*Final Report*

# Longitudinal analysis of employment outcomes for vulnerable and other migrants

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## Executive Summary

This report uses data from the HILDA Survey to examine gaps in employment rates between migrants to Australia and their Australian-born counterparts, highlighting groups of migrants for whom employment rates are particularly low, and exploring the extent to which migrants' labour market outcomes 'catch up' with those of the Australian-born the longer migrants remain in Australia.

Key findings are listed below.

Some of the findings generally confirm what we already know from existing studies using HILDA Survey or other data:

- Employment rates for male migrants are on average 4.4 percentage points lower than those for Australian-born. When we compare migrants with Australian-born individuals with similar characteristics (e.g. education level, age, household composition), the gap is 4.1 percentage points.
- Employment rates for female migrants are on average 6.9 percentage points lower than those for Australian-born. When we compare migrants with Australian-born individuals with similar characteristics (e.g. education level, age, household composition), the gap is 7.5 percentage points.
- For both genders, the employment gap between migrants and Australian-born is higher for migrants with poor English language skills, for refugees, and for recent arrivals. The gap is lower for migrants that arrive in Australia prior to school-leaving age.
- The employment gap between migrants and their Australian-born counterparts falls with time since arrival.

Some of the findings suggest a partial reassessment of existing conclusions may be required:

- Earlier studies based on cross-section data may have over-estimated the speed at which migrants catch up with Australian-born in terms of employment rates. This is because cross section studies cannot control for unobserved factors that influence both the length of time migrants stay in Australia and their employment outcomes. Because we use panel data, however, we are better able to control for such factors. In effect we get an upper and lower bound on how long it takes migrants to catch up.

- Employment rates for male economic migrants take between 12 and 25 years to ‘catch up’ with those for otherwise similar Australian-born men. The bottom of this range is in line with existing estimates but the top of this range is about double existing estimates.
- Male refugees start off with lower employment rates than other migrants but catch up at a slightly faster rate each year. Our fastest estimate suggest that it takes male refugees 22 years to catch up with Australian-born employment rates, and our slowest estimate suggests that even after 25 years there may still be an employment gap of as much as 10 percentage points.

And some of the findings are new:

- Migrants’ probability of being employed is more sensitive to gender, age and health than is the case for the Australian-born. The picture is less clear for education level: migrants with middling levels of education (Year 12, or post-school but below tertiary) appear to experience the biggest migrant employment gap.
- In terms of employment catch up, female economic migrants look very similar to male refugees. Our fastest estimate suggests catch up after 22 years and our slowest estimate suggests there may still be a gap of as much as 10 percentage points even after 25 years.
- Our estimates suggest that employment rates for female refugees don’t catch up with those for otherwise similar Australian-born. Even after 25 years there is still an employment rate gap of between 10 and 20 percentage points.
- On average, employed migrants report similar levels of skills use in their jobs to those reported by the Australian-born.
- There is some evidence that skills use starts off slightly lower for female migrants and catches up to that for Australian-born women over time since migration.
- For male migrants there is no clear evidence that skills use increases with time since arrival.

Taken together these conclusions have a number of implications for policy in key areas such as labour supply, productivity and skills, and social inclusion. First, the evidence here confirms earlier evidence showing that there is an employment gap for migrants in the Australian labour market, although on average this employment gap is not particularly large. When considered alongside evidence that migrants on average have higher levels of education than the Australian-born and that where migrants are employed they report similar levels of wages and skills use to their Australian-born counterparts, at first glance this might suggest little need for policy intervention to provide additional labour market assistance to migrants in general.

But this optimistic conclusion overlooks the evidence presented here that many migrants – those with poor English language proficiency, women, refugees, recent arrivals – face a much larger (and in the case of women and refugees a more persistent) employment gap. Even if the large employment rate gaps for these groups are partly driven by differences in labour supply between migrants and their Australian-born counterparts, the implication is that Australia has not yet realised the full labour market potential of its migrant population. Another implication is that migrants in these groups may be at higher risk of social exclusion than their Australian-born counterparts. Policy designed to boost the employment rates of migrants in these groups, whether through demand or supply side measures, is therefore likely to have an important role to play looking forward. For example, recent migrants may require additional help finding and retaining employment, and this help may be required over a longer period of time following arrival than previously thought. This is particularly the case for women migrants and for refugees. The importance of policy efforts aimed at improving the English language skills of migrants is also here reinforced.

## 1. Introduction

Recent OECD data show that Australia has the highest foreign-born share of the population among the English speaking OECD countries (at 26.5% in 2009). Among OECD countries more widely, only Luxembourg has a higher share of foreign born individuals in the population.[1] And this proportion grows slowly each year with positive net migration accounting for almost half of overall population growth annually (Kostenko et al., 2009). Economic benefits to Australia from migration include increased labour supply and improved skills levels in the working age population[2], both vital in the context of ageing populations and skills shortages, with a recent Productivity Commission report (Productivity Commission, 2006) concluding that immigrants not only boost total Australian GDP, but also make a net positive contribution to per capita Australian GDP, and increasingly so as the proportion of Skill Stream migrants grows over time.

Existing evidence on labour market outcomes for immigrants themselves, however, suggests a more mixed picture. On the one hand, on average employed migrants appear to earn broadly similar wages to the Australian-born once compositional differences between the two groups, e.g. in terms of education levels, are accounted for (e.g. Antecol et al., 2006; Chiswick et al., 2008). On the other hand, on average migrants are less likely to be employed (e.g. Antecol et al., 2006), less likely to participate in the labour market and more likely to be unemployed than otherwise similar Australian-born individuals (e.g. Productivity Commission, 2006). Note that this combination of lower participation rates and higher unemployment rates suggests both demand and supply side factors play a role in the migrant employment rate gap.[3]

There is also considerable variation in labour market outcomes across different groups of migrants. For example, immigrants differ in terms of gender, visa status and English language proficiency, all of which have been shown by previous studies to be strongly associated with labour market outcomes (e.g. Cobb-Clark, 2003; Productivity Commission, 2006; Wilkins, 2007; Chiswick et al., 2008). Employment and participation gaps (but not wage gaps) have

[1] Source: http://www.oecd.org/document/30/0,3746,en_2649_37415_48326878_1_1_1_37415,00.htm.
[2] The skilled composition of migrants to Australia relative to comparator countries is likely to reflect differences in immigration rules (Antecol et al. 2003). The UK has recently moved towards similar skill-based rules for non-EU migrants.
[3] The employment rate, defined as the proportion of the working-age population in employment, can be decomposed into two component parts, one capturing the participation rate, and the other capturing the employment rate of labour market participants. In other words, employment rate = (number employed/working-age population) = (number employed/ number participating) x (number participating/working-age population).

also been shown to be larger in the early years following arrival in Australia, shrinking as immigrants assimilate more fully into the labour market over time, e.g. as English language skills improve (e.g. Antecol et al., 2006; Productivity Commission., 2006). Given this existing evidence the labour market outcome that we primarily focus on in this report is employment, rather than wages. We also examine what migrant and Australian-born workers say about the extent to which they use their skills in their jobs.

Specifically, we use HILDA Survey data to address the following research questions:

1. How do employment outcomes for migrants compare with those for Australian-born? Is there a migrant 'employment penalty' and if so how big is it?

2. What characteristics of migrants are associated with better employment outcomes, and who are the most vulnerable migrants in terms of employment outcomes?

3. Does the migrant employment-rate gap fall over time since migration and if so how long does it take for migrants to achieve employment parity with Australian-born? How does this vary for different groups of migrants?

4. If migrants are employed, do their occupations match their skills as well as for the Australian-born? Does the matching of skills and occupations improve over time since migration?

The issues addressed by the above research questions are important for Australian policy. Information on which groups of migrants have poor labour market outcomes, or take the longest to catch up with Australian-born, could potentially support the Australian Government in designing and targeting interventions aimed at improving such outcomes. Further, because the HILDA Survey is such a rich (and to date under-utilised) source of information for migration researchers, we also believe this research can make a wider contribution to the international evidence base on migration.

Most existing studies of labour market outcomes for migrants, whether in Australia or in the wider international literature, are based on cross-sectional data, e.g. from one or more Census (see Borjas, 1999). By using HILDA Survey data, however, we can potentially get better answers to some of the questions above, at least in some respects.[4] We return to this issue later in the report, but one reason for this is because the HILDA data allow us a degree of control for unobserved differences between migrants, which can otherwise lead to biased estimates of employment catch up, that is simply not possible with cross section data.[5] The HILDA data, covering the period 2001-2009, are also more recent than the most recent Australian Census data (2001) analysed to date. Third, only HILDA Survey data allow us to answer the questions regarding reported skill use (research question 4). In doing so we break new ground in directly exploiting what individuals say about skill use, and how it changes over time, as opposed to inferring conclusions about skill use from studying wages.[6] Fourth, and from an international perspective, partly because there are so many migrants in Australia as a proportion of the population, the HILDA Survey has detailed information on more migrants than similar household surveys in other countries.

Set against the advantages of the HILDA Survey data, however, is the disadvantage that, for most migrants, no information is collected on the visa class of migrants, other than to distinguish between refugee/humanitarian migrants and others (who we describe as *economic migrants* in what follows). As a consequence we cannot examine differences in employment outcomes between migrants granted permanent refugee status on-shore and those granted refugee status off-shore, between Skill Stream and Family Stream migrants, between migrants on temporary visas and those on permanent visas, or for different groups within these broad visa classes. There are also few migrants that arrive after 2001 in the HILDA Survey.

The remainder of this report is structured as follows. The following section provides a brief discussion of the historical policy context for the study. Section 3 reviews existing literature on labour market outcomes for migrants, concentrating on Australian studies but also drawing on the wider international literature. Section 4 then discusses the data and methods we use in

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[4] A small number of studies for Australia have used data from the Longitudinal Study of Immigrants to Australia (LSIA) (e.g. Cobb-Clark, 2003). Because of the sampling frame for the LSIA (it tracks *new* migrants for at most three to four years), however, it cannot be used to analyse differences in labour market outcomes between Australian-born and the overall stock of migrants in Australia, nor can it be used to analyse longer term outcomes for migrants such as employment assimilation beyond the first few years.

[5] For example, different arrival cohorts may differ in unobserved ways that can confound estimates of wage or employment convergence. Further, not all migrants stay permanently in the destination country, with those that choose to return migrate likely to differ in observed and unobserved ways from those that choose to stay (and therefore get measured by the Census). In studies based on cross-sectional data this can introduce bias that leads us to overestimate the extent to which migrants catch up with Australian-born. See Borjas (1999) for more details.

[6]Other papers have studied occupational categories for migrants and how they vary with time since arrival, with a similar purpose (e.g. Chiswick et al. 2005). Cobb-Clark et al. (2005) examines school enrolment and job search in the years following migration. But as far as we are aware none have studied reported skill use.

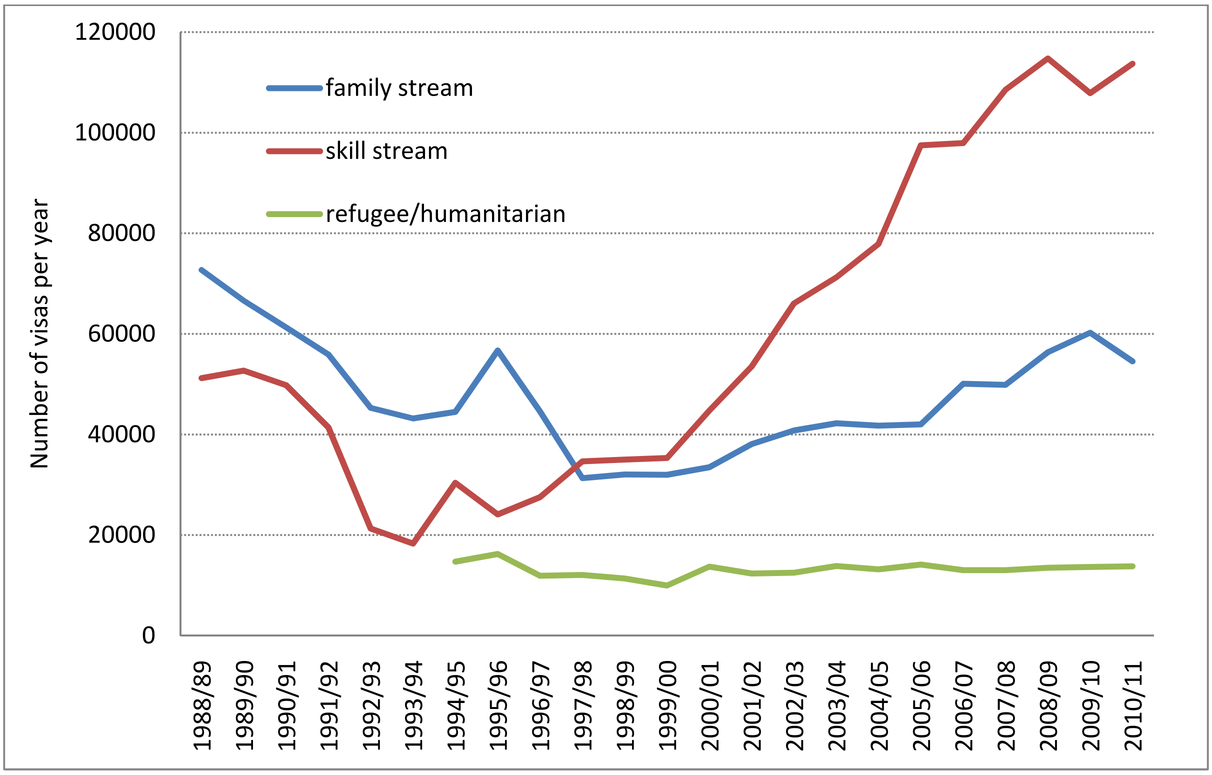
the study. Section 5 presents and discusses the analysis for each of the four research questions. Section 6 draws conclusions and briefly discusses possible policy implications. Appendices provide further details on data and methods.

## 2. Historical Policy Context

Prior to 1973 the White Australia policy in effect favoured immigration from certain countries including Britain and other European countries. This was replaced in 1973 with a more skills-focussed entry policy, and the stress on selection of immigrants on skills grounds, alongside entry on social and humanitarian grounds, has grown ever since (Productivity Commission, 2006).

Figure 1 shows the numbers of Family Stream and Skill Stream (permanent) visas granted each year since the late 1980s. Note in particular that the share of Skill Stream visas has risen steadily since the mid-1990s. The number of humanitarian/refugee visas granted each year has remained pretty steady over the last 30 years or so, at between 10,000 and 15,000 (Hugo et al., 2011), and Figure 1 includes these figures since the mid 1990s.[7]

**Figure 1: Family Stream, Skill Stream and Refugee/Humanitarian Visas Granted 1988/89-2010/11**




Sources (for various years): Productivity Commission (2006), Hugo et al. (2011), DIAC Migration Program Statistics.

[7] During this time there have been two noticeable temporary peaks in the number of irregular maritime arrivals (in the last two years and also in 1999/2000 and 2000/2001).

Skill Stream visas are awarded by means of a points score – based on factors including age, skills, work experience and English language ability – with overall numbers capped each year. These criteria were strengthened in 1999 (Productivity Commission, 2006). Family Stream visas are awarded on the basis of family relationships to sponsors, again up to an annual limit, but with no equivalent language or other skills requirements. From 1996, both Skill Stream and Family Stream migrants are subject to a two-year waiting period before they can claim various Income Support payments (e.g. New Start Allowance).

The number of temporary migrants coming to Australia – including overseas students, business long stay, and working holiday makers – has also increased over this period (Productivity Commission, 2006), which is reflected in a growing stock of temporary migrants in Australia at any one time (DIAC, 2011). There have also been changes in the policies governing temporary migration, including increased working rights (e.g. for overseas students), and increased scope to transition from temporary to permanent resident status from within Australia (Productivity Commission, 2006).

This study uses the HILDA Survey data to address the research questions listed in the introduction. But the wide range of arrival dates for migrants in the HILDA Survey sample, even after we make the age restrictions set out in the data section, means that we have different cohorts of migrants that arrived under very different migration policies. And with the increased skills focus of entry policy over time we would therefore expect migrant cohorts to become increasingly skilled over time, although this is not necessarily the case for refugee/ humanitarian migrants.

This has two particular implications for our study and its relevance looking forward. First, the 'raw' migrant employment gap – the difference in the employment rates of migrants and Australian-born, not controlling for other observable factors – might be expected to narrow over time as the average skills levels of migrants increase over successive arrival cohorts. Cully (2011) presents some evidence of this for Australia using Labour Force Survey data. But our *conditional* estimates of the migrant employment-rate gap – estimates that control for education level and arrival cohort among other things – are less likely to be affected by changes in the composition of arrival cohorts, and as such can be used as a guide to size of the migrant employment-rate gap looking forwards.

Second, descriptive analysis of how the migrant employment gap changes with years since arrival (e.g. Figure 2 in this report) will confound the actual relationship between employment and years since arrival with the increased employability of more recent cohorts resulting from the increased skills focus in entry policy. As a result the employment rates of more recent arrivals will be higher, and the employment rates of less recent arrivals will be lower, than if we were comparing employment rates over time for a single arrival cohort.[8] Again, this is not an issue for estimates of migrant employment catch-up that control for arrival cohort and other observable characteristics, such as those presented in Figures 3 and 4 in this report.[9] In particular, the fixed effects estimates of the rate of employment catch up presented in Figures 5 and 6, because they offer the highest possible degree of control for other factors that may influence employment rates, provide our best estimates of what might happen in terms of employment rates over time for the *current* migrant arrival cohort.

[8] This may flatten the observed association between the migrant employment rate and time since arrival.
[9] Different arrival cohorts will catch up with the Australian-born at similar rates, but starting from different initial employment gaps.

# 3. Literature Review

In what follows we mostly restrict attention to studies published since 1999. For a review of the theoretical literature and international empirical evidence prior to 1999, see Borjas (1999). For a brief review of empirical evidence specific to Australia prior to 1999, see the introduction to McDonald and Worswick (1999).

### 3.1. Economic Theory

The economic effect of migration on the host country's economy, and labour market outcomes for migrants themselves relative to natives, depend on the skill distribution among migrants compared to that of natives. Several explanations have been put forward as to why the skill distribution among migrants might differ systematically from both the source countries' and the host country's overall skill distribution. First, migrants are a non-random selection of the overall population as a result of entry policy – the granting of a visa depends on the characteristics of the migrant – which in Australia, as discussed in Section 2, has been focused on attracting highly-skilled migrants, at least over recent decades. These immigrant selection criteria will result in systematic differences between the migrant and the Australian-born population (e.g. Miller, 1999; Cobb-Clark, 1993; Cobb-Clark, 2003). Second, individuals select themselves into migration: they leave their home country only if they expect a net pay-off from doing so. Their pay-off from migration depends on their skills, and on the expected returns to skills in the source country relative to the destination country. If wages differ less between high-skilled and low-skilled in the destination country than in the source country, mainly the low-skilled population is attracted to the destination country, and vice versa (Borjas, 1999). Third, regardless of selection there will be some *loss* of skills (or at least loss of skill relevance) after migration if skills are not perfectly transferable across countries (e.g. language skills, knowledge of institutions and availability of social networks, or formal recognition of educational degrees). Taken together, these factors can influence migrants' skills compared to natives' skills, and relative labour market outcomes, in an uncertain direction.

There is also likely to be variation between different migrant groups. For example, very young migrants or migrants who arrive in their host country before leaving full-time education acquire a higher share of their human capital in the host country. Their loss of human capital due to the migration decision is thus likely to be smaller than for individuals who migrate at later in their life-cycle (e.g. Clark and Lindley, 2009). Differences in cultural background may influence to what extent formerly acquired skills are useful in the destination country, with skills likely to be more transferable between countries that are culturally more similar (e.g. Kostenko et al., 2009). Moreover, the reason for migrating might affect the migrant's labour market success. Economic migrants will come to a country only if the expected returns to their skills are high enough to justify the migration decision, while refugees or humanitarian migrants are more likely to come to a country independent of transferability of skills and returns to skills. Refugees and humanitarian migrants might therefore experience a greater loss of skills on average than economic migrants. Similarly, migrants that are not the primary applicant (e.g. partners) make their migration decision in a family context, and might migrate even if their individual loss of skills is high (Mincer, 1978; Baker and Benjamin, 1997; Blau et al. 2003; Cohen-Goldner et al. 2009). As a result, the partners of primary applicants (more likely to be women) might have a lower level of transferable skills than the primary applicants themselves.

Economic theory also predicts that the gap between migrants' and natives' skills, and in turn their labour market outcomes, may not be constant over time. After arriving in the host country migrants face an incentive to invest in country-specific human capital (e.g. building up social networks, or acquiring formal education), thereby closing the labour market outcomes gap with natives over time. So migrants might have lower wages than natives at the time of arrival in the destination country, but might then experience faster wage growth in subsequent years. This adjustment process might also differ for different groups of migrants, for example depending on their time horizon: the longer a migrant plans to stay in the destination country, the higher is the incentive to invest in country-specific human capital, as the migrant receives returns on those investments for a longer time. Time horizons may differ between migrants on temporary and permanent visas (e.g. Dustman, 1999) – again likely to be important in Australia given the large share of temporary migrants in overall migration flows – and between economic migrants and refugees who are less likely to be able to return to their source country (e.g. Cortes, 2004), for example. So, a migrant's economic success relative to the native population is likely to vary by his or her personal characteristics at the time of arrival, it might change over time in the host country, and the speed of assimilation might vary by his or her individual characteristics.

### 3.2. Empirical Evidence, International

There is a substantial international empirical literature on labour market outcomes for immigrants, usually compared to natives, using data from the US and elsewhere. Although some studies examine employment probabilities (e.g. Aslund and Rooth, 2007), the outcome measure that has attracted the most attention is wages, with 'years since migration' one of the most widely explored explanatory variables (to capture labour market assimilation). The bulk of this evidence suggests immigrants receive lower wages than otherwise comparable natives in the early years following arrival, but experience faster wage growth over time as they assimilate, with the gap disappearing after around 15 years (at least in the US). Much of this literature is based on cross section data, however, which leaves open the possibility that what appears to be assimilation could be at least partly picking up differences in (observed or unobserved) characteristics between successive cohorts of immigrants and/or between those that return migrate and those that remain (see Borjas, 1999). Studies using longitudinal data tracking migrants (and natives) over time are less common, particularly those tracking individuals over long periods, but notable exceptions include Hu (2000), Aslund and Rooth (2007), Cohen-Goldner and Eckstein (2008) and Blume et al. (2009). Hu (2000), for example, concludes that analysis of longitudinal (Health and Retirement Survey) data for US immigrants presents a more pessimistic portrait of immigrants' economic success than that suggested by Census data.

Unsurprisingly, there is widespread evidence in the international literature that migrant labour market outcomes vary with migrant characteristics. For example, Borjas (1999) reports big differences between different cohorts of US immigrants. Card (2005) reports differences by gender and education level for US immigrants. Hu (2000) reports differences between Hispanic and non-Hispanic migrants into the US. Cortes (2004) reports differences between refugees and other US immigrants. There is also evidence in the international literature that labour market conditions at the time of entry can have longer term effects on migrants' labour market outcomes (e.g. Aslund and Rooth, 2007, for Sweden).

### 3.3. Empirical Evidence, Australia

This project also builds on a wealth of existing research evidence on the labour market outcomes of migrants to Australia, although again much of this evidence stems from studies of cross sectional data (e.g. Productivity Commission, 2006, and the Census) or short duration longitudinal studies (e.g. Cobb-Clark, 2003, and the Longitudinal Study of Immigrants to Australia (LSIA)). Wilkins (2007) and Kostenko (2009) are partial exceptions, both using data from waves 1-5 of the HILDA Survey. Wilkins (2007), however, is a purely descriptive study, although it gives a useful overview of labour market outcomes for migrants by English speaking background. Kostenko (2009) examine the subjective well being of migrants, finding some evidence for improvement in subjective wellbeing with duration since arrival.[10]

This project's focus on employment outcomes rather than wages reflects the finding in the existing Australian migration literature that, on average, hourly wages are broadly similar for employed migrants and employed Australian-born, even shortly after migration (e.g. Antecol et al., 2006; Chiswick et al., 2008), whereas migrants' *employment rates* are substantially worse compared to those for the Australian-born, at least in the early years following migration (e.g. Antecol et al., 2006). Chiswick et al. (2008) argues that the high incidence of collective wage bargaining and the award wage system in Australia act to compress wages over the entire wage distribution and limit wage differences between Australian-born and migrants for those who are employed. Recent studies of the migrant assimilation process in Australia – our third research question – have therefore tended to focus on employment, unemployment and labour force participation rather than wages (e.g. Miller, 1999; Cobb-Clark, 2003; Cobb-Clark et al., 2005; Antecol et al., 2006) or on occupational attainment (Chiswick et al., 2005; Kostenko et al., 2009). All find evidence of assimilation in employment rates, participation rates, unemployment rates or occupational 'rank'.

The second research question reflects existing Australian evidence of the importance of migrant characteristics such as education level and English language proficiency (e.g. Antecol et al., 2003; Productivity Commission, 2006; Wilkins, 2007), with studies generally concluding that English language ability (sometimes measured by an indicator for coming from a non-English-speaking-background country) the single most important predictor of labour market outcomes. Visa class also matters, e.g. with labour market outcomes apparently worse for refugees than for other migrants (e.g. Miller, 1999; Cobb-Clark, 2003; Hugo et al., 2011). So too does gender (e.g. Wilkins, 2007), which may partly reflect that some female migrants self-select into migration based on their spouses' expected labour market success rather than their own (Cobb-Clark et al., 2005).

[10] Note that Kostenko et al. (2009) include individual level random effects in their model to better control for unobserved heterogeneity. We use a similar approach here to model labour market assimilation.

The fourth question stems from earlier findings using the LSIA that in addition to poor employment prospects, those migrants who find employment often work in occupations below their qualification level at first, but with some upward mobility subsequently (Chiswick et al., 2005). The drop (and the steepness of the recovery) is bigger for refugees than for economic migrants and bigger for high skilled relative to low skilled migrants. Kostenko et al. (2009) also uses the LSIA to examine the occupational attainment of recent immigrants at two years after migration. They find that non-Western immigrants are disproportionately channelled into inferior jobs post migration. No earlier studies, however, have directly examined self-reports of skill use.

## 4. Data and Methods

This section provides a brief discussion of the data (the HILDA Survey) and the methods (descriptive statistics and multivariate regression) used to address the research questions. Further details can be found in Appendix 1 and 2.

### 4.1. Data

This project uses 9 waves of the annual HILDA Survey for the period 2001-2009. The survey covers a broad range of topics including labour market participation, income and education. The sampling unit is the household, and individual interviews (usually face-to-face interviews) are conducted annually with all members of a selected household above age 15. The sample of households that were included in the study in 2001 is representative of all Australian households occupying private dwellings in that year.[11] All individual survey members are followed up regardless of whether they still reside in the originally sampled household, as long as they still reside in Australia. If they form a new household, all other members of their new household enter the sample.[12]

Because there are so many migrants in Australia as a proportion of the population, and because the HILDA Survey follows sample members for a long time[13], has a large sample size and does not systematically exclude or under-represent migrants, it is a very rich source of information for migration researchers. After restricting the sample to individuals aged 15 to 64 who are no longer in school or in continued full-time study after school, and after removing observations with missing information in key variables,[14] the sample for analysis includes 89,908 observations on 16,537 individuals, of which 3,716 were born overseas.[15] The HILDA Survey is the only dataset internationally that allows this many migrants to be tracked alongside natives for this length of time, and with this amount of detail.

[11] There are only minor exclusions such as members of non-Australian defence forces, overseas-residents and households in very sparsely populated areas. Cross-sectional weights are provided for each wave of the HILDA Survey – based on age, gender, region, household composition and employment status – which can be used to make the HILDA sample appear more representative of the Census population (see Summerfield, 2010). In what follows we use unweighted HILDA data, but weighted results are available on request.
[12] For more detailed information on the HILDA survey see Summerfield (2010).
[13] About 50% of those who were interviewed in 2001 are still interviewed 9 years later.
[14] Item non-response is rare. 172 observations had to be removed because information on their country of birth, country of school completion, time of arrival in Australia or language skills was unavailable. 19 observations had to be removed from the sample because it was not possible to determine whether they are still in school/in continued full-time study after leaving school. Another 32 observations were removed because of missing information on their marital status or health condition was unavailable.
[15] Where we examine questions about migrants ‘catching up’ with the Australian-born in terms of labour market outcomes we restrict the age range to 15-54 year olds. This restriction is discussed in Appendix 1.

But the advantages of HILDA must be set against its main disadvantages for the purposes of migration research. First, for most migrants no information is collected on visa class, other than to distinguish between refugee/humanitarian migrants and others (which we call economic migrants).[16] As a consequence we cannot examine differences in employment outcomes between migrants granted permanent refugee status on-shore and those granted refugee status off-shore, between Skill Stream and Family Stream migrants, between migrants on temporary visas and those on permanent visas, or for different groups within these broad visa classes. Second, new respondents enter the study only if they become a member of a household that had been sampled in 2001 or if a continuing individual respondent moves into their household. As a result, the survey includes few migrants who arrived in Australia after 2001 (184 individuals).[17] And many of those migrants included in wave 1 of the HILDA Survey had already been resident in Australia for many years, with 24 years the average length of time that HILDA Survey migrants have been in Australia. This still leaves 3,608 observations on migrants that have arrived within the last 10 years, however.

A third point is that migrants that return to their source country (or move to a third country) either never make it into the HILDA sample (if they leave Australia prior to wave 1) or subsequently drop out of the HILDA sample (if they leave Australia after wave 1). If return migration is non-random[18] this will have implications for interpreting the data on the extent to which migrants ‘catch up’ with the Australian-born over time. But this is also true of Census and other cross section data, and we argue in the following section that we are actually better able to deal with this issue using the HILDA Survey data than has been the case for earlier studies using cross-section data.

### 4.2. Methods

We use the HILDA Survey data in both its pooled form (essentially treating the data as one large cross section, with each observation treated as if it were for a separate individual)[19] and its panel form (treating the data explicitly as a panel study tracking individuals through time).

[16] From wave 4 onwards there is a question on migration category which allows us to distinguish between Skill Stream, Family Stream and other migrants, but it is only asked for 133 individuals (excluding those who arrived in 1999 or earlier, migrants from New Zealand, and temporary migrants), 28 of whom answer ’don’t know’ or ‘none of the above’.

[17] Further, given the HILDA sampling frame it is unlikely that these 184 individuals are representative of the wider cohort of post-2001 migrants.

[18] For example if ‘unsuccessful’ migrants return and ‘successful’ migrants remain.

[19] An alternative would be to focus only on wave 1, which would have advantages in terms of comparability with the 2001 Census and avoiding attrition problems between wave 1 and later waves, but at the cost of much reduced sample size.

Most empirical analyses of migrants' labour market outcomes relative to natives' labour market outcomes have used cross section data, either from a single survey or Census, or from more than one cross sectional data source pooled together (e.g. Antecol et al., 2006).

We begin our analysis of each research question with presentation and discussion of relevant descriptive statistics using the pooled HILDA data. This approach is most suited to highlighting differences in the 'raw' data between migrants and Australian-born – very much in the spirit of Wilkins (2007) – or between different groups of migrants. For example, we can use simple comparisons of the raw data for migrants and Australian-born to get a measure of the overall gap in employment rates for the two groups. Such differences are often what we are most interested in. For example, if we want to know whether to target scarce resources on migrants or, say, individuals with a long term health condition, then it is the raw employment gap for the two groups that we want to compare.

On the other hand, we know that migrants and Australian-born individuals are, on average, different: in obvious respects such as language and country in which they undertook schooling, but also in other respects such as highest education level, health and age (see Table 1).[20] Many of these characteristics are themselves highly correlated with employment probabilities. The implication is that the 'raw' migrant employment gap combines what we might think of as the 'true' migrant employment gap with the effect of these differences in characteristics on the employment probability. In other words, the raw gap we obtain from the descriptive analysis is not comparing like with like. And if we want to know *why* there is an employment gap, and how we might best intervene to reduce it, then multivariate regression models that control for compositional differences between migrants and Australian-born are likely to be more useful. For each research question we therefore also report analysis based on such multivariate models.

[20] Migrants in HILDA are on average almost 4 years older than the Australian-born and are more likely to have children living in the household. The picture with respect to skills is mixed. On average migrants have higher formal qualifications, consistent with Australian immigration policy that favours high-skilled migrants over low-skilled migrants in the visa granting process. A tertiary education is about 50% more likely among the migrant population than among the Australian-born population and migrants are about 50% less likely to have highest education level below Year 12. On the other hand, migrants fall considerably behind the Australian-born population with respect to their English language skills: although the majority of the migrants speak English at least 'very well', there is a considerable minority without good English language skills.

**Table 1: Characteristics of Migrants and Australian-born, Sample Means**

| | Australian-born | Migrants | Difference |
|---|---|---|---|
| Female | 52% | 52% | 0 |
| Age | 40.00 | 44.63 | 4.62** |
| Number of resident children | 0.90 | 0.96 | 0.06** |
| Long-term health condition | 22% | 22% | 0 |
| *Highest Education* | | | |
| [1] Postgraduate (master or doctorate) | 3% | 6% | 3pp** |
| [2] Graduate diploma, graduate certificate | 5% | 7% | 1pp** |
| [3] Bachelor or honours bachelor | 13% | 17% | 4pp** |
| [4] Advanced diploma, diploma | 9% | 10% | 1pp** |
| [5] Certificate III or IV | 22% | 18% | -3pp** |
| [6] Certificate I or II | 2% | 1% | -1pp** |
| [7] Certificate, not defined | 0 | 1% | 0 |
| [8] Year 12 | 15% | 17% | 2pp** |
| [9] Year 11 and below | 31% | 23% | -7pp** |
| [10] Undetermined | 0 | 0 | 0 |
| Has post-school qualification ([1]-[7]) | 54% | 60% | 6pp** |
| Has tertiary degree ([1]-[3]) | 21% | 30% | 9pp** |
| *Language Skills* | | | |
| English is the only language | 97% | 62% | -35pp** |
| Speaks English very well | 3% | 20% | 18pp** |
| Speaks English well | 0 | 12% | 11pp** |
| Speaks English not well | 0 | 5% | 5pp** |
| Speaks English not at all | 0 | 0 | 0** |

Note: ** denotes means that are statistically different at the 99% level. Figures are rounded, so there may be small differences in the reported 'difference' and the difference implied by the reported means. 'pp' denotes percentage points. Ages 15-64.

The standard regression model using cross section data to compare labour market outcomes for migrants relative to natives tends to focus on wages as the outcome measure (see Borjas, 1999). The estimation equation for natives includes socioeconomic control variables (such as education and health), year, and age, where age can be interpreted as capturing the accumulation of human capital over the life cycle, and where the year-effects capture changes in the macroeconomic context over time. For migrants, the estimation equation might also include years since migration and additional controls for age at arrival and year of arrival. The coefficient on years since migration represents the extent to which the wage growth of migrants exceeds that of natives, e.g. due to the acquisition of country-specific human capital over time. Age at arrival is included as an additional control variable to measure differences in the loss of human capital between very young migrants who acquire most or all of their human capital in the destination country and thus experience low losses of human capital when they migrate, and older migrants. Year of arrival is included to account for otherwise unobserved differences in the composition of different migrant cohorts.[21]

We follow the approach outlined above using the pooled HILDA Survey data.[22] We make some modifications, however. First, as we discuss in Section 3.3, previous research for Australia has shown that differences in skills and productivity are reflected more in differences in employment probabilities rather than in hourly wages (e.g. Antecol et al., 2006; Chiswick et al., 2008). We therefore adopt employment probability as the labour market outcome of primary interest (for research questions 1-3). We also explore self-reported skill use (for those employed) as an additional outcome measure (research question 4). Second, our model allows for differences in the adjustment process for economic migrants and refugees. Given the key role of Australia's skilled migration program, the gap in terms of characteristics between economic migrants and refugees/humanitarian migrants is expected to be particularly apparent in Australia (e.g. see Miller, 1999). We know from previous studies elsewhere (e.g. Cortes, 2004) that outcomes for refugees can differ significantly from outcomes for other migrant groups. If anything, given the skills focus of entry policy, we might expect such differences to be more pronounced for Australia.

Because our focus is on employment status for research questions 1-3, we have regression equations with a binary dependent variable. (This is not the case for research question 4, where the skills use measure is reported on a 7 point scale.) For ease of interpretation and consistency across research questions, we adopt an ordinary least squares (OLS) regression approach – called a linear probability model (LPM) where the dependent variable is binary – although our conclusions are robust to alternative (logit) specifications.[23] All models are estimated separately by gender.

For research question 1 – *is there a migrant employment penalty and how big is it?* – the relevant LPM is as follows:

[21] Assume that there were no controls for year of arrival in the model, and at the same time, for example the visa granting policy of a country became less skills focussed over time. In that situation, recent arrivals would have a less favourable skill composition because of the visa granting policy, and thus less favourable labour market outcomes, than older arrivals. Without a control for the policies that are in place at the time of arrival, this would lead to an upward bias in the estimated coefficient of 'years since arrival'. What is in fact a change in the composition of migrant cohorts would appear as an 'adjustment' of migrants to the source country's labour market over time.

[22] We allow errors to be correlated between different observations for the same individuals.

[23] In practice, these models tend to be used somewhat interchangeably, and in most cases conclusions do not depend on the particular model chosen (for more details see Greene, 2008).

(1) $Prob(Y_i = 1) = X_i'\beta_X + \beta_M M_i$

$Y_i$ is a dummy variable that takes the value one if person *i* is employed and zero otherwise. $X_i$ is a vector of socioeconomic control variables that includes age, age$^2$, year, the presence of a long-term health condition, the presence of children in the household, education level and marital status. $M_i$ is a dummy variable that takes the value one if the person was born outside Australia and zero otherwise. The coefficient $\beta_M$ gives the migrant employment penalty (or gap), conditioned on the observed characteristics $X_i$. The coefficients in the vector $\beta_X$ show the impact of the socio-economic controls for health, education etc. on the employment probability for both migrants and Australian-born, with the impacts assumed to be equal for both groups.

For research question 2 – *what characteristics of migrants are associated with better employment outcomes?* – we use two slightly different versions of the LPM. First, we allow the migrant employment gap to differ by visa category (refugee/humanitarian versus other), by English language proficiency, and by whether the migrant attended secondary school in Australia, as follows:

(2) $Prob(Y_i = 1) = X_i'\beta_X + \beta_M M_i + \beta_R M_i R_i + \beta_L M_i L_i + \beta_{AA} M_i AA_i$

The additional variables are as follows: $R_i$ is a dummy variable that takes the value one if a migrant arrived in Australia as a refugee or under a humanitarian migration program, and zero otherwise; $L_i$ measures the language skills for individual *i* as a dummy variable equal to one if English is the only language the individual speaks at home or if the individual speaks English "very well", and zero otherwise; $AA_i$ measures the age of arrival in Australia, specified as a dummy equal to one if the migrant attended at least some secondary school in Australia and zero otherwise.[24] The coefficient $\beta_M$ now gives the migrant employment gap for a migrant who is not a refugee, with good English language skills, and who finished school outside Australia (we call this the baseline case); $\beta_R$ gives the additional gap from being a refugee; $\beta_L$

[24] Alternatively, this can be thought of as a dummy equal to one if the migrant arrived in Australia aged less than 18 and zero otherwise.

gives the additional gap from poorer English language skills; and $\beta_{AA}$ gives the compensating schooling effect from having attended secondary school in Australia.

Second, we extend this approach to allow the migrant employment gap to differ across *all* observed characteristics in $X_i$ (including age, education level, health), and for the effects of these characteristics to further vary across the key dimensions of visa category, language skills and schooling in Australia, as follows:

(3) $$Prob(Y_i = 1) = X_i'\beta_X + \beta_M M_i + \beta_R M_i R_i + \beta_L M_i L_i + \beta_{AA} M_i AA_i + (M_i X_i)'\beta_{MX} + (R_i X_i)'\beta_{RX} + (M_i L_i X_i)'\beta_{LX} + (M_i AA_i X_i)'\beta_{AAX}$$

Individual coefficients are more difficult to interpret in (3), so we present results in the form of predicted migrant employment penalties for migrants with different combinations of characteristics.

For research question 3 – *does the migrant employment-rate gap fall over time since migration?* – the relevant model is as follows:

(4) $$Prob(Y_i = 1) = X_i'\beta_X + \beta_M M_i + \beta_R M_i R_i + \beta_{AA} M_i AA_i + (M_i YA_i)'\beta_{YA} + (M_i X_i)'\beta_{MX} + M_i(\delta_{1M} \cdot YSM_i + \delta_{2M} \cdot YSM_i^2) + R_i(\delta_{1R} \cdot YSM_i + \delta_{2R} \cdot YSM_i^2)$$

The additional variables in (4) are $YA_i$ which captures year of arrival in Australia (grouped into decades) and $YSM_i$ which denotes years since migration. The latter variable is the standard way to capture the adjustment process, i.e. the assimilation of migrants in terms of employment probabilities, with the squared term allowing for curvature in the relationship, e.g. if migrants catch up faster in early years compared to later years. The effects of the variables $M_i$, $R_i$ and $AA_i$ are now interpreted as migrant penalties and compensating effects *at the time of arrival*. The last term on the right hand side of (4) allows the assimilation process to differ between economic migrants and refugees.

Note that we have made a number of restrictions in (4): year of arrival is specified in bands not single years and age at arrival is a binary dummy not a continuous variable measured in years. The reason for this is that, in the absence of such restrictions, models such as (4) face the following identification problems: first, 'age at arrival' plus 'years since migration' equals the migrants' age; second, 'year of arrival' plus 'years since migration' equals the current year. Consequently, these effects cannot be separated from each other without imposing further identifying restrictions. In specifying 'age at arrival' and 'year of arrival' in broader intervals we follow a standard approach in the literature (see Borjas, 1999). For further details see Appendix 2.

Also note we have dropped the English language variable from (4). The reason is that assimilation may in some part be *driven* by improved English language skills. In other words, just as one of the factors influencing the magnitude of the migrant employment gap in (2) is poor English language skills, one of the *mechanisms* for labour market assimilation of migrants is improvements in language skills.[25]

For research question 4 – *how does skill use in employment compare for migrants and Australia-born?* – we use the HILDA Survey question on self-reported skill utilisation in the job currently held by individual $i$, measured on a scale of 1 to 7, as the dependent variable. Again we take an OLS approach, although we also estimate the models as ordered probits to check robustness of the key conclusions. Because the skill use question is only asked for those that are employed, the sample is restricted to employed migrants and employed Australian-born.

We estimate four versions of the skills use model, echoing equations (1)-(4) on employment. First, to provide an estimate of the overall migrant skills use gap, conditioned on the observed characteristics in $X_i$, we estimate the following equation:

$$(5) \qquad Skill_i = X_i'\gamma_X + \gamma_M M_i + \varepsilon_i$$

Second, to examine how any migrant skills use gap varies with key migrant characteristics (visa category, English language ability, schooling in Australia), we estimate the following, with coefficients interpreted as for research question 2:

[25] We explore this issue by also estimating the impact of years since migration separately for those from English speaking background countries and those from non-English speaking background countries, where English speaking background proxies for English language ability on arrival. Results, which are consistent with English language acquisition being a key mechanism for migrant employment assimilation, are available from the authors on request.

$$(6) \quad Skill_i = X_i'\gamma_X + \gamma_M M_i + \gamma_R M_i R_i + \gamma_L M_i L_i + \gamma_{AA} M_i AA_i + \varepsilon_i$$

Third, to examine how any migrant skills use gap varies with all observed migrant characteristics we estimate the following:

$$(7) \quad Skill_i = X_i'\gamma_X + \gamma_M M_i + \gamma_R M_i R_i + \gamma_L M_i L_i + \gamma_{AA} M_i AA_i + (M_i X_i)'\gamma_{MX} + (R_i X_i)'\gamma_{RX} + (M_i L_i X_i)'\gamma_{LX} + (M_i AA_i X_i)'\gamma_{AAX} + \varepsilon_i$$

Fourth, to examine whether employed migrants catch up with the employed Australian-born in terms of reported skills use over time, we estimate the following model, with coefficients interpreted as for (4) above:

$$(8) \quad Skill_i = X_i'\gamma_X + \gamma_M M_i + \gamma_R M_i R_i + \gamma_{AA} M_i AA_i + \gamma_{YA} M_i YA_{i_i} + (M_i X_i)'\gamma_{MX} + M_i(\delta_{1M} \cdot YSM_i + \delta_{2M} \cdot YSM_i^2) + R_i(\delta_{1R} \cdot YSM_i + \delta_{2R} \cdot YSM_i^2) + \varepsilon_i$$

Estimating the above models using the pooled data (or any other cross section data) leaves us with the potential problem that migrants might differ in unobserved ways, e.g. in terms of their preferences, ability and motivation, that also impact on labour market outcomes. This doesn't matter for estimating the average migrant employment gap, or employment gaps for different groups of migrants, but it can matter for interpreting what *causes* differences in migrant employment penalties across different groups, and for designing appropriate policy responses. For example, the difference in the migrant employment gap between those with and without good English language skills may pick up both the effect of language skills and the effects of other unobserved factors that are themselves correlated with language skills. Interventions to improve the language skills of migrants might therefore have less (or more) impact on employment outcomes than that suggested by cross section estimates in models such as (2). Equally, such unobserved factors can lead to biased estimates of employment or skills catch up over time (see Appendix 2). For example, if less motivated migrants are both more likely to return migrate and less likely to be employed relative to other migrants, then cross section estimates of assimilation that do not control for (unobservable) motivation may *overestimate* catch up rates.

To the extent that unobserved differences between migrants are *time invariant*, however, we can exploit the panel nature of the HILDA Survey data to estimate models that control for time invariant unobserved heterogeneity with individual fixed effects. In particular, fixed effects can give unbiased estimates of 'catch up' even if the time-invariant unobserved factors (e.g. motivation) are correlated with years since migration.[26]

Our fixed effects version of equation (4) – how migrants' employment rates catch up with Australian-born employment rates over time since arrival – is as follows[27]:

$$(9) \qquad Prob(Y_{it} = 1) = \alpha_i + X'_{it}\beta_X + (M_i X_{it})'\beta_{MX} + M_i(\delta_{1M} \cdot YSM_{it} + \delta_{2M} \cdot YSM^2_{it})$$

Our fixed effects version of equation (8) – how the migrant skill use gap falls over time since arrival – is as follows:

$$(10) \qquad Skill_{it} = \alpha_i + X'_{it}\gamma_X + (M_i X_{it})'\gamma_{MX} + M_i(\delta_{1M} \cdot YSM_{it} + \delta_{2M} \cdot YSM^2_{it}) + \varepsilon_{it}$$

Such fixed effects estimates also come with a health warning, however, following studies by Beenstock et al. (2010) and Lubotsky (2011) which show they could *underestimate* the rate at which migrants catch up with natives if the returns to host country-specific human capital are increasing over time.[28] Cobb-Clark et al. (2012) discusses this point in more detail and uses the HILDA Survey data to estimate the extent of both the upwards bias in the pooled cross

[26] In principle, a fixed effects version of (2) or (6) might also allow us to be more confident in placing a causal interpretation on the impact of English language skills on the probability of employment and on reported skill use. In practice, however, the fixed-effects model relies on variation in variables over time for a given individual (within variation). Unfortunately, there is little within variation in reported English language ability for migrants in the HILDA Survey, and it could also be that what variation there is could reflect measurement error rather than genuine changes in language ability (as many migrants report a deterioration of English language ability as an improvement). As a result we do not estimate a fixed effects model for the impact of English language ability on employment or skills use here.

[27] For identification reasons, in (9) and (10) we restrict the coefficients on age and age$^2$ to be equal for migrants and Australian-born. We also drop the interaction between migrant dummies and year dummies. Also note that time-invariant observed factors, such as gender or refugee status, are 'absorbed' by the fixed effects. So although such factors are *controlled for* in a fixed effects model, their impact on employment probability cannot be separately identified. All such variables are therefore dropped from $X_{it}$ in the fixed effects models. For more details see Appendix 2. We also simplify by constraining the assimilation rate, but not the initial gap, to be the same for refugees and other migrants.

[28] In such a context, immigrants' earnings growth may be slower than that of natives (who already have a high level of host country-specific human capital) despite migrants accumulating host country specific human capital each year at a higher rate than natives. The argument concerns earnings catch up, but can also apply to employment catch up and (although this is less clear) skills catch up.

section estimates of employment catch up and the downwards bias in the fixed effects estimates of employment catch up for Australia over this period. As a result, we interpret the pooled estimates from equations (4) and (8) as giving *upper bound* estimates of the rate of employment/skills catch up, and the fixed effects estimates from equations (9) and (10) as giving *lower bound* estimates, with the 'true' impact of time spent in Australia somewhere in between.

# 5. Results and Discussion

## 5.1. The Migrant Employment Rate Gap

In this section we first report the average migrant employment gap in the raw data then we report the average migrant employment gap where we compare migrants with Australian-born individuals with similar observed characteristics. These estimates suggest an average employment rate gap of around 4 percentage points for men and around 7 percentage points for women.

Table 2 reports the employment rates (expressed as a proportion of the working age population) for Australian-born and migrants, separately for men and women. For men the migrant employment rate is 4.4 percentage points lower than the Australian-born employment rate and for women it is 6.9 percentage points lower. Both differences are statistically significant at the 99% level. So these provide us with our estimates of the 'raw' migrant employment gap. These estimates are close to those of Wilkins (2007), who used data from the first five waves of the HILDA Survey. They are also broadly in line with the (raw) *participation* gap, across both men and women, suggested by the Productivity Commission (2006) report, based on 2001 Census data.

**Table 2: Employment Outcomes of Australian-born and Migrants**

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | Australian born | Migrants | Diff. | Australian born | Migrants | Diff. |
| Employed/working age pop. (unweighted) | 83.9% | 79.5% | -4.4pp** | 69.2% | 62.3% | -6.9pp** |
| Number of observations | 33,495 | 9,411 | | 36,762 | 10,240 | |

Notes: ** denotes means that are statistically different at the 99% level. Figures are rounded, so there may be small differences in the reported 'difference' and the difference implied by the reported means. 'pp' denotes percentage points. Ages 15-64.

When we control for differences in a standard set of observed characteristics between Australian-born and migrants, following the multivariate regression approach (1) outlined in Section 4.2, we get very similar estimates of the *conditional* migrant employment gap, i.e. what the gap would be if migrants had the same observed characteristics as Australian-born. Table 3 shows the resulting estimates, separately for women and men. On average, migrants' probability of employment is 4.1 percentage points lower for males and 7.5 percentage points lower for females compared to Australian-born with the same characteristics in terms of educational level, age, health, marital status and the presence of children. The fact that these estimates are so close to the ‘raw’ migrant employment gap estimates presented above suggests that these compositional differences between Australian-born and migrants mostly cancel one another out, so that the net employment gap driven by compositional differences between the two groups is close to zero.

The higher migrant gap for women compared to men could reflect factors such as language differences between genders that we have not yet controlled for, or more generally might reflect the fact that men are more often the primary visa applicant, while women are more often family migrants. Family migrants are expected to have less favourable labour market outcomes than primary applicants as they might self-select into migration based on their spouses’ expected labour market success, rather than their own (e.g. see Cobb-Clark et al., 2005). These estimates are broadly in line with the Productivity Commission’s (2006) estimate of the *participation* gap for migrants (men and women together), based on 2001 Census data and conditioned on similar control variables.

**Table 3: Average Migrant Employment-Rate Gap Controlling for Observed Characteristics, Pooled Data, Coefficients (Standard Errors)**

| | Men | Women |
|---|---|---|
| Average migrant gap (percentage points) | -4.1** | -7.5** |
| | (0.8) | (1.0) |
| Language, refugee, schooling in Australia controls | No | No |
| Other characteristics controls | Yes | Yes |
| Number of observations | 42,906 | 47,002 |
| R-squared | 0.222 | 0.163 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). ‘Other characteristics controls’ include dummies for year (2001-2009), highest education (four dummies), long-term health condition, children, marital status, and continuous variables for age and age$^2$.Ages 15-64.

### 5.2. Which Migrants Face the Biggest Employment Rate Gaps?

In this section we first present descriptive analysis of the main characteristics that are associated with employment rates for migrants and for Australian-born. We then present regression analysis that allows us to estimate the associations of employment probability with particular characteristics, holding all other factors equal. English language proficiency is shown to be particularly important, but many other characteristics are significantly associated with the probability of employment for migrants.

Table 4 shows characteristics of employed and non-employed migrants to gain a first insight into the question of what characteristics lead to labour market success. Employed migrants are more often males, younger, more educated, and healthier than non-employed migrants. (These patterns are similar for the Australian-born.) Specific to migrants, however, employment probabilities are higher for those with better English language proficiency, those who arrived in Australia prior to the end of secondary education and those with an Australian post-school qualification. Moreover, refugee status appears to be an important risk factor for non-employment. While refugees make up only 10% of the employed migrant population, they account for 17% of the non-employed migrant population.

**Table 4: Characteristics of Employed and Non-employed Migrants**

| | Non-employed Migrants | Employed Migrants | Difference |
|---|---|---|---|
| Female | 67% | 46% | -21pp** |
| Age | 48.42 | 43.04 | -5.38** |
| Number of resident children | 0.95 | 0.97 | 0.01 |
| Long-term health condition | 42% | 14% | -27pp** |
| Has post-school qualification | 44% | 66% | 22pp** |
| Has tertiary degree | 18% | 35% | 17pp** |
| *Language Skills* | | | |
| English is the only language | 53% | 66% | 13pp** |
| Speaks English very well | 17% | 22% | 5pp** |
| Speaks English well | 16% | 10% | -7pp** |
| Speaks English not well | 12% | 3% | -10pp** |
| Speaks English not at all | 1% | 0 | -1pp** |
| Is refugee | 17% | 10% | -7pp** |
| Completed school in AUS | 38% | 53% | 15pp** |
| Completed post-school in AUS | 24% | 44% | 20pp** |
| Number of observations | 5,787 | 13,864 | |

Note: ** denotes means that are statistically different at the 99% level. Figures are rounded, so there may be small differences in the reported ‘difference’ and the difference implied by the reported means. ‘pp’ denotes percentage points. Ages 15-64.

An alternative way to cut the data is to look at employment probabilities for migrants and Australian-born separately by characteristics, as in Table 5. The upper panel shows employment rates for migrants and Australian-born who are male, young, childless, do not have health problems, and have no post school qualification or tertiary education. In any given category the employment rates for migrants are significantly lower than for an Australian-born with the same characteristic. The middle panel shows that the same is true for women, older individuals with children, and for those with health problems and higher education. The lower panel presents the relation between a certain characteristic such as gender and the employment rate within the sub-population of migrants and Australian-born. Where the overall impact of the characteristic is negative (e.g. poor health, female), then a negative difference between its impact for Australian-born and for migrants (the right hand side column of the bottom panel) suggests it has a *stronger negative* effect among migrants than among Australian-born. Where the overall impact of the characteristic is positive (e.g. higher education), then a positive difference between its impact for Australian-born and for migrants suggests it has a *stronger positive* effect among migrants than among Australian-born. So not only are employment rates lower for migrants than for the Australian-born, they are also more sensitive towards socio-economic characteristics such as gender, age, health and education than is the case for the Australian-born. In other words, such characteristics tend to have a *bigger disadvantaging* or *bigger advantaging* impact for migrants than for Australian-born.

**Table 5: Employment Rates by Characteristics for Migrants and Australian-born**

| | Non-Migrants | Migrants | Diff |
|---|---|---|---|
| Male | 84% | 80% | -4pp** |
| Young (youngest half of the sample) | 79% | 77% | -3pp** |
| No resident children | 76% | 69% | -7pp** |
| No long-term health condition | 82% | 78% | -4pp** |
| No post-school qualification | 68% | 59% | -8pp** |
| No university degree | 73% | 66% | -7pp** |

| | Non-Migrants | Migrants | Diff |
|---|---|---|---|
| Female | 69% | 62% | -7pp** |
| Old (oldest half of the sample) | 72% | 66% | -6pp** |
| Has resident children | 76% | 72% | -4pp** |
| Long-term health condition | 55% | 45% | -10pp** |
| Has post-school qualification | 84% | 78% | -5pp** |
| Has university degree | 88% | 82% | -6pp** |

| | Non-Migrants | Migrants | Diff |
|---|---|---|---|
| Female vs. male | -15pp | -17pp | -3pp** |
| Young vs. old | -7pp | -11pp | -3pp** |
| Resident children vs. no resident children | 0 | 3pp | 3pp** |
| Long-term health condition vs. no long term health condition | -27pp | -33pp | -6pp** |
| Post-school qualification vs. no post school qualification | 16pp | 19pp | 3pp** |
| University degree vs. no university degree | 16pp | 17pp | 1pp |

Note: ** denotes means that are statistically different at the 99% level. Figures are rounded, so there may be small differences in the reported 'difference' and the difference implied by the reported means. 'pp' denotes percentage points. Ages 15-64.

We now turn to results from multivariate regression analysis as set out in Section 4.2. First consider equation (2) which provides estimates of how the conditional migrant employment gap varies across visa class (refugee/humanitarian versus other), English language proficiency, and age of arrival. In summary, we see large differences in the employment gap for different types of migrant, for both men and women, conditioned on our standard set of observed characteristics. Results are presented in Table 6, but they require a little more work to interpret than those presented in Table 3. Here, the 'baseline case' migration gap is for an economic migrant who finished school before migrating to Australia and who speaks English 'very well' or better. For men with these characteristics the conditional migrant employment gap is 1.2 percentage points and not statistically significant. For women it is 5.2 percentage points and statistically significant at the 99% level. If the migrant is a refugee, the employment probability goes down by another 3.6 percentage points for men (4.8 percentage points for women), although neither estimate is statistically significant. In contrast, the additional gap from poor English language skills is large and highly statistically significant: 15.5 percentage points for men and 19.5 percentage points for women.[29] Having been schooled in Australia has no additional impact for men but has a significant compensating effect for women, which essentially reduces the employment rate gap for non-refugees with good English language skills to zero.[30]

**Table 6: Migrant Employment Gap by Key Characteristics, Pooled Data, Coefficients (Standard Errors)**

| | Men | Women |
|---|---|---|
| Baseline case migrant gap (non-refugee, schooling outside Australia, good language skills), percentage points | -1.2 | -5.2** |
| | (1.1) | (1.4) |
| Additional refugee gap | -3.6 | -4.8 |
| | (2.5) | (3.0) |
| Additional poor language gap | -15.5** | -19.5** |
| | (2.0) | (2.2) |
| Compensating Effect of Schooling in Australia | -0.0 | 5.5** |
| | (1.4) | (1.9) |
| Other characteristics controls | Yes | Yes |
| Number of observations | 42906 | 47002 |
| R-squared | 0.228 | 0.171 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other characteristics controls' include dummies for year (2001-2009), highest education (four dummies), long-term health condition, children, marital status, and continuous variables for age and age$^2$. Ages 15-64.

[29] We also estimate two alternative versions of (2) which include a dummy variable for coming from a non-English speaking background, which has been shown to be strongly associated with labour market outcomes for migrants in previous research (e.g. Wilkins, 2007). Because coming from an English speaking background is highly correlated with English language ability, however, existing studies tend to use one or other measure to capture language and not both. For example, Wilkins (2007) uses English speaking background in place of English language ability, but the Productivity Commission (2006) uses English language ability in place of English speaking background. In this report we follow the latter approach, partly because the questions on English language refer to current language ability, and partly because they are easier to interpret (and arguably easier to act upon for policy makers) than a catchall dummy for English speaking background. Nevertheless, when a dummy for non-English speaking background is included in (2) *in place of* the language dummy, it has a large, negative and statistically significant impact on employment probability for both men and women, as we would expect. When it is included *alongside* the language dummy it has small and negative impact on employment probability, statistically insignificant for women, with the coefficient on the language dummy falling slightly for both men and women to compensate.

[30] One potential explanation for the gender difference in this effect is that Australian schooling proxies here for migration at an early age and therefore migration *not* driven by spousal earnings. Note that the zero (voluntary) migrant employment gap once language skills and place of schooling are taken into account, for both men and women, suggests there is no employment discrimination against migrants in Australia, at least if we are prepared to assume that those with different schooling and language backgrounds are not discriminated against differently.

Now consider results from estimating equation (3) which allows the migrant employment gap to differ across all observed characteristics in $X_i$ with the impact of these factors allowed to vary additionally by refugee status, English language proficiency and whether schooling was received in Australia. Results are presented in Tables 7 (for men) and 8 (for women) in the form of predicted employment penalties for migrants with different combinations of characteristics. Each table also includes a column which reports the employment rate for Australian-born individuals across characteristics. These Australian-born columns show well-known associations between employment rates and long term health conditions, education levels, and so on.

The results are consistent with the descriptive patterns presented in Table 5, although Tables 7 and 8 give a little more detail and have the advantage of holding other things equal. The predicted migrant employment gap is generally bigger for younger than for older migrants[31] (true for both men and women, but not for those with schooling in Australia); bigger for married than for unmarried migrants (both men and women, although the opposite is the case for refugees); bigger for migrants with a long term health condition compared to migrants in good health (both men and women, but not for those with schooling in Australia); smaller for migrants with children (for both men and women). Also note that the migrant employment gap appears bigger for those with middling levels of education: migrants with less than Year 12 and migrants with tertiary education tend to be closer to Australian-born in terms of employment rates than those with education levels in between (for both men and women). Further, for female migrants with post-school education, the employment gap is bigger for those whose post-school education took place outside Australia.[32] For men, the two-way combinations of characteristics that are associated with the biggest migrant employment gap are being young with poor English language skills, and having a long term health condition with poor English language skills. For women, it is being young with poor English language skills or being a refugee with a post-school but sub-degree level qualification gained outside Australia.

[31] This may be at least partly capturing the impact of years since migration (see section 5.3).
[32] There is no clear pattern in this respect for men.

**Table 7: Migrant Employment Gap across all Characteristics, Percentage Points, Pooled Data, Men**

| *Migrant Gap by Characteristics* | *Australian-born* | 'Baseline case' Migrants | Refugees | Schooling in Australia | Poor Language Skills |
|---|---|---|---|---|---|
| Age 25 | 86.4% | -5.1pp | -5.6pp | -0.3pp | -27.6pp |
| Age 35 | 92.1% | -2.1pp | -5.7pp | 2.2pp | -12.9pp |
| Age 45 | 88.8% | -1.0pp | -4.6pp | 1.2pp | -7.2pp |
| Age 55 | 76.5% | -1.8pp | -2.3pp | -3.4pp | -10.5pp |
| *Migrant has/is...* | | | | | |
| married/de facto: no | 77.3% | -0.6pp | -7.0pp | -2.8pp | -11.3pp |
| married/de facto: yes | 86.7% | -3.8pp | -2.9pp | -0.1pp | -18.1pp |
| long-term health condition: no | 89.4% | -2.0pp | -3.2pp | -2.2pp | -11.9pp |
| long-term health condition: yes | 64.7% | -5.4pp | -7.5pp | 3.2pp | -29.6pp |
| children: no | 83.5% | -4.4pp | -6.9pp | 0.3pp | -15.8pp |
| children: yes | 84.0% | -0.4pp | -0.3pp | -2.6pp | -16.1pp |
| Education: less than year 12 | 77.6% | 0.8pp | -3.5pp | 1.5pp | -14.0pp |
| Education: year 12, no post-school | 86.2% | -4.0pp | -12.8pp | -6.2pp | -16.9pp |
| Education: non-tertiary post-school | 84.6% | | | -0.8pp | |
| Education: tertiary | 88.2% | | | -1.0pp | |
| Education: non-tertiary post-school, AUS | | -5.8pp | -6.8pp | | -16.8pp |
| Education: tertiary, AUS | | -1.7pp | 7.1pp | | -16.1pp |
| Education: non-tertiary post-school, other country | | -0.8pp | -4.9pp | | -16.5pp |
| Education: tertiary, other country | | -3.3pp | -12.1pp | | -21.8pp |
| Other characteristics controls (entered separately) | | | Yes | | |
| Number of observations | | | 42,906 | | |
| R-squared | | | 0.233 | | |
| F-Test of Model Significance (p-value) | | | 0.000 | | |

Notes: the reported figures show the migrant employment rate gap for individuals with the given characteristics set at the given values compared to Australian-born individuals with characteristics set at the same value. Ages 15-64.

**Table 8: Migrant Employment Gap across all Characteristics, Percentage Points, Pooled Data, Women**

| *Migrant Gap by Characteristics* | *Australian-born* | 'Baseline case' Migrants | Refugees | Schooling in Australia | Poor Language Skills |
|---|---|---|---|---|---|
| Age 25 | 67.1% | -12.8pp | -7.4pp | -4.8pp | -34.4pp |
| Age 35 | 78.7% | -2.9pp | -7.4pp | 0.2pp | -20.9pp |
| Age 45 | 77.3% | 1.3pp | -6.0pp | 2.1pp | -14.0pp |
| Age 55 | 63.2% | -0.3pp | -3.3pp | 1.1pp | -13.6pp |
| *Migrant has/is...* | | | | | |
| married/de facto: no | 68.9% | -2.8pp | -7.6pp | 1.4pp | -15.9pp |
| married/de facto: yes | 69.0% | -5.0pp | -4.7pp | -1.7pp | -23.7pp |
| long-term health condition: no | 73.7% | -3.4pp | -5.6pp | -1.2pp | -20.9pp |
| long-term health condition: yes | 52.3% | -7.7pp | -5.6pp | 1.0pp | -22.3pp |
| children: no | 77.9% | -9.3pp | -9.1pp | -1.9pp | -24.4pp |
| children: yes | 60.6% | 0.3pp | -2.3pp | 0.4pp | -18.2pp |
| Education: less than year 12 | 57.9% | -3.2pp | -5.5pp | -1.3pp | -29.1pp |
| Education: year 12, no post-school | 71.6% | -14.9pp | -27.2pp | 2.6pp | -26.3pp |
| Education: non-tertiary post-school | 72.2% | | | -0.3pp | |
| Education: tertiary | 80.2% | | | -2.6pp | |
| Education: non-tertiary post-school, AUS | | 1.2pp | 6.3pp | | -18.0pp |
| Education: tertiary, AUS | | -4.5pp | -1.0pp | | -9.4pp |
| Education: non-tertiary post-school, other country | | -15.6pp | -33.0pp | | -26.2pp |
| Education: tertiary, other country | | -11.1pp | -19.5pp | | -31.8pp |
| other characteristics controls (entered separately) | | | Yes | | |
| # observations | | | 47,002 | | |
| R-squared | | | 0.175 | | |
| F-Test of Model Significance (p-value) | | | 0.000 | | |

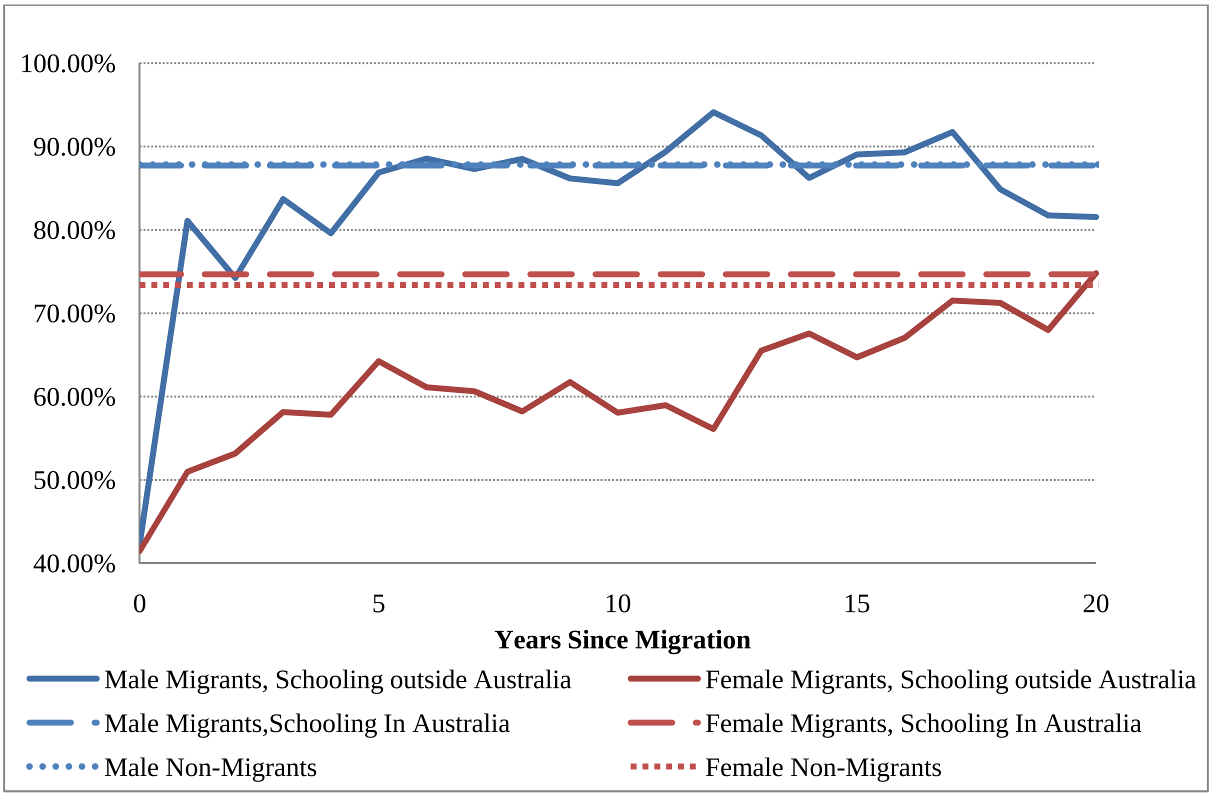
Notes: the reported figures show the migrant employment rate gap for individuals with the given characteristics set at the given values compared to Australian-born individuals with characteristics set at the same value. Ages 15-64.

### 5.3. Do Migrants ‘Catch Up’ with the Australian-born?

In this section we first present descriptive analysis of how the employment rate for migrants increases over time since arrival in Australia. We then present regression analysis that estimates the length of time it takes migrants to catch up with Australian-born in terms of employment rates, separately by gender and for refugees and economic migrants. Because no estimator is perfect, in each case we present two sets of estimates, one of which provides an upper bound to the ‘true’ rate of catch up, and the other which provides a lower bound. The results suggest that it takes migrants longer than previously thought to catch up with the Australian-born, particularly for women and refugees of both genders.

In Section 3 we discussed how theory predicts – and international empirical evidence generally supports – that migrants are likely to have relatively poor labour market outcomes at the time of their arrival, compared to otherwise similar Australian-born individuals, but that their relative outcomes will improve over time as they acquire relevant human capital in the destination country. Here we take a first descriptive pass at this issue for employment rates. Figure 2 shows employment rates for migrants and Australian-born aged 15-54. The blue lines represent males and the red lines represent females. Among the Australian-born population (dotted lines), the employment rate (expressed as a proportion of the working age population) is just under 90% for males and just over 70% for females. Migrants who received their schooling in Australia (the dash-dotted lines) have almost identical employment rates to their Australian-born counterparts. The solid lines show the employment rate for migrants who arrived in Australia after finishing school over time spent in Australia. After about 5 years, men’s employment rates are similar to those of the Australian-born. For women, however, the picture is somewhat different. Not only is their employment rate much lower than that of men, but the gap between female migrants and Australian-born women is much bigger and longer lasting: it takes around 20 years for female employment rates to catch up with those for the Australian-born.

**Figure 2: Employment Probabilities for Migrants and Australian-born, by Years since Migration**




Note: Ages 15-54.

Whilst the evidence of Figure 2 is *consistent* with employment rate convergence over time, it does not necessarily indicate a *causal* relationship between years since migration and employment rates. As discussed in Section 4.2 and further in Appendix 2, there may be compositional differences between migrants that stay longer in Australia and migrants that either return migrate or migrate on to a third country. To the extent that such differences are observed, we can control for them in multivariate analysis of the pooled data (estimating equation (4)). To the extent that such differences are unobserved but time invariant, we can control for them in multivariate fixed effects analysis (estimating equation (9)). Because each approach has advantages and disadvantages, and because they may provide upper and lower bound estimates respectively of employment catch up (see Section 4.2), both are presented and discussed here.

First consider estimates of how the migrant employment gap evolves over time since migration based on estimating equation (4) on the pooled data. Table 9 shows the estimated coefficients on the YSM and $YSM^2$ variables from the model together with indicators of the model performance. To help interpret the regression results, Figures 3 and 4 plot the gap in predicted employment probabilities for economic migrants and refugees over time since migration compared to those for Australian-born. In each case the solid line represents the labour market adjustment for economic migrants (non-refugees) and the dashed line represents labour market adjustment for refugees/humanitarian migrants. Recall that we omit the English language variable, so the YSM variables will capture the effect of language improvement over time together with any other change in human capital over time.

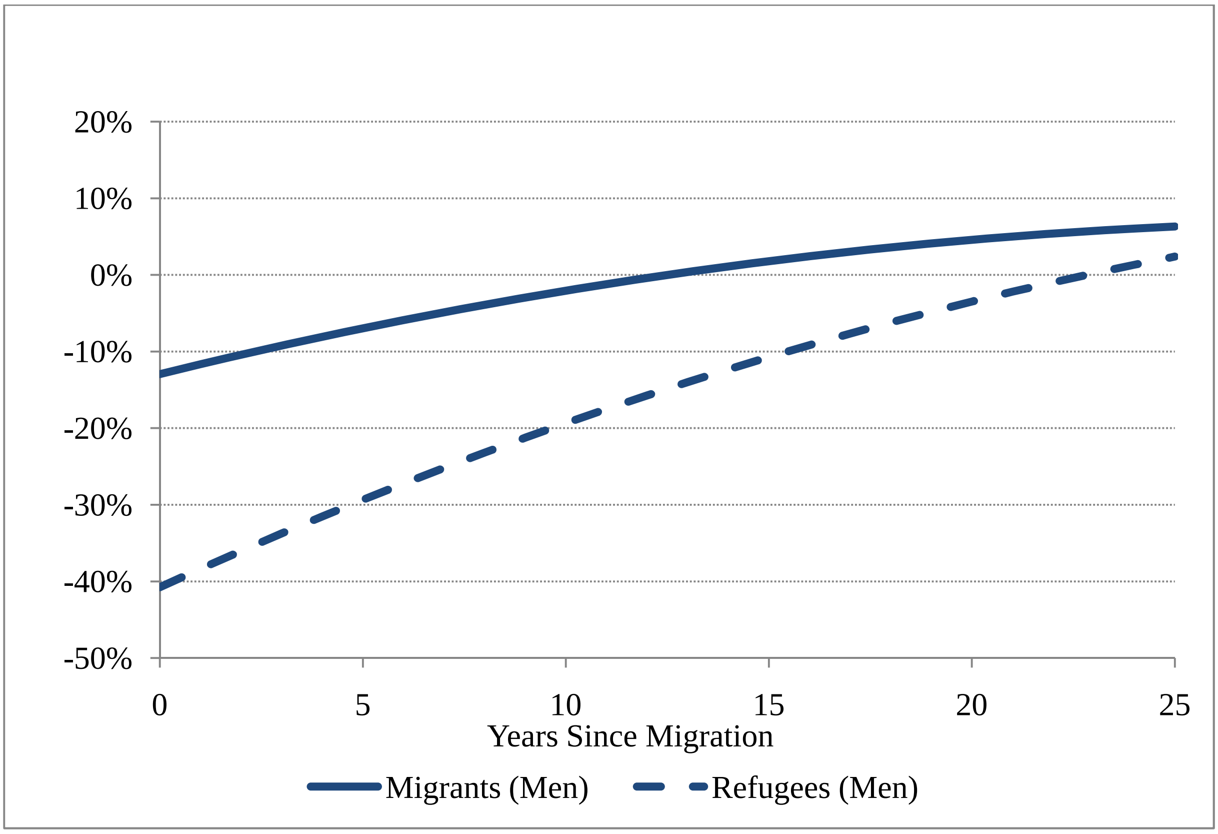
Table 9 and Figure 3 suggest that the migrant employment gap for men falls over time since arrival, but at a decreasing rate (the speed of adjustment slows down in later years). For male economic migrants, the employment gap disappears after about 12 years, after which migrants have a slightly higher employment rate than the Australian-born. Antecol et al. (2006) find a similar pattern for Australia and the US using Census data. Note, however, that the length of time it takes to catch up according to this model is longer than the 5 years suggested by the descriptive analysis (Figure 2). So, while (male) migrants as a whole have similar labour market outcomes to the Australian-born as a whole after only a few years, they still fall behind Australian-born *with similar characteristics* for several further years. The positive selection (on observables) of economic migrants (e.g. with higher qualification levels than the Australian-born) acts to obscure the true duration of the migrant employment gap in the raw data.

**Table 9: Employment and Years since Migration, Coefficients (Standard Errors), Pooled**

| | Men | Women |
|---|---|---|
| YSM | .013** | .015** |
| | (.004) | (.005) |
| $YSM^2$ | -.0002** | -.0001 |
| | (.0001) | (.0001) |
| Refugee dummy*YSM | .011 | .007 |
| | (.007) | (.008) |
| Refugee dummy*$YSM^2$ | -.0001 | -.0001 |
| | (.0001) | (.0002) |
| Control for English language skills | No | No |
| Other controls | Yes | Yes |
| Number of observations | 35863 | 39477 |
| R-squared | 0.149 | 0.135 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other controls' include dummies for year (2001-2009), highest education (four dummies), long-term health condition, children, marital status, and continuous variables for age and $age^2$, which we allow to have different impacts on migrants and Australia-born. The model also controls for refugee status and schooling in Australia. For more details see equation (4) in Section 3.2. Ages 15-54.

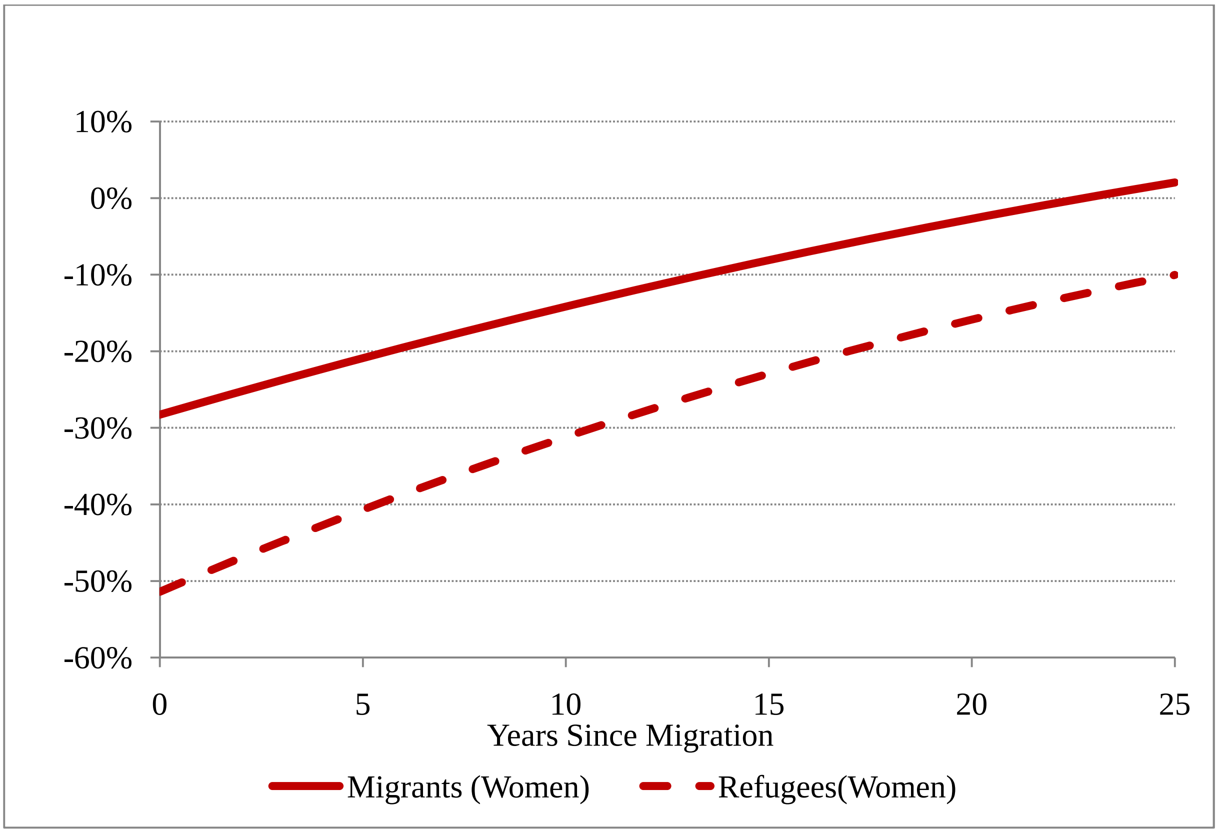
**Figure 3: Predicted Employment Gap by Years since Migration, Pooled Data, Men**




Note: We assume the slope of these employment convergence profiles does not vary with observed migrant characteristics (other than refugee status). The initial gap, however, does vary with migrant characteristics. Here we set cohort of arrival equal to 2000-2009, age of arrival at beyond secondary school age, with all other characteristics at the relevant sample means. Similar plots for alternative cohorts are available from the authors on request.

For male refugees we sum the coefficients on YSM and on YSM interacted with the refugee dummy (and similarly for the squared terms). The suggestion is that the migrant employment gap for refugees starts off larger but falls more rapidly than for other migrants, although the difference is not statistically significant. Cortes (2004) suggests a similar pattern for the US: male refugees appear to suffer from a higher loss of skills than economic migrants at the time of their arrival, but have higher returns to investments in their skills over time. But because the initial gap is larger, it still takes refugees almost twice as long as other migrants – around 22 years – to catch up with the Australian-born.

**Figure 4: Predicted Employment Gap by Years since Migration, Pooled Data, Women**




Note: We assume the slope of these employment convergence profiles does not vary with observed migrant characteristics (other than refugee status). The initial gap, however, does vary with migrant characteristics. Here we set cohort of arrival equal to 2000-2009, age of arrival at beyond secondary school age, with all other characteristics at the relevant sample means. Similar plots for alternative cohorts are available from the authors on request.

For women, the migrant employment gap for both economic migrants and refugees starts off larger than the male equivalents, but also falls over time since arrival, albeit in a more linear fashion (the quadratic term is smaller and statistically insignificant).[33] In practice this means the annual increase in employment probability is initially similar to that for men, but that the rate does not fall as fast as years since migration increase. As for men, the migrant employment gap for female refugees is initially larger but falls faster than that for other female migrants, although again the difference is statistically insignificant. According to this model, it takes female economic migrants around 22 years to catch up with their Australian-born counterparts. But female refugees still face an employment gap of around 10 percentage points even after 25 years.

[33] To the best of our knowledge ours is the first study for Australia to look at employment assimilation over a longer period separately for women migrants. Antecol et al. (2006) focuses on men. Productivity Commission (2006) does not present separate analysis by gender. Cobb-Clark et al. (2005), however, presents evidence on education enrolment by gender that is consistent with this pattern.

As discussed in Section 4.2 and Appendix 2, however, estimating the above models using the pooled HILDA Survey data, as for previous studies using cross-section data, leaves us with the potential problem that migrants might differ in unobserved ways, e.g. in terms of their preferences, ability and motivation, that also impact on labour market outcomes. Assuming that migrants with lower employment probabilities are the more likely to leave Australia, such unobserved factors can mean that cross-section estimates of employment catch up are upwards biased. In other words, the estimates above are likely to overestimate the rate at which migrant employment rates catch up with Australian-born employment rates. Nevertheless, we can be confident that the 'true' rate of catch up is *no higher* than that suggested by the cross section estimates discussed above.

To obtain estimates that are free from this bias, although potentially subject to a *downwards* bias as discussed in Section 4.2, we estimate the fixed effects version of (4) as given by equation (9). Table 10 and Figures 5 and 6 present the relevant estimates. Recall that we make some additional restrictions for the fixed effects model including dropping the interaction between years since migration and the refugee dummy to focus on the key parameter.[34] For comparison purposes Table 10 presents the same restricted model estimated on the pooled data.

**Table 10: Employment and Years since Migration, Coefficients (Standard Errors), Pooled versus Fixed Effects**

| | Pooled OLS | | Fixed Effects | |
|---|---|---|---|---|
| | Men | Women | Men | Women |
| YSM | .015** | .016** | .008** | .014** |
| | (.004) | (.005) | (.004) | (.005) |
| $YSM^2$ | -.0002** | -.0002 | -.0001 | -.0002* |
| | (.0001) | (.0001) | (.0001) | (.0001) |
| Control for English language skills | No | No | No | No |
| Other controls | Yes | Yes | Yes | Yes |
| Number of observations | 35863 | 39477 | 35863 | 39477 |
| R-squared | 0.149 | 0.135 | 0.041 | 0.060 |
| R-squared: within | | | 0.019 | 0.034 |
| R-squared: between | | | 0.062 | 0.074 |
| F-Test Model Significance (p-value) | 0.000 | 0.000 | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other controls' include all time-varying controls but exclude time-invariant observed factors. Coefficients on YSM and $YSM^2$ are constrained to be equal for refugees and other migrants and coefficients on age and $age^2$ are constrained to be equal for migrants and Australian-born. For more details see equations (4) and (12) in Section 3.2. The correlation between the fixed effects and the observed right hand side variables is -0.167 and -0.125 respectively. Ages 15-54.

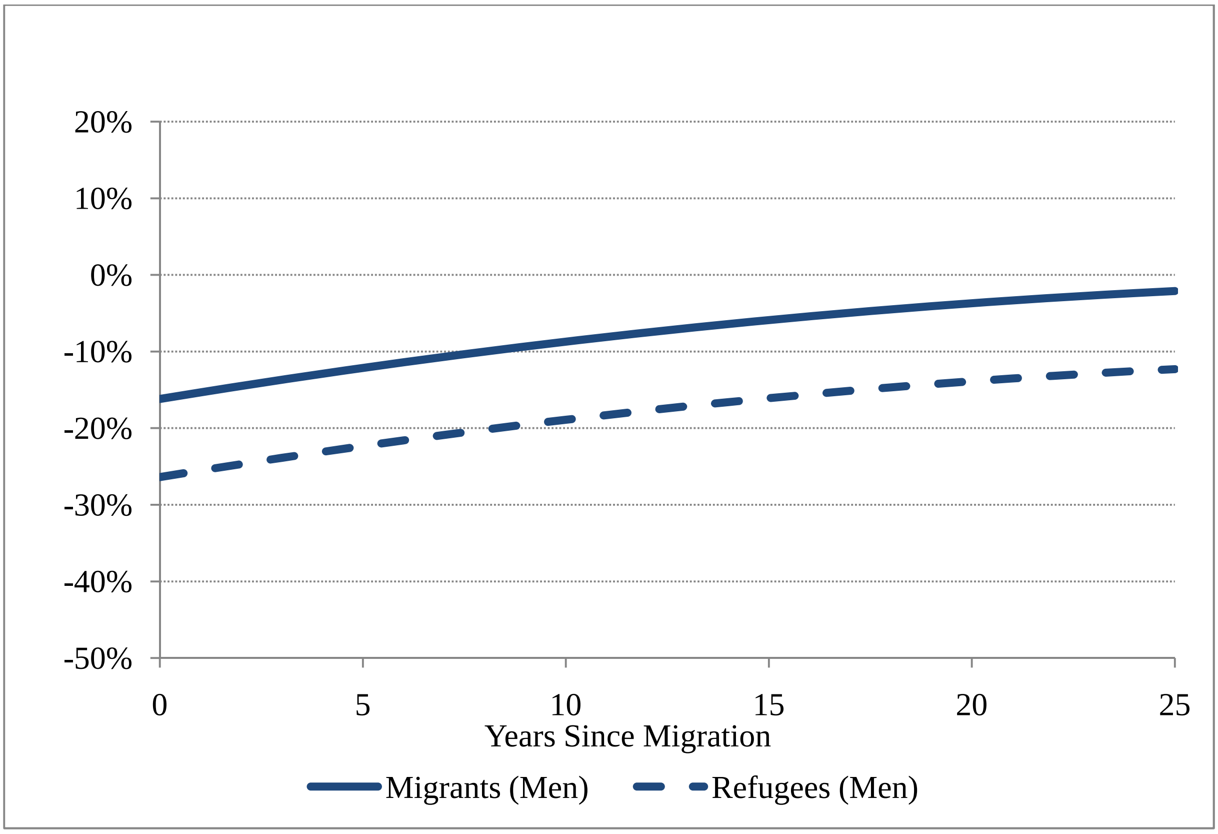
[34] In other words we restrict the coefficient on years since migration and its squared term to be equal for refuges and other migrants.

Note that the pooled results presented in Table 9 and the pooled results presented in Table 10, with the additional restrictions, are very similar for both men and women. So restricting age and year effects to be the same for migrants and Australian-born has little impact on estimates of employment catch up. But, although similar for women, the fixed effects estimates are markedly different to both sets of pooled estimates for men.

First consider these fixed effects estimates for men. Again we see the migrant employment gap falling over time since arrival, and at a decreasing rate. But the rate at which men catch up is slower in the fixed effects estimates than in the pooled equivalents (almost twice as slow). For male economic migrants the fixed effects estimates suggest it takes at least 25 years for the employment gap to disappear. This is considerably longer than the catch up suggested by our own pooled estimates and by previous estimates based on cross section data (e.g. Antecol et al., 2006), which suggests either that such cross section estimates of employment assimilation are biased upwards by non-random return migration, that the fixed effects are biased downwards, or both. And although we don't know for sure which one of these possibilities is true, we do know that the rate of employment catch up for male migrants is between our two estimates, i.e. between 0.08 and 0.15 per year. In other words, it takes between 12 and 25 years for the employment gap to disappear.

For male refugees the fixed effects estimates suggest it takes even longer to catch up – even after 25 years there is still a 10 percentage point employment gap relative to Australian-born with similar observed and time-invariant unobserved characteristics – because the initial employment gap is bigger.

**Figure 5: Predicted Employment Gap by Years since Migration, Men, Fixed Effects Model**

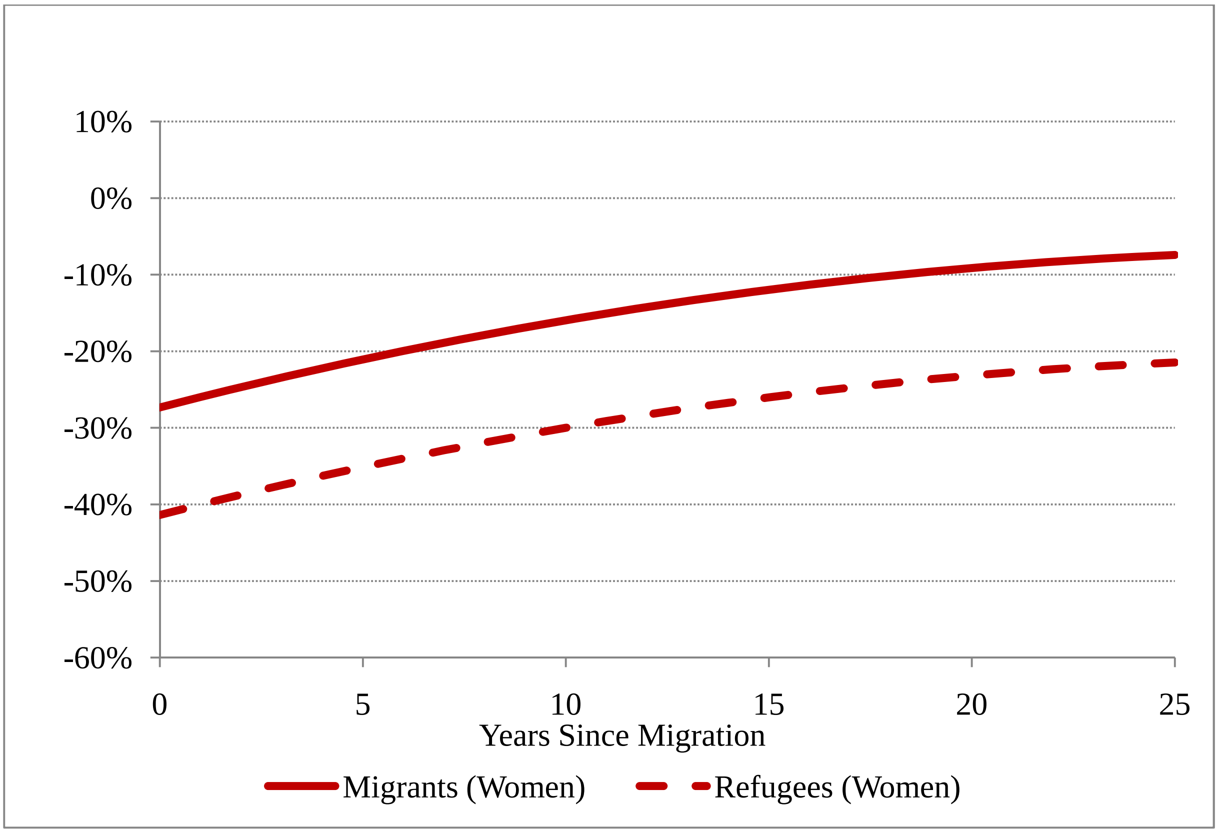



Note: To facilitate comparison with Figure 3 the initial employment gap here is estimated by regressing the estimated fixed effects from (12) on the refugee dummy, cohort of arrival dummies and the age at arrival dummy. We then set cohort of arrival equal to 2000-2009 and age of arrival at beyond secondary school age as before. Coefficients on YSM and $YSM^2$ are constrained to be equal for refugees and other migrants.

Next consider the fixed effects estimates for women. Again we see the migrant employment gap falling over time since arrival at a decreasing rate, but here the differences are smaller between the pooled and fixed effects estimates. The initial rate of catch up is only slightly lower in the fixed effects estimates and the curvature (the degree to which the catch up rate falls over time) is slightly larger. On their own the fixed effects estimates suggest female economic migrants (female refugees) still face an employment gap of just under 10 (just over 20) percentage points after 25 years. Taken together with the cross section estimates, we can conclude that the employment gap is between 0 and 10 percentage points after 25 years for female economic migrants and between 10 and 20 percentage points after 25 years for female refugees.[35]

[35] Note that the average length of time that female migrants in the HILDA Survey have been in Australia is 24 years (given our sample restrictions).

**Figure 6: Predicted Employment Gap by Years since Migration, Women, Fixed Effects Model**




Note: To facilitate comparison with Figure 4 the initial employment gap here is estimated by regressing the estimated fixed effects from (12) on the refugee dummy, cohort of arrival dummies and the age at arrival dummy. We then set cohort of arrival equal to 2000-2009 and age of arrival at beyond secondary school age as before.

The finding that migrants may take longer than previously thought to catch up with Australian-born in terms of employment rates has important implications for both policy and research. Whether this is driven by migrants' preferences for employment or additional barriers faced in accessing employment, for Australian policy makers concerned with skill shortages and social inclusion this raises questions about how effectively migrants integrate in the Australian labour market and whether additional interventions can be designed, or existing interventions extended, to improve access to jobs. For researchers, this raises questions about the most appropriate methods for estimating the labour market assimilation of migrants and the extent to which migrants acquire host country-specific human and/or social capital in the years after arrival.

### 5.4. Migrants' Reported Skill Use in Employment

In this section we examine what migrants and Australian-born individuals who are in employment say about the extent to which they use their skills and abilities in their job. We first present descriptive and regression analysis of the average skills use gap. We then explore how the skills use gap varies with key characteristics of migrants. Finally we repeat the analysis of the previous subsection to see whether the skills use gap shrinks over time since arrival. We show that the skills use gap is small on average, although larger for women than men and larger for those with poor English language proficiency. For women we present evidence that shows the skills use gap narrows over time since arrival. For men it is unclear.

We have shown evidence of an employment gap that shrinks over time for migrants. But previous studies for Australia suggest there is little evidence of a wage gap for migrants that are employed, and little evidence of wage assimilation. The absence of such a wage gap may indicate that migrants and Australian-born use their skills to similar degrees when in employment. And the absence of any wage assimilation may suggest a similar absence of skills use 'catch up' over time. But there is some evidence for Australia that casts doubt on this conclusion. For example, Chiswick et al. (2005) use LSIA data to show a 'drop' in occupational class for migrants coming to Australia, followed by a catch-up in occupational class in the first few years after migration. Is this drop in occupational class reflected in a migrant skills use gap? Here we explore the skill use of employed migrants using the HILDA Survey question asking respondents to what extent they agree, on a 1-7 scale, with the statement *"I use many of my skills and abilities in my current job"*.

As for the employment rate analysis, we first compare reported skill use for all employed migrants and all employed Australian-born to get a 'raw' skills use gap, in Table 11. For those that are employed, male migrants report that they use their skills and abilities to the same extent as Australian-born men. For employed women, however, migrants report that they use their skills and abilities to a lesser extent than the Australian-born. The gap for women is statistically significant, although small in magnitude.

**Table 11: Skill Use of Australian-born and Migrants**

| | Men | | | Women | | |
|---|---|---|---|---|---|---|
| | Australian-born | Migrants | Difference | Australian-born | Migrants | Difference |
| Average skill use | 5.44 | 5.43 | -0.01 | 5.33 | 5.27 | -0.06** |
| Number of observations | 24,471 | 6,401 | | 22,864 | 5,606 | |

Notes: Skills use is measured on a seven point scale according to the degree to which respondents agree with the statement *"I use many of my skills and abilities in my current job"*, with 1 indicating 'strongly disagree' and 7 indicating 'strongly agree'. Ages 15-64.

Next we estimate equation (5) to provide an estimate of the overall migrant skill-use gap conditioned on the observed characteristics in $X_i$, very much as for the conditional migrant employment gap discussed in Section 5.1. Results are presented in Table 12, and show a slightly larger skills use gap for women, and a small but now statistically significant skills use gap for men. But really these gaps are still very small. And note the low R-squared, which suggests that equation (5) explains very little of the variation in reported skills use.

**Table 12: Migrant Skills Gap Controlling for Observed Characteristics, Pooled Data, Coefficients (Standard Errors)**

| | Men | Women |
|---|---|---|
| Average migrant skills gap (7 point scale) | -0.09* | -0.18** |
| | (0.04) | (0.04) |
| Language, refugee, schooling in Australia controls | No | No |
| Other characteristics controls | Yes | Yes |
| Number of observations | 30875 | 28470 |
| R-squared | 0.029 | 0.039 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other characteristics controls' include dummies for year (2001-2009), highest education (four dummies), long-term health condition, children, marital status, and continuous variables for age and age$^2$. Ages 15-64.

We can extend the analysis of Table 12 to allow the skills use gap to vary across key migrant characteristics in addition to gender. Results are presented in Table 13. As for employment probabilities, we see an additional skills gap for those with poor English language ability. We also see a small compensating effect of schooling in Australia (statistically significant for women). Employed refugees have a *smaller* skills use gap on average compared to economic migrants with otherwise similar characteristics, although the differences are again very small and statistically insignificant.

**Table 13: Migrant Skills Gap by Key Characteristics, Pooled Data, Coefficients (Standard Errors)**

| | Men | Women |
|---|---|---|
| Baseline case migrant gap (non-refugee, schooling outside Australia, good language skills, | -0.08 | -0.21** |
| | (0.05) | (0.06) |
| Additional refugee gap | 0.09 | 0.03 |
| | (0.11) | (0.13) |
| Additional poor language gap | -0.60** | -0.40** |
| | (0.09) | (0.11) |
| Compensating Effect of Schooling in Australia | 0.09 | 0.19* |
| | (0.07) | (0.07) |
| Other characteristics controls | Yes | Yes |
| Number of observations | 30875 | 28470 |
| R-squared | 0.033 | 0.041 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other characteristics controls' include dummies for year (2001-2009), highest education (four dummies), long-term health condition, children, marital status, and continuous variables for age and age$^2$. Ages 15-64.

Next we allow the employed migrant skills gap to vary across all observed migrant characteristics (estimating equation (7)). Results are presented in Tables 14 (men) and 15 (women). Again English language ability comes through as the characteristic most strongly associated with skills use. Elsewhere, as for the employment gap, the employed migrant skills use gap is slightly bigger for younger than for older migrants (true for both men and women) and slightly bigger for married compared to unmarried migrants (both men and women). Associations with long term health conditions and education levels are more mixed, although again for women it appears as if middling levels of education are associated with larger skills use gaps. The two-way combinations of characteristics associated with the largest skills use gap for men are being young with poor English language ability and holding a post-school but sub-degree qualification from outside Australia with poor English language ability. For women it is having Year 12 as highest education level coupled with poor English language ability and being a refugee with a post-school but sub-degree qualification from outside Australia.

As for the analysis of employment rates, each table also includes a column showing the association of skills use and these key characteristics for Australian-born workers. Note, for example, that skills use rises with age and education level for both men and women in this group.

**Table 14: Migrant Skills Use Gap across all Characteristics, Pooled Data, Men**

| *Migrant Gap by Characteristics* | *Australian-born* | 'Baseline case' Migrants | Refugees | Schooling in Australia | Poor Language Skills |
|---|---|---|---|---|---|
| Age 25 | 5.31 | -0.22 | -0.49 | 0.08 | -1.11 |
| Age 35 | 5.40 | -0.08 | -0.13 | 0.04 | -0.56 |
| Age 45 | 5.49 | -0.02 | 0.08 | 0.02 | -0.41 |
| Age 55 | 5.58 | -0.06 | 0.13 | 0.04 | -0.66 |
| *Migrant has/is...* | | | | | |
| married/de facto: no | 5.29 | -0.04 | 0.42 | 0.11 | -0.72 |
| married/de facto: yes | 5.51 | -0.13 | -0.31 | 0.03 | -0.71 |
| long-term health condition: no | 5.47 | -0.10 | -0.07 | 0.01 | -0.69 |
| long-term health condition: yes | 5.32 | -0.13 | -0.29 | 0.23 | -0.82 |
| children: no | 5.43 | -0.08 | -0.11 | 0.00 | -0.84 |
| children: yes | 5.47 | -0.13 | -0.11 | 0.10 | -0.56 |
| Education: less than year 12 | 5.25 | -0.03 | 0.20 | 0.12 | -0.89 |
| Education: year 12, no post-school | 5.25 | -0.03 | -0.10 | -0.03 | -0.48 |
| Education: non-tertiary post-school | 5.54 | | | 0.03 | |
| Education: tertiary | 5.61 | | | 0.04 | |
| Education: non-tertiary post-school, AUS | | -0.17 | -0.29 | | -0.60 |
| Education: tertiary, AUS | | -0.11 | -0.12 | | -0.87 |
| Education: non-tertiary post-school, other country | | -0.20 | 0.03 | | -1.06 |
| Education: tertiary, other country | | -0.12 | -0.33 | | -0.89 |
| Other characteristics controls (entered separately) | | | Yes | | |
| Number of observations | | | 30874 | | |
| R-squared | | | 0.036 | | |
| F-Test of Model Significance (p-value) | | | 0.000 | | |

Notes: the reported figures show the migrant employment rate gap for individuals with the given characteristics set at the given values compared to Australian-born individuals with characteristics set at the same value. Ages 15-64.

**Table 15: Migrant Skills Use Gap across all Characteristics, Pooled Data, Women**

| *Migrant Gap by Characteristics* | *Australian-born* | 'Baseline case' Migrants | Refugees | Schooling in Australia | Poor Language Skills |
|---|---|---|---|---|---|
| Age 25 | 5.12 | -0.48 | -0.15 | -0.24 | -0.84 |
| Age 35 | 5.31 | -0.26 | -0.19 | 0.00 | -0.42 |
| Age 45 | 5.45 | -0.12 | -0.14 | 0.09 | -0.29 |
| Age 55 | 5.53 | -0.08 | -0.01 | 0.03 | -0.47 |
| *Migrant has/is...* | | 0.00 | 0.00 | 0.00 | 0.00 |
| married/de facto: no | 5.26 | -0.13 | -0.12 | 0.09 | -0.36 |
| married/de facto: yes | 5.39 | -0.30 | -0.11 | -0.10 | -0.60 |
| long-term health condition: no | 5.35 | -0.24 | -0.13 | -0.01 | -0.48 |
| long-term health condition: yes | 5.38 | -0.24 | -0.02 | -0.20 | -0.75 |
| children: no | 5.40 | -0.14 | -0.03 | -0.11 | -0.67 |
| children: yes | 5.30 | -0.35 | -0.20 | 0.03 | -0.37 |
| Education: less than year 12 | 5.03 | -0.17 | -0.22 | -0.01 | -0.48 |
| Education: year 12, no post-school | 5.19 | -0.40 | -0.42 | 0.02 | -1.00 |
| Education: non-tertiary post-school | 5.42 | | | -0.17 | |
| Education: tertiary | 5.65 | | | 0.02 | |
| Education: non-tertiary post-school, AUS | | -0.33 | 0.31 | | -0.29 |
| Education: tertiary, AUS | | -0.14 | -0.17 | | -0.47 |
| Education: non-tertiary post-school, other country | | -0.33 | -1.18 | | -1.02 |
| Education: tertiary, other country | | -0.25 | -0.54 | | -0.82 |
| other characteristics controls (entered separately) | | | Yes | | |
| # observations | | | 28470 | | |
| R-squared | | | 0.044 | | |
| F-Test of Model Significance (p-value) | | | 0.000 | | |

Notes: the reported figures show the migrant employment rate gap for individuals with the given characteristics set at the given values compared to Australian-born individuals with characteristics set at the same value. Ages 15-64.

Our penultimate set of results on the migrant skills gap uses the pooled data to examine whether employed migrants catch up with the employed Australian-born in terms of reported skills use over time. We start with a descriptive first pass at the data as presented in Table 16. Among Australian-born males, only about 10% of the individuals disagree ([1]-[3]) with the statement *"I use many of my skills and abilities in my current job"*. The corresponding share among male migrants within the first three years after arrival is almost twice as high. When years since migration increase, the distribution of answers to this question becomes more and more similar to that for the Australian-born population, and is almost identical for migrants who have lived in Australia for 11 years or more (actually slightly higher for migrants than

Australian-born). The same pattern occurs for women: in the first three years after arrival, disagreement is over twice as likely for migrants than for Australian-born, but after 11 years the distribution of answers are almost identical. As for employment rates, the gap between Australian-born and migrants in the first years after arrival in Australia is bigger for women than for men.

**Table 16: Self-reported Utilisation of Skills in the Current Job**

| **Male** | | Migrants | | | | |
|---|---|---|---|---|---|---|
| | Non- | Years Since Migration: | | | | |
| | Migrants | 0-1 | 2-3 | 4-6 | 7-10 | >=11 |
| [1] Strongly disagree | 2.7% | 7.3% | 5.3% | 3.0% | 2.7% | 2.0% |
| 2 | 3.6% | 7.3% | 10.6% | 6.0% | 5.4% | 3.4% |
| 3 | 4.6% | 5.2% | 7.1% | 4.5% | 8.1% | 4.6% |
| 4 | 9.5% | 8.3% | 10.0% | 12.0% | 9.3% | 10.0% |
| 5 | 19.1% | 19.8% | 15.3% | 17.4% | 20.1% | 18.4% |
| 6 | 37.0% | 25.0% | 30.6% | 33.3% | 36.2% | 37.8% |
| [7] Strongly agree | 23.5% | 27.1% | 21.2% | 23.7% | 18.2% | 23.8% |
| Total | 100% | 100% | 100% | 100% | 100% | 100% |
| Mean | 5.436 | 5.094 | 4.959 | 5.297 | 5.199 | 5.481 |
| **Female** | | Migrants | | | | |
| | Non- | Years Since Migration: | | | | |
| | Migrants | 0-1 | 2-3 | 4-6 | 7-10 | >=11 |
| [1] Strongly disagree | 3.5% | 12.0% | 8.1% | 6.2% | 4.2% | 3.5% |
| 2 | 4.4% | 5.4% | 10.1% | 8.0% | 6.1% | 4.9% |
| 3 | 5.4% | 8.7% | 5.4% | 5.5% | 5.6% | 5.6% |
| 4 | 10.7% | 12.0% | 14.9% | 13.5% | 12.2% | 9.9% |
| 5 | 17.8% | 16.3% | 15.5% | 21.8% | 19.9% | 17.7% |
| 6 | 34.1% | 29.3% | 26.4% | 27.7% | 29.3% | 34.6% |
| [7] Strongly agree | 24.0% | 16.3% | 19.6% | 17.3% | 22.7% | 24.0% |
| Total | 100% | 100% | 100% | 100% | 100% | 100% |
| Mean | 5.333 | 4.685 | 4.770 | 4.889 | 5.162 | 5.329 |

We further explore this question using regression analysis on the pooled data, controlling for other observable differences between migrants and the Australian-born, with results presented in Table 17 and Figures 7 and 8. These estimates also suggest that the employed migrant skills use gap for both men and women falls over time since arrival, and at a decreasing rate. This is equally true of economic migrants and refugees, with both groups, for both genders, catching up with their Australian-born equivalents within 10-15 years after arrival. The wider initial gap for refugees is countered by the faster growth in reported skills use over time, although as for employment rates these differences are not statistically significant.[36] The fact that migrants subsequently report higher skills use in employment than their Australian-born counterparts helps explain why the overall migrant skills use gap is close to zero.

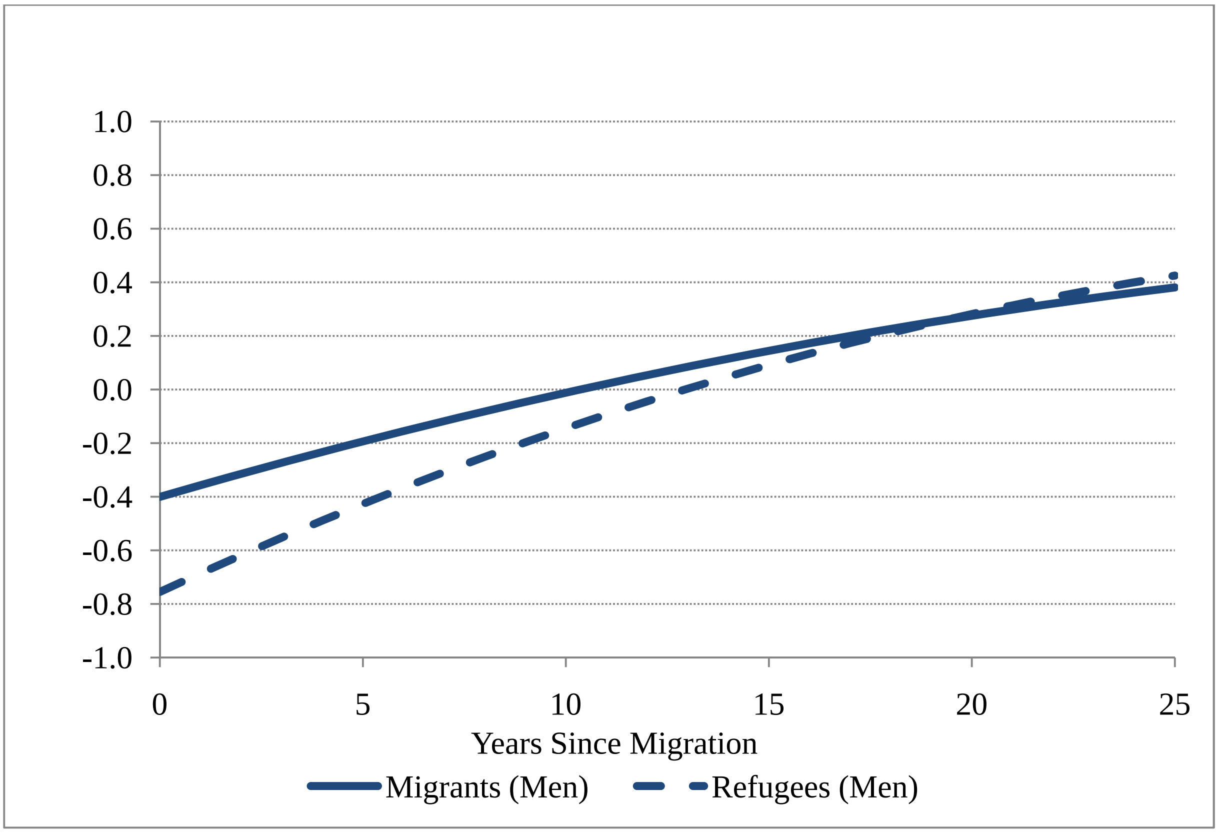
**Table 17: Skills Use and Years since Migration, Pooled Data, Coefficients (Standard Errors)**

| | Men | Women |
|---|---|---|
| YSM | .044* | .059* |
| | (.021) | (.023) |
| $YSM^2$ | -.001 | -.001 |
| | (.0003) | (.0004) |
| Refugee dummy*YSM | .026 | .026 |
| | (.032) | (.046) |
| Refugee dummy*$YSM^2$ | -.0004 | -.0005 |
| | (.001) | (.001) |
| Control for English language skills | No | No |
| Other controls | Yes | Yes |
| Number of observations | 27210 | 25630 |
| R-squared | 0.032 | 0.042 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 |

Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other controls' include dummies for year (2001-2009), highest education (four dummies), long-term health condition, children, marital status, and continuous variables for age and $age^2$, which we allow to have different impacts on migrants and Australia-born. The model also controls for refugee status and schooling in Australia. For more details see equation (8) in Section 4.2. Ages 15-54.

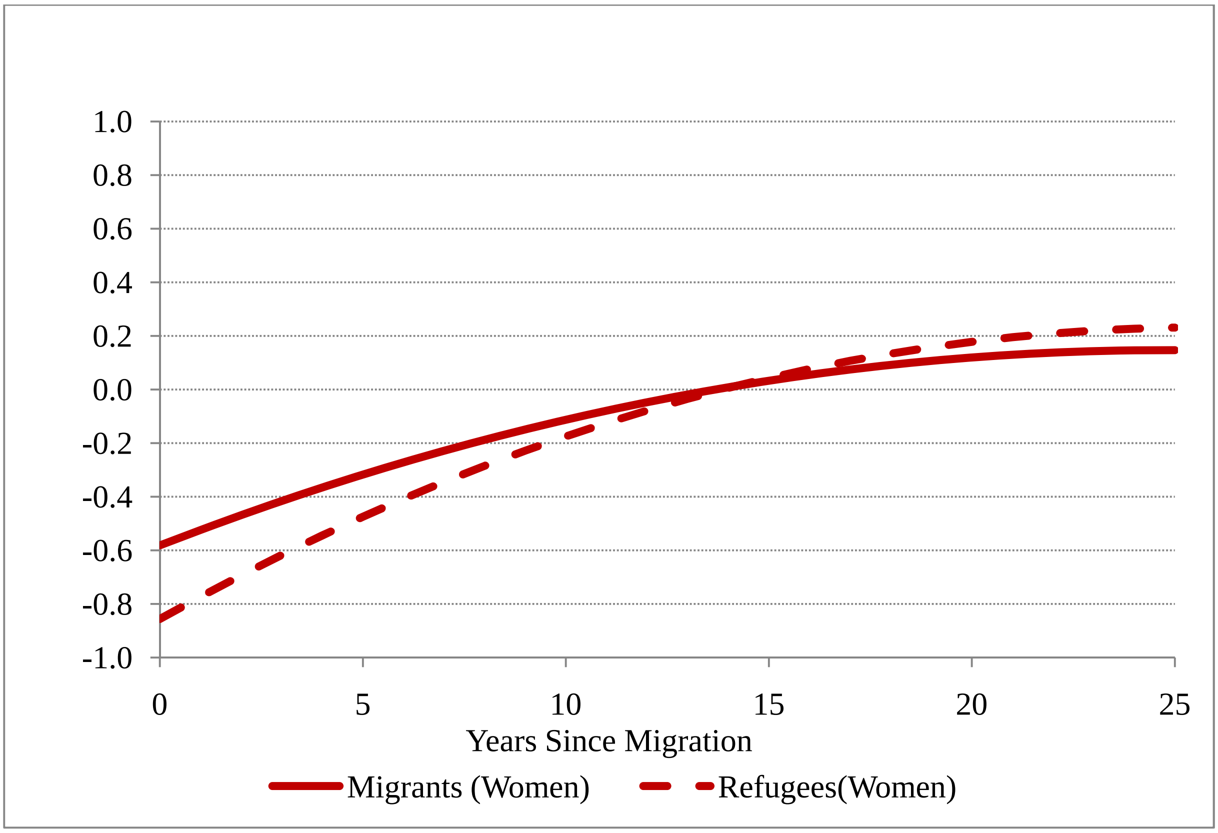
[36] Note that these estimates combine any increases in skills use for those that remain in employment over time with any change in average skills use resulting from unobservable compositional changes in those employed.

**Figure 7: Predicted Skills Use Gap by Years since Migration, Pooled Data, Men**




Note: We assume the slope of these skills use convergence profiles does not vary with observed migrant characteristics (other than refugee status). The initial gap, however, does vary with migrant characteristics. Here we set cohort of arrival equal to 2000-2009, age of arrival at beyond secondary school age, with all other characteristics at the relevant sample means.

**Figure 8: Predicted Skills Use Gap by Years since Migration, Pooled Data, Women**




Note: We assume the slope of these skills use convergence profiles does not vary with observed migrant characteristics. The initial gap, however, does vary with migrant characteristics. Here we set cohort of arrival equal to 2000-2009, age of arrival at beyond secondary school age, with all other characteristics at the relevant sample means.

The final set of results on skills use is for the fixed effects version of the above pooled model (estimating equation (10)), as presented in Table 18 and Figures 9 and 10. In contrast to the pooled estimates, these estimates are driven only by *within* changes in skills use, i.e. changes in skills use for given individuals over time. Note that, as for employment, we make some additional restrictions for the fixed effects model including dropping the interaction between years since migration and the refugee dummy. For comparison purposes Table 18 presents the same restricted model estimated on the pooled data. As for the employment analysis, note that the pooled results presented in Table 17 and the pooled results presented in Table 18, with the additional restrictions, are very similar for both men and women. So restricting age and year effects to be the same for migrants and Australian-born has little impact on estimates of skills use catch up.

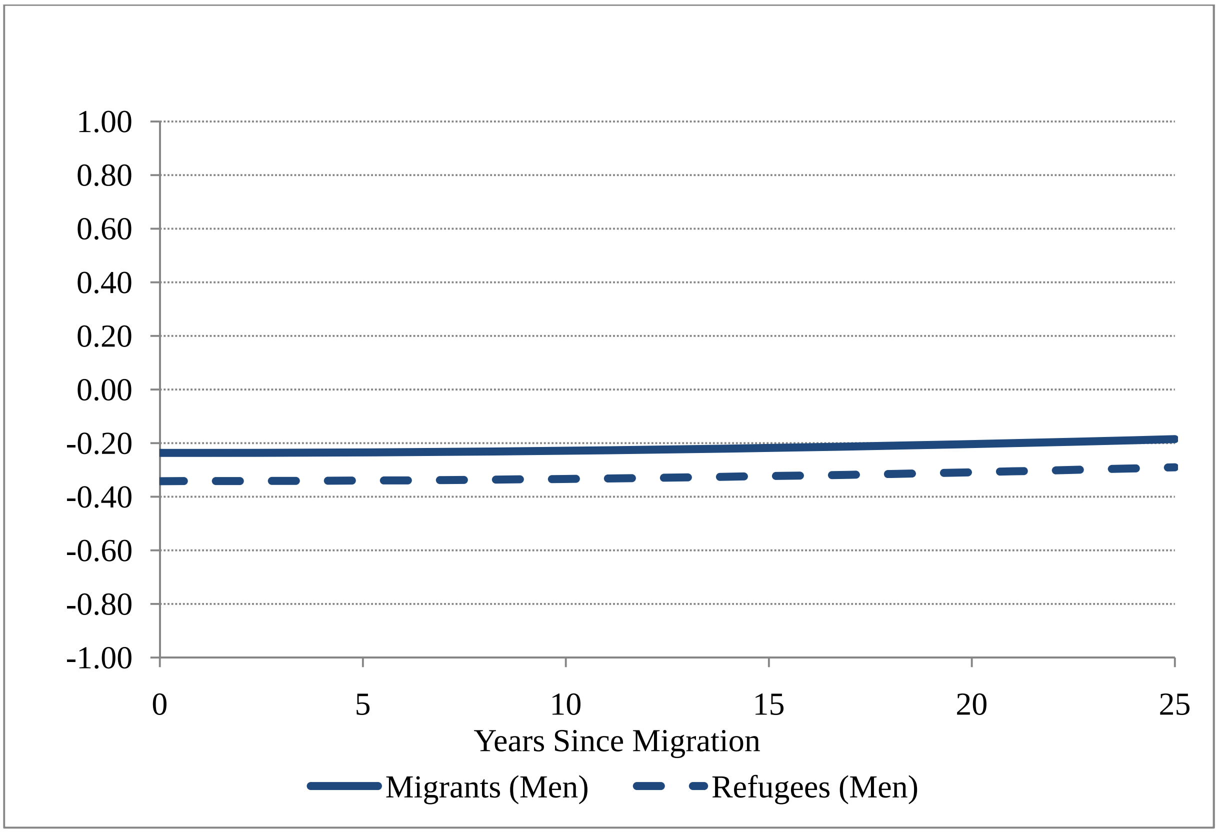
As was the case for the employment catch-up analysis, the fixed effects estimates are markedly different to the pooled estimates for men, although not for women. For women we again see catch up in around 15 years, and if we interpret the pooled estimates as an upper bound and the fixed effects estimates as a lower bound, the fact that they are so close together implies that we can be reasonably confident that we have correctly captured the skills use catch-up process, despite a low R-squared. But for men we see *zero* catch up in reported skills use over time in the fixed effects model. This is entirely plausible – zero skills use assimilation is consistent with zero wage assimilation, and cross section estimates of skills use catch up are likely to be biased upwards because of non-random return migration. But as for employment catch-up we cannot rule out a downwards bias in the fixed effects estimates which could be larger for men than for women, and again both sets of estimates for men come with a warning concerning low R-squareds.

**Table 18: Skills Use and Years since Migration, Coefficients (Standard Errors), Pooled versus Fixed Effects**

| | Pooled OLS | | Fixed Effects | |
|---|---|---|---|---|
| | Men | Women | Men | Women |
| YSM | .046* | .061* | .000 | .052* |
| | (.020) | (.022) | (.019) | (.024) |
| $YSM^2$ | -.0001 | -.001* | .0001 | -.001* |
| | (.0003) | (.0004) | (.0004) | (.0004) |
| Control for English language skills | No | No | No | No |
| Other controls | Yes | Yes | Yes | Yes |
| Number of observations | 27210 | 25630 | 27210 | 25630 |
| R-squared | 0.032 | 0.042 | 0.002 | 0.014 |
| R-squared: within | | | 0.007 | 0.011 |
| R-squared: between | | | 0.001 | 0.016 |
| F-Test of Model Significance (p-value) | 0.000 | 0.000 | 0.000 | 0.000 |

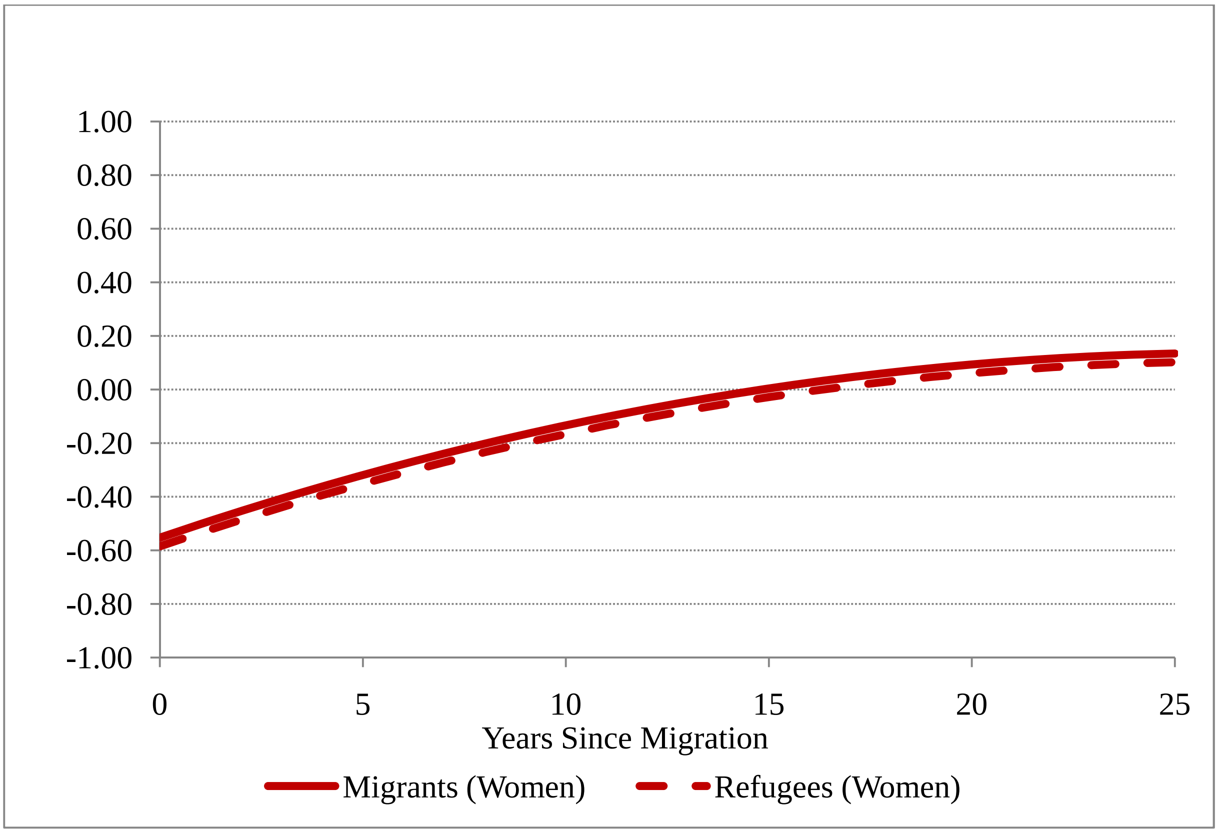
Notes: ** and * denote statistical significance at the 99% (95%) level respectively. Standard errors are in parentheses (clustered at individual level). 'Other controls' include all time-varying controls but exclude time-invariant observed factors. Coefficients on YSM and $YSM^2$ are constrained to be equal for refugees and other migrants and coefficients on age and $age^2$ are constrained to be equal for migrants and Australian-born. For more details see equations (4) and (9) in Section 4.2. The correlation between the fixed effects and the observed right hand side variables is -0.167 and -0.125 respectively. Ages 15-54.

**Figure 9: Predicted Skills Use Gap by Years since Migration, Men, Fixed Effects Model**




Note: To facilitate comparison with Figure 7 the initial skills use gap here is estimated by regressing the estimated fixed effects from (10) on the refugee dummy, cohort of arrival dummies and the age at arrival dummy. We then set cohort of arrival equal to 2000-2009 and age of arrival at beyond secondary school age as before. Coefficients on YSM and $YSM^2$ are constrained to be equal for refugees and other migrants.

**Figure 10: Predicted Skills Use Gap by Years since Migration, Women, Fixed Effects Model**




Note: To facilitate comparison with Figure 8 the initial skills use gap here is estimated by regressing the estimated fixed effects from (10) on the refugee dummy, cohort of arrival dummies and the age at arrival dummy. We then set cohort of arrival equal to 2000-2009 and age of arrival at beyond secondary school age as before. Coefficients on YSM and $YSM^2$ are constrained to be equal for refugees and other migrants.

## 6. Conclusions and Policy Implications

We structure our conclusions by the four research questions posed in the introduction, before moving on to a brief discussion of general implications for policy.

*(1) How do employment outcomes for migrants compare with those for Australian-born? Is there a migrant 'employment penalty' and if so how big is it?*

Employment rates for migrants, expressed as a proportion of the relevant working age population, are lower than employment rates for the Australian-born. The 'raw' migrant employment penalty is 4.4 percentage points for men and 6.9 percentage points for women. The 'conditional' migrant employment penalty – comparing migrants with Australian-born individuals with similar observed characteristics – is 4.1 percentage points for men and 7.5 percentage points for women. These estimates are close to those presented by Wilkins (2007). Note, however, that we prefer the term 'employment gap' over 'employment penalty', given that these employment rate gaps are likely to be driven by a combination of supply side and demand side factors, reflected in both lower participation rates and higher unemployment rates for migrants.

*(2) What characteristics of migrants are associated with better employment outcomes, and who are the most vulnerable migrants in terms of employment outcomes?*

First and foremost, female migrants not only have lower employment rates than male migrants, they also exhibit a larger employment gap relative to their Australian-born counterparts than do male migrants.

Looking beyond gender, many of the characteristics associated with higher probability of employment for migrants are the same characteristics associated with higher probability of employment for the Australian-born: being 'prime' age, being in good health, having no children under 16 living in the household (for women), and having higher levels of education. But migrants are *more sensitive* than the Australian-born to many of these characteristics. For example, the employment gap associated with having a long term health condition is higher for migrants than for the Australia-born. The exception is education level, for which the pattern is slightly different: it is migrants with middling levels of education (Year 12/post school but below degree level) that appear to experience the biggest employment gap relative to their Australia-born counterparts.

There are also characteristics specific to migrants that influence their probability of employment. Controlling as far as possible for other observed differences between migrants, we find the following: refugees have lower employment rates than economic migrants; migrants that arrive prior to school leaving age have higher (adult) employment rates than those that arrive in Australia at older ages; migrants that have been in Australia for longer have higher employment rates than those that have only recently arrived (see below); but migrants from more recent arrival cohorts do better than those from earlier arrival cohorts (for a given length of time in Australia); and migrants with poor English language ability have lower employment rates than those with better English language ability.

*(3) Does the migrant employment-rate gap fall over time since migration and if so how long does it take for migrants to achieve employment parity with Australian-born? How does this vary for different groups of migrants?*

Employment rates for migrants increase over time since migration. Looking at the raw data, it appears to take about 5 years for men but at least 20 years for women to catch up with the Australian-born average employment rate. But as for the overall employment gap, this picks up differences in characteristics between migrants and the Australian-born as well as any process of employment rate 'catch up'. When we condition on other characteristics in a regression framework, we show that it takes male economic migrants 12-25 years to catch up with their Australian-born counterparts. It takes longer for women, with the 'fastest' estimate suggesting catch up after 22 years, and the 'slowest' estimate suggesting there is still an employment gap of around 10 percentage points even after 25 years.

Refugees start off with lower employment rates than other migrants but catch up at a slightly faster rate each year. Nevertheless, our estimates suggest that it takes male refugees at least 22 years to catch up with Australian-born employment rates. The 'slowest' estimate suggests that male refugees still face an employment gap of around 10 percentage points even after 25 years. For women, our estimates suggest somewhere between a 10 and 20 percentage point gap in employment rates even after 25 years.

Earlier studies based on cross-section data have focussed only on men, have not considered refugees separately from other migrants, and may also have over-estimated the speed at which migrants catch up because they were less able to account for confounding factors correlated with both length of stay in Australia and probability of employment. In addressing these gaps in the Australian evidence base, we highlight the fact that key groups of migrants, including women and refugees of both genders, may never fully catch up with the Australian-born in terms of employment rates.

*(4) If migrants are employed, do their occupations match their skills as well as for the Australian-born? Does the matching of skills and occupations improve over time since migration?*

On average there is only a very small gap in reported skill use between employed migrants and employed Australian-born. There is some evidence that the gap may be larger for women, for those with poor English language skills, and for those only recently arrived in Australia, but these conclusions are sensitive to the degree to which we control for other factors in regression analysis.

Taken together these conclusions have a number of implications for policy in key areas such as labour supply, productivity and skills, and social inclusion. Given the nature of the project, we stick to broad-brush policy implications in these areas, rather than making specific recommendations.

First, the evidence here confirms earlier evidence showing that migrants do experience an employment gap in the Australian labour market, although on average this employment gap is not particularly large. When considered alongside evidence that migrants on average have higher levels of education than the Australian-born and that where migrants are employed they report similar levels of wages and skills use to their Australian-born counterparts, at first glance this might suggest little need for policy intervention to provide additional labour market assistance to migrants as a whole.

But this optimistic conclusion overlooks the evidence presented here that many migrants – those with poor English language proficiency, women, refugees, recent arrivals – face a much larger (and in the case of women and refugees a more persistent) employment gap. Even if the large employment rate gaps for these groups are partly driven by differences in labour supply between migrants and their Australian-born counterparts, the implication is that Australia has not yet realised the full labour market potential of its migrant population. Another implication is that migrants in these groups may be at higher risk of social exclusion than their Australian-born counterparts. Policy designed to boost the employment rates of migrants in these groups, whether through demand or supply measures, is therefore likely to have an important role to play looking forward. For example, recent migrants – especially refugees and female migrants – may require additional help finding and retaining employment, and this help may be required over a longer period of time following arrival than previously thought. The importance of policy efforts aimed at improving the English language skills of migrants is also here reinforced.

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## Appendix 1: Data Issues

### Imputing Refugee Status

One of the key issues of interest in this project is whether there are differences in labour market outcomes for migrants that enter Australia on different visa types. In particular we are interested in outcomes for those with refugee/humanitarian visas compared to others (bearing in mind that we cannot make further splits in these categories given data constraints). The separate identification of economic adjustment for the two groups requires the identification of refugees in the data set. For the majority of migrants in the HILDA Survey, information on whether they arrived in Australia as a refugee or under a humanitarian migration program is observed directly: participants were asked about their refugee status at the time of arrival in Australia in wave 4 (2004). Migrants who entered the survey after 2004 were asked about their refugee status at the time of their first interview. The question was asked to overseas born respondents (excluding migrants with a New Zealand citizenship at the time of arrival in Australia) who were a permanent resident or Australian citizen at the time of the survey. Unfortunately, however, this information is not available for 32% of migrants for reasons set out in Table A1.

**Table A1: Information on Refugee Status for Migrants**

| | Frequency |
|---|---|
| Is not a refugee | 2252 |
| Is a refugee | 268 |
| Total number missing | 1196 |
| Information is missing because migrant... | |
| ... was not a permanent resident or Australian citizen at the time the question was asked | 154 |
| ... entered HILDA before 2004 and left HILDA permanently before 2004 | 793 |
| ... entered HILDA before 2004 and missed the interview in 2004 | 203 |
| ... did not know or refused to answer | 46 |
| Total number of migrants | 3716 |

Nevertheless, we can infer humanitarian/refugee status for these 32% of cases as follows. First, as permanent residency is usually granted to refugees and humanitarian migrants, we assume that migrants who were not permanent residents or Australian citizens at the time of the survey did not enter Australia as a refugee. For the remaining 1,042 cases, the refugee status was approximated using information on their country of birth. As Hugo et al. (2011) show, the distribution of birthplaces differs substantially between refugees and other migrants. Based on Census data, they identified 39 countries of birth that are predominantly made up from refugees. For most birthplaces, the information in HILDA matches their results, and the overall inflow of refugees among migrants who were born in one of these 39 countries is high.[37]

In some cases, it is possible to further refine the humanitarian/refugee definition by using additional information on migrants' time of arrival. Refugee inflows are usually related to historic events in an individual's source country and change over time. We have split the group of countries identified by Hugo et al. (2011) into two sub-groups: the first group comprises birthplaces for which the percentage share of refuges among migrants is high, but the small absolute number of individuals who were born in that country and for whom the refugee status is observed does not allow us to identify any time patterns in the refugee inflow. Migrants who are born in one of these countries are assumed to have arrived in Australia under a refugee or humanitarian migration program regardless of their time of arrival (see Table A2). The second group comprises birthplaces that are assumed to be a refugee source country only in specific time periods (see Table A3). Migrants who are born in one of these countries are assumed to have arrived in Australia under a refugee or humanitarian migration program only if they arrived in Australia in the relevant period.[38]

[37] The only exception is Egypt, for which we do not observe a substantial inflow of refugees at any point in time. Deviating from Hugo et al. we have therefore classified migrants who were born in Egypt as non-refugees.
[38] A decrease in the inflow of refugee often occurs about one to two years after the end of a war, humanitarian crisis or other event that may have resulted in large numbers of refugees.

**Table A2: Birthplaces Assumed to be Refugee Source Countries**

| Country of birth | Observed percentage share of refugees among migrants |
|---|---|
| Sudan | 75.0% |
| Burma (Myanmar) | 33.3% |
| Cambodia | 83.3% |
| Laos | 100.0% |
| Vietnam | 59.1% |
| East Timor | 80.0% |
| Afghanistan | 77.8% |
| El Salvador | 100.0% |
| Democratic Republic of Congo | 100.0% |
| Liberia | 100.0% |
| Eritrea | 100.0% |
| Ethiopia | 100.0% |
| Somalia[a] | 0.0% |
| Tanzania[a] | 0.0% |
| Sierra Leone[a] | N/A |
| North Korea[b] | N/A |

Notes: [a] Although we do not observe any refugees from this country at any point in time, we followed the classification by Hugo et al. (2011), due to the extremely low number of observations with known refugee status (0-2) that is available in HILDA. [b] North Korea is neither classified as a refugee source country by Hugo et al., nor do we observe for any migrant in HILDA who was born in the country whether the person entered Australia as a refugee. However, we assume that migrants from North Korea arrived in Australia as refugees due to the extreme political situation in the country. This rule in fact applies to only one person in the sample of analysis.

**Table A3: Birthplaces Assumed to be Refugee Source Countries in Certain Time Periods**

| Country of birth | Time of Arrival | Observed percentage share of refugees among migrants | Migrants coded as refugees | Corresponding historic event |
|---|---|---|---|---|
| Albania, Bosnia and Herzegovina, Croatia, Federal Republic of Yugoslavia, Serbia, Montenegro, (Former Yugoslav Republic of) Macedonia | <1991, >1997 | 23.59% | No | Balkan wars 1991-1995 |
| | 1991-1997 | 52.6% | Yes | |
| Bulgaria, Romania, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Russian Federation, Ukraine | >1991 | 9.1% | No | Fall of Iron Curtain in 1989/1990 |
| | <=1991 | 50.9% | Yes | |
| Iran | <1979 | 0% | No | Iranian Revolution in 1979 |
| | >=1979 | 30.0% | Yes | |
| Iraq | <1979 | N/A | No | Saddam Hussein comes to power in 1979, first and second gulf war. |
| | >=1979 | 58.8% | Yes | |
| Chile | >1992 | 16.7% | No | Pinochet resigns in 1990 |
| | <=1992 | 43.8% | Yes | |

In accordance with Hugo et al. (2011), immigrants who were born in any of the other 84 countries of birth that are observed in the HILDA Survey and that are not listed in Table A2 or Table A3 are assumed to have entered Australia not as refugees or humanitarian settlers.[39] The results of applying these rules to the individuals with missing data for refugee status are summarised in Table A4.

[39] For 64 of these countries, no migrant is observed to have entered Australia as a refugee. For 15 countries, the refugee inflow from these countries was low (0.1-20%). In the remaining five cases (Uruguay, Malta, Austria, Bangladesh, Samoa) the percentage share of refugees exceeds 20%, but the figure is based on less than 5 refugees.

**Table A4: Imputed Refugee Status**

| | Is not a refugee | Is a refugee | Total |
|---|---|---|---|
| Information is missing because migrant... | | | |
| ... was not a permanent resident or Australian citizen at the time the question was asked | 154 | 0 | 154 |
| ... entered HILDA before 2004 and left HILDA permanently before 2004 | 644 | 149 | 793 |
| ... entered HILDA before 2004 and missed the interview in 2004 | 159 | 44 | 203 |
| ... did not know or refused to answer | 35 | 11 | 46 |
| Total number of missings | 992 | 204 | 1196 |

## Age Ranges

Unless otherwise stated, our analysis is for the 15-64 age group, which we interpret as working age. This is consistent with earlier studies such as Productivity Commission (2006) (although they also report separate information for the 65+ age group) and Wilkins (2007). But where we examine questions about migrants 'catching up' with the Australian-born in terms of labour market outcomes we restrict the age range to 15-54 year olds. The reason we restrict the maximum age to <55 years is to help separately identify 'catch up' from differences in labour market attachment driven by differences in retirement behaviour, e.g. because of differential access to pensions between migrants and Australia-born.[40]

[40] We check robustness to varying these age restrictions. Our conclusions are unchanged and results are available on request.

## Appendix 2: Identification Issues When Estimating 'Catch Up'

There are a number of identification issues that need to be considered when estimating employment, wage, earnings or skill use 'catch up' rates for migrants. These issues are not unique to this study, and implications and possible fixes have been widely discussed (see e.g. Borjas, 1999). But for clarity we briefly set out the main issues, and our approach to them, here. Because we exploit longitudinal data we go further than many previous studies in explicitly addressing some of these identification issues.

**Selection and attrition**

Studies of labour market outcomes for migrants face (at least) two sample selection issues, and these need to be kept in mind when interpreting results from different studies, including this one. First, consider the initial selection into migrant status. Voluntary immigrants self select on the basis of the costs and benefits of migrating – we normally think about expected labour market returns in the host country compared to the source country – which are likely to be correlated with both their observed and unobserved characteristics. Further selectivity is imposed by the institutional context, e.g. with further differences between Skills Stream and Family Stream migrants. For refugees and humanitarian migrants the decision is also likely to be different, as are their observed and unobserved characteristics (see Cortes, 2004).[41] This has a number of implications. In general, conclusions for one particular cohort of migrants in one particular country do not necessarily generalise to other cohorts in other contexts. More specifically, where we use pooled data to study labour market outcomes and only control for cohort of arrival in broad categories (e.g. decades), there may still be unobserved differences across individuals *within* migrant cohorts that are correlated with observed variables. Fixed effects estimates that exploit the longitudinal structure of the HILDA Survey, however, are better able to control for such unobserved differences.

Second, consider selection in terms of *return* migration. There may be selection into *wave 1* of the HILDA Survey driven by non-random return migration from Australia prior to 2001. There may also be non-random attrition between waves of the HILDA Survey. For example, migrants that do less well in the Australian labour market may be more likely to return migrate after a few years than those that do better. So again we need to be careful about interpreting our results (and those in the literature more widely), particularly regarding the

[41] They may also have spent a longer time out of the labour market e.g. during the migration process.

labour market assimilation of migrants over time and particularly where we use a cross-sectional approach. If migrants that have been here longer report higher employment probabilities – as demonstrated in Section 5.3 – this could be because of assimilation, because unsuccessful migrants leave Australia prior or subsequent to HILDA wave 1 (selection), or some combination of both. In other words, if return migration is non-random, then the 'years since migration' variable in the regression model for research question 3 may be endogenous and estimates of its impact may be biased. The most likely sign for such a bias is positive.

We can get an idea of the extent of return migration by exploring attrition of migrants between waves of the HILDA Survey. Table A5 shows HILDA Survey sample size and attrition over time. In particular, note that attrition is more common among migrants than among non-migrants, consistent with return migration.

**Table A5: Attrition and Sample Size over Time**

| | Number of observations | | | Numbers of individuals that left sample *permanently* (did not come back by 2009) | | | |
|---|---|---|---|---|---|---|---|
| Survey Year | Non-migrants | Migrants | Migrants/ Total | Non-Migrants | Migrants | Non-migrants left /Non-migrants | Migrants left/ Migrants |
| 2001 | 8,373 | 2,856 | 25.4% | 693 | 396 | 8.3% | 13.9% |
| 2002 | 7,869 | 2,441 | 23.7% | 566 | 218 | 7.2% | 8.9% |
| 2003 | 7,684 | 2,242 | 22.6% | 526 | 173 | 6.8% | 7.7% |
| 2004 | 7,464 | 2,117 | 22.1% | 454 | 157 | 6.1% | 7.4% |
| 2005 | 7,654 | 2,111 | 21.6% | 418 | 137 | 5.5% | 6.5% |
| 2006 | 7,732 | 2,073 | 21.1% | 428 | 144 | 5.5% | 6.9% |
| 2007 | 7,709 | 1,933 | 20.0% | 448 | 93 | 5.8% | 4.8% |
| 2008 | 7,717 | 1,899 | 19.7% | 522 | 95 | 6.8% | 5.0% |
| 2009 | 8,055 | 1,979 | 19.7% | N/A | N/A | N/A | N/A |
| # Individuals | 12,821 | 3716 | 22.5% | | | | |

We can get an idea of the non-random nature of return migration from Table A6, which shows how attrition is related to observed characteristics of respondents. We report individual characteristics at the time of the first interview, in the first column for individuals who are still interviewed in the last available wave of 2009, and in the second column for individuals who have left the HILDA Survey before 2009. There are small, but statistically significant differences between both groups in their employment probability as well as in their skill utilisation, with individuals with less favourable labour market outcomes being more likely to leave the sample. Respondents who leave the survey are about two years younger, are less likely to have a post-school qualification, and are more often migrants compared to their counterparts who stay in the survey. Among migrants, poor English language skills and refugee status are correlated with a higher probability of panel attrition, and respondents who had been in Australia for a shorter period of time are more likely to leave the survey. These significant differences in observed characteristics suggest that individuals who leave the survey might also differ systematically from those that remain in terms of their unobserved characteristics.

**Table A6: Attrition by Characteristics for Individuals**

| | Stay until 2009 | Leave HILDA | Diff | SE(Diff) | |
|---|---|---|---|---|---|
| Employment (employed/total) | 0.73 | 0.71 | -0.02 | 0.01 | * |
| Skill Use | 5.39 | 5.29 | -0.10 | 0.03 | ** |
| Female | 0.52 | 0.49 | -0.03 | 0.01 | ** |
| Age | 37.32 | 35.28 | -2.04 | 0.22 | ** |
| Number of resident children | 0.76 | 0.76 | 0.00 | 0.02 | |
| Long-term health condition | 0.19 | 0.21 | 0.02 | 0.01 | ** |
| Has post-school qualification | 0.50 | 0.45 | -0.05 | 0.01 | ** |
| Has university degree | 0.21 | 0.16 | -0.05 | 0.01 | ** |
| Is Migrant | 0.21 | 0.26 | 0.05 | 0.01 | ** |
| If Migrant: | | | | | |
| *Language Skills* | | | | | |
| English is only language spoken at home | 0.63 | 0.54 | -0.09 | 0.02 | ** |
| Speaks very well or English is only language spoken at home | 0.82 | 0.75 | -0.07 | 0.01 | ** |
| Is refugee | 0.11 | 0.16 | 0.05 | 0.01 | ** |
| Years since Migration | 21.97 | 18.60 | -3.37 | 0.48 | ** |
| Completed school in AUS | 0.49 | 0.45 | -0.03 | 0.02 | |
| Completed post-school in AUS | 0.59 | 0.61 | 0.02 | 0.02 | |
| Completed post-school in AUS/NZ, but school elsewhere | 0.08 | 0.08 | 0.00 | 0.01 | |

One way to minimise the extent to which selection due to unobserved differences within ten year cohorts and selection due to non-random return migration might bias assimilation estimates – at least to the extent that such unobserved differences are *time-invariant* – is to exploit the longitudinal nature of the HILDA Survey data to estimate fixed effects models for assimilation (equations (9) and (10)). As discussed in Sections 5.3 and 5.4 such estimates suggest a rather different assimilation pattern to that suggested by the cross-section estimates, at least for men.

**Identities in Equations (4) and (8)**

To estimate equations (4) and (8) we have to make a number of restrictions for identification purposes. These issues are not unique to this study, and our ‘fixes’ follow what might be thought of as standard practice in this regard (for more details see Borjas, 1999). Here the discussion focuses on equation (4), but the same points apply to equation (8).

The first identification issue in (4) is that ‘age at arrival’ plus ‘years since migration’ equals the migrants’ age. The second identification issue in (4) is that ‘year of arrival’ plus ‘years since migration’ equals the current year. Consequently, these effects cannot be separated from each other without imposing further identifying restrictions. Here we specify ‘age at arrival’ and ‘year of arrival’ in broader intervals: a single dummy for age at arrival that distinguishes only between those that arrive prior to secondary school leaving age and those that arrive beyond secondary school leaving age, and ten year intervals for year (cohort) of arrival. This is not without cost: we are unable to control (at least using the pooled data) for unobserved differences across migrants *within* ten year cohorts or differences in labour market outcomes driven by differences in age at arrival within either of the broad binary age at arrival categories. Such uncontrolled differences could plausibly bias our estimates of the speed of employment assimilation. For example, if migrants that arrive towards the end of a ten year arrival cohort have unobserved characteristics that on average make them more employable than migrants that arrive earlier in the ten year arrival cohort, then there may be a downwards bias on the estimated impact of years since migration. We do, however, examine the sensitivity of our results to variations of these restrictions, with results available on request. Whether we control for actual year of arrival rather than decade of arrival (instead restricting by assuming that the year effects are common to migrants and Australian-born) or whether we control for actual age at arrival in years rather than pre/post secondary school (instead assuming that age and age-squared effects are common to migrants and Australian-born), the key results are encouragingly robust.

Of course another way of controlling for such differences where we have longitudinal data such as the HILDA Survey, and any other time-invariant differences between individuals whether observed or unobserved, is to estimate fixed effects models such as (9) and (10). But here too we need to make some additional restrictions. First, because we can now use only *within* variation for identification, we effectively have fewer observations to play with, which begins to bite for subgroups such as refugees. We therefore restrict the effect of years since migration on employment and skills use to be the same for refugees and other migrants. Second, because the variables for current age and years since migration become collinear for migrants in (9) and (10), we restrict the age coefficients to be the same for migrants and Australian-born.[42]

**Fixed Effects and Variation over Time**

The fixed-effects model relies on variation in variables over time for a given individual. If all the variation in employment status or skill use occurs only *between* individuals and not *within* individuals, so any given individual stays either employed or not employed over the entire period of observation, then the estimator is not identified. In Table A7 we show the extent of within-individual variation over time for key variables. Both employment and skill use display considerable variation over time within individuals. There is less variation in some of the key explanatory variables such as language and number of children, which restricts what we can learn about the impacts of these variables in fixed effects models. Note that we drop factors that are time invariant by definition from the fixed effects analyses.

[42] We make a similar restriction on the year dummies. Note that separate identification of age and year effects is made possible only by our assumptions regarding their functional form. This is not an issue for the estimated impacts of years since migration, however, and our key conclusions are highly robust to omission/inclusion of the year dummies.

**Table A7: Time Variation of Key Variables**

| | Information at the Time of ... | | |
|---|---|---|---|
| | First Interview | Last Interview | *#Changes Between First Interview and Last Interview* |
| Employment: no | 4,537 | 4,616 | |
| Employment: yes | 12,000 | 11,921 | |
| | | | *7,495* |
| *Skill Use* | | | |
| missing: no answer | 1,741 | 2,532 | |
| missing: not asked | 3,903 | 4,202 | |
| [1] Strongly disagree | 447 | 288 | |
| 2 | 522 | 409 | |
| 3 | 564 | 501 | |
| 4 | 1,104 | 1,078 | |
| 5 | 1,753 | 1,876 | |
| 6 | 3,488 | 3,410 | |
| [7] Strongly agree | 3,015 | 2,241 | |
| | | | *39,820* |
| Long-term Health Condition: no | *13,273* | *12,476* | |
| Long-term Health Condition: yes | *3,264* | *4,061* | |
| | | | *10,519* |
| Children: no | *10,048* | *9,630* | |
| Children: yes | *6,489* | *6,907* | |
| | | | *3,828* |
| Married/De facto: no | *6,188* | *5,724* | |
| Married/De facto: yes | *10,349* | *10,813* | |
| | | | *3,918* |
| English is only language spoken at home | 14,664 | 14,660 | |
| speaks English very well | 1,088 | 1,094 | |
| speaks English well | 500 | 500 | |
| speaks English not well | 253 | 254 | |
| speaks English not at all | 32 | 29 | |
| | | | *3,518* |
| Country of Post school Education: Australia/NZ | 7,157 | 8,151 | |
| Country of Post school Education : Other Country | 856 | 832 | |
| | | | *29* |
| Country of Last School Year: Australia/NZ | 14,529 | 14,529 | |
| Country of Last School Year: Other Country | 1986 | 1986 | |
| | | | *0* |

**Fixed Effects and Period Effects**

Beenstock et al. (2010) and Lubotsky (2011) show that if the returns to host country-specific human capital increase over time – say because of technological progress or globalisation – then immigrants' earnings growth may be slower than that of natives despite migrants accumulating host country specific human capital at a faster rate than natives. This can impart a downwards bias to fixed effects estimates of earnings assimilation, and by implication, to fixed effects estimates of employment assimilation and also (although this is less clear) skills use assimilation. Cobb-Clark et al. (2012) discuss this in the Australian context in more detail, providing estimates of the extent of the downwards bias in estimated employment assimilation for men.