The Impact of Immigration on Native Workers in Australia

Jaai Parasnis, Dietrich Fausten and Russell Smyth
Monash University

Corresponding Author:
Jaai Parasnis
Department of Economics
Monash University
Caulfield VIC 3145
Australia

Phone: 613 9903 1566
Fax: 613 9903 1128
Email: Jaai.Parasnis@buseco.monash.edu.au

Abstract
Immigration leads to a change in the supply of workers across skill groups. The resulting impact on employment and earnings of native workers is estimated using an innovative approach developed by Borjas (2003). The approach takes into account the skill differentials in the labour force and defines skill groups of workers in terms of their education and work experience. We find that an increase in the proportion of immigrants has a significant positive effect on labour market outcomes for native workers. This finding challenges widely held perceptions that immigration erodes labour market outcomes for native workers.

Keywords:
Immigration, Australia, Employment, Earnings

JEL Classification:
F22, J61

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1. Introduction

Immigration has always played an important role in Australia’s development process. Immigration constitutes an increase in labour supply and hence gives rise to concerns about its impact on native workers. Consistent with the analysis in previous studies, a person is defined as a migrant if born overseas and as a native if born in Australia. The public debate and policy concerns surrounding the issue have inspired a substantial body of research that examines the impact of immigration on employment or earnings in Australia. Investigations of the effect of immigration on Australian labour market outcomes can be divided into three methodologically differentiated groups, those using time series analysis, cross sectional data, and Computable General Equilibrium (CGE) models.

Until recently, most of the attempts at analysing the consequences of immigration for employment and wages in Australia used an empirical macroeconomic approach and aggregate time series data. Recent examples include Pope and Withers (1993), Shan et al., (1999), Tian and Shan (1999) and Greasley et al., (2000). These studies find no causal relationship between immigration and unemployment and conclude that immigration has no effect on unemployment in Australia. The study by Pope and Withers (1993) uses a system of equations approach. These authors, however, also fail to identify any significant effect of immigration on unemployment.

The studies using time series analysis suffer from severe measurement problems. They typically measure immigration in terms of the net immigration rate. This is a variable known to suffer from several problems (Australian Bureau of Statistics, 1995). It includes all short-term as well as long-term movements. In addition, the
underlying data cannot distinguish between multiple movements of individual persons. The exact nature and magnitude of bias due to measurement errors in the net immigration rate is unknown. Further, these studies estimate the effect of immigration on aggregate unemployment rather than on native workers. Chapman and Cobb-Clark (1999) note that it is important to analyse the effect on native workers for two reasons. First, public concern about immigration centres foremost around its effect on native workers. Secondly, immigration can simultaneously increase aggregate unemployment while improving the employment outcomes for native workers with immigrants bearing the burden of increased unemployment. Recent studies respond to these concerns by refocusing the investigation on the narrower effect of immigration on the labour market outcomes for native workers. Time series analysis is also constrained by data limitations that make it impossible to account for factors such as skill composition and demographic characteristics which are likely to influence the labour market impacts. Hence, the analysis is restricted to estimating the relationship between immigration and aggregate labour market outcomes in the absence of information about other related variables. Due to these limitations, the limited findings from time series analysis need to be supplemented by other approaches.

Chapman and Cobb-Clark (1999) implement a novel approach and develop a comparative static theoretical model to illustrate the effect of immigration on the job prospects of Australian natives. These prospects are captured by the ratio of ‘vacancies to the unemployment rate’. The authors conclude that using feasible Australian values for immigrant spending and the labour force participation rate, immigration increases the overall employment prospects of unemployed natives. However, the authors acknowledge that their analysis is decidedly short-run. Further,
the model can only be empirically simulated, and estimations using actual data are not possible using this approach.

Addison and Worswick (2002) use cross-sections of labour markets and variations in the proportions of immigrants in these markets to identify the effect of immigration on natives’ labour market outcomes. Australia is divided into 48 labour markets on the basis of six States and eight Occupational categories. The analysis is carried out for six years in the period 1982-1996. Again, the conclusion is that recent immigrants do not significantly affect the real wages of native Australians. More importantly, the conclusion remains unchanged when the specific impact on less educated or young Australian workers is analysed. The study, however, suffers from the implicit assumption of extreme labour immobility that is inherent in the area approach. There are likely to be substantial labour movements across the occupation-state labour markets (e.g. the market for Managers and Professionals in New South Wales and Victoria) defined by the study, reducing the ability of the estimations to capture the impact of immigration.

Computable General Equilibrium (CGE) models have made an important contribution to the identification of the labour market consequences of immigration. Peter and Verikios (1996) and Chang (2004) are recent examples that simulate the impact of immigration. However, results from CGE models are often difficult to assess as they depend in part on the assumptions made regarding the elasticities of substitution when incorporating immigration into the model. Further, the quantitative results can only be obtained by simulations.
The present paper complements the existing studies by estimating the impact of immigration on native workers using pooled data analysis. In a recent article, Borjas (2003) implements an innovative approach to identify the effect of immigration on various skill groups of workers in the United States and, hence, on the labour market outcomes of native workers in those skill groups. We employ this approach to estimate the impact of immigration on native workers in Australia. In contrast to the area approach of Addison and Worswick (2002) which exploits variations in labour supply changes across geographical areas due to immigration, the Borjas approach exploits the variation across different skill groups of immigration shocks to the supply of workers. Section 2 describes the Borjas (2003) approach and compares it with other existing methods. Data sources and construction of the dataset used in the empirical estimations are described in section 3. Section 4 presents the model and section 5 the estimation and results. Section 6 explores alternative definitions of skills. The results are discussed in section 7 and section 8 concludes.

2. The Approach

Immigration increases the labour supply in the host country. However, this increase is not uniformly distributed across all skill groups. The proportion of immigrants entering the workforce varies across time as well as across different groups of workers. Borjas (2003) exploits these variations in the shifts in labour supply across skill groups caused by immigration. The approach makes two important contributions: it captures the skill differentials in the workforce and it enables econometric estimations of the impact of immigrants on native workers who are likely to be close substitutes, i.e. on natives with similar skills.
An important feature of this approach is that it takes into account the skill heterogeneity of the labour force. The literature on human capital including the work of Becker (1975) and the more recent work of Card and Lemieux (2001) emphasises the importance of experience as well as education in determining workers’ skills. Drawing on this insight, the labour force is differentiated into different skill groups on the basis of education and experience in the labour market. Hence, this approach assumes that workers with similar education but different levels of experience are not perfect substitutes. They do, however, participate in the national labour market. Immigration is most likely to affect those native workers directly who are close substitutes to immigrants. Those are the native workers belonging to the same skill group as the migrants. The impact of immigration can, thus, be examined by considering immigration as a supply shock that affects various skill groups and estimating how the labour market outcomes of native workers in the different skill groups are affected by this shock.

Empirical efforts to estimate a model of immigration and its effects on native workers are constrained by the lack of a detailed dataset. Typically, in most countries the census is the only data source that enables one to distinguish between immigrants and natives while also providing information about other characteristics including employment and earnings. Since the census is conducted only at regular time intervals (every 5 years in Australia and every 10 years in the United States), time series analysis has to rely on other aggregate data which cannot isolate the impact on native workers. As seen in the above section, some studies rely on simulations in a bid to quantify impacts of immigration on the labour market. Studies attempting econometric estimation of the impact of immigration on native workers have to add a cross-sectional dimension to census or other survey data. Even if census data is
available since, say the 1950s, the absence of annual data means that census data across time does not generate a sufficient number of observations for meaningful time series analysis. This is frequently achieved by carrying out the analysis across geographical areas.

The approach based on skill groups suggested by Borjas (2003) is an improvement over such ‘area’ approaches since it does not rely on the assumption of geographically segregated labour markets within a country. Hence it can capture the impact of immigration which would otherwise be dispersed throughout the economy due to labour movements. Further, the skill group approach allows us to exploit the observed variation in immigrant proportion across education-experience groups to estimate the impact on native employment and earnings. It, thus, overcomes the shortcomings of other approaches where the results are obtained by simulations and are crucially shaped by the assumed values of elasticities.

3. Data

The data is drawn from Household Sample Files (HSF) of the 1981, 1986, 1991, 1996 and 2001 Census of Population and Housing. The sample files comprise of a one percent sample of the population. The sample is restricted to men aged 18-64 who are in the labour force.

3.1 Constructing the skill groups

The labour force is divided into skill groups defined in terms of educational level and work-related experience. In order to construct the skill groups, workers are first sorted into five educational groups based on their highest educational qualification achieved. These educational groups are High School Dropouts, High School Graduates,
Diploma and (vocational) Certificate Holders, Graduate Degree Holders and Postgraduates.

The Census does not provide any direct measure of work experience. Hence, experience is defined as the number of years since the person completed formal education. Thus, years of experience are calculated as $\left(\text{Age} - A_e\right)$, where $A_e$ is the assumed age of labour market entry for workers in a particular education group. The highest level of qualification attained provides an indication of the age of labour market entry. It is assumed that a typical high school dropout worker enters the labour market at the age of 16 years, a high school graduate at the age of 18, diploma and vocational certificate holders enter the labour market when 19, a bachelor degree holder at the age of 21 and a postgraduate at the age of 23 years. For the purposes of the present analysis, it is assumed that workers with roughly the same years of experience are likely to be similar and the data is aggregated into work experience groups using five year experience intervals workers with 0-5 years of experience, 6-10 years of experience and so on through to 40 years or more.

This measure of work experience is bound to be imprecise. While it can be expected to reflect the years of experience quite accurately in the case of native male workers, it is likely to contain measurement errors when women are included in the sample. Hence we restrict the analysis to male workers. This measure is also likely to be problematic for migrant workers, especially if experience acquired in the home country and in Australia are valued differently by the Australian employer. Aggregation of groups into 5 year experience bands can be expected to reduce this problem but it could still be significant. This issue is further explored in section 6.
3.2 Measuring immigrant share in the skill group

A skill group \((i, j, t)\) can be defined as a group of workers with educational attainment \('i'\) and experience level \('j'\), observed in calendar year \('t'\). The five education groups and nine experience levels observed across five census years give us 225 skill groups. The supply shock to a skill group from immigration is measured by the share of migrant workers in the skill group. This proportion of migrants in a skill group is given by the variable

\[
p_{ijt} = \frac{M_{ijt}}{M_{ijt} + N_{ijt}}
\]  

where \(M_{ijt}\) is the number of migrant workers and \(N_{ijt}\) is the number of native workers in skill group \((i, j, t)\). Figure 1 maps these ratios to illustrate the immigrant supply shocks to various skill groups for the period 1981-2001. Note the variation in these shocks within the education categories as well as across time. These variations make it possible to estimate econometrically the impact of these shocks on the labour market outcomes of native workers. Further, immigrants form a larger proportion of skill groups consisting of workers with Postgraduate Degrees (Panel A in Figure 1) compared to the skill group consisting of ‘High School Dropouts’ (Panel E in Figure 1). In fact, compared to all other educational groups, the group “Postgraduate Degree Holders” has a higher proportion of immigrant workers, thus confirming that immigrants in Australia are relatively skilled. Except for the postgraduate degree holders, the share of immigrant workers increases with years of experience; immigrants form a small proportion of workers with 0-5 years of work experience.
Figure 1 The Immigrant Supply Shock, 1981-2001.

A. Postgraduate Degree Holders

B. Graduate Diploma and Bachelor Degree Holders

C. Diploma and Certificate (Vocational) Holders

D. High School Graduates

E. High School Dropouts
3.3 Measuring the labour market outcomes of native workers

The labour market outcomes of native workers are measured by their average real earnings and average employment of native workers in each skill group. Earnings data used in the estimations are weekly earnings of an individual deflated to 1989-90 dollars using the CPI (Australian Bureau of Statistics, 2004). Employment is measured in terms of weekly hours worked. Employment is also measured in terms of the fraction of time worked, defined as the proportion of normal (full time) weekly hours worked. This is calculated by dividing the weekly hours worked by 37.5 hours.

Figures 2 and 3 show that education does play an important role in labour market outcomes. Hours worked increase across all experience groups and years with the level of education, although these increments diminish after 30 years of work experience. Workers with higher education levels also earn more than those with lower education. This holds across all experience groups as well as time. Thus the data indicates that both education and experience play a role in determining the labour market outcomes. Also note that there is substantial variation in native labour market outcomes across skill groups. This feature will facilitate econometric estimations.
Figure 2- Weekly Hours Worked by Native Workers- Education Groups

A. Hours worked-1981

B. Hours Worked-1986

C. Hours Worked- 1991

D. Hours Worked- 1996

E. Hours Worked- 2001

PostGraduates
Graduates
Diploma & Certificate Holders
High School Graduates
High School Dropouts
Figure 3- Weekly Log (Real Income) of Native Workers, Education Groups

A. Log(Income) - 1981

B. Log(Income) - 1986

C. Log(Income) - 1991

D. Log(Income) - 1996

E. Log(Income) - 2001
4. The Model

The model used in the literature to estimate the labour market impact of immigration involves regressing native wages and/or employment on some measure of immigrant penetration.\(^1\) Borjas (2003) outlines the labour demand theory behind the reduced form equation used frequently in the literature. The underlying assumption is that immigration constitutes an exogenous increase in the supply of labour. Consider the labour demand function in the pre-immigration period,

\[
\log w_{kt} = D_{kt} + \varepsilon \log N_{kt} + \varphi
\]  

(2)

where \( k \) and \( t \) denote the skill group and time respectively, \( w \) represents real wages and \( N \) denotes the supply of labour.

An exogenous inflow of immigrants changes wages,

\[
\Delta \log w_{kt} = \Delta D_{kt} + \varepsilon \log \left[ \frac{N_{kt}(1 + n_{kt}) + M_{kt}}{N_{kt}} \right] + \xi \approx \Delta D_{kt} + \varepsilon (n_{kt} + m_{kt}) + \xi
\]  

(3)

where \( n_{kt} \) is the proportionate change in the number of natives in skill group \( k \) and \( m_{kt} = M_{kt}/N_{kt} \) is the proportionate change of migrants in the group.

The change, \( n_{kt} \), is given by the native labour supply function,

\[
n_{kt} = S_{kt} + \sigma \Delta \log w_{kt} + \mu
\]  

(4)

\(^1\) For example, Addison and Worswick (2002) use a regression of the log of (mean) weekly earnings of native workers on the proportion of recent immigrants.
Substituting equation (4) into (3) leads to the reduced form equation,

$$\Delta \log w_{kt} = X_{kt} + \varepsilon^* m_{kt} + \xi^*$$  \hspace{1cm} (5)

where $X_{kt} = \frac{\Delta D_{kt} + \varepsilon S_{kt}}{1 - \dot{\varepsilon} \sigma}$ and $\varepsilon^* = \frac{\varepsilon}{1 - \dot{\varepsilon} \sigma}$.

The estimating equations used in the next section are transformations of Equation (5).

Thus the estimations attempt to capture the interaction in a simple model of demand and supply of labour in the presence of immigration. In addition to the variables included above, the econometric estimation of Equation (5) needs to control for fixed effects such as education and experience, which affect the right hand side variables.

**5. Estimation and Results**

The estimation equation employed in the present study is given by

$$y_{ijt} = \theta p_{ijt} + s_i + x_j + \pi_t + (s_i \times x_j) + (s_i \times \pi_t) + (x_j \times \pi_t) + \varphi_{ijt}$$  \hspace{1cm} (6)

where $y_{ijt}$ = mean value of a particular labour market outcome for native men who have education $i$ ($i = 1, \ldots, 5$), experience $j$ ($j = 1, \ldots, 9$) and are observed at time $t$ ($t = 1981, 1986, 1991, 1996$ and 2001).

$s_i$ = a vector of fixed effects indicating the group’s educational attainment.

$x_j$ = a vector of fixed effects indicating the group’s work experience

$\pi_t$ = a vector of fixed effects indicating the time period.

The dependent variables used are the mean values of weekly hours worked, fraction of time worked (weekly hours worked/37.5 hours) and log of real weekly income of native workers in skill group $(i, j, t)$.
The vectors of fixed effects $s_i, x_j$ and $\pi_t$ consist of dummy variables to control for differences in labour market outcomes across education groups, experience groups and time respectively. The interaction terms $(s_i \times \pi_t)$ and $(x_j \times \pi_t)$ are included in the estimations to control for the possibility that the impact of education and experience changes over time. Further, the experience profile for a particular labour market outcome may differ across schooling groups and, hence, we include the interaction term $(s_i \times x_j)$ in the estimations. The presence of these terms enables us to identify the impact of immigration on native labour market outcomes from the changes that occur within education-experience cells over time. The estimates of the adjustment coefficient $\theta$ (and the associated t-statistics) for various specifications with hours worked, fraction of time worked and log of real income as dependent variables are reported in Table 1.
### Table 1-Impact of Immigrant Share on Native Labour Market Outcomes in the Skill Group

<table>
<thead>
<tr>
<th>Specification</th>
<th>Dependent Variable</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hours worked</td>
<td>Fraction of time worked</td>
<td>Log Income</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\theta$</td>
<td>$R^2$</td>
<td>$\theta$</td>
<td>$R^2$</td>
</tr>
<tr>
<td></td>
<td>(t-statistics)</td>
<td>(t-statistics)</td>
<td>(t-statistics)</td>
<td>(t-statistics)</td>
</tr>
<tr>
<td>Basic estimates</td>
<td>8.132</td>
<td>0.985</td>
<td>0.217</td>
<td>0.985</td>
</tr>
<tr>
<td></td>
<td>(2.131)</td>
<td></td>
<td>(2.131)</td>
<td></td>
</tr>
<tr>
<td>Unweighted regression</td>
<td>9.568</td>
<td>0.945</td>
<td>0.255</td>
<td>0.945</td>
</tr>
<tr>
<td></td>
<td>(3.072)</td>
<td></td>
<td>(3.072)</td>
<td></td>
</tr>
<tr>
<td>Includes log native force as a regressor</td>
<td>9.661</td>
<td>0.985</td>
<td>0.258</td>
<td>0.985</td>
</tr>
<tr>
<td></td>
<td>(2.442)</td>
<td></td>
<td>(2.442)</td>
<td></td>
</tr>
<tr>
<td>Instrumental variable analysis</td>
<td>9.186</td>
<td>0.985</td>
<td>0.245</td>
<td>0.985</td>
</tr>
<tr>
<td></td>
<td>(2.344)</td>
<td></td>
<td>(2.344)</td>
<td></td>
</tr>
</tbody>
</table>

All regressions reported above are weighted by the sample size used to calculate the dependent variables ($N_{ij}$), unless otherwise specified. All regressions have 225 observations and include education, experience and period fixed effects, as well as interactions between these fixed effects.
The adjustment coefficient $\theta$ is positive and significant across all specifications. Thus, for any given skill group the proportion of migrants has a positive effect on the labour market outcomes of native workers in that skill group. This impact is robust with respective to alternative work measures: weekly hours worked, fraction of time worked and (log of) real weekly income. The first row of Table 1 reports the estimates of $\theta$ from the basic weighted least squares regression including all fixed and interaction effects. The remaining three rows of Table 1 report the estimates from a variety of specifications estimated to determine the sensitivity of the results. The results in the second row are from unweighted regressions.

The definition of the measure of the immigrant share ($p_{jt}$) can lead to interpretation problems, as a rise in $p_{jt}$ can reflect either an increase in the number of immigrants ($M_{jt}$) or a decrease in the number of native workers ($N_{jt}$) in the skill group. This ambiguity can be resolved by including the log of the size of the native labour force, $\log(N_{jt})$, as an additional independent variable. The results are reported in the fourth row of Table 1, and the parameter $\theta$ remains positive and significant. Hence we can conclude that $\theta$ is a reliable indicator of the effect of an increase in immigration on native workers.

The results reported in the last row of Table 1 use Instrumental Variable analysis to correct for possible endogeneity. The labour force participation decision may introduce endogeneity into the analysis as the variable $p_{jt}$ measures the share of immigrant workers among labour force participants. The immigrant share in the population of all men in skill group $(i, j, t)$ is used as an instrument to correct for
endogeneity. The effect on native labour market outcomes remains positive and significant after this correction.

It is interesting to look at the effect of the immigrant share in a skill group on the labour market outcomes of immigrants in that skill group. We can detect no significant evidence of this effect in our dataset. The adjustment coefficients $\theta$ (and the associated t-statistics) for the estimations using hours worked, fraction of time worked and log of real income of immigrants in the skill group are 2.380 (0.542), 0.063 (0.542) and 0.169 (0.744), respectively. While the estimations identify a small, positive effect, this effect is not statistically significant.

The results are easier to interpret when $\theta$ is converted into an elasticity. The elasticity, percentage change in native earnings associated with percentage change in labour supply, can be calculated as

$$\frac{\partial \log w_{ijt}}{\partial m_{ijt}} = \frac{\theta}{(1 + m_{ijt})^2}$$

(7)

where $m_{ijt} = \frac{M_{ijt}}{N_{ijt}}$, represents the percentage increase in the labour supply of group $(i, j, t)$ attributable to migration. Table 2 reports the elasticities for hours worked and income for the census years. The elasticities for the fraction of time worked are same as those for hours worked. These elasticities are calculated using the estimate of $\theta$ from the basic model containing all fixed effects and interaction terms reported in Table 1 above.
Table 2- Elasticities

<table>
<thead>
<tr>
<th>Year</th>
<th>% increase in labour supply due to immigration</th>
<th>Elasticity (Hours worked)</th>
<th>Elasticity (Log Income)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981</td>
<td>0.38</td>
<td>0.15</td>
<td>0.37</td>
</tr>
<tr>
<td>1986</td>
<td>0.44</td>
<td>0.14</td>
<td>0.34</td>
</tr>
<tr>
<td>1991</td>
<td>0.38</td>
<td>0.15</td>
<td>0.37</td>
</tr>
<tr>
<td>1996</td>
<td>0.35</td>
<td>0.16</td>
<td>0.39</td>
</tr>
<tr>
<td>2001</td>
<td>0.34</td>
<td>0.16</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Average 0.378 0.16 0.37

The elasticities indicate that immigration has a significant positive impact on native workers. A 10 percent supply shock (that is, an immigrant flow that increases the number of workers in the skill group by 10 percent) increases the hours worked by more than one percent and weekly income by three to four percent. The estimates of elasticities are consistent across time, mainly due to the fact that the increase in labour supply due to immigration does not vary significantly over time.

Overall, the econometric results are consistent and statistically significant across a considerable range of specifications. The approach, based on observing skill groups over time, permits a large number of observations and significant variation in the data, both of which contribute to the robustness of our results.

6. Refining the Definition of Skills

In the analysis so far, skill groups have been defined using educational level and work experience. The problems with our measure of work experience were acknowledged
in section 3.1 while constructing the skill groups. Ideally, in the case of immigrant workers, the experience measure should capture ‘effective’ experience in the labour market. In this section, we explore whether our results are substantially influenced by the measure of work experience.

Borjas (2003) acknowledges the problem with defining the effective experience measure for migrant workers and attempts to mitigate it by refining the definition of skills in various ways. This can be achieved by using the year of arrival of the migrant worker to estimate the years of experience acquired in the source country and econometrically estimating the ‘value’ of a year of source country experience. It is not possible to measure ‘effective’ years of experience for immigrant workers in Australia in a similar way as the Australian census data gives the exact year of arrival only for those immigrants who arrived a few years (typically 5 years) before the census and aggregates earlier arrivals into one group.

There is an alternative way of defining skills that obviates the need to measure the experience in the labour market by using compensation as a proxy for skill. Similarly educated workers who fall in the same general location of the wage distribution are assumed to have the same skills. Borjas (2003) implements this definition of skill groups as follows. The data within each education group is sliced into twenty quantiles based on the wage distribution of native workers. The econometric estimations are then carried out across the ‘education-experience-period’ groups. However, Australian data do not offer enough variation in earnings within each of the five education groups to slice the data into twenty groups. Hence, we first aggregate the five educational groups into two major groups, workers with post tertiary education and those without. These two educational groups are then divided into quartiles (four
groups) based on the earnings distribution of the native workers. The immigrant supply shock to each quartile within the education group is then calculated as

$$\hat{p}_{ikt} = \frac{M_{ikt}}{M_{ikt} + N_{ikt}}$$  \hspace{1cm} (8)

where $M_{ikt}$ and $N_{ikt}$ are the number of migrants and native workers, respectively, in the education group $i$, quartile $k$ ($k = 1, \ldots, 4$) at time $t$ ($t = 1981, 1991, 1996, 2001$).

The equation

$$y_{ikt} = \theta \hat{p}_{ikt} + s_i + q_k + \pi_t + (q_k \times s_i) + (s_i \times \pi_t) + (q_k \times \pi_t) + \varphi_{ikt}$$  \hspace{1cm} (9)

where $q_k$ is a vector of fixed effects controlling for the quartiles, and $s_i$ and $\pi_t$ are the fixed effects associated with the education group and time, respectively, is estimated using the weighted least squares method. This alternative way of defining skill groups drastically reduces the number of groups to 32 education-quartile-period cells. Logs of real weekly earnings and of weekly hours worked by native workers are the independent variables. $\theta$ (and the associated t-statistics) are estimated to be 4.86 (1.069) for the earnings variable, and 5.162 (0.122) for the weekly hours worked variable. Thus, $\theta$ is statistically insignificant. The reduced number of observations might be the reason for the lack of statistical significance of the estimates.

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2 This analysis is restricted to 1981, 1991, 1996 and 2001, as the data for 1986 did not exhibit enough variation to implement this definition of skill groups.

3 The sample size of the education-quartile-period cells are used as weights in the regressions.
7. Discussion of the Results

Borjas (2003) originally applied this approach to the United States and found that immigration has a significant negative impact on native workers. A ten percent increase in labour supply due to immigration reduces weekly earnings of native workers by about four percent and the fraction of time worked by 3.7 percentage points. These United States findings, that immigrants have a significant negative impact, stand in sharp contrast to the Australian results reported above which find a significant positive impact of immigration (or no impact at all depending on the specification) on native workers. However our findings for Australia are consistent with the evidence from related Australian studies. The simulations by Chapman and Cobb-Clark (1999) as well as studies using time series analysis (reviewed in the introduction) find a limited positive effect of immigration on labour market outcomes in Australia.

The study by Addison and Worswick (2002) is in the same spirit as the approach developed by Borjas (2003) and applied to Australia in this paper. They use a cross-section of State labour markets in Australia and variations in the proportions of immigrant across these markets to identify the effect of immigrants on the labour market outcomes for natives. The results from pooled estimations indicate insignificant but positive effects; a ten percent increase in the recent immigration proportion between 1982 and 1996 leads to a 0.05 percent increase in log native wages. In their reported estimations using instrumental variable analysis, only the estimates for 1990 are statistically significant and are again positive. With the implied elasticity of 0.121, a ten percent increase in the recent immigrant presence in 1990 results in a 1.21 percent increase in the log of native wages. Overall the authors
conclude that recent immigrants do not significantly affect the real wages of native workers, though the few estimates that are statistically significant indicate a positive effect.

One reason why Addison and Worswick (2002) fail to find significant effects might be their specification of geographical labour markets based on State boundaries. However, if labour is geographically mobile, natives are likely to respond to impacts of immigration by moving to other cities or states. In Australia it seems plausible that such movements occur across states and, hence, separation of labour markets on the basis of state boundaries might understate the labour market impact of immigration. Borjas (2003) finds that such spatial arbitrage which would tend to equalise opportunities for workers of given skills across regions effectively reduces the national impact of immigration by two-thirds.

The prevalence of such labour movements within Australia is well documented. A significant proportion of internal migration does occur across states. Between 1991 and 1996, more than three-quarters of a million people moved interstate (Bell and Graeme, 2000). Garnaut et al., (2003) note that migrant settlement in 1981-1996 was concentrated most strongly in the two biggest cities, Sydney and Melbourne. However, the overall drift of population, mainly natives and established migrants, away from New South Wales and Victoria to states in the north and west, as documented by Bell and Graeme (2000), suggests that there is substantial offsetting internal migration.

In an earlier study, Pope and Withers (1993) estimate a simultaneous equation system and calculate long-run equilibrium elasticities. These elasticities, indicated that the
change in aggregate unemployment attributable to a change in migration, are -0.09 for 1861-1901, -0.11 for the period 1902-1945 and -0.08 between 1946 and 1981 (Pope and Withers, 1993, p.730). The elasticities are negative for all time periods thus indicating some modest positive effect of immigration on employment. While these estimates relate to aggregate employment as against employment of native workers, it is plausible to infer that immigration would lead to better employment prospects for native workers as well if it leads to aggregate job creation over a period of time.

In fact, the evidence that immigration improves aggregate employment over time together with the evidence that migrants have higher unemployment rates compared to natives (e.g. Miller and Neo (2003) and Thapa (2004)) tend to support the proposition by Harrison (1984) that migration has a positive effect on natives’ labour market outcomes. He argues that immigration generates additional job opportunities, and that immigrants experience high unemployment rates specifically because they are unable to compete a ‘fair share’ of jobs away from residents who are already entrenched in the labour market. Presuming that the combined increase in aggregate employment and in migrant unemployment exceeds the relevant immigrant inflow, immigration would benefit native workers.

The theoretical literature suggests many reasons why increases in the proportion of immigrants may lead to better labour market outcomes for native workers. First, if demand shifts are associated with changes in immigrant proportions, then the positive correlation found in our estimations could be the consequence of such positive shifts in demand. Secondly, if immigration induces capital adjustment then more factors of production would expand production possibilities in the host country. In such a scenario a higher proportion of immigrants might benefit native workers.
In the context of the wage rigidities in the Australian labour market, the theoretical model developed by Oslington (1998) offers another explanation for the positive effect of immigrants on native workers. He shows that the inflow of migrants whose wages are flexible reduces unemployment of non-migrant factors of production as well. Australian immigration policy encouraging skilled migration might result in precisely such an inflow. As discussed in section 3.2, immigrants form a high proportion of workers with postgraduate qualifications compared to other educational groups, especially those with no high school education.

8. Conclusion

This paper estimates the impact of immigration on native workers using the approach developed by Borjas (2003). The approach takes into account the differences in skills of workers. Our empirical results lend support to the previous findings for Australia. Increases in the proportion of immigrants are correlated with improved labour market outcomes for native workers. The findings from the present investigation, however, stand out against earlier results. In the present study the effects are positive like in the other studies and statistically significant. In contrast to the earlier studies, our findings are also quantitatively significant and robust across a variety of specifications. This approach is an innovative attempt to exploit the variations in immigrant proportion across skill groups while allowing for factor movement across regions within the country. It is hence an improvement over the studies involving restrictive assumptions of local labour markets.
References


