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Employment, income, and skill alignment of humanitarian migrants in the Australian labour market: Metropolitan and regional contexts, 2000–2016

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Abstract

Humanitarian migration to Australia has reached new levels, accompanied by unprecedented complexity and diversity. Little is known about labour market integration for these newcomers, nor about how well their skills match those required for or relevant to their employment. Here we analyse how labour force engagement and skill alignment are influenced by migration status, including migration scheme, region of birthplace, applicant status, year of arrival, citizenship, and internal migration after settlement, and metropolitan versus regional geographic location of settlement. In particular, we focus on employed humanitarian visa holders who arrived between 2000 and 2016. Using the 2016 Australian Census and Migrants Integrated Dataset (ACMID) for quantitative analysis, our modelling established that they were not as likely to be in the labour force as skilled visa holders. Similarly, humanitarian visa holders who were employed were less likely to be in jobs that matched their skills and more likely to have lower income levels. Moreover, there were significant differences in skill alignment between those settling in metropolitan and in regional areas. The relative probability of being over-skilled was correlated with migration scheme, origin, duration since arrival, internal movement in the year preceding the census, proficiency in spoken English, family status, and gender. Labour market outcomes varied by visa subtype and by metropolitan versus regional settlement. We conclude that the design of migration policy requires further important consideration, both to improve the outlook for this vulnerable population and to address chronic skill shortages in Australia.

KEYWORDS

Australian labour market, employment, humanitarian migrants, income, metropolitan/regional areas, skill mismatch

1 | INTRODUCTION

Immigration accounts in a large part for the doubling over the last 50 years of Australia's population, a third of whom were born overseas (8.42 million on 2021 census night). That figure swells to over a half the population when we include all those with at least one parent born overseas (ABS, 2022). Australia's migration programme is arguably one of the world's most closely managed immigration programmes, with all persons apart from New Zealanders requiring a visa to enter (Hugo, 2014a). This programme enables substantial control over the scale and composition of migration flows. Permanent immigrants enter under capped programmes such as skilled, family and special eligibility. As shown by the 2016 Australian Census and Migrants Integrated Dataset (ACMID), the humanitarian programme accounted for about 10% of the 2.2 million permanent migrants arriving between 1 January 2000 and 9 August 2016 (census night), with 32% coming under family programmes (mainly partner and parent schemes) and 58% under a range of skilled visas (ABS, 2018).

This study investigates the economic integration of 16 to 64 year old humanitarian entrants into the Australian labour force. Of particular interest, we examine the extent to which they participate, their employment prospects and the extent to which their skills are underused and prevent them from reaching their full potential as contributors to the skilled workforce. According to the ACMID data, those employed in this group made up only 38% of the sample population, 10% were unemployed, and 52% were not engaged in the labour force, many undertaking studies. This participation was much lower than for other migrants, and for the Australian population as a whole. When disaggregated by gender, there was evidence of an even lower representation in the labour force of employed female humanitarian migrants (27%) compared with males (48%).

We addressed the effects of settlement in metropolitan versus regional areas, and in specific states and territories of Australia, to inform policy decisions aimed at redressing imbalances and inequities. Our study therefore does much to close an important knowledge gap, exploring how migration status, migrant characteristics, and settlement location influence the employment, income, and skill alignment of humanitarian migrants arriving in Australia between 2000 and 2016.

Humanitarian migrants were disproportionately located in metropolitan (89.2%) compared with regional areas (10.8%), especially among those more recently arrived. We compare these differences through three research questions (RQs):

RQ1: How is migration status, especially visa category and applicant status, of humanitarian migrants associated with labour market participation and employment?

RQ2: For employed humanitarian migrants, is there an association between income and migrant status and skill mismatch (controlling for other factors)?

RQ3: For employed humanitarian migrants, is there a skill mismatch, and how is it determined by visa category and other migrant status factors?

Skill alignment is the *degree of match or mismatch* (under-educated, over-educated) between what employers demand and the qualifications or skills workers possess (for employed migrants). In the analysis, visa category of migrants is an independent variable of particular interest. To understand how migration status shapes employment, income, and skill alignment differently, we disaggregated humanitarian migrants by visa category (that is, refugees, global special humanitarian migrants, and other special humanitarian migrants). We analysed two subsamples—disaggregated by *metro* (regional versus metropolitan). Skilled migrants are the reference group for the explanatory variable *visa category*.

We seek to go beyond studies such as those by Cheng, Wang, and Taksa (2021) and Cheng, Wang, Jiang, et al. (2021), which concentrated on labour force participation (LFP) and employment prospects of humanitarian migrants in Australia, to look specifically at those who were employed, and consider how well their jobs fitted with their qualifications and experience. Our study offers three advances. First, it adds to the relatively small body of quantitative research into resettlement outcomes of humanitarian migrants, particularly labour market outcomes. It is the first to use linked ACMID data to analyse skill alignment issues and explore how they are associated with the income of employed humanitarian migrants in regional and metropolitan areas of Australia. By using linked large-scale data along with rich information at the individual level, it also contributes to micro-level research on humanitarian migrants. This study can therefore supplement macro-level policymaking and contribute to well-known skill shortage problems. Second, it contributes to diverse studies on humanitarian migrants' labour market performance by examining the differential effects of migration status and geographical contexts of settlement on skill alignment, which is a meaningful domain of employment outcome. Third, it helps to inform current public debates on humanitarian migrants' labour

Key insights

This article addresses employment, income, and skill alignment in the Australian labour market for humanitarian migrants, and considers their potential to fill workforce gaps in a rapidly expanding twenty-first century economy. A unique integrated dataset has enabled analysis of migrants' characteristics and circumstances to gauge varying levels of labour market suitability for these migrants in contrast with those entering under skilled visa schemes. We found differences between humanitarian migrants, notably those with refugee status and other special humanitarian entrants. That finding exposes a need to secure equitable benefits for all visa categories and for a host economy in need of this valuable human resource that too often is underestimated.

market performance and their potential to help overcome skill shortages in Australia.

2 | OVERVIEW OF THE LITERATURE

This section provides background to Australia's humanitarian programme and considers differences in the programme's refugee and other special humanitarian components. Studies have shown that the economic contributions of migrants gaining entry under this programme have largely been ignored. However, they offer a potential source of underutilised human capital for Australia's increasing labour force demands in a rapidly expanding economy. It is vital that we understand more about how their skills are likely to match their employment and income goals, which will contribute to more successful settlement and greater personal satisfaction of humanitarian migrants in their host country. Important gaps exist, and two in this article relate to skill alignment among those employed and to how demand for skills may vary between urban and regional settlement outcomes for humanitarian migrants, according to whether they had refugee status or were other special programme entrants.

2.1 | Australia's refugee and humanitarian programme

Australia's current refugee and humanitarian programme assists refugees and others in need of humanitarian assistance (hereafter, 'humanitarian' will sometimes include 'refugee'). Founded on 1978 initiatives, the programme gives opportunities to people fleeing persecution and suffering. Source regions have changed significantly over time, reflecting global developments (DIAC, 2011). Each wave of entrants brings its own employment and educational characteristics, levels of proficiency in English, and cultural and religious orientations. Accordingly, there is a constant need to evaluate and revise policies and schemes to optimise labour market integration and social integration. In linked 2016 census–migration data, the basis for our analysis, sources of humanitarian migrants were the Middle East (31%), Southern and Central Asia (21%), sub-Saharan Africa (15%), South-East Asia (13%), North Africa (11%), and other regions such as Europe, Oceania and Antarctica, North-East Asia, and the Americas (less than 10%). The small percentage from Europe (4%) represents a considerable drop compared with 2000–2001 (about 45%), showing the programme's response to volatility in global circumstances.

The humanitarian programme offers onshore and offshore pathways to refugees and others seeking protection from persecution, war, or other threats to human well-being and rights. It serves two functions, providing resettlement for refugees who are overseas (designated under the Refugee Convention), and for those already in Australia deemed to be refugees seeking protection (the onshore protection/asylum component). For migrants entering under the programme, refugee visa holders accounted for 45% of our sample population. The remainder entered under the special humanitarian programme (SHP), for persons supported by a proposer in Australia who were subjected to substantial discrimination and violation of rights in their home countries but were outside that country when they applied. We disaggregated this SHP component into *global special humanitarian* (33%) and *other special humanitarian* (22%).

A comprehensive study by Hugo (2014b) on the economic contributions made by migrants gaining entry into Australia under the programme found that they were a significant stock of unrecognised and generally understudied human capital. Common impediments to their LFP have been well documented, especially for those from non-English speaking backgrounds (Cobb-Clark, 2006; Colic-Peisker, 2008; Colic-Peisker & Tilbury, 2006; Hugo, 2011, 2014b; Iredale & D'Arcy, 1992). They face barriers concerning English language proficiency and education, and with qualification recognition and acceptance, culture shock, social isolation, exclusion, and discrimination (Cheng, Wang, Jiang, et al., 2021; Connor, 2010; Hugo, 2011).

Given that, over the last two decades, Australia's migration programme has transitioned to a greater emphasis on skilled migration to support the demand for skilled workers in a rapidly expanding economy, we must not overlook the potential of better-integrating refugees in the skilled workforce and regional economies. Unlike other entrants, humanitarian migrants are most likely to stay for their entire life and raise their families in Australia (Hugo, 2014b), so it is vital that their skills match with their employment and income goals, because this seems to contribute to successful settlement and personal satisfaction in their host country.

2.2 | Skill alignment

Following Quintini (2011), we take *skill alignment* to be the degree of match or mismatch between what employers demand and the qualifications or skills that workers have to offer. At the macro level, this alignment concerns what Pellizzari and Fichen (2017, p. 3) define as the 'allocation of workers to jobs that could improve the realized equilibrium in either employment levels or output.' What they call *micro mismatch* is our focus: migrant skills higher (or lower) than required, within each worker–job pair.

Empirical investigations in Australia and New Zealand confirm that the successful settlement of refugees depends on whether they can convert their skills and qualifications for use in their host country (Fleay et al., 2013; O'Donovan & Sheikh, 2014). For Australia, limited numbers of studies have examined the extent of skill mismatch and its adverse impacts on wages, job satisfaction, and future employment prospects for graduates, an important segment of the workforce (Mavromaras et al., 2009, 2013, 2015). For EU countries, immigrants had a disproportionately high risk of skill mismatch (Nieto et al., 2015; Støren & Wiers-Jenssen, 2010). Tani (2021) has identified the positive role of occupational licensing in reducing education–occupation mismatches for highly educated migrants in Australia; but no study systematically addresses immigrants' skill alignment, in particular its relationship with humanitarian migration status and geographical locations of settlement. We aim to make good that deficiency.

Research has focused on how well and how long refugees take to secure stable employment, and the extent to which many choose self-employment to overcome some of the barriers (see Connor, 2010; Hugo, 2011). Recent studies note that refugees who have experienced significant socio-economic adversity in their early years of settlement, such as financial hardship and living in a disadvantaged neighbourhood, are less likely to find paid jobs (Cheng, Wang, & Taksa, 2021), and only 1% of a recent cohort of refugees initiated entrepreneurship within four years from arrival (Cheng, Wang, Jiang, et al., 2021).

The effectiveness of regional resettlement policies to address skilled labour shortages in areas experiencing population decline and egress of young people has received limited attention (Hugo, 2008; Hugo et al., 2006). Refugees in particular have limited access to social networks for support in finding work. Research has reported that migrants who are middle-aged, female, parents, carers, or unemployed, and with lower educational attainment, are associated with heightened exposure to such adversity (DSS, 2019). Refugees have little or no chance to explore their employment options and preferred locations before arriving in Australia (Hugo, 2014b). They have difficulty accumulating work experience, another prerequisite for most employers, so many end up in low-skilled and low-paying jobs that require few qualifications and attributes, despite skills acquired in their home country.

Since the mid-1990s, when the issue of where migrants would settle became an important consideration with the introduction of state-specific regional schemes, we find that South Australia and the Northern Territory became regions worthy of support to boost lagging population and move towards development goals (Hugo, 2008).

3 | DATA AND METHODS

This section contains several sub-sections. First, it describes the data set used in the analysis, a description of the analytical sample—with details of the regional distribution of labour market participants and skill matching details. That is followed by variable definitions and descriptive statistics for the variables included in the empirical modelling. Following those descriptions are details of the theoretical underpinnings of the empirical modelling methods used. This work includes details of how selection bias is addressed, resulting in labour market participation and employment status models. A wages model is also discussed. The section concludes with general issues related to applying the models to these data.

3.1 | The 2016 Australian census and migrants integrated dataset (ACMID)

Our study subjected 2016 ACMID's microdata—Confidentialised Unit Record File (CURF, from the Australian Bureau of Statistics: ABS Cat No. 3417.0.55.001, 2016)—to sophisticated statistical analysis in the ABS environment DataLab. The dataset covers the largest sample of immigrant groups coming to Australia under skilled, family, special eligibility, and refugee and humanitarian programmes. It is a valuable resource, with no sparse-data caveats, for exploring labour market outcomes, specifically employment, income and skill alignment of humanitarian migrants, at the disaggregated level—distinguished by geographical location (metropolitan versus regional). These data link 1,924,551 (88%) of 2,166,014 records from the permanent migrant database administered by the Department of Social Service (DSS) with 2016 census data (ABS, 2018), offering detailed information on the demographic, social, economic, and geographic characteristics of migrants. The 2016 ACMID covers individual permanent visa holders who arrived between 1 January 2000 and 9 August 2016 (census night). Fine-grained information on migrants' origins, visa classes, citizenship, movements, and geographical contexts of resettlement enables us to distinguish between humanitarian migrants who realised their skills sufficiently and those who did not.

3.2 | Analytical samples

The analytical samples, derived from the ACMID, include individuals with these four characteristics:

1. participated in the labour market or not; employed or unemployed (our variable *EmpUnemp*); and if employed, how skills are aligned with the level of skills demanded (our variable *Skill_mis*);

2. aged 16–64;
3. arrived between 2000 and 2016; and
4. differentiated between metropolitan and regional areas (our variable Metro).

Table 1 shows the analytical sample sizes for three regression models (elaborated below in 3.4), disaggregated into sub-samples distributed between three key outcome variables *EmpUnemp*, *Skill_mis*, *Income*, and *Metro* (regional and metropolitan). The empirical results support our breakdown of the ACMID data into two natural sub-groups (Regional and Metropolitan). That is, we find statistically significant differences between coefficients for several important variables such as *VisaType*.

3.3 | Variable definitions and descriptions

Table 2 shows labels and descriptions for our variables. Table 3 presents summary statistics—count, mean, standard error—for continuous variables for each sub-samples in three categories of labour market outcomes. Table 4 gives proportions for the categorical variables for each of the two sub-samples across three outcome models.

Our outcome variable, *Skill mismatch*, is categorical: under-educated, over-educated, and skill-matched. *Skill mismatch* indicates the difference between skill levels possessed and skill levels required in Australian jobs. The Australian and New Zealand Standard Classification of Occupations (ANZSCO) defines occupation skill level as a function of the range and complexity of tasks to be performed (ABS, 2019). ANZSCO uses five skill levels: the greater the range and complexity of tasks, the higher the required level. A migrant's skill level is measured by a combination of the extent of formal education and training, previous experience in a related occupation, and the amount of on-the-job training required.

Predictor variables in these models include a set of variables measuring migration status. *VisaType* indicates the main schemes for humanitarian migration. Other predictor variables include region of birth (*RoBirth*), applicant status (*AppStatus*), year of arrival (*Year_arrival*), Australian citizenship or not (*Aust_citizen*), and internal migration across Local Government

TABLE 1 Labour market distribution of humanitarian/skilled migrants by location.

	Employed-unemployed		Skill mismatch		Income	
Labour market outcomes	Regional	Metropolitan	Regional	Metropolitan	Regional	Metropolitan
Participated in the labour market	93,256	585,026				
Column percent	82.1	80.1				
Not in the labour market	20,277	145,344				
Column percent	17.8	29.9				
TOTAL	113,533	730,370				
Column percent	100	100				
Employed	87,021	537,885				
Column percent	93.3	91.94				
Unemployed	6,229	47,154				
Column percent	6.7	8.1				
TOTAL	93,250	585,039				
Column percent	100	100				
Under-educated			22,193	98,457		
Column percent			27.0	19.2		
Skill-matched			38,283	250,661		
Column percent			46.5	48.9		
Over-educated			21,838	162,922		
Column percent			26.5	31.8		
TOTAL			82,314	512,040		
Column percent			100	100		
Employed and income earners						
TOTAL					85,395	528,754
Column percent					100	100

TABLE 2 Variable labels and description.

Label	Description
Skill_mis	Skills from formal education versus required by jobs (three categories)
LFP	Labour force participation (participant and not in labour force; dichotomous)
EmpUnemp	Employment and unemployment (dichotomous)
Income	Total personal weekly income (14 categories; mid-point treated as continuous)
VisaType	Visa classification and subtype (four categories)
RoBirth	Region of birth (nine categories)
AppStatus	Primary or secondary applicant (dichotomous)
Year_arrival	Year of arrival in Australia
Aust_citizen	Australian citizenship (dichotomous)
Move_lga	Change in residential location in the past 1 year (dichotomous)
State	Destination state or territory
IER	Index of economic resources (national area)
IEO	Index of Education and Occupation (national area)
Age & Agesq	Age of person (and age squared)
Gender	Gender (dichotomous)
Marital	Registered marital status (five categories)
Family_comp	Family composition (four categories)
Disability	Disabled household member (core activity needs assistance; dichotomous)
English	Proficiency in spoken English (three categories)
Edu	Highest educational attainment (five categories)
Religion	Religion group (three categories)
VoluntaryWk	Voluntary work undertaken (dichotomous)
ChildCareNopay	Provide unpaid childcare (four categories)
WkEngaged	Engagement with the labour market (four categories)
Housing	Housing tenure (three categories)

Areas (LGAs) in the 12 months preceding census night (*Move_lga*). We also include important *control variables*, including demographic (*Age*, *Gender*, *Marital status*, *Family composition and Disability*), and socio-economic (*English*, *Education*, *Religion*, *Voluntary work*, *Unpaid childcare* and *Housing*); definitions are in Table 2.

3.4 | Regression methods

3.4.1 | Participation and employment

Sample selection bias occurs naturally in modelling labour supply. The probabilities of being a labour force

TABLE 3 Descriptive statistics for continuous variables in three categories of models.

	1. Employed-unemployed				2. Skill mismatch				3. Income			
	Regional ($N = 110,834$)		Metropolitan ($N = 732,994$)		Regional ($N = 84,000$)		Metropolitan ($N = 536,744$)		Regional ($N = 83,404$)		Metropolitan ($N = 533,156$)	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Age	36.752	10.734	35.473	9.738	37.727	9.876	36.194	8.666	37.743	9.855	36.201	8.650
IER	4.874	2.918	5.111	3.009	5.060	2.897	5.282	3.002	5.058	2.897	5.281	3.001
IEO	5.072	2.491	5.352	2.838	5.200	2.455	6.692	2.686	5.200	2.454	6.694	2.685

TABLE 4 Proportions (as percentages) for categorical variables in three categories of models.

	1. Employed-unemployed		2. Skills mismatch		3. Income	
	Regional	Metropolitan	Regional	Metropolitan	Regional	Metropolitan
VisaType						
Skilled	87.6	83.1	93.3	90.9	93.3	91.0
Refugees	7.3	7.1	3.5	3.4	3.5	3.4
Global special humanitarian	2.8	5.8	1.5	2.7	1.5	2.7
Other special humanitarian	2.3	3.9	1.7	3.0	1.7	3.0
RoBirth						
Middle East	3.1	7.6	1.9	4.2	1.9	4.2
Southern and Central Asia	21.4	29.4	21.0	30.6	21.0	30.6
Sub-Saharan Africa	17.9	9.6	17.9	9.4	17.8	9.4
South-East Asia	13.4	12.5	13.0	12.3	13.0	12.3
North Africa	1.9	2.2	1.3	1.4	1.3	1.4
Europe	26.2	18.5	28.7	21.3	28.7	21.4
Oceania and Antarctica	4.8	2.2	4.6	2.1	4.6	2.1
North-East Asia	7.8	15.3	7.8	15.5	7.7	15.5
America	3.6	2.8	3.8	3.1	3.8	3.1
AppStatus						
Primary	52.9	55.8	60.2	63.7	60.4	63.9
Secondary	47.1	44.2	39.8	36.3	39.6	36.1
Year_arrival						
2000	2.4	3.4	2.4	3.5	2.3	3.5
2001	2.9	3.7	2.9	3.8	2.9	3.8
2002	3.1	3.8	3.2	3.9	3.2	3.9
2003	4.0	5.1	4.2	5.3	4.2	5.3
2004	4.4	5.7	4.5	5.9	4.5	5.9
2005	6.3	6.6	6.5	6.8	6.5	6.8
2006	8.6	8.1	9.0	8.4	9.0	8.3
2007	10.2	9.9	10.7	10.6	10.7	10.6
2008	13.3	11.5	14.1	12.2	14.1	12.2
2009	10.3	8.9	10.7	9.2	10.7	9.2
2010	7.0	6.6	7.0	6.6	7.0	6.6
2011	7.1	6.6	7.1	6.5	7.1	6.5
2012	7.1	5.9	7.2	5.9	7.3	5.9
2013	5.5	4.9	4.9	4.4	4.9	4.4
2014	3.7	4.0	3.0	3.4	3.0	3.4
2015	2.6	3.4	1.9	2.7	1.9	2.7
2016	1.4	1.9	0.6	0.9	0.6	0.9
Aust_citizen						
Australian	55.0	54.7	56.4	56.0	56.4	56.0
Non-Australian	45.0	45.3	43.6	44.0	43.6	44.0
Move_lga						
Did not move	82.1	80.3	83.6	81.5	83.6	81.5
Moved across LGAs	17.9	19.7	16.4	18.5	16.4	18.5
State						
NSW	23.4	33.5	22.6	33.8	22.6	33.9
Vic	14.4	28.4	13.3	28.0	13.3	28.0
Qld	42.5	11.5	43.2	11.5	43.2	11.5

TABLE 4 (Continued)

	1. Employed-unemployed		2. Skills mismatch		3. Income	
	Regional	Metropolitan	Regional	Metropolitan	Regional	Metropolitan
SA	3.0	6.4	3.1	5.8	3.1	5.8
WA	12.9	16.7	14.3	17.2	14.4	17.2
Tas	2.2	0.5	1.7	0.4	1.7	0.4
NT	1.5	0.9	1.7	1.0	1.8	1.0
ACT	0.1	2.1	0.1	2.3	0.1	2.3
Gender						
Female	46.5	47.0	41.8	41.5	41.7	41.4
Male	53.5	53.0	58.2	58.5	58.3	58.6
Marital						
Never married	28.7	28.8	25.7	26.2	25.7	26.2
Widowed	0.7	0.6	0.4	0.3	0.4	0.3
Divorced	3.3	2.8	3.6	2.9	3.6	2.9
Separated	2.2	2.0	2.2	1.7	2.2	1.7
Married	65.1	65.8	68.2	68.8	68.2	68.9
Family_comp						
Couple family, no children	17.0	18.2	19.1	21.5	19.2	21.5
Couple family with children	57.2	60.6	55.3	58.2	55.2	58.1
One-parent family	6.0	7.0	4.3	5.1	4.3	5.0
Other family or single	19.7	14.2	21.2	15.3	21.3	15.3
Disability						
None	96.2	94.8	97.7	97.3	97.7	97.3
Family member disabled	3.8	5.2	2.3	2.7	2.3	2.7
English						
English only	36.7	23.7	39.4	26.6	39.4	26.7
Very well/well	56.3	67.9	56.7	69.3	56.7	69.3
Not well/not at all	7.0	8.4	3.9	4.0	3.9	4.0
Religion						
Christian	51.9	38.9	52.6	38.1	52.6	38.1
Secular	24.1	25.0	25.5	27.3	25.5	27.3
Other religion	24.1	36.1	21.9	34.6	21.9	34.6
VoluntaryWk						
Not volunteer	81.5	83.1	82.4	83.5	82.4	83.6
Volunteer	18.5	16.9	17.6	16.5	17.6	16.4
ChildCareNopay						
Not provided	57.9	58.4	58.6	58.8	58.6	58.9
Care own child	38.3	38.6	38.2	38.6	38.3	38.6
Care other	3.1	2.4	2.5	2.0	2.5	2.0
Care own and other	0.7	0.6	0.7	0.5	0.7	0.5
Housing						
Owned outright	6.8	5.5	6.5	5.2	6.5	5.2
Owned with mortgage	40.7	45.3	43.9	48.6	43.9	48.6
Rented	52.5	49.1	49.6	46.2	49.6	46.2
WkEngaged						
Fully engaged	64.9	65.5				
Partially engaged	18.3	15.5				
At least partially engaged	3.4	2.9				
Not engaged	13.4	16.1				

(Continues)

TABLE 4 (Continued)

	1. Employed-unemployed		2. Skills mismatch		3. Income	
	Regional	Metropolitan	Regional	Metropolitan	Regional	Metropolitan
Edu						
Postgraduate/GradDip/Grad	15.5	23.7				
Bachelor's degree	27.8	31.4				
Advanced dip/diploma	13.4	11.0				
Certificates I–IV	16.1	9.2				
Secondary education and below	27.3	24.7				
Skill_mis						
Under-educated					26.9	19.2
Skill-matched					46.6	49.0
Over-educated					26.5	31.8

Note: Percentages may not add to 100% because of rounding.

participant, of being employed, and employment income are interrelated. For example, potential bias arises from the exclusion of non-working persons (non-participants) from assessment of our variable of interest: employed–unemployed. The decision to accept a job or not is not independent of the choice of being a labour force participant, so being employed may be systematically correlated with unobservable factors that affect the choice to be a labour market participant. If this interdependency—labelled sample selection bias—is ignored econometrically, estimated coefficients may be biased and inconsistent, leading to false conclusions and poor policy prescription.

Since Heckman (1978, 1979) published, it has been commonplace in econometric analysis to correct for sample selection bias when estimating labour supply models through a two-equation system. In our case, the first equation is participation and the second is employment. For both, a limited dependent variable (probit) model is used: for probability of LFP, the complete random sample is used to determine the probability of being included in the sample for the second-stage employment equation. Heckman showed that including a selection bias 'correction term' from the first equation in the second equation accounts for the non-randomness of the employment equation sub-sample. Stata's (version 17) heckprobit is used for analysis, which produces consistent, asymptotically efficient estimates for all the parameters in such models (Stata, 2019). We note one proviso or limitation: Heckman-based selection models assume that the selection mechanism is because of model observables, if because of unobserved, the process may not fully address all aspects of self-selection bias.

Following Cameron and Trivedi (2010), let y_2* denotes the outcome of interest (employed versus unemployed) and y_1* the choice to be an LFP where y_1* determines whether y_2* is observed (and * marks a latent variable), then the two-equation model has a bivariate selection equation for y_1:

$$Y_1 = \{1 \text{ if } y_1 * > 0 \quad \{0 \text{ if } y_1 * \leq 0. \tag{1}$$

And the resultant outcome equation for y_2:

$$Y_2 = \{1 \text{ if } y_1 * > 0 \quad \{- \text{if } y_1 * \leq 0. \tag{2}$$

That is, employed or unemployed is only observed if the individual is an LFP. This allows the system with additive errors to be represented as

$$\begin{aligned} Y_1{}^* &= \mathbf{X}_1{}'\beta_1 + \varepsilon_1 \\ Y_2{}^* &= \mathbf{X}_2{}'\beta_2 + \varepsilon_2, \end{aligned} \tag{3}$$

where each **X** is a vector of an exogenous variables (predictors and controls), each β is a coefficient to be estimated, and ε_1 and ε_2 are assumed to be correlated but jointly normally distributed and homoscedastic.

For the labour market, both Y_1 (participation in the labour market verses not in the labour market) and Y_2 (employed verses unemployed) are estimates as (binary) probit models.

Coefficients for probit models can be interpreted, after calculation of the marginal effects, as the change in probability of observing the dependent variable (Y_1 or Y_2),: when there is a small or marginal change of one unit in the explanatory variable if continuous; or if binary, the change in probability after a 'switch' of the explanatory variable from zero to one; or if categorical, the change in probability after a 'switch' of the explanatory variable from the reference group to another group.

3.4.2 | Income

Our analysis of the impact of visa category, skill mismatch, and other exogenous variables was carried out by applying ordinary least squares (OLS) regressions to the two sub-samples (metropolitan and regional). In this case, the dependent variable is 'individual income'—which we use as a proxy for returns to employment as the ACMID data do not include wage or earnings variables. To assist the proxy application, we restrict the sample to those employed and report a non-zero income. We are cognisant of the potential for bias in this examination. That is, there may be a sample selection issue (see above), but we are not able to apply the Heckman method as the first stage model cannot be defined. That is, the first stage employed versus unemployed cannot be analysed with the set of explanatory variables we wish to include in the second (main) equation, as those in the sample who are unemployed do not have a skill mismatch record.

As outlined by Heckman (1979), it is not appropriate to run two models separately and insert, as a selection bias control, an inverse Mills ratio (IMR) from the first equation into the second. Nonetheless, we did explore this approach and found that the results were not quantitatively different to the outcome from OLS. Similarly, applying the Heckman method to the problem but excluding the skill mismatch variable also gave results that support conclusions from the OLS model. For example, coefficients on the variables of interest are always statistically significant and of the same sign.

The OLS can be specified as (Greene, 2008)

$$Y_i = \mathbf{X}_i'\beta + \varepsilon_i \tag{4}$$

where, as previously, Y is the outcome (income), $\mathbf{X}$ a vector of explanatory variables, β a coefficient to be estimated, and errors (ε_i) are assumed to have zero-mean random constant variance.

For OLS model with income as the dependent variable, coefficients are interpreted as the difference in average income for the specific group compared with the base for categorical variables such as visa type. For a continuous variable, the interpretation is the change in income for a one-unit change in the explanatory variable.

3.4.3 | Skill mismatch

Because skill mismatch is a categorical outcome variable, we use a multinominal probit (MNP) regression model to investigate the relationship between it and the independent variables. The three categories: under-educated, skill-matched, over-educated. The MNP represents individual i, alternative j (U_{ij}), as the sum of deterministic components V_{ij} that depend on the independent variable and unknown (unobserved) random components ε_{ij}. The MNP in this case is a three-outcome model with the outcome for the i^{th} person and j^{th} choice given by Cameron and Trivedi (2010).

$$U_{ij} = V_{ij} + \varepsilon_{ij} \text{ for } j = 1,2,3 \tag{5}$$

The standard MNP model is then:

$$U_{ij} = X_{ij}\beta + \varepsilon_{ij} \tag{6}$$

where $\mathbf{X}$ is a vector of independent regressors, and errors (ε_{ij}) are assumed to be random with constant variance and zero mean. The probability that alternative j is the outcome for individual i is given by

$$p_{ij} = \Pr(y_i = j) = \Pr(\varepsilon_{ik} - \varepsilon_{ij}) \leq (\mathbf{X}_{ij} - \mathbf{X}_{ik})'\beta \text{ for all } k \tag{7}$$

$$= F(\mathbf{X}'\beta) \tag{8}$$

where, for the MNP, F() is the standard normal cumulative distribution function.

Following the regression, average marginal effects (AMEs, averaged over the joint distribution of the independent variables) can be calculated. For the MNP model, a positive AME indicates that an increase in the explanatory variable of one (small) unit—or for a dummy variable, a switch from zero to one—is associated with an increase in the probability of the dependent variable taking the j^{th} value. Similarly, a negative AME is associated with a decrease in probability. Across the three possible outcomes, the sum of the estimated changes in AME for each explanatory variable is zero (total probability sums to one). For example, for applicant status equal to secondary compared with primary applicant, for regional areas, under-educated AME is 0.031 (secondary applicants 3.1% more likely to be under-educated compared with primary applicants); for skill-matched the AME is −0.161; for over-educated 0.129; and net changes are zero.

3.4.4 | General issues

In the regression models, as well as the explanatory variables of particular interest, we include a comprehensive suite of control variables. That is, there are numerous individual characteristics expected to influence the outcome, but other than when of particular interest, we do not focus on these. In many cases, control variables are to incorporate observed heterogeneity and known effects such as age and English language ability. In other cases, they may act as a proxy for unobserved heterogeneity. For example, we include a three-category variable for religion (Christian, secular and other religion) and suggest this may be a proxy for unobservable attitudes of migrants and of employees, and we have no priors as to the possible influence on the outcome. In addition, we analyse sub-samples of migrants in metropolitan and regional areas (non-metropolitan). This analysis yields a simple yet powerful account of geographical heterogeneity: a method adopted in seminal studies (Alesina et al., 2016). Estimation of the models is carried out within the ABS DataLab environment using Stata/SE 17.0.

4 | EMPIRICAL RESULTS

Here we consider implications of the regression model results for our specific research questions RQ1–3. We are particularly interested in how migration status—represented by visa category, region of birth, applicant status, Australian citizenship, year of arrival, and internal migration cross local government areas (LGAs)—influences LFP, employment, income and (for those employed) skill mismatch for migrants in the humanitarian programme.

4.1 | Participation and employment

The application of the Heckman type control for sample selection results in two outcomes: LFP (versus not in the labour force) and, conditional on being a participant, employment (versus unemployment). Both models are estimated by probit, and coefficients are converted to (average) marginal effects—interpreted as changes in probabilities.

Results for the two areas of settlement (metropolitan versus regional) for LFP and employment versus unemployment are presented in Table 5. First, for explanatory variables relating to migrant status for LFP, it is clear that humanitarian migrants when compared with skilled visa holders have much lower rates of participation. Among them, the lowest rates are for recent arrivals, secondary applicants (most often females) compared with primary applicants and migrants from the Middle East. It was not surprising to find higher rates for migrants who had taken up Australian citizenship (statistically significant but small), most likely linked to earlier arrival with more time to secure employment (Hugo, 2011).

More general findings, consistent with LFP for the general Australian population, are that males were more likely to be in the labour force, as were those with good English proficiency and those with postgraduate qualifications. The age structure of humanitarian labour force participants exhibited a similar profile as age increases: participation decreases at older ages, but at a diminishing rate. Several other control variables have statistically significant coefficients such as state or territory, marital status, family composition. Overall, these differences in LFP were not consistent between metropolitan and regional areas, reflecting considerable differences in the labour market they faced.

We next examine labour market success—that is, probability of being employed—conditional on being a labour force participant. First, we consider observations about explanatory variables relating to migrant status. Most importantly, compared with skilled visa holders, unemployment was higher among the humanitarian migrants, particularly those in regional areas, and within this broader category, higher for global humanitarian and other special humanitarian migrants than for refugee visa holders. In addition, unemployment was higher for secondary applicants, migrants from the Middle East, later arrivals (generally)—and for settlement area, those who migrated across local government areas in the 12 months preceding the 2016 Census, and non-Australian citizen migrants (marginally in metropolitan, and no association in regional areas).

To summarise (noting that these results are consistent with the general Australian population):

1. gender has a significant but very small association with metropolitan (but not with regional);
2. age has a very small nonlinear association with the probability of being employed;
3. better English ability and higher education are associated with an increased probability of being employed, but English is more important in metropolitan areas, and education in regional areas; and
4. other control variables are generally statistically significant, with differences evident between metropolitan and regional contexts.

Findings on **RQ1** then, addressed by the comprehensive results for the four models shown in Table 5, demonstrate that migration status is strongly associated with labour market participation, and with labour market outcome or success in gaining employment.

4.2 | Income

RQ2 relates to associations among income, migrant status and skill alignment for those employed. Using ordinary least squared (OLS) models, coefficients are interpreted as the difference in average income, and income in the models is personal income used as a proxy for earnings (not included in the dataset). Robust (or sandwich estimator of variance) standard errors were used to minimise heteroscedasticity in both models (Zeileis, 2004).

Explanatory variables relating to migrant status show that skilled visa holders have significantly higher

TABLE 5 Heckprobit regression estimates of labour force participation and employment: average marginal effects for two sub-samples—metropolitan and regional.

	1. LFP		2. Employed-unemployed	
Variables	**(a) Regional dy/dx**	**(b) Metropolitan dy/dx**	**(c) Regional dy/dx**	**(d) Metropolitan dy/dx**
Explanatory variables:				
VisaType (skilled = ref.)				
Refugees	−0.081***	−0.070***	0.025***	0.013***
Global special humanitarian	−0.063***	−0.064***	0.035***	0.014***
Other special humanitarian	−0.077***	−0.041***	0.056***	0.035***
AppStatus (primary = ref.)				
Secondary	−0.035***	−0.028***	0.033***	0.032***
Aust_citizen (Australian = ref.)				
Non-Australian	0.012***	0.006***	−0.001	0.003***
RoBirth (Middle East = ref.)				
Southern and Central Asia	0.065***	0.052***	−0.006	−0.005***
Sub-Saharan Africa	0.057***	0.053***	−0.006	−0.006***
South-East Asia	0.043***	0.034***	−0.022***	−0.013***
North Africa	0.060***	0.045***	0.021**	0.034***
Europe	0.058***	0.063***	−0.017***	−0.026***
Oceania and Antarctica	0.049***	0.039***	0.000	−0.009***
North-East Asia	0.018**	0.005***	0.006	0.003
America	0.031***	0.031***	−0.016**	−0.014***
Year_arrival (2000 = ref.)				
2001	0.008	−0.004*	0.003	−0.001
2002	0.006	0.001	−0.002	−0.004*
2003	0.004	−0.002	−0.006	−0.003*
2004	0.007	−0.005**	0.002	−0.002
2005	0.005	−0.005**	0.000	0.002
2006	0.011*	−0.003	0.004	0.001
2007	0.006	−0.002	−0.001	−0.001
2008	0.011*	−0.006***	0.004	−0.002
2009	0.011*	−0.008***	0.001	−0.001
2010	0.003	−0.014***	0.006	0.005**
2011	−0.004	−0.015***	0.009	0.007***
2012	−0.004	−0.019***	0.006	0.005**
2013	−0.032***	−0.033***	0.012**	0.010***
2014	−0.041***	−0.040***	0.015*	0.026***
2015	−0.049***	−0.049***	0.036***	0.048***
2016	−0.060***	−0.039***	0.107***	0.166***
Move_lga (did not move = ref.)				
Moved across LGAs	0.004	0.006***	0.033***	0.018***
Control variables:				
State (NSW = ref.)				
Vic	0.005	−0.002**	−0.001	0.009***
Qld	0.015***	0.004***	0.011***	0.019***
SA	0.017***	−0.006***	−0.006	0.017***
WA	0.018***	0.010***	−0.009***	0.022***
Tas	−0.029***	−0.029***	−0.007	0.003
NT	0.028***	0.020***	−0.034***	−0.018***

(Continues)

TABLE 5 (Continued)

Variables	1. LFP (a) Regional dy/dx	1. LFP (b) Metropolitan dy/dx	2. Employed-unemployed (c) Regional dy/dx	2. Employed-unemployed (d) Metropolitan dy/dx
ACT	−0.048	0.009***	0.049	−0.006***
IE R (continuous)	0.002***	0.001***	0.000	−0.001***
IEO (continuous)	−0.003***	−0.001***	−0.002***	−0.001***
Age (continuous)	0.025***	0.029***	−0.004***	−0.006***
AgeSq (continuous)	−0.000***	−0.000***	0.000***	0.000***
Gender (female = ref.)				
Male	0.054***	0.062***	0.002	−0.003***
Marital (never married = ref.)	(base)	(base)	(base)	(base)
Widowed	−0.075***	−0.057***	−0.001	−0.011**
Divorced	−0.009	−0.010***	−0.007	−0.009***
Separated	−0.018**	−0.028***	−0.01	−0.008***
Married	−0.011***	−0.006***	−0.017***	−0.017***
Family_comp (couple family, no children = ref.)				
Couple family with children	−0.045***	−0.044***	0.005**	0.004***
One-parent family	−0.038***	−0.036***	0.010**	0.014***
Other family or single	−0.019***	−0.014***	0.004	0.011***
Disability (none = ref.)				
Family member disabled	−0.042***	−0.033***	−0.007	−0.005***
English (speak English only = ref.)				
Very well/well	−0.009***	−0.007***	0.006***	0.009***
Not well/not at all	−0.077***	−0.073***	−0.003	0.010***
Edu (postgraduate/GradDip/grad = ref.)				
Bachelor's degree	−0.002	−0.007***	−0.003	−0.007***
Advanced dip/diploma	−0.012***	−0.025***	0.002	−0.007***
Certificates I–IV	0.001	−0.007***	0.010***	0.004***
Secondary education and below	−0.052***	−0.072***	0.011***	0.001
Religion (Christian = ref.)				
Secular	0.000	0.000	0.005**	0.006***
Other religion	−0.023***	−0.014***	0.003	0.007***
Vo luntaryWk (not voluntary = ref.)				
Volunteer	−0.009***	−0.003***	0.025***	0.030***
ChildCareNopay (not provided = ref.)				
Care own child	−0.021***	−0.026***	0.010***	0.016***
Care other	0.009**	0.022***	0.021***	0.024***
Care own and other	−0.016	−0.027***	0.017	0.030***
Housing (owned outright = ref.)				
Owned with mortgage	0.022***	0.021***	−0.004	−0.008***
Rented	0.015***	0.011***	0.007**	0.003**
WkEngaged (fully engaged = ref.)				
Partially engaged	0.015***	0.012***		
At least partially engaged	0.064***	0.069***		
Not engaged	−0.510***	−0.480***		
N	88,078	617,626	88,078	617,626
Wald test of indep. Eqns (*p*-value)		0.0000		0.0000

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

personal income than humanitarian migrants, while among them refugees have more weekly income than other special humanitarian, but less than global special humanitarian migrants. Of note, the income of regional was somewhat less than of metropolitan migrants. There was lower income for secondary than for primary applicants (accentuated in regional areas) and for non-Australian citizen compared with Australian citizen migrants, for migrants from the Middle East, and for those who did not move across local government areas, particularly in regions. Later humanitarian arrivals (in 2015 and 2016) in regional areas were the most likely to have lower incomes than those who had arrived earlier or than those settled in metropolitan areas. Those migrants in skill-mismatched jobs (over-educated and under-educated) had much lower personal income than those in matched jobs, with the over-educated experiencing a loss some 50% greater than the under-educated. This trend was more evident in regional than in metropolitan areas.

Generally, as with labour market participation and employment, results tend to be consistent with the Australian population, for example:

1. irrespective of regional or metropolitan location, males typically have higher incomes;
2. English ability was associated with higher income, but not uniformly matched with skill alignment;
3. income increases with age, but at a diminishing rate;
4. income in New South Wales is higher than in other States, except for regional Western Australia and metropolitan parts of the Australian Capital Territory;
5. those who have never been married have lower income than married, separated, or divorced in metropolitan areas; and
6. other variables that have a statistically significant positive association with personal income are those who settled in communities with higher IER and IEO (see Table 2)—noting that these two measures are continuous scales from zero (indicating least access to economic resources and education and occupation opportunities) to 10 (most access). Those with varying positive and negative associations: housing tenure type, family composition, religion, involvement in voluntary work, and unpaid childcare duties.

In summary, Table 6 shows that personal income for employed migrants is strongly associated with visa type, other variables specific to migrants, and to skill alignment.

4.3 | Skill mismatch

We now focus on our third research question (**RQ3**). As noted above, to examine, influences on skill mismatch MNP regression models are used for the sample of employed. The dependent variable is a three-category measure (under-educated, approximately 20% of the sample; skill-matched, about 50%; over-educated, about 30%; see Table 1), and our main explanatory variables are related to migration status. As previously indicated, we have separate models for metropolitan and regional areas.

Following regression, average marginal effects were calculated (AMEs, averaged over the joint distribution of the independent variables) for the MNP model. They were interpreted as follows: a positive AME indicates that an increase in the explanatory variable of one (small) unit (or for a dummy variable, a switch from zero to one) is associated with an increase in the probability of the dependent variable taking the j^{th} value; similarly, a negative AME is associated with a decrease in probability. Across the three possible outcomes, the sum of the estimated changes in AME for each explanatory variable is zero (to ensure that the total probability across all outcomes is one). For example, for Applicant status equal to secondary compared with primary, for regional, the under-educated AME is 0.031 (secondary applicants are 3.1% more likely to be under-educated, compared with primary applicants); for skill-matched, the AME is −0.161 (16.1% less likely to be matched); for over-educated 0.129 (about 13% more likely to be over-educated); and net changes are zero.

Our observations about explanatory variables relating to migrant status:

1. There are no ambiguities: compared with skilled-visa holders, humanitarian migrants are more likely to be under-skilled, and less likely to be skill-matched or over-skilled.
2. The largest effect was observed for other special humanitarian migrants in metropolitan areas with about 20% of them more likely to be under-skilled compared with skilled migrants; in regional areas, this falls to about 8%.
3. Applicant status is important; secondary applicants are less likely to be matched and about 13% more likely to be under-skilled or over-skilled.
4. Migrants who are Australian citizens are less likely to be matched and more likely to be under-skilled or over-skilled.
5. *Year of post-resettlement* influenced skill mismatch (over-educated or under-educated) in metropolitan and regional areas. This finding is in line with previous studies (Connor, 2010; Hugo, 2011, 2014b); that the longer humanitarian immigrants have lived in Australia, the greater the probability that their skills matched with job requirements.
6. Internal migration in the 12 months before 2016 census night had a positive association with the skills-matched outcome for humanitarian migrants,

TABLE 6 OLS regression estimates of income for two sub-samples: metropolitan and regional.

Variables	Regional Coef.	Metropolitan Coef.	Variables	Regional Coef.	Metropolitan Coef.
Explanatory variables:			**Control variables:**		
VisaType (skilled = ref.)			*State (NSW = ref.)*		
Refugees	−303.343***	−140.382***	Vic	−54.670***	−89.965***
Global special humanitarian	−260.941***	−111.362***	Qld	−84.715***	−156.341***
Other special humanitarian	−465.962***	−288.859***	SA	−48.017***	−229.688***
Skill_mis (matched = ref.)			WA	83.652***	−88.278***
Under-educated	−309.080***	−285.436***	Tas	−80.660***	−244.024***
Over-educated	−472.599***	−434.268***	NT	24.612	−44.099***
RoBirth (Middle East = ref.)			ACT	21.98	12.457**
Southern and Central Asia	−115.875***	1.108	*IER (continuous)*	21.865***	4.656***
Sub-Saharan Africa	22.285	168.220***	*IEO (continuous)*	19.298***	47.603***
South-East Asia	−140.684***	19.068***	*Age (continuous)*	89.327***	119.044***
North Africa	−57.218*	15.712*	*AgeSquared (continuous)*	−0.944***	−1.337***
Europe	−72.462***	167.794***	*Gender (female = ref.)*		
Oceania and Antarctica	5.025	146.973***	Male	270.553***	267.605***
North-East Asia	−318.562***	−207.932***	*Marital (never married = ref.)*		
America	−25.055	128.754***	Widowed	−53.099	13.616
Ap pStatus (primary = ref.)			Divorced	31.332**	61.310***
Secondary	−372.019***	−316.992***	Separated	32.391*	23.906***
Year_arrival (2000 = ref.)			Married	49.752***	48.374***
2001	−34.17	−6.005	*Family_comp (couple family, no children = ref.)*		
2002	−29.24	−3.663	Couple family with children	−97.545***	−74.071***
2003	−18.794	−3.166	One-parent family	−48.473***	−56.052***
2004	−12.211	−24.774***	Other family or single	30.402***	−37.434***
2005	−20.08	−20.896***	*Disability (none = ref.)*		
2006	−42.442**	−34.007***	Family member disabled	−9.421	8.378
2007	−55.705***	−51.136***	*English (speak English only = ref.)*		
2008	−93.499***	−55.463***	Very well/well	−3.983	−88.076***
2009	−84.230***	−44.435***	Not well/not at all	−319.990***	−406.730***
2010	−10.378	43.784***	*Religion (Christian = ref.)*		
2011	30.183	69.307***	Secular	31.049***	48.833***
2012	50.940**	77.420***	Other religion	38.231***	−13.031***
2013	14.94	60.440***	*VoluntaryWk (not volunteer = ref.)*		
2014	−15.886	42.802***	Volunteer	−16.799**	11.711***
2015	−101.076***	35.383***	*ChildCareNopay (not provided = ref.)*		
2016	−157.378***	34.371***	Care own child	15.053**	−5.549**
Aust_citizen (Australian = ref.)			Care other	−23.579	−34.564***
Non-Australian	−68.035***	−46.626***	Care own and other	−33.252	−99.956***
Move_lga (did not move = ref.)			*Housing (owned outright = ref.)*		
Moved across LGAs	38.237***	8.913***	Owned with mortgage	21.145*	35.118***
			Rented	−37.354***	−103.731***
_cons				−438.995***	−1111.271***
N				66,702	454,653
R^2 adjusted				0.384	0.415

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

suggesting that skills are better matched by migrating elsewhere in Australia.

There are several general findings:

1. Males are more likely to be over-skilled in metropolitan but not in regional areas, whereas in regions, males are about twice as likely to be in matched jobs.
2. The influence of variables usually included in examining migrant labour market outcomes appears to be consistent with prior work. For example, English language ability is strongly associated with job mismatch.
3. Humanitarian migrants more likely to have a heightened risk of being in a skill mismatched job (or over-educated) were females, those at older ages, those in a couple family with no children, those with disabled family members to care for and those in rental accommodation. They were also most likely to be secondary applicants, or females undertaking caring roles in the family.

More generally, we found numerous differences between coefficients for metropolitan and regional models; sufficient to warrant separate models, but as shown in Table 7 the differences tend to be cumulative as opposed to strikingly different. It is clear that humanitarian migrants face a skill mismatch, and the degree of mismatch is strongly associated with migrant status, specifically visa category, applicant status, Australian citizenship, region of birth, year of arrival, and internal migration post settlement; all have a statistically significant relationship with the matching variables.

5 | DISCUSSION AND CONCLUSION

Here, we address who wins and who loses among our humanitarian migrants and consider whether differences need to be addressed according to how persons enter under the components of the humanitarian programme and where they settle and find employment. We discuss some limitations of this study using the cross-sectional data, and further research will be needed to understand the causality of observed patterns of skill alignment for humanitarian migrants and those on skilled migration visas. The insights into differences in the labour market experience and outcomes of humanitarian settlers compared with skilled visa holders provided here expand our knowledge and can be a valuable basis for policy refinements to improve migrants' settlement outcomes in Australia's regional and urban areas.

5.1 | Who wins and who loses among employed humanitarian migrants?

Several insights have been yielded about the importance of recognising metropolitan and regional differences in the labour market by focusing on the resettlement location of humanitarian migrants in Australia who have attained permanent residence, and by considering whether they were successfully engaged in the labour market, or indeed their employment and income matched the skills and qualifications brought with them. Noting relatively low LFP among humanitarian migrants, our analysis found that only a third of them were in jobs that matched their skills, more than a third were under-educated indicating that they were in jobs that required higher skills, and under a third over-educated for skills required in the Australian jobs in which they engaged. Compared with skilled-visa migrants, the humanitarian visa holders fared much worse in the labour market and their economic integration and income rewards were much slower to materialise, but this also varied between refugee and other special humanitarian recipients. There were significant differences in employment and skill-mismatch between settlement locations that corresponded with their visa scheme, birthplace, time since arrival, whether they had relocated internally in the 12 months before the census, and a range of demographic and socio-economic characteristics.

Our modelling showed that overall LFP was low for humanitarian migrants, with unemployment higher among recent arrivals, secondary applicants, and those of Middle East origins, and outcomes were influenced by proficiency in English and educational achievement. These factors are in line with earlier studies that sought to capture the circumstances and economic contribution of humanitarian migrants in Australia (Cheng, Wang, & Taksa, 2021; Cheng, Wang, Jiang, et al., 2021; Hugo, 2011, 2014b). When compared with skilled visa holders, the skills match of humanitarian migrants employed at the time of the 2016 census was most likely to be under-skilled and less likely to be matched or over-skilled, reflecting their lower skill levels, employment experience, English proficiency and education levels. Those with skill mismatch (under-educated and over-educated) had poorer personal income and were most likely secondary applicants, from the Middle East, in the other special humanitarian visa category or settled in regional areas. Skill alignment outcomes obviously varied by education, English proficiency, time since arrival and gender, with metropolitan males more likely to be over-skilled, but regional males more likely to be matched and effectively using their skills, or instead under-skilled for jobs and with higher risk of being unemployed.

TABLE 7 Multinomial probit regression results: subsample models (by metro) for humanitarian migrants: skill mismatch and predicted marginal effects of factors influencing skills matched or skills mismatched.

Variables	1. Regional (a) under-educated dy/dx	1. Regional (b) skill-matched dy/dx	1. Regional (c) over-educated dy/dx	2. Metropolitan (d) under-educated dy/dx	2. Metropolitan (e) skill-matched dy/dx	2. Metropolitan (f) over-educated dy/dx
Explanatory variables:						
VisaType (skilled = ref.)						
Refugees	0.066***	−0.033***	−0.033***	0.067***	−0.006	−0.061***
Global special humanitarian	0.072***	−0.093***	0.020	0.086***	−0.036***	−0.050***
Other special humanitarian	0.079***	−0.042**	−0.037***	0.197***	−0.149***	−0.048***
AppStatus (primary = ref.)						
Secondary	0.031***	−0.161***	0.129***	0.055***	−0.172***	0.117***
Aust_citizen (Australian = ref.)						
Non-Australian	0.026***	−0.030***	0.004	0.023***	−0.026***	0.003*
RoBirth (Middle East = ref.)						
Southern and Central Asia	0.007	−0.088***	0.081***	−0.015***	−0.033***	0.048***
Sub-Saharan Africa	0.153***	−0.135***	−0.018	0.066***	−0.012**	−0.054***
South-East Asia	0.041***	−0.127***	0.086***	−0.018***	0.005	0.013***
North Africa	−0.049***	−0.009	0.058***	−0.049***	0.006	0.043***
Europe	0.157***	−0.157***	0.001	0.106***	−0.042***	−0.064***
Oceania and Antarctica	0.108***	−0.085***	−0.023	0.075***	0.017**	−0.091***
North-East Asia	0.060***	−0.213***	0.153***	0.004	−0.104***	0.100***
America	0.006	−0.039**	0.033**	−0.020***	0.027***	−0.007
Year_arrival (2000 = ref.)						
2001	−0.014	0.026	−0.012	0.000	0.018***	−0.018***
2002	−0.026*	0.032**	−0.006	−0.003	0.025***	−0.022***
2003	−0.015	0.038**	−0.023*	−0.005	0.021***	−0.016***
2004	−0.014	0.030**	−0.016	−0.007**	0.017***	−0.009**
2005	0.006	0.005	−0.011	0.004	0.007	−0.011**
2006	0.037***	−0.003	−0.034***	0.019***	−0.008*	−0.012***
2007	0.016	−0.016	0.001	0.024***	−0.026***	0.002
2008	0.026**	−0.041***	0.015	0.028***	−0.024***	−0.004
2009	−0.007	−0.006	0.013	0.012***	−0.004	−0.008*
2010	−0.028**	0.042***	−0.015	−0.005	0.051***	−0.046***
2011	−0.022*	0.047***	−0.024*	−0.002	0.055***	−0.053***
2012	0.002	0.023	−0.025*	−0.010**	0.065***	−0.056***
2013	−0.051***	0.058***	−0.007	−0.033***	0.080***	−0.047***
2014	−0.070***	0.055***	0.015	−0.051***	0.094***	−0.043***
2015	−0.074***	−0.003	0.077***	−0.059***	0.111***	−0.052***
2016	−0.092***	0.008	0.083***	−0.071***	0.149***	−0.078***
Move_lga (did not move = ref.)						
Moved across LGAs	−0.024***	0.019***	0.005	−0.009***	0.003	0.007***
Control variables:						
State (NSW = ref.)						
Vic	−0.008	0.013**	−0.005	−0.005***	−0.001	0.005***
Qld	0.041***	−0.057***	0.016***	0.023***	−0.027***	0.004*

TABLE 7 (Continued)

Variables	1. Regional (a) under-educated dy/dx	(b) skill-matched dy/dx	(c) over-educated dy/dx	2. Metropolitan (d) under-educated dy/dx	(e) skill-matched dy/dx	(f) over-educated dy/dx
SA	−0.006	0.013	−0.007	0.005**	−0.029***	0.024***
WA	0.056***	−0.083***	0.027***	0.042***	−0.059***	0.017***
Tas	0.006	0.051***	−0.057***	−0.005	0.024**	−0.019*
NT	0.058***	−0.090***	0.031**	0.070***	−0.108***	0.038***
ACT	−0.085	−0.064	0.149	−0.019***	0.055***	−0.036***
IER (continuous)	0.003***	0.004***	−0.007***	0.005***	−0.004***	−0.002***
IEO (continuous)	−0.012***	0.013***	−0.002**	−0.014***	0.028***	−0.014***
Age (continuous)	−0.006***	−0.026***	0.032***	−0.011***	−0.015***	0.027***
Gender (female = ref.)						
Male	0.116***	−0.111***	−0.006	0.078***	−0.061***	−0.017***
Marital (never married = ref.)						
Widowed	−0.039	−0.027	0.066**	0.000	−0.017	0.017
Divorced	0.008	−0.029**	0.021**	0.024***	−0.021***	−0.003
Separated	0.018	−0.022	0.005	0.019***	−0.009	−0.010*
Married	0.003	−0.008	0.005	−0.003*	−0.005*	0.008***
Family_comp (couple family, no children = ref.)						
Couple family with children	0.053***	0.006	−0.059***	0.044***	0.015***	−0.059***
One-parent family	0.031***	0.043***	−0.074***	0.023***	0.010**	−0.033***
Other family or single	−0.014**	0.050***	−0.036***	0.012***	−0.013***	0.001
Disability (none = ref.)						
Family member disabled	−0.007	0.024**	−0.017	−0.010***	0.012***	−0.002
English (speak English only = ref.)						
Very well/well	−0.073***	0.030***	0.042***	−0.076***	0.006***	0.070***
Not well/not at all	0.066***	0.038***	−0.104***	0.098***	−0.036***	−0.061***
Religion (Christian = ref.)						
Secular	−0.020***	0.020***	0.000	−0.012***	0.019***	−0.007***
Other religion	−0.042***	−0.001	0.043***	−0.019***	−0.024***	0.043***
VoluntaryWk (not volunteer = ref.)						
Volunteer	−0.055***	0.042***	0.014***	−0.044***	0.046***	−0.002
ChildCareNopay (not provided = ref.)						
Care own child	−0.040***	0.023***	0.016***	−0.035***	0.013***	0.023***
Care other	0.008	−0.026**	0.018	0.001	−0.019***	0.018***
Care own and other	−0.041**	0.021	0.02	−0.029***	−0.002	0.031***
Housing (owned outright = ref.)						
Owned with mortgage	0.019***	−0.017**	−0.001	0.006**	−0.005	−0.001
Rented	0.040***	−0.071***	0.031***	0.030***	−0.085***	0.055***
N	67,702			460,575		
R^2 count (adjusted)			0.069			0.085

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

In line with other studies (Colic-Peisker & Tilbury, 2006; Hugo, 2014a), our findings reveal that the successful resettlement of humanitarian migrants in Australia depends on how well they can convert skills, experience and educational qualifications acquired overseas, to secure appropriate employment. Our analysis shows a relatively large proportion of humanitarian migrants not in the labour force, a high representation of unemployed in the labour force and a low proportion of those employed in jobs that matched their skill levels, indeed considerably lower than for skilled migrants. Many of them were actually under-qualified for the jobs in which they engaged, whereas more than a quarter were over-qualified at the time of the 2016 census. This finding reinforces the point Hugo (2014b) made about 'brain waste' and its negative impact on the economy and the migrants themselves.

It is uncertain whether success in migration is truly to be assessed by whether one has a job or not, or a job skill-aligned with experience, education, and ability to speak English, or personal income attainments or area of settlement. However, all these measures serve as a starting point for more penetratingly qualitative studies, capable of yielding fuller answers to questions about who—among humanitarian migrants—wins, loses, or is compromised in the Australian labour market, and about the relative effects of metropolitan and regional settlement. There is a need for further in-depth studies on differences between refugee and special humanitarian visa holders, and where they settle, noted here, to establish how their diverse cultural backgrounds, circumstances before settlement, and other characteristics play a part in their successful economic and social integration. Our analysis and dataset are offered as valuable preliminaries, steering towards insights for a more qualitative or sociological understanding of the questions we have raised (Boese, 2015).

5.2 | Limitations and suggestions for future research

5.2.1 | Data and causality

A major limitation has been that we observed sample participants on only one occasion, so we could not track individuals to control for individual heterogeneity (fixed effects) nor address temporal effects. Ours is, therefore, an analysis of association but not of causation, although in several cases one can reasonably infer causality; for example, English language ability is (strongly) associated with the probability of being employed and we suggest this is causal. After exploratory data analysis, our next move was to include a suite of explanatory variables, including proxies for unobserved heterogeneity such as Religion.

5.2.2 | Focus on humanitarian migrants

Although the data used in this study are comprehensive, longitudinal census and linked administrative data covering migrants' differential access to social security, health care, and education/training systems could usefully identify multi-scalar and multi-dimensional causal factors, processes, and consequences for and of humanitarian migrants' employment prospects, the extent of matching in their skills, and impact on earnings. The Multi-Agency Data Integration Project (MADIP) microdata resource that the ABS aims to produce is an example of a large-scale longitudinal dataset that will integrate well with administrative data from health care, education, centrelink and personal taxation. In addition, specialised surveys of humanitarian migrants could deepen quantitative studies to improve our understanding of how migrant history and adversity (exacerbated by COVID-19), and their employment experiences over the life course, influence their labour market performance and skill use in Australia. Targeted qualitative data collection in future research will enable an analysis of mechanisms through which Australia's refugee and humanitarian migrants overcome adversity, using multi-scalar (personal, community and institutional) and multi-dimensional (social, cultural, economic and political) linkages of great value for the design of migrant services to enhance employability and use of skills.

5.2.3 | The dynamic and causes of adversity for humanitarian migrants choosing to find employment that uses their skills

Future efforts need to examine the mechanisms underlying adversity, such as the frequency and severity of adverse life events and employment disadvantages connected with particular settlement location; and intergenerational effects of parents or intra-family effects of parental adversity on children's labour market outcomes. These prospective variables were not captured by ACMID data but are significant for development of sound public policy in Australia and elsewhere.

5.2.4 | Skill transfer

Finally, we note that the difficulties in transferring skills acquired in their place of origin to Australia are not just a problem for humanitarian immigrants but are relevant for all immigrants. Policymakers (and employers) have the power to assist immigrants to quickly and successfully transfer their skills to suit Australian labour market practices. It is not up to the humanitarian migrants themselves to solve this problem but needs a new approach with employers taking the lead in resolving some differences in skills recognition and attitudes to diverse skills among immigrant groups from a range of countries.

6 | CONCLUSION

Evidence presented here suggests that Australia's humanitarian settlers who are in the labour market are more likely to have heightened risk of being in skill-mismatched jobs; yet they are a valuable asset, with untapped potential to fill gaps in metropolitan and regional workforces. It seems that there is some risk for migrants being under-qualified or over-qualified for work in specific locations, others find a match with their previous employment, education, and experience and engage in suitable jobs—although considerably less than do their skilled migrant counterparts. It is important to note the differences between the component visa categories in the humanitarian programme, and their distinctive strong associations with labour market outcomes and success—specifically those granted refugee and others special humanitarian visas. Several studies (Cheng, Wang, & Taksa, 2021; Cheng, Wang, Jiang, et al., 2021; Hugo, 2011, 2014b) show the extent to which diverse humanitarian settlers must be able to negotiate the many structural, linguistic, and cultural barriers that limit access to employment commensurate with skills and education. Although integration into the labour force tends to improve over time, it must be borne in mind, as Hugo (2014a, p. 880) states, that:

Humanitarian settlers' labour market experience converges toward that of the Australian-born over time but they experience greater difficulty than other migrant groups in adjusting economically, socially and culturally.

Our analysis provides insights into differences in the labour market experience of humanitarian settlers, their employment, income, and skills-match, exacerbated or enhanced by where they settle, compared with migrants in the skilled programme. It is not surprising that humanitarian visa holders initially experience less labour market success given their diverse origins and the wide range of skills, qualifications, cultures and employability attributes they bring with them. On the other hand, skilled visa holders, having conformed to Australia's relatively rigid employment and job requirements, are more likely to have much better labour market and settlement outcomes to match their expectations, given that they are able to make considered decisions and choices. Nevertheless, it is useful to compare and contrast labour market outcomes for humanitarian and skilled migrants, ultimately towards more informed policy choices founded on a better appreciation of migrants' capacity to contribute within the skilled and semi-skilled labour markets. Generally, the underuse of migrant skills, in both the humanitarian and the skilled programmes, tends to be greater for those who arrive with higher educational qualifications—preventing them from reaching their full potential. However, there were a significant number of humanitarian migrants who had lower skills and education than needed in the Australian labour force, but nevertheless met a demand for unskilled and semi-skilled workers, in both metropolitan and regional contexts. Australia needs policies that open a variety of pathways to integrate our diverse humanitarian migrants productively into their new communities—to ensure that they achieve all that they are capable of and to give Australia the best use of a considerable but underestimated human resource.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

This study subjected the 2016 Australian Census and Migrants Integrated Dataset's (ACMID) microdata - Confidentialised Unit Record File (CURF, from the Australian Bureau of Statistics: ABS Cat No. 3417.0.55.001, 2016) - to sophisticated statistical analysis in the Australian Bureau of Statistics (ABS) environment 'DataLab'. The ABS requires applications to access detailed microdata, such as the 2016 ACMID used in this study.

ETHICS STATEMENT

There is no research ethics issue.

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ENDNOTE

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REFERENCES

Alesina, A., Harnoss, J., & Rapoport, H. (2016). Birthplace diversity and economic prosperity. *Journal of Economic Growth*, *21*(2), 101–138. https://doi.org/10.1007/s10887-016-9127-6

Australian Bureau of Statistics (ABS). (2018). *3417.0.55.001 - microdata: Australian census and migrants integrated dataset* (Vol. 2016). https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/3417.0.55.001Main+Features12016?OpenDocument

Australian Bureau of Statistics (ABS). 2019. *Australian and New Zealand standard classification of occupations, 2013*, Version 1.3. Cat. No. 1220.0. Released 5 November, Canberra.

Australian Bureau of Statistics (ABS). 2022. *2021 census: All persons QuickStats*. 2021 Census data released on 29 June. https://www.abs.gov.au/census/find-census-data/quickstats/2021/AUS

Boese, M. (2015). The roles of employers in the regional settlement of recently arrived migrants and refugees. *Journal of Sociology*, *51*(2), 401–416. https://doi.org/10.1177/1440783314544994

Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics Using Stata* (Revised ed.). Stata Press.

Cheng, Z., Wang, B. Z., Jiang, Z., Taksa, L., & Tani, M. (2021). English skills and early labour market integration: Evidence from humanitarian migrants in Australia. *International Migration*, *1–21*. https://doi.org/10.1111/imig.12889

Cheng, Z., Wang, B. Z., & Taksa, L. (2021). Labour force participation and employment of humanitarian migrants: Evidence from the building a new life in Australia longitudinal data. *Journal of Business Ethics*, *168*, 697–720. https://doi.org/10.1007/s10551-019-04179-8

Cobb-Clark, D. A. (2006). Selection policy and the labour market outcomes of new immigrants. In D. A. Cobb-Clark & S. E. Khoo (Eds.), *Public Policy and Immigrant Settlement* (pp. 27–52). Edward Elgar. https://doi.org/10.4337/9781781007518.00012

Colic-Peisker, V. (2008). The 'visibly different' refugees in the Australian labour market: settlement policies and employment realities. In S. McKay (Ed.), *Refugees, recent migrants and employment: challenging barriers and exploring pathways*. Routledge.

Colic-Peisker, V., & Tilbury, F. (2006). Employment niches for recent refugees: Segmented labour market in twenty-first century Australia. *Journal of Refugee Studies*, *19*(2), 203–229. https://doi.org/10.1093/jrs/fej016

Connor, P. (2010). Explaining the refugee gap: Economic outcomes of refugees versus other immigrants. *Journal of Refugee Studies*, *23*(3), 377–397. https://doi.org/10.1093/jrs/feq025

Department of Immigration and Citizenship (DIAC). (2011). *A significant contribution: The economic, social and civic contributions of first and second generation humanitarian entrants, summary of findings*. Department of Immigration and Citizenship.

Department of Social Services (DSS). (2019). *30 June 2018 valuation report*. https://www.dss.gov.au/sites/default/files/documents/12_2019/j18_valuation_report_-_final.pdf

Fleay, C., Hartley, L., & Kenny, M. A. (2013). Refugees and asylum seekers living in the Australian community: The importance of work rights and employment support. *Australian Journal of Social Issues*, *48*, 473–496. https://doi.org/10.1002/j.1839-4655.2013.tb00294.x

Greene, W. (2008). *Econometric analysis*. Pearson Education Inc.

Heckman, J. J. (1978). Dummy endogenous variables in a simultaneous equation system. *Econometrica*, *49*(1), 931–959. https://doi.org/10.2307/1909757

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153–161. https://doi.org/10.2307/1912352

Hugo, G. (2008). Australia's state-specific and regional migration scheme: An assessment of its impacts in South Australia. *Journal of International Migration and Integration*, *9*(2), 125–145. https://doi.org/10.1007/s12134-008-0055-y

Hugo, G. (2011). *Economic, social and civic contributions of first and second generation humanitarian entrants*. Final report to Department of Immigration and Citizenship.

Hugo, G. (2014a). Change and continuity in Australian international migration policy. *International Migration Review*, *48*(3), 868–890. https://doi.org/10.1111/imre.12120

Hugo, G. (2014b). The economic contribution of humanitarian settlers in Australia. *International Migration*, *52*(2), 31–52. https://doi.org/10.1111/imig.12092

Hugo, G., Khoo, S. E., & McDonald, P. (2006). Attracting skilled migrants to regional areas: What does it take? *People and Place*, *14*(3), 25–36.

Iredale, R., & D'Arcy, B. (1992). *The continuing struggle; refugees in the Australian labour market*. Australian Government Publishing Service.

Mavromaras, K., McGuinness, S., & Fok, Y. (2009). Assessing the incidence and wage effects of overskilling in the Australian labour market. *The Economic Record*, *85*(268), 60–72. https://doi.org/10.1111/j.1475-4932.2008.00529.x

Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P., & Wei, Z. (2013). Job mismatches and labour market outcomes: Panel evidence on university graduates. *The Economic Record*, *89*(286), 382–395. https://doi.org/10.1111/1475-4932.12054

Mavromaras, K., Sloane, P., & Wei, Z. (2015). The scarring effects of unemployment, low pay and skills under-utilization in Australia compared. *Applied Economics*, *47*(23), 2413–2429. https://doi.org/10.1080/00036846.2015.1008762

Nieto, S., Alessia, M., & Ramos, R. (2015). Educational mismatches in the EU: Immigrants vs natives. *International Journal of Manpower*, *36*(4), 540–561. https://doi.org/10.1108/IJM-11-2013-0260

O'Donovan, T., & Sheikh, M. (2014). Welfare reforms and the refugee resettlement strategy: An opportunity to achieve meaningful employment outcomes for New Zealanders from refugee backgrounds? *Kotuitui*, *9*, 82–88. https://doi.org/10.1080/1177083X.2014.944193

Pellizzari, M., & Fichen, A. (2017). A new measure of skill mismatch: Theory and evidence from PIAAC. *IZA Journal of Labor Economics*, *6*(1), 1–30. https://doi.org/10.1186/s40172-016-0051-y

Quintini, G. (2011). *Over-qualified or under-skilled: A review of existing literature. Social, OECD, employment and migration working papers 121*. OECD Publishing.

StataCorp. (2019). *Stata statistical software: Release 16*. StataCorp LLC.

Støren, L., & Wiers-Jenssen, J. (2010). Foreign diploma versus immigrant background: Determinants of labour market success or failure? *Journal of Studies in International Education*, *14*(1), 29–49. https://doi.org/10.1177/1028315308327951

Tani, M. (2021). Occupational licensing and the skills mismatch of highly educated migrants. *British Journal of Industrial Relations*, *59*(3), 730–756. https://doi.org/10.1111/bjir.12574

Zeileis, A. (2004). Econometric computing with HC and HAC covariance matrix estimators. *Journal of Statistical Software*, *11*(10). https://doi.org/10.18637/jss.v011.i10

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