log hourly wage which just falls below the 10 per cent level of significance.

Overall, the results show strong evidence for migrant selection. Migrants are flowing 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 HILDA and the census, we see some negative association between immigration and unemployment. In all cases, these associations are small in size and only significant at the 10 per cent level.

We re-do the estimation, splitting the sample by male/female. (See Tables 2-3 and 8-9.) For men, in both data sets, we find no statistically significant association between immigration and labour market outcomes. In SIH, both the positive association between immigration and hours and participation seem to be concentrated in the female sub-sample. In Census and HILDA, we find a positive association between immigration and the unemployment rate, that is that more immigration seems related to more unemployment. The effect 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 (from say 20% to 25%), the unemployment rate for females increases by about 0.6 percentage points. Note that we only find this effect in the combined HILDA/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. 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.

It may be that the labour market outcomes of different types of workers in fact have different responses to immigration in which case 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.

The results are broadly consistent with what we find in the main sample. For the SIH (see Tables 4 through 6) the only statistically significant relationship that we find is for females. Specifically, we find that increased immigration is associated with decreased unemployment. (See Table 6.)

In the HILDA / Census data (see Tables 10 through 12), we find no relationship between any of the earnings variables and immigration for this younger group. We do find a weak positive association between immigration and participation in the full sample (Table 10). We again find a positive relationship between immigration and unemployment for females (Table 12).

Through 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 very long time. To check if our results are driven by how we classify individuals, we re-estimate the model comparing `incumbents' to `immigrants'. We define incumbents as those born in Australia plus those who have migrated to Australia more than five years previously. Immigrants are now re-defined as those who migrated to Australia within the last five years.

We are only able to do this 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 13.

We find that recent immigration is positively associated with the participation rate of incumbents, but otherwise find no significant relationship between recent immigration and the labour market outcomes of incumbents. We only present the results for the full sample as splitting by male and female does not provide any additional insight.

Overall, 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.

5 Discussion and conclusion

In this paper we use a simple and data driven approach to address whether or not the labour market outcomes of Australian-born workers are related to patterns of migration. We do this by constructing 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 no evidence that the labour market outcomes of Australian-born workers are negatively related to immigration. If anything, there is some evidence for small positive associations. However, these associations are economically small and only just statistically significant, so the evidence is scant. Our results are consistent across two very different data sets.

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 (defined by education and experience) is an individual labour market and that there is no substitutability of workers across different labour markets. Specifically, the approach is assuming 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.

A separate, but related question, is whether or not immigrants with a particular level of education and experience are competing against Australian-born workers with the same levels of experience and education. It could be that experience and education obtained outside of Australia has a lower value in the local labour market and that in fact these 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.

In future work, we plan to examine this issue by looking at the similarity of wages and occupations between immigrants and Australian-born individuals within skill group cells. Early analysis suggests migrants within a particular skill group have an occupational profile that is most similar to Australian-born workers with similar skills (see Table 14). Within our sample there is not evidence of large-scale occupational downgrading by migrants.

We will also use different classifications into skill groups for individuals to test the robustness of our results to the specific education-experience groups used. Some papers have argued that there should be many fewer education-experience cells. We will estimate models with 9 or 12 groups instead of 40. Early work in this area suggests that the broad story remains the same. Migrants move into better performing labour markets, but there is no strong evidence of statistically significant associations between immigration and the labour market outcomes of the Australian-born.

It is important to note however 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.

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 no 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, they 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 the reality is that we do not 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 need to be living in private dwellings in order to be counted. If short-term migrants are living in hostels or other 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, that 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.

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Figure 1 **Migrant share by Education and Experience: SIH**

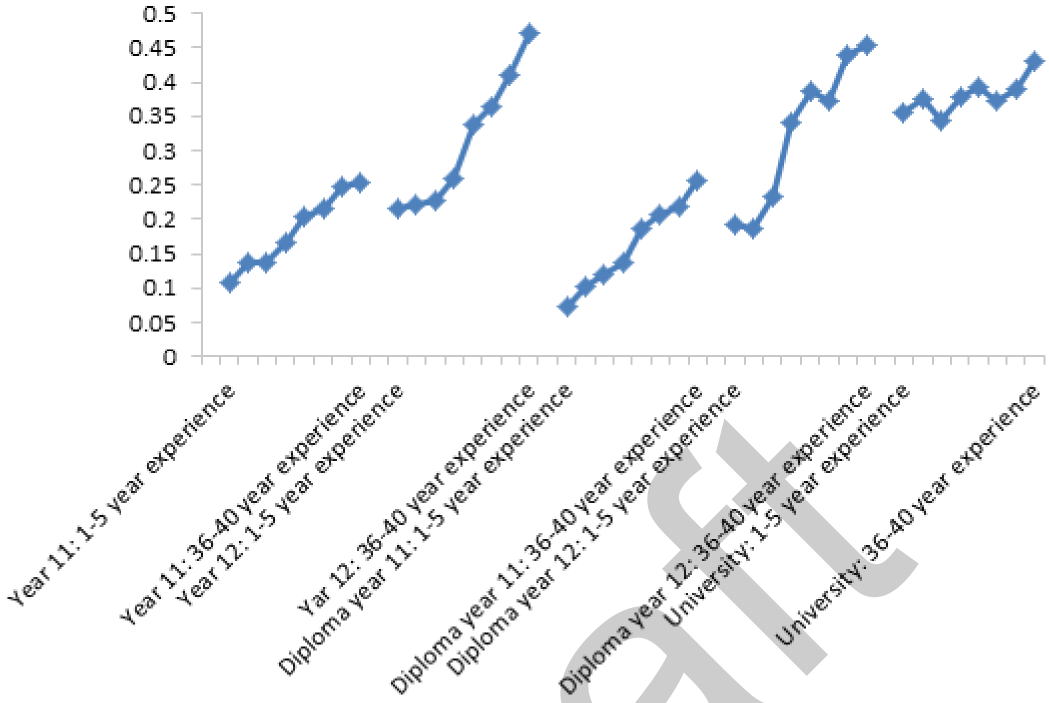

Figure 2 **Annual earnings of Australian born workers by education and experience: SIH**

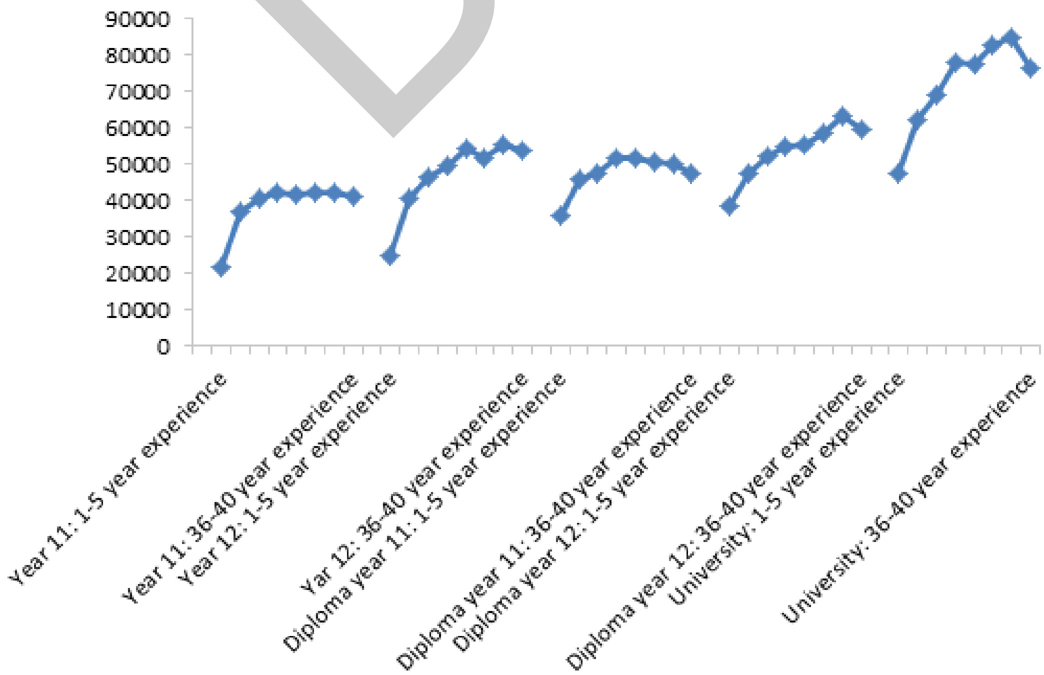

Figure 3 **Annual earnings of Australian born workers by education groups**

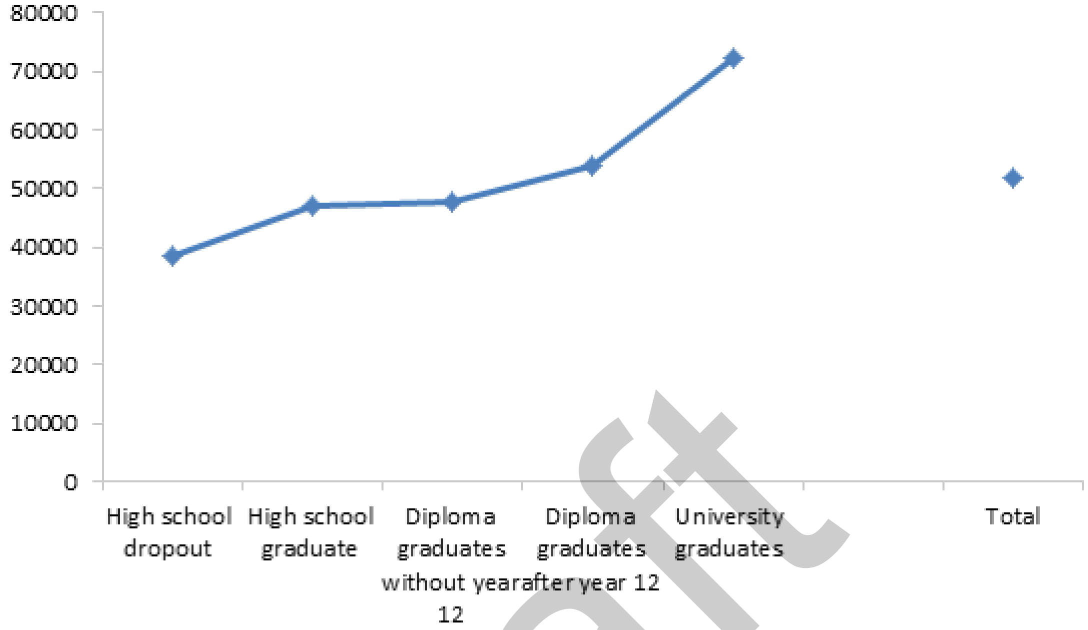

Figure 4 **Annual earnings of Australian born workers by experience groups**

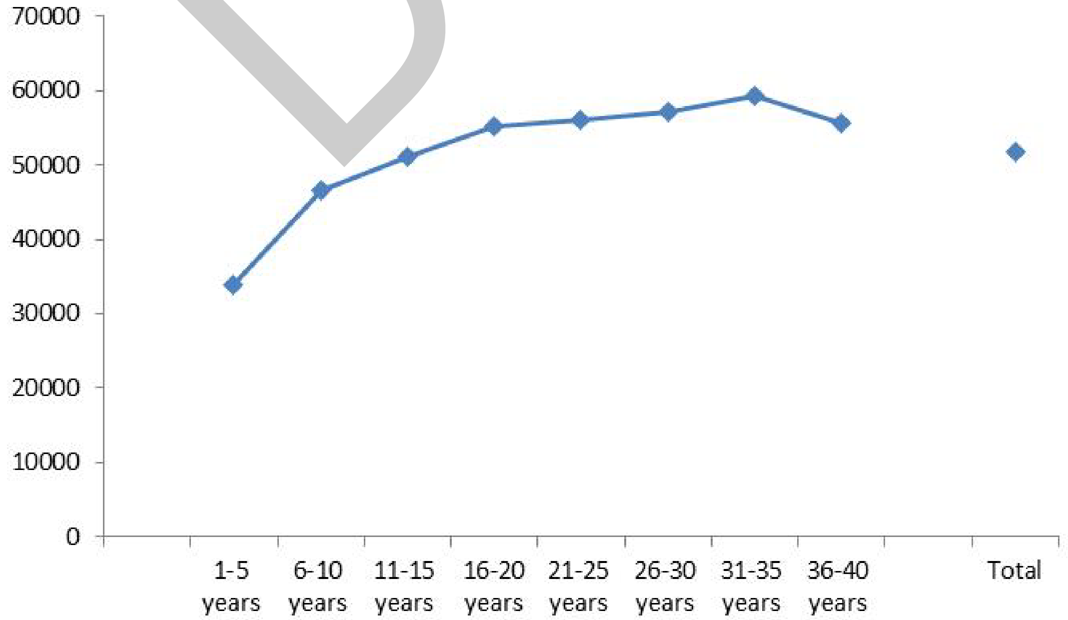

Figure 5 **Unemployment rate of Australian born workers by education groups**

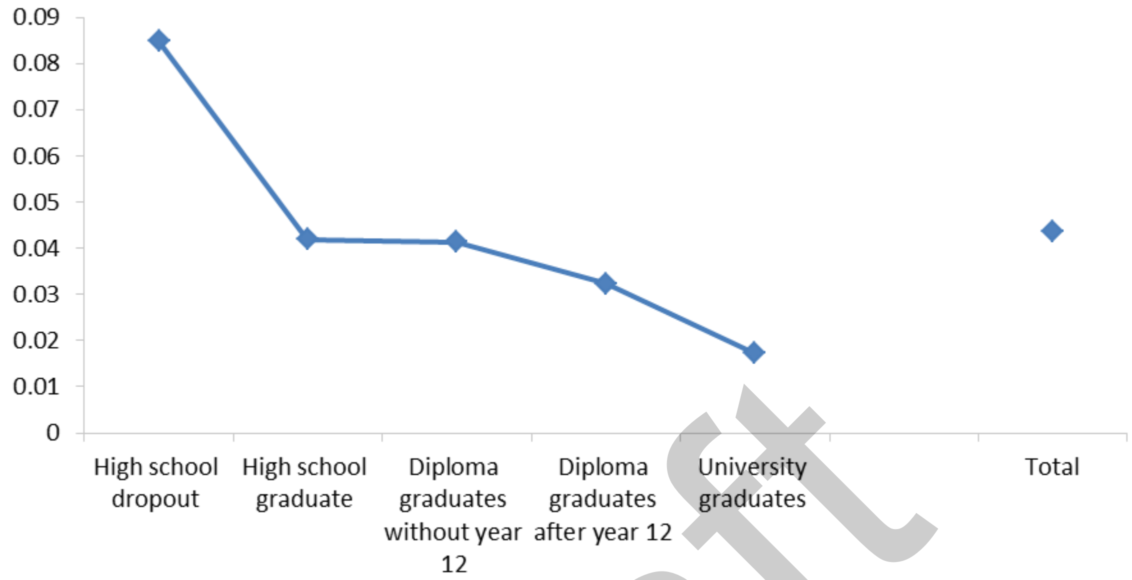

Figure 6 **Unemployment rate of Australian born workers by experience groups**

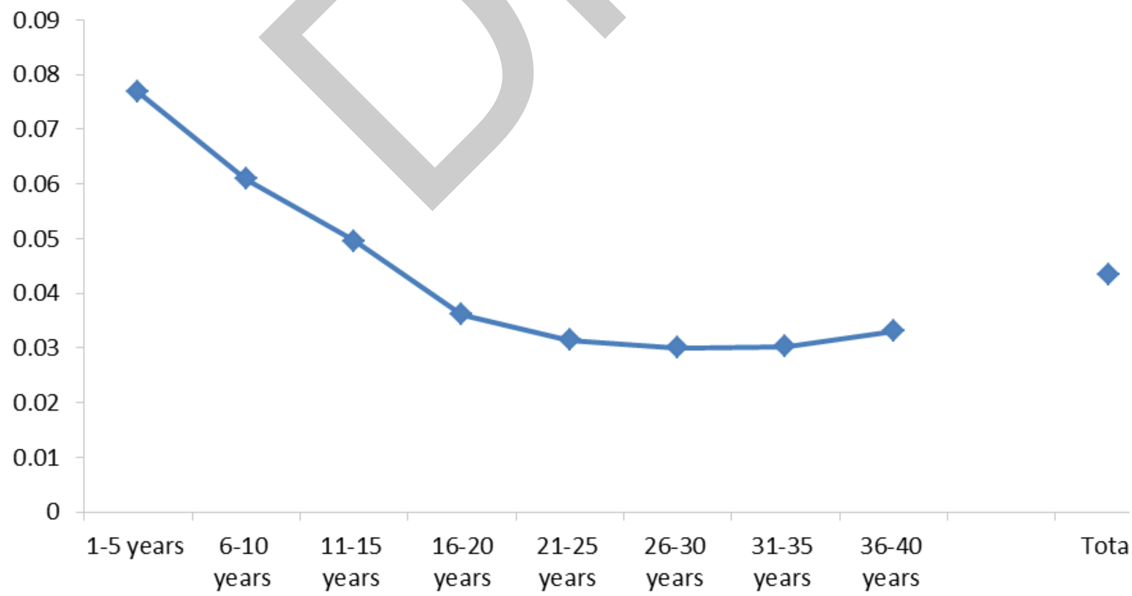

Figure 7 **Migrant share by education and experience, Census**

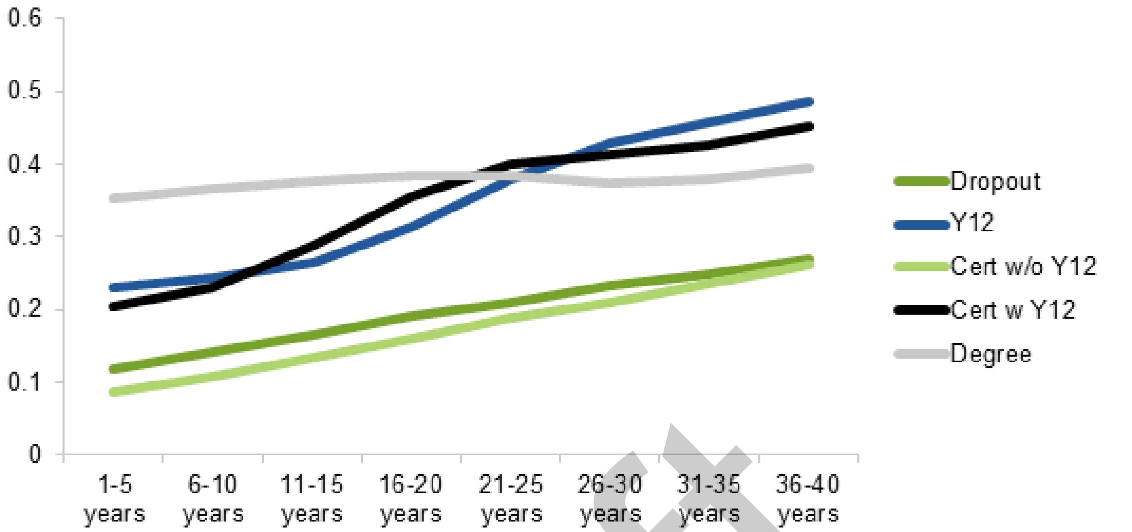

Figure 8 **Annual earnings by education and experience, HILDA**

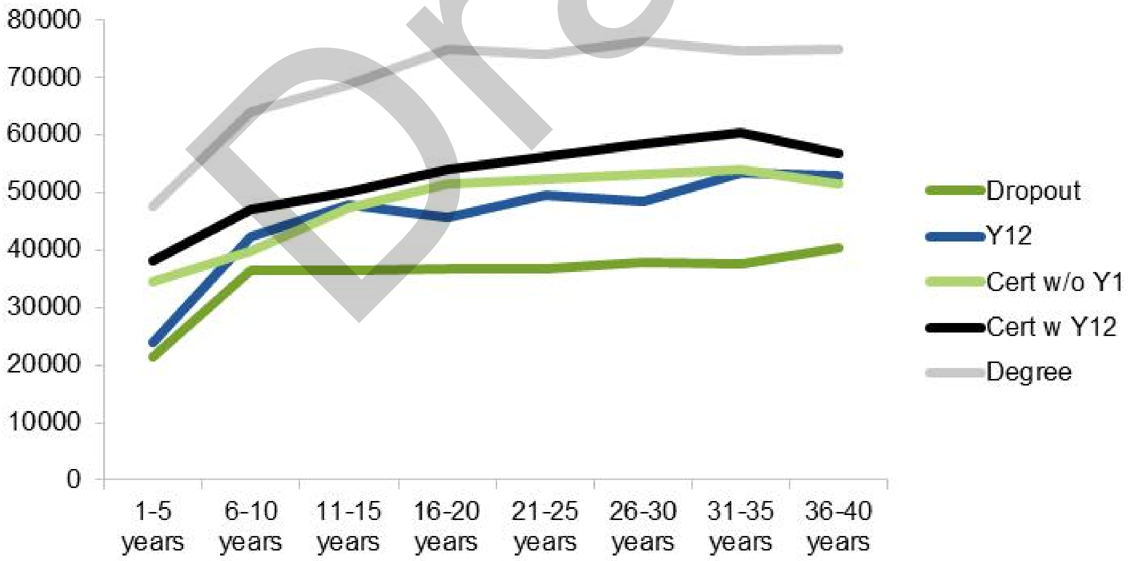

Figure 9 **Distribution of migrant share changes between periods: Census data**

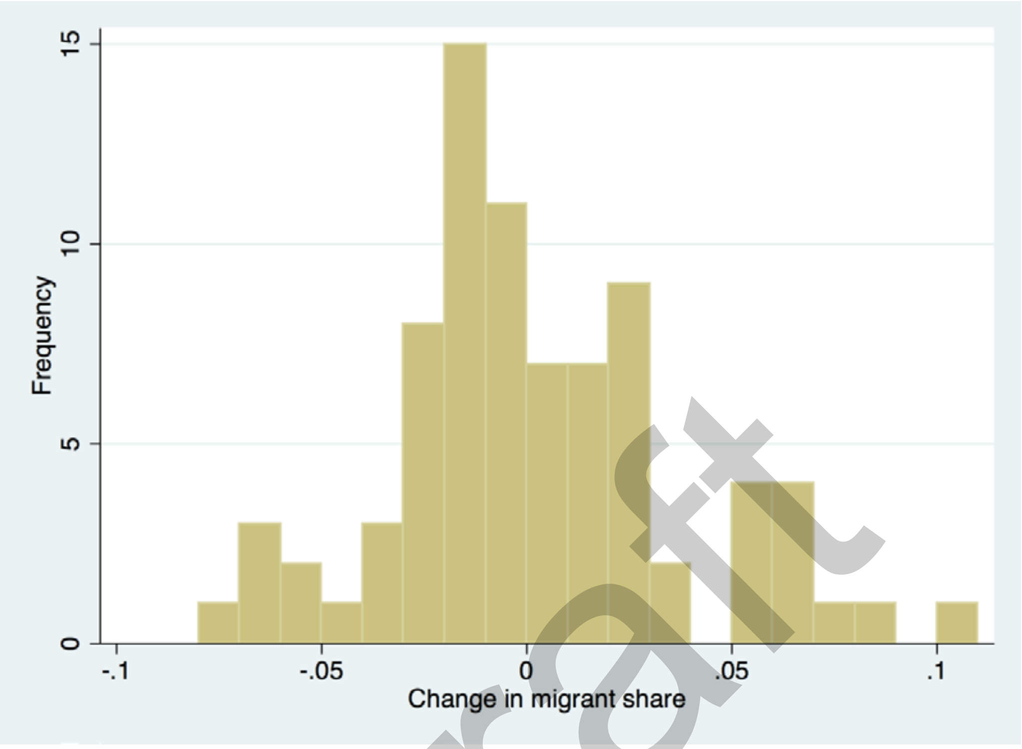

Figure 10 **Distribution of migrant share changes between periods: SIH data**

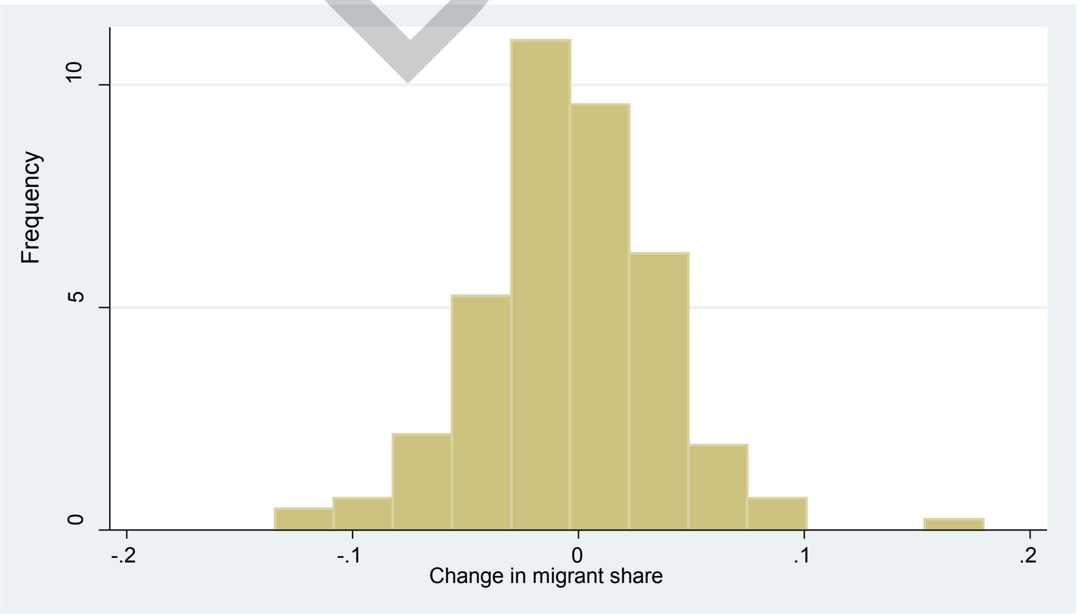

Table 1: Estimated values of θ from equation (1): SIH, full sample

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	1.910***	1.654***	1.516***	7.427**	.244**	-.216***
	(.370)	(.303)	(.233)	(2.899)	(.120)	(.059)
Weighted, dummies but no interactions						
θ	-0.060	-0.058	-.1259*	0.627	0.080	-0.007
	(0.151)	(0.142)	(0.072)	(3.238)	(0.095)	(0.057)
Weighted, all dummies						
θ	0.188	0.032	-0.081	7.153*	.464**	-0.025
	(0.162)	(0.180)	(0.198)	(4.291)	(0.213)	(0.044)
Unweighted, all dummies						
θ	.388**	0.179	0.035	8.549*	.464**	-0.035
	(0.177)	(0.186)	(0.196)	(4.662)	(0.207)	(0.040)

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

Table 2: Estimated values of θ from equation (1): SIH, male only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	1.891***	1.625***	1.535***	5.736*	.063	-.169***
	(.405)	(.319)	(.250)	(3.184)	(.095)	(.056)
Weighted, dummies but no interactions						
θ	-0.191	-0.168	-.173*	-1.674	0.012	-0.014
	(0.119)	(0.116)	(0.091)	(2.866)	(0.058)	(0.037)
Weighted, all dummies						
θ	0.089	0.095	0.070	-0.407	0.113	-0.043
	(0.169)	(0.189)	(0.201)	(3.458)	(0.084)	(0.054)
Unweighted, all dummies						
θ	0.082	0.061	0.055	0.455	0.132	-0.063
	(0.190)	(0.198)	(0.226)	(3.642)	(0.094)	(0.061)

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

Table 3: Estimated values of θ from equation (1): SIH, female only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.053***	1.855***	1.384***	17.18***	.484***	-.254***
	(.335)	(.311)	(.234)	(4.046)	(.156)	(.063)
Weighted, dummies but no interactions						
θ	-0.083	-0.058	-0.077	-0.610	-0.007	-0.006
	(0.124)	(0.122)	(0.084)	(2.878)	(0.120)	(0.059)
Weighted, all dummies						
θ	0.173	0.161	-0.022	8.451*	.208*	-0.042
	(0.185)	(0.173)	(0.204)	(4.887)	(0.104)	(0.055)
Unweighted, all dummies						
θ	.2894	.298	-0.019	10.002*	.210*	-0.020
	(.252)	(.260)	(.221)	(5.497)	(.105)	(.043)

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

Table 4: Estimated values of θ from equation (1): SIH, 15 years of experience or less

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	1.880**	1.652***	1.557***	6.535	.442**	-.339***
	(.611)	(.483)	(.379)	(4.439)	(.146)	(.096)
Weighted, dummies but no interactions						
θ	-0.082	-0.152	-0.230	2.310	0.129	-.131**
	(0.215)	(0.211)	(0.148)	(4.231)	(0.097)	(0.057)
Weighted, all dummies						
θ	0.263	-0.064	-0.227	3.222	0.175	-0.096
	(0.329)	(0.443)	(0.386)	(9.157)	(0.207)	(0.089)
Unweighted, all dummies						
θ	0.309	-0.133	-0.196	1.070	0.219	-0.025
	(0.323)	(0.441)	(0.335)	(9.050)	(0.248)	(0.083)

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

Table 5: Estimated values of θ from equation (1): SIH, 15 years of experience or less, male only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	1.642**	1.396**	1.383***	4.672	.232**	-.250**
	(.649)	(.522)	(.386)	(5.298)	(.094)	(.085)
Weighted, dummies but no interactions						
θ	-0.179	-0.252	-0.161	-5.697*	0.000	-0.044
	(0.196)	(0.245)	(0.181)	(3.189)	(0.066)	(0.069)
Weighted, all dummies						
θ	0.318	0.243	0.365	-5.364	-0.049	0.036
	(0.229)	(0.277)	(0.393)	(4.016)	(0.106)	(0.088)
Unweighted, all dummies						
θ	0.287	0.198	0.368	-6.402	-0.057	0.027
	(0.199)	(0.257)	(0.360)	(4.300)	(0.109)	(0.096)

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

Table 6: Estimated values of θ from equation (1): SIH, 15 years of experience or less, female only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.568***	2.407***	1.770***	21.90***	.779**	-.428***
	(.483)	(.386)	(.328)	(6.568)	(.220)	(.106)
Weighted, dummies but no interactions						
θ	0.057	0.024	-0.093	7.536	0.117	-.173*
	(0.262)	(0.223)	(0.226)	(6.093)	(0.137)	(0.082
Weighted, all dummies						
θ	0.122	-0.064	0.022	8.046	0.100	-.183*
	(0.357)	(0.353)	(0.546)	(7.343)	(0.160)	(0.099)
Unweighted, all dummies						
θ	0.086	-0.235	-0.202	6.511	0.221	-0.132
	(0.359)	(0.339)	(0.465)	(7.387)	(0.202)	(0.123)

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

Table 7: Estimated values of θ from equation (1): HILDA, full sample

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.010***	1.786***	1.648***	5.175	0.241**	-0.261***
	(0.382)	(0.313)	(0.227)	(3.919)	(0.119)	(0.071)
Weighted, dummies but no interactions						
θ	0.183	0.481***	0.263*	6.078	-0.007	-0.007
	(0.189)	(0.165)	(0.141)	(5.824)	(0.089)	(0.065)
Weighted, all dummies						
θ	0.058	0.621	0.669	10.884	0.074	0.082*
	(0.645)	(0.603)	(0.398)	(15.484)	(0.081)	(0.048)
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.

Table 8: Estimated values of θ from equation (1): HILDA, male only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.108***	1.842***	1.730***	5.397	0.097	-0.222***
	(0.401)	(0.321)	(0.231)	(4.425)	(0.094)	(0.071)
Weighted, dummies but no interactions						
θ	0.211	0.454**	0.290*	8.814	0.001	-0.013
	(0.240)	(0.209)	(0.167)	(6.630)	(0.083)	(0.053)
Weighted, all dummies						
θ	0.619	1.155	1.092	17.855	0.009	0.039
	(0.794)	(0.812)	(0.668)	(17.650)	(0.053)	(0.040)
Unweighted, all dummies						
θ	0.604	1.194	1.196*	18.35	-0.014	0.027
	(0.836)	(0.809)	(0.646)	(18.73)	(0.043)	(0.034)

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

Table 9: Estimated values of θ from equation (1): HILDA, female only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.190***	2.028***	1.589***	15.337***	0.502***	-0.303***
	(0.370)	(0.322)	(0.241)	(4.782)	(0.162)	(0.073)
Weighted, dummies but no interactions						
θ	0.098	0.356*	0.285	0.027	-0.077	0.012
	(0.275)	(0.207)	(0.228)	(7.585)	(0.130)	(0.074)
Weighted, all dummies						
θ	-1.067	-0.583	-0.468	8.176	-0.033	0.124**
	(0.769)	(0.791)	(0.519)	(19.932)	(0.092)	(0.052)
Unweighted, all dummies						
θ	-0.718	-0.232	-0.476	19.85	-0.037	0.099**
	(0.730)	(0.764)	(0.568)	(21.28)	(0.079)	(0.039)

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

Table 10: Estimated values of θ from equation (1): HILDA, 15 years of experience or less, full sample

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.328***	2.041***	1.845***	9.459	0.461**	-0.398***
	(0.629)	(0.503)	(0.382)	(6.225)	(0.166)	(0.120)
Weighted, dummies but no interactions						
θ	0.010	0.222	0.241	7.005	0.103	-0.027
	(0.502)	(0.301)	(0.223)	(9.792)	(0.085)	(0.055)
Weighted, all dummies						
θ	-0.028	0.576	0.517	-8.579	0.180*	0.179
	(0.464)	(0.539)	(0.700)	(23.87)	(0.096)	(0.109)
Unweighted, all dummies						
θ	-0.038	0.658	0.550	-8.074	0.151	0.171
	(0.498)	(0.571)	(0.698)	(25.65)	(0.104)	(0.104)

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

Table 11: Estimated values of θ from equation (1): HILDA, 15 years of experience or less, male only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.183***	1.867***	1.645***	10.106	0.271**	-0.314**
	(0.674)	(0.539)	(0.360)	(6.938)	(0.122)	(0.115)
Weighted, dummies but no interactions						
θ	0.025	0.325	0.302	10.47	0.057	0.006
	(0.464)	(0.319)	(0.207)	(9.753)	(0.095)	(0.052)
Weighted, all dummies						
θ	0.322	1.139	1.290	4.434	0.059	0.086
	(0.859)	(0.784)	(0.743)	(26.85)	(0.076)	(0.081)
Unweighted, all dummies						
θ	0.368	1.217	1.260*	7.792	0.043	0.091
	(0.881)	(0.706)	(0.692)	(27.80)	(0.071)	(0.076)

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

Table 12: Estimated values of θ from equation (1): HILDA, 15 years of experience or less, female only

	Log annual earnings	Log weekly earnings	Log of wage rate	Weekly hours	Participation rate	Unemployment rate
Weighted, time dummies only						
θ	2.995***	2.829***	2.216***	22.86**	0.917***	-0.504***
	(0.507)	(0.386)	(0.382)	(9.508)	(0.247)	(0.124)
Weighted, dummies but no interactions						
θ	0.312	0.387	0.303	6.596	0.103	-0.053
	(0.699)	(0.435)	(0.407)	(11.606)	(0.102)	(0.059)
Weighted, all dummies						
θ	-0.796	-0.607	-0.485	-14.50	-0.002	0.274*
	(1.311)	(1.328)	(0.856)	(32.68)	(0.101)	(0.130)
Unweighted, all dummies						
θ	-1.170	-0.356	-0.595	-11.03	0.026	0.272**
	(1.106)	(1.375)	(0.978)	(33.80)	(0.119)	(0.116)

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

Table 13: Estimated values of θ from equation (1): HILDA, 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	0.277	0.683	0.622	2.677	0.915***	-0.110
	(1.272)	(1.131)	(0.820)	(14.30)	(0.235)	(0.086)
Weighted, dummies but no interactions						
θ	0.178	0.138	-0.026	8.848	0.298**	-0.478***
	(0.309)	(0.295)	(0.292)	(12.72)	(0.132)	(0.136)
Weighted, all dummies						
θ	0.091	0.274	-0.482	29.89	0.287**	0.119
	(1.152)	(1.095)	(0.717)	(32.47)	(0.135)	(0.101)
Unweighted, all dummies						
θ	-0.224	-0.049	-0.647	26.26	0.280*	0.111
	(1.220)	(1.181)	(0.917)	(32.18)	(0.146)	(0.084)

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

Table 14: Three most common occupations by skill group and migrant / Australian-born status

	Education	Experience	Top 3 professions					
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
Australian born	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