Migration and labour market outcomes

Gabriela D'Souza[*]

Introduction

This paper uses the methodology employed by Breunig et al [2017] to identify the labour market effects of migration. The initial paper was commissioned by the Productivity Commission as supplemental analysis to its report investigating Australia's migrant intake. In the years since the publication of this report and analysis immigration has become a much more pertinent topic of discussion among policy-makers. In light of renewed debate on the increasing number of migrants into Australia and the impacts this has on the labour market, a revisit of the Breunig et al [2017] paper was deemed essential.

The focus of the report, which this short research note accompanies, is temporary migration. The analysis conducted here might cover some temporary migrants but is unable to provide a granular picture. This was in part due to the inadequacy of current data sources in identifying temporary migrants. For example, there are no apparent datasets that collect information on immigrants at the individual level and that contain information about visa subclass. The best data available to date on the labour market outcomes of temporary migrants is the ACTEID dataset. However this this only allows the user to investigate the outcomes of migrants on the aggregate via TableBuilder. It is currently not available to researchers at the individual level. Another challenge for migration researchers when analysing temporary migration is the short duration for which temporary migrants call Australia home.

Temporary migrants often do not stay in Australia for very long and can fall outside of the remit of regular surveys administered by statistical agencies. And, in instances where temporary migrants are surveyed, they are often not asked specific questions about the visa they arrived on or the visa they are currently on which may not be the same. Compounding these challenges is that access to data on temporary migrants is restricted and difficult to obtain, making program evaluation challenging.

Some research has relied on administrative data, however this is not readily available to researchers outside of the public sector. This forces researchers to adopt imperfect approaches to evaluating the program including making key assumptions about the current visa status of migrants.

Context

Much of the debate on migration, particularly as it pertains to temporary workers, has revolved around whether migrants take away the jobs of local workers. That is, do migrants take on jobs that would have otherwise been filled by Australian skilled workers. Indeed this fear about temporary migrants taking the jobs of local workers underpins many of the protections and restrictions on migrants' access to, and eligibility for, visas to live and work in Australia.

The balance of these protections has changed frequently in step with community apprehension about jobs and wages. Nonetheless, the focus remains on these concerns and not the benefits to business and the wider economy of being able to boost the availability of skills and experience.

Independent modelling commissioned by the Productivity Commission [Breunig et al., 2017] found no concrete evidence that the entry of migrants had a negative effect on the labour market outcomes of Australian-born workers, or incumbent workers (migrants that had arrived in previous years). In the years since the publication of the final Productivity Commission report, immigration has become a more prominent topic in the national policy debate, albeit more focused on permanent migration.

The growing number of migrants, both temporary and permanent, make a revisit of the research examining the impacts of migrants on the local labour market an important contribution to the current policy debate.

[*] Affiliate researcher at Monash University, Department of Econometrics and Business Statistics

The literature on the effects of migration in Australia is relatively limited, with most of our insight on this effect coming from overseas. Some of the most cited and popular studies use a natural experiment, the Mariel Boatlift. The south of Florida experienced an influx of migrants over a short period of time, between 15 April and 31 October 1980. This increased the Miami labour force by seven percent and provided economists with a natural experiment - a sudden change in the usual operation of the labour market, which allowed researchers to examine the impact of changes on local workers. Card [1990] found that the influx of workers had no effect on the wages or unemployed rates of less skilled workers, or on the outcomes of migrants who had arrived earlier. Borjas (2017), using the same experiment, found that the Marielitos – the new migrants – had a negative impact on the labour market outcomes of high school dropouts. He reasoned that high school dropouts would be most affected by the entry of low-skilled migrants. Further research by Clemens and Hunt [2017] suggested that the reason for these differences in estimates was because of differences in composition of the survey sample.

Other research borrows models from the international trade literature and uses skill-share instruments to identify the impact of migrants on local labour markets. Much of the predominantly USA analysis aims to identify the impact of migrants on the outcomes of US born workers. Borjas [2003], found that the influx of migrants into closed labour markets worsened the employment prospects of US born workers. However a review of this research by Card and Peri [2016] has since refuted those claims suggesting that the effects depend upon the substitutability between the local and native sub populations. Card and Peri [2016] also assert that the results obtained from using Borjas [2003] are negatively biased. That is if the estimates of wage impacts are negative, the true effect is likely to be either less negative than displayed, or even positive. If the estimates of correlation between proportion of migrants and wages are positive, it is likely that the true results are more positive than those displayed.

Some local estimates, which use similar methodology to the one chosen here, suggest that the effects are positive, as in the case of Parasnis et al [2006] which used Census of population and housing data from 1981, 1986, 1991, 1996 and 2001. Using different segments of the population Breunig et al. [2017] find no evidence of a negative effect on local workers from the increase in migration over the years 2001-2011.

Methodology description

This paper uses new waves of the ABS Survey of Income and Housing data to derive estimates of the impact of migrants on the labour market outcomes of local workers. A number of labour market outcomes were considered including labour force participation rate, weekly wages, annual earnings and unemployment rate.

This paper uses skill shares instead of location-based shares as the former places less restrictions on the ability of the model to take into account that people may move location to improve their pay or employment propsects. Previous literature looked at location-specific effects however this, has been deemed to be an ineffective way of measuring the impact of migration as it does not allow for flexibility movement of migrants and natives in their job search[Brell and Dustmann, 2019].

This paper uses skill-shares variables to estimate the relationship between immigration and local labour market outcomes. In order to do this, the working age population was divided into five education groupings as below:

1. High school dropouts (no further education)
2. High school graduates (no further education)
3. High school dropouts with cert/diploma level qualification
4. High school graduates with cert/diploma level qualifications
5. Bachelor and postgraduate degree holders.

For each level of education an archetypal age was created, at which a person in that category would enter the labour market, typically 17 years old for High school dropouts; 19 years for High school graduates; 21 years for those whose highest qualification was at Certificate or diploma level; and 23 years for bachelor and postgraduate degree holders.

Based on the age at which the person entered the labour market, a potential experience variable was created, which is defined as the difference between age and the age at entry into the labour market. PPersons in the sample were then divided into 8 different experience groups each spanning 5 years.

Recent migrants were definted as those who had arrived in Australia after 1996, and those who were either born in Australia or arrived before 1996 were defined as incumbents. Most of the analysis that follows concerns migrants that arrived after 1996. Nineteen ninety-six is a watershed moment as it marked the beginning of subsequent waves of temporary skilled migration in Australia. In addition to this, the permanent migrant intake began to skew much more in favour of skilled migration than family migration after 1996.

For each grouping of education and experience group at a particular point in time, the impact of recent migrants on that particular skills grouping was estimated using the following regression.

$$w_{ijt} = \theta_W p_{ijt} + s_i + r_j + \pi_t + s_i \times r_j + s_i \times \pi_t) + t_j \times \pi_t) + \epsilon_{ijt}$$

Where θ_W is our parameter of interest. p_{ijt} is the proportion of migrants within each education-experience cell and $p_{ijt} = \frac{M_{ijt}}{M_{ijt}+N_{ijt}}$

w_{ijt} refers to the outcomes of local workers in each of the education-experience categories listed earlier, at a given point in time. The parameter of interest that is to be estimated and an inference drawn from is the θ_W, parameter, which represents the extent to which migrants affect the outcomes contained in w_{ijt}. The other variables included in the earlier equation allows the researcher to control for education (r_j), experience (s_i) and time (π_t).

So for each possible grouping of education, and skills at a particular point in time, we estimate the impact of the migrants on that particular skills grouping.

Some caveats

The version of the microdata we were able to access classifies some categories differently to what is in the expanded CURF (Confidentialised Unit Record Files) categories [1]

There were data inconsistencies between the different years of the Survey of Income and Housing and therefore some assumptions had to be made and make some variables were imputed.

1. Country of birth variable is not available in the basic CURF so the YOABC variable, which is the year of arrival in Australia, had to be used The drawback to this is that the most recent arrival category is 1996 to year of collection which is 20 years ago.

2. Age categories in the basic data have been collapsed so the age groups have been split assuming a random allocation to single ages. This has ruled out the use of survey weights in the estimates. However we do not expect this to be an issue as weights are determined by groupings of the local labour market.

Descriptive statistics

Figure 1 shows the average annual earnings of workers by the different education groups for the 2015-16 sample of the Survey by migrant classification (born in Australia versus not). Bachelor and postgraduate degree holders out-earn on average almost all other education categories. On average, it appears that migrants earn less than Australian-born workers across all categories. However, looking at other sources like the ACTEID (figures available in the main report), we find that migrants in certain categories, like 457 visaholders, tend to have higher annual earnings than permanent migrants and Australian-born workers. The difference between these two results could be due to two reasons

[1] Future improvements to the ABS data catalogue through Datalab should make future work using these datasets much easier.

2. The two groups are different. The results here pertain to migrants (anyone in the survey who was not born in Australia)

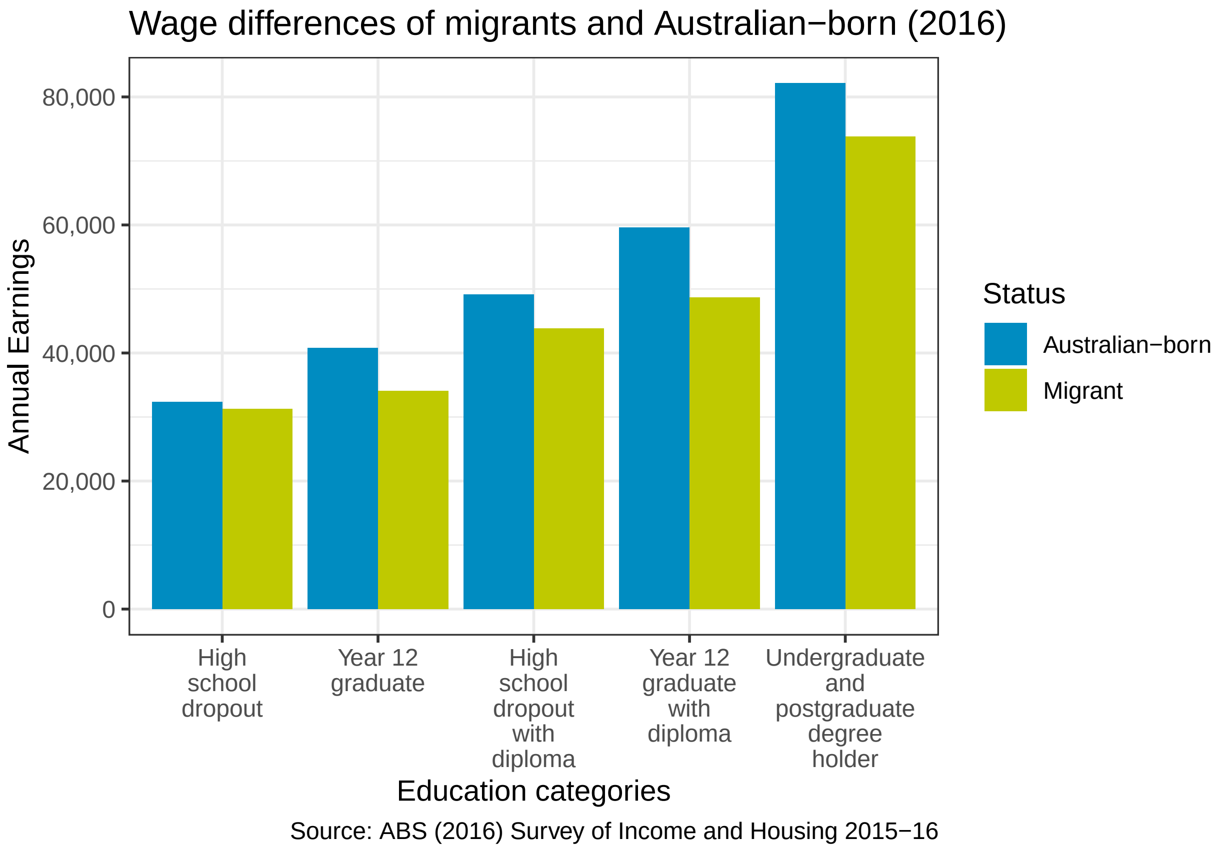
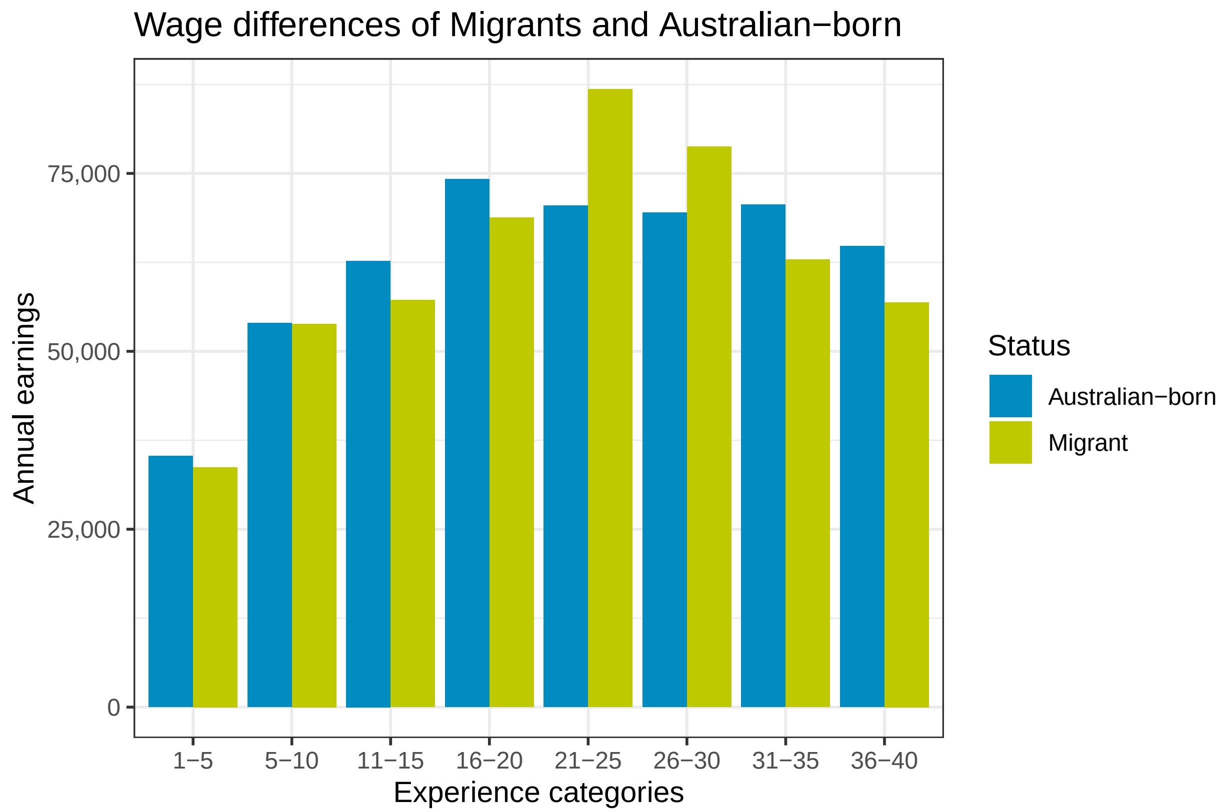
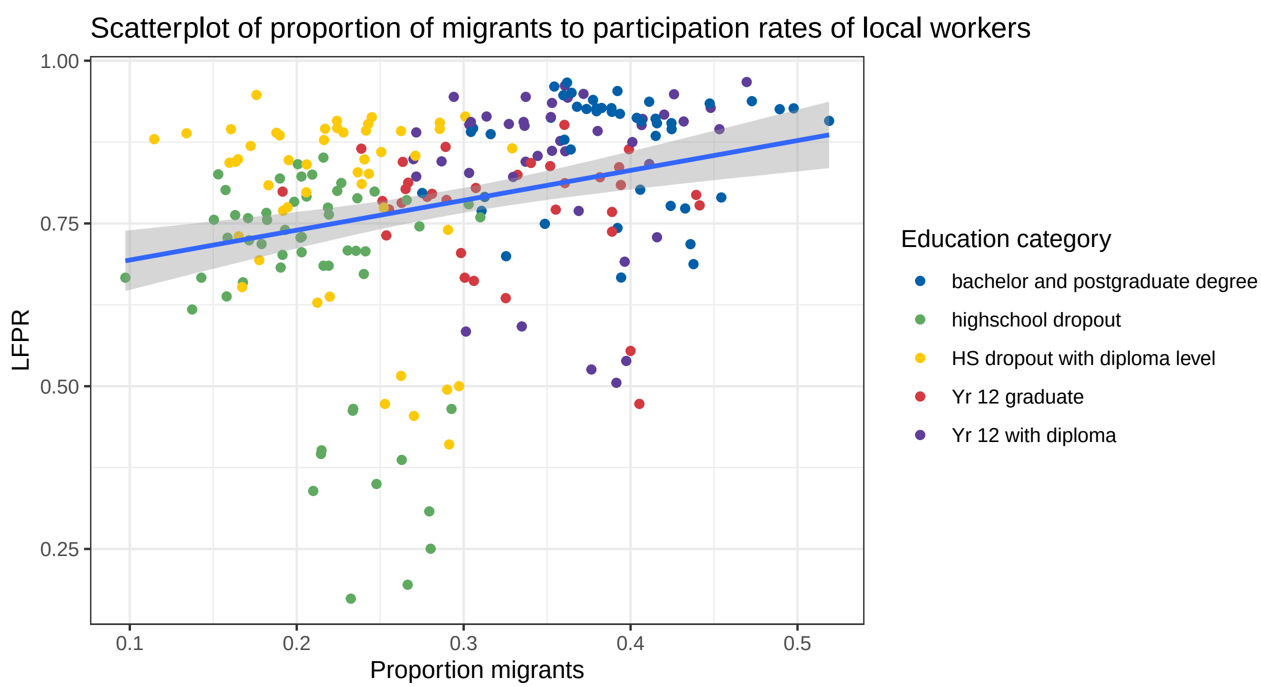


Figure 2 shows the average annual earnings of migrants and Australian-born by experience categories. Migrants earn more than Australian-born workers in the 21-30 years of experience category, but the reverse is true for other experience categories. This is partly because migrants, who are newer entrants to the labour market have not had the necessary experience to gain an increase in their earning potential. In addition to this, theory suggests that more time spent in the labour market allows workers to adapt to the local labour market and gain more information about the jobs that are best suited to their skills [Ioannides and Datcher Loury, 2004].



Source: ABS (2016) Survey of Income and Housing 2015−16

Figure 3 shows rgw relationship between the labour force participation rate of the different education categories and migrants across the full sample of data (years 2003-2016). Occupations with higher levels of qualifications also have high concentrations of migrants. A slight positive correlation between migrant concentration and labour force participation rates of local workers is observed.



Source: Authors' analysis of ABS (2017) Survey of Income and Housing 2003−2016

Results

This section presents the results of the regression. In each education experience cell we regressed the year, education, experience variables and migrant proportion on the relevant labour market outcome. The regressions that follow use the outcomes of incumbents both those who were born in Australia and those who arrived before 1996 as the dependent variable. The methodology used here closely follows that of Borjs [2003] and Breunig et al [2017]. Our estimates vary quite significantly from those of Borjas [2003] but follow closely those found by Breunig et al [2017] with some noticeable differences (for more on this see Table 1 in Chapter 2 of the main report).

Table 5 presents the final estimates of the regression. These estimates are weighted and standard errors are clustered at the education category level. For the labour force participation rate we weight the estimates by the local population; for wages (both annual and weekly) we weight the estimates by the local persons employed. For the unemployment rate we weight the estimates by the local labour force.

First we look at the unemployment rate of workers. We regress the variables - education category , experience, and year against the unemployment rate of incumbent workers and find a negative relationship between immigrant concentration in a skill-education group and the unemployment rate of local workers. Caution should be exercised when interpreting this figure as this effect is not statistically significant.
On the participation rate we find that recent migrants is associated with a significant positive effect on the participation of local workers.
Weekly wages and recent migrant concentration is positively associated, however this relationship is not statistically significant. However we find that there is a statistically significant positive relationship between the wages earned by incumbent workers and recent migrants.

Table 5: Weighted estimates of regressions

	Beta	std.error	p-value
Annual wage	0.8920375	0.2226076	0.0000614
Labour participation rate	0.9574894	0.4437301	0.0309419
Weekly wage	0.2229411	0.2695213	0.4081382
Unemployment rate	-0.0254201	0.0484258	0.5996332

Conclusion

This paper has looked at the possible impact of recent migrants on the local labour market outcomes of incumbent workers (Australian-born workers and those who arrived before 1996). The evidence presented here suggests that the outcomes of local workers has not been adversely affected by recent migrants (defined as those who have arrived in Australia since 1996). In this paper we look at four different labour market outcomes of incumbent workers - the unemployment rate, the labour force participation rate, weekly wages and annual earnings. We find that the recent migrants have a negative but statistically not significant effect on the unemployment rate of local workers. We find a positive relationship between the labour force participation rate of local workers and the proportion of migrants. We also find that wages are positively correlated with proportion of migrants. We note that these estimates are likely to be negatively biased (see Card and Peri [2016] for more on this), so the true results could be even more positive than those displayed here.

In conclusion our research upholds the findings of the Breunig et al [2017] paper. We find that immigration has largely been a positive for incumbent workers with positive effects observed when considering a number of outcomes of local workers.

References

George J Borjas. The labor demand curve is downward sloping: Re-examining the impact of immigration on the labor market. *The quarterly journal of economics*, 118(4):1335–1374, 2003.

Courtney Brell and Christian Dustmann. Immigration and wage growth: The case of australia. Technical report, Centre for Research and Analysis of Migration, 2019.

Robert Breunig, Nathan Deutscher, and Hang Thi To. The relationship between immigration to australia and the labour market outcomes of australian-born workers. *Economic Record*, 93(301):255–276, 2017.

David Card. The impact of the mariel boatlift on the miami labor market. *ILR Review*, 43(2):245–257, 1990.

David Card and Giovanni Peri. Immigration economics by george j. borjas: a review essay. *Journal of Economic Literature*, 54(4):1333–49, 2016.

Michael A Clemens and Jennifer Hunt. The labor market effects of refugee waves: reconciling conflicting results. *ILR Review*, page 0019793918824597, 2017.

Yannis M Ioannides and Linda Datcher Loury. Job information networks, neighborhood effects, and inequality. *Journal of economic literature*, 42(4):1056–1093, 2004.

Jaai Parasnis, Dietrich Fausten, Russell Smyth, et al. The impact of immigration on native workers in australia. Technical report, Monash University, Department of Economics, 2006.

Table 1: Weighted regression estimates for unemploymentrate

	(1)	(2)	(3)
(Intercept)	0.069 ***	0.094 ***	0.113 ***
	(0.005)	(0.004)	(0.007)
year2005-06	-0.008	-0.009 *	-0.021 *
	(0.008)	(0.004)	(0.010)
year2007-08	-0.006	-0.009 *	-0.027 *
	(0.008)	(0.004)	(0.011)
year2009-10	0.006	0.008 *	0.012
	(0.007)	(0.004)	(0.009)
year2011-12	0.003	0.001	-0.002
	(0.007)	(0.004)	(0.010)
year2013-14	0.014	0.010 *	0.001
	(0.007)	(0.004)	(0.009)
year2015-16	0.016	0.028 ***	0.053 ***
	(0.009)	(0.005)	(0.013)
proportion migrant	-0.191 ***	-0.047 *	-0.025
	(0.031)	(0.021)	(0.022)
educat		-0.011 ***	-0.017 ***
		(0.001)	(0.002)
experiencegroup		-0.005 ***	-0.011 ***
		(0.001)	(0.001)
year2005-06:experiencegroup			0.002
			(0.002)
year2007-08:experiencegroup			0.005 *
			(0.002)
year2009-10:experiencegroup			0.002
			(0.002)
year2011-12:experiencegroup			0.002
			(0.002)
year2013-14:experiencegroup			0.002
			(0.002)
year2015-16:experiencegroup			-0.001
			(0.002)
year2005-06:educat			0.002
			(0.003)
year2007-08:educat			0.000
			(0.003)
year2009-10:educat			-0.005 *
			(0.002)
year2011-12:educat			-0.002
			(0.003)
year2013-14:educat			-0.001
			(0.003)
year2015-16:educat			-0.007 *
			(0.003)
experiencegroup:educat			0.002 ***
			(0.000)
N	289	247	247
R2	0.136	0.632	0.699
logLik	524.328	630.975	655.828
AIC	-1030.656	-1239.950	-1263.655

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 2: Weighted regression estimates for participation rate

	(1)	(2)	(3)
(Intercept)	0.597 ***	0.419 ***	0.435 ***
	(0.035)	(0.034)	(0.072)
year2005-06	-0.032	-0.025	-0.024
	(0.050)	(0.038)	(0.099)
year2007-08	-0.050	-0.048	-0.075
	(0.052)	(0.039)	(0.104)
year2009-10	-0.122 **	-0.116 ***	-0.174
	(0.044)	(0.033)	(0.090)
year2011-12	-0.081	-0.064	-0.010
	(0.047)	(0.035)	(0.096)
year2013-14	-0.120 *	-0.112 **	-0.092
	(0.048)	(0.036)	(0.094)
year2015-16	-0.117 *	-0.023	0.253
	(0.052)	(0.043)	(0.129)
proportion migrant	1.531 ***	1.002 ***	0.957 ***
	(0.199)	(0.193)	(0.215)
educat		0.032 ***	0.020
		(0.009)	(0.022)
experiencegroup		0.050 ***	0.044 **
		(0.005)	(0.014)
year2005-06:educat			0.000
			(0.025)
year2007-08:educat			0.007
			(0.027)
year2009-10:educat			0.017
			(0.024)
year2011-12:educat			-0.014
			(0.025)
year2013-14:educat			-0.005
			(0.025)
year2015-16:educat			-0.025
			(0.030)
educat:experiencegroup			0.004
			(0.004)
year2005-06:experiencegroup			-0.000
			(0.019)
year2007-08:experiencegroup			0.003
			(0.019)
year2009-10:experiencegroup			0.005
			(0.017)
year2011-12:experiencegroup			-0.005
			(0.017)
year2013-14:experiencegroup			-0.001
			(0.017)
year2015-16:experiencegroup			-0.046 *
			(0.020)
N	289	247	247
R2	0.186	0.482	0.509
logLik	-11.327	83.068	89.815
AIC	40.653	-144.136	-131.630

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 3: Weighted regression estimates annual wages

	(1)	(2)	(3)
(Intercept)	10.194 ***	9.682 ***	9.784 ***
	(0.067)	(0.030)	(0.062)
year2005-06	0.079	0.082 **	0.075
	(0.096)	(0.031)	(0.085)
year2007-08	0.154	0.139 ***	0.061
	(0.097)	(0.032)	(0.090)
year2009-10	0.155	0.148 ***	0.118
	(0.086)	(0.029)	(0.080)
year2011-12	0.267 **	0.255 ***	0.244 **
	(0.089)	(0.029)	(0.083)
year2013-14	0.301 **	0.317 ***	0.291 ***
	(0.093)	(0.031)	(0.083)
year2015-16	0.432 ***	0.296 ***	0.148
	(0.104)	(0.035)	(0.106)
proportion migrant	2.491 ***	0.844 ***	0.892 ***
	(0.360)	(0.156)	(0.174)
educat		0.157 ***	0.106 ***
		(0.008)	(0.018)
experiencegroup		0.088 ***	0.075 ***
		(0.004)	(0.012)
year2005-06:educat			0.005
			(0.020)
year2007-08:educat			0.038
			(0.021)
year2009-10:educat			0.021
			(0.020)
year2011-12:educat			0.025
			(0.020)
year2013-14:educat			0.030
			(0.020)
year2015-16:educat			0.043
			(0.024)
educat:experiencegroup			0.008 **
			(0.003)
year2005-06:experiencegroup			-0.001
			(0.015)
year2007-08:experiencegroup			-0.006
			(0.015)
year2009-10:experiencegroup			-0.005
			(0.014)
year2011-12:experiencegroup			-0.014
			(0.014)
year2013-14:experiencegroup			-0.015
			(0.014)
year2015-16:experiencegroup			0.004
			(0.016)
N	298	256	256
R2	0.264	0.886	0.894
logLik	-199.571	133.194	143.001
AIC	417.142	-244.389	-238.002

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 4: Weighted regression estimates weekly wages

	(1)	(2)	(3)
(Intercept)	6.461 ***	6.102 ***	6.203 ***
	(0.055)	(0.026)	(0.053)
year2005-06	0.090	0.093 ***	0.098
	(0.079)	(0.027)	(0.073)
year2007-08	0.243 **	0.232 ***	0.155 *
	(0.080)	(0.028)	(0.077)
year2009-10	0.278 ***	0.243 ***	0.173 *
	(0.071)	(0.025)	(0.069)
year2011-12	0.340 ***	0.333 ***	0.280 ***
	(0.073)	(0.026)	(0.071)
year2013-14	0.376 ***	0.400 ***	0.356 ***
	(0.076)	(0.027)	(0.072)
year2015-16	0.450 ***	0.363 ***	0.088
	(0.086)	(0.030)	(0.091)
proportion migrant	1.759 ***	0.207	0.223
	(0.296)	(0.137)	(0.150)
educat		0.135 ***	0.093 ***
		(0.007)	(0.015)
experiencegroup		0.055 ***	0.043 ***
		(0.003)	(0.010)
year2005-06:educat			-0.004
			(0.017)
year2007-08:educat			0.033
			(0.018)
year2009-10:educat			0.028
			(0.017)
year2011-12:educat			0.028
			(0.017)
year2013-14:educat			0.033
			(0.018)
year2015-16:educat			0.061 **
			(0.020)
educat:experiencegroup			0.005 *
			(0.002)
year2005-06:experiencegroup			0.002
			(0.013)
year2007-08:experiencegroup			-0.001
			(0.013)
year2009-10:experiencegroup			0.001
			(0.012)
year2011-12:experiencegroup			-0.004
			(0.012)
year2013-14:experiencegroup			-0.012
			(0.012)
year2015-16:experiencegroup			0.021
			(0.013)
N	298	256	256
R2	0.291	0.869	0.883
logLik	-141.280	166.636	181.420
AIC	300.561	-311.272	-314.840

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.