Australian Government
Australian Institute of Family Studies

Building a New Life in Australia

The Longitudinal Study of Humanitarian Migrants

Income support payments and employment dynamics: The experience of humanitarian migrants in Australia

Appendices

March 2026

Appendix A: Technical notes

Box 1: Research questions

1. What are the patterns of transition from income support payments to employment among humanitarian migrants over a 10 year period?
2. What factors influence the transition from income support payments to employment among humanitarian migrants over time?

Conceptual framework

The conceptual framework draws on 2 viewpoints to better understand the transition from government income support to employment, both of which are particularly relevant to humanitarian migrants. While migration pathways vary, the employment barriers they face – such as limited job readiness and insufficient access to labour market resources – often reflect those faced by other groups in the broader population experiencing disadvantage.

Viewpoint 1: Barriers to exiting from government income support to employment

Individuals without alternative means of subsistence, with lower levels of human capital and poor health conditions or having large families and young children, tend to remain on government income support (Mood, 2013). Another perspective, especially for humanitarian migrants, argued that generous government income support, when compared to the living standards in their home countries, undermines the virtue of self-sufficiency and the preference for work (Koopmans, 2010). Any stigma associated with applying for government income support weakens as one becomes accustomed to it (Mood, 2013). Moreover, it has been shown that time out of the labour market may lead to:

- human capital depreciation (one loses skills when not using them)
- the loss of important networks that may limit chances of finding a job
- low productivity (Mood, 2013).

Viewpoint 2: Government income support as a facilitator of employment transition

International research shows that government income support can increase employment probability through improving the health capital, enhancing labour skill training (e.g. vocational training or upskilling opportunities) and relaxing constraints on infant and child care for individuals (Zhou et al., 2024). To emphasise this point from a humanitarian migrant perspective in a multi-country study, Brell and colleagues (2020) argued that government income support can play a facilitative role in labour market integration by helping migrants meet their basic needs.

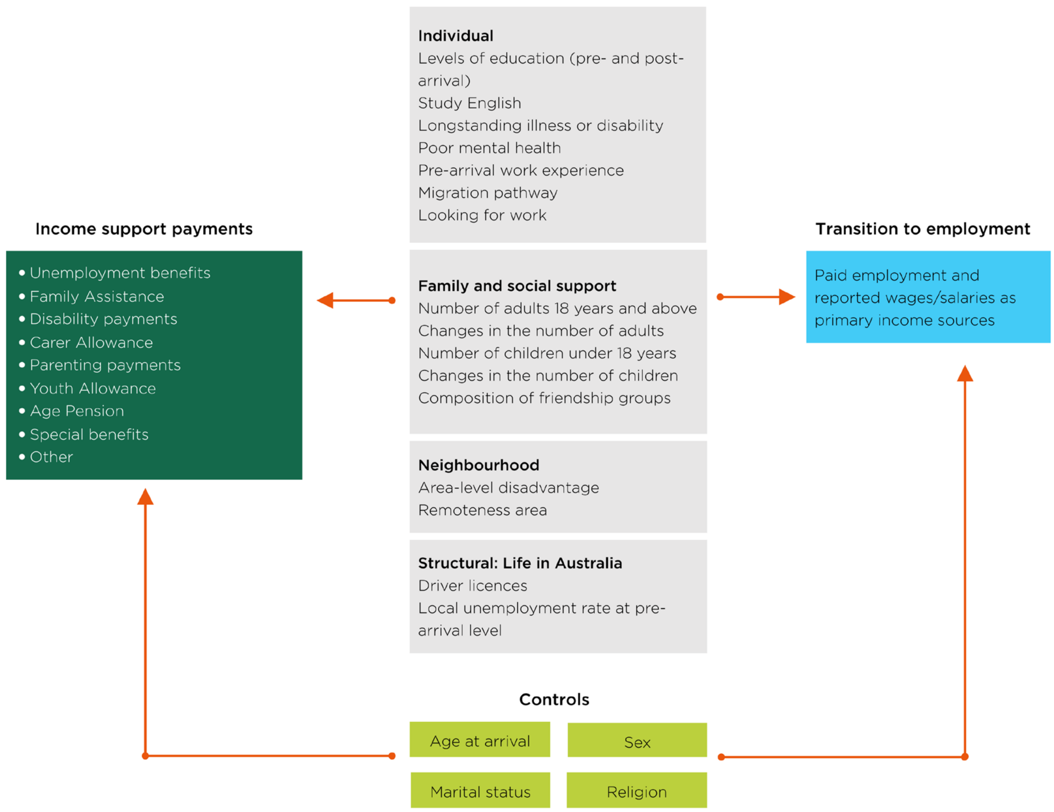
In the Australian context, humanitarian migrants can focus on acquiring language skills and vocational training through settlement services (Renzaho et al., 2025). These foundational supports can enhance their employability and productivity, leading them to exit income support payments relatively quickly in comparison to other efforts, including self-directed efforts. More broadly, it can be expected that helping humanitarian migrants access the formal labour market by building their skills and capabilities, along with income support payments, can reduce their vulnerability, increase their incomes and improve labour market outcomes.

Application of the conceptual framework in this policy brief

This brief does not seek to evaluate the relative merits of the 2 viewpoints or determine which aligns best with the data. Rather, it adopts the first viewpoint as a practical framework for exploring the transition from income support payments to employment.

More specifically, the conceptual framework described above was tested through a statistical model in which the decision to transit to work overtime was modelled as a set of multidimensional factors (i.e. the second research question). It is important to note that this study does not have access to all the necessary variables required for a comprehensive assessment of the first viewpoint.

Figure A1: Conceptual framework



Factors associated with income support payments and employment transition

Building on the first viewpoint – which explores how individual and contextual factors shape reliance on government income support – this study takes a multidimensional approach to better understand employment outcomes among humanitarian migrants.

Research highlights that individual characteristics, such as health status, education level and caregiving responsibilities, interact with broader social, neighbourhood and structural conditions to shape employment trajectories (Mood, 2013; Shergold, 2019). In light of these complexities, this study takes into account the factors shown in Figure A1, across the 4 dimensions outlined below.

Individual

Research consistently shows that humanitarian migrants often arrive with serious health challenges, including disabilities, depression and PTSD. In addition, limited education prior to arrival and poor English proficiency can make it very difficult for them to obtain work (Correa-Velez et al., 2015; Kristiansen et al., 2022; van Kooy et al., 2024, 2025). These challenges, among other settlement challenges, such as securing housing (Bevelander et al., 2019), can contribute to prolonged reliance on income support payments (Mood, 2013).

Moreover, humanitarian migrants often possess valuable skills but face barriers that prevent their previous qualifications from being recognised (Settlement Council of Australia, 2019). These challenges often stem from complex and opaque processes within regulatory bodies, which can delay or prevent access to employment opportunities that align with their skills. A recent study conducted by the Australian Institute of Family Studies (AIFS) confirmed these findings, which revealed that skilled humanitarian migrants experienced a loss of occupational status and considerable downward occupational mobility when entering the workforce (van Kooy et al., 2025). However, pre-arrival education and work experience in host countries were often seen as important predictors of transition to work (van Kooy et al., 2025).

When humanitarian migrants use numerous channels to search for jobs (e.g. service providers or informal networks), they are more likely to transition to employment (Correa-Velez et al., 2015).

The mode of arrival for humanitarian migrants can impact their transition to employment. Research indicates that those who arrived via the onshore pathway were more likely to transition to work than those who arrived via the offshore pathway (van Kooy et al., 2025). The difference between these groups may, in part, be attributed to variations in both length of residence and demographic characteristics.[1]

Family and social support

Humanitarian migrant families tend to be larger on average than Australian families.[2] Theoretically, there is a positive relationship between family size and economic participation for both poor and non-poor (Hill, 1971). Larger families tend to have greater financial needs, which can increase the likelihood that individuals will engage in paid work. However, caring responsibilities associated with elderly, disabled and dependent children limit the time available to pursue employment opportunities (Mood, 2013; Sánchez-Domínguez & Abenza, 2021). In this context, income support payments play a crucial role, as the level of financial support varies with family size; that is, larger families receive more support (Services Australia, 2025).

The effects of family size on employment transition may vary by sex. Research from AIFS confirms that mothers' employment rates are closely tied to the age of their youngest child, with participation increasing gradually as children grow older (Baxter, 2023). Additional findings from the OECD indicate that both the age and number of children significantly affect migrant women's ability to engage in paid work (OECD, 2023).

The evidence regarding fathers is mixed. Most studies suggest that family size has little impact on fathers' employment outcomes (Baxter, 2019; Cools et al., 2017). However, international research indicates that humanitarian migrant fathers with larger families may face increased financial pressure, leading them to accept casual or part-time work (Humpage et al., 2020). This shift can result in the loss of certain government benefits tied to unemployment or low-income thresholds while still leaving them financially insecure despite working. Conversely, a study spanning multiple European countries suggests a positive association between larger family size and improved employment outcomes, such as access to more or better job opportunities (Baranowska-Rataj & Matysiak, 2022).

Social contact with the broader Australian community has been positively associated with the transition to employment of humanitarian migrants (Heggebø et al., 2020; van Kooy et al., 2025). However, connections within one's own cultural or ethnic community can also offer important advantages, such as emotional support, shared language and access to informal job networks (Song et al., 2024). While integration into the wider society may enhance access to diverse opportunities and foster a sense of belonging, strong ties within ethnic communities can provide stability and resilience during the early stages of settlement (UNHCR, 2024). Therefore, it is expected that humanitarian migrants with limited resources and limited contact with either their own ethnic community or the broader Australian population, especially during the initial years of settlement, may face greater challenges in securing employment and be more likely to depend on income support payments.

1 Typically, onshore participants tend to be younger, are more likely to live alone and have greater work experience prior to arrival than their offshore counterparts, all of which may enhance their prospects for employment in Australia (van Kooy et al., 2025).

2 According to the *Refuge and Family Futures in Australia* report, which studied recently arrived refugee families from Syria, Iraq and Afghanistan, the average family size of refugee households was 4.55 people (Collins et al., 2023), whereas the average family size in Australia is 2.5 people (Australian Bureau of Statistics [ABS], 2024).

Neighbourhood characteristics

Humanitarian migrants' employment outcomes may be influenced by the level of socio-economic disadvantage in the areas where they settle. Those living in low- to medium-disadvantage areas are generally expected to be less reliant on income support payments and more likely to transition to employment (van Kooy et al., 2024).

This assumption may also extend to those residing in urban areas, where access to services, infrastructure and job opportunities is generally more abundant compared to those in rural areas (Zhou et al., 2024). However, evidence specific to humanitarian migrants remains limited and mixed. Notably, van Kooy et al. (2025) found that residing in major cities reduced the likelihood of an initial transition into employment for humanitarian migrants, suggesting that urban residence did not uniformly translate to improved labour market outcomes for this group.

This contradiction highlights the importance of considering additional contextual factors. Urban environments may present barriers such as overcrowding, high living costs, competition for low-skilled jobs and limited social cohesion, which can offset the advantages of proximity to services (Renzaho et al., 2025). Conversely, rural or regional areas, despite offering fewer job opportunities, may foster stronger community ties or provide targeted support programs that facilitate employment (Beauchamp & McMahon, 2023).

Life in Australia

Evidence suggests that migrants and refugees face challenges in securing employment due to local economic conditions (e.g. high unemployment rates), and this challenge persists over time (Fasani et al., 2022). Local systems also play a role in determining employment outcomes. For example, access to essential services, infrastructure and obligatory employment requirements, such as holding a driver licence, can significantly influence job prospects (Colic-Peisker & Tilbury, 2007; Refugee Council of Australia, 2019; van Kooy et al., 2025).[3]

Taken together, employment transitions in Australia are shaped by a complex mix of personal, family, social, neighbourhood and structural factors. These elements influence both access to job opportunities and the speed at which economic self-sufficiency is achieved. Accordingly, the analysis incorporates these factors to estimate the likelihood of employment among humanitarian migrants.[4]

As part of the analysis, a set of demographic characteristics, such as age (van Kooy et al., 2024), sex (Al-Hamad et al., 2024), marital status (Hansen & Lofstrom, 2011; van Kooy et al., 2024) and religion (Hebbani, 2014; Sarkar et al., 2019), is included in all models to account for differences in individual circumstances that may influence employment outcomes and reliance on government income support. These variables are not the primary focus of the analysis but are essential to ensuring robust comparisons across groups.

Generally, the likelihood of transitioning to work decreases with age, as older migrants are more likely to rely on income support payments (van Kooy et al., 2024). Male migrants and those who were married were more likely to transition to employment compared to their female counterparts, while individuals who were single or without partners were less likely to do so (Hansen & Lofstrom, 2011; van Kooy et al., 2024). This may reflect perceptions of responsibility but its effect may vary depending on household composition and caregiving responsibilities (Al-Hamad et al., 2024). Religion also plays a role in shaping employment transitions, with some evidence suggesting its effect may vary by sex (Sarkar et al., 2019). However, research specifically examining the role of religion among humanitarian migrants remains limited.

Analyses

The analyses focused on participants in the Building a New Life in Australia (BNLA) study who reported income support payments as their main source of income (as opposed to wages, salaries or other sources).[5] The status of income receipt can change over time; that is, from reliance on income support payments to employment and vice versa. However, from the viewpoint of Research Question 2, the income recipient's employment state over

3 In addition, limited access to transport can restrict job search efforts and attendance at interviews or workplaces, especially for those living in outer suburbs or regional areas with poor public infrastructure (SETSCoP, 2024). Similarly, a lack of affordable and culturally appropriate child care can prevent parents, particularly women, from entering the workforce (Baxter, 2023). Discrimination in hiring practices and workplace environments further compounds these challenges, with studies showing that refugee and migrant women often experience racial bias and exclusion (Hebbani, 2024; Rezaei et al., 2023).

4 While a range of structural and social factors are known to influence employment outcomes for humanitarian migrants, not all could be included in the statistical model. Some variables were excluded because they were either statistically insignificant in preliminary analyses, highly correlated with other variables or constrained by data availability.

5 Other forms of income include financial support from others and personal savings.

time is mainly considered here due to a very low employment rate in Wave 1 of the BNLA study (see Figure D4, Appendix D). This study focused on 3 equal time points in the BNLA study: Wave 1 (baseline data collected in 2013–14), Wave 5 (2017–18) and Wave 6 (2023).[6]

The analysis section comprised 2 parts. The first part focused on descriptive analysis to address Research Question 1. These analyses revealed trends in income support payments, including both short-term (i.e. recipients in Wave 1) and long-term (i.e. recipients in Waves 5 and 6) reliance, as well as transitions to employment over time. The distribution of short- and long-term reliance on income support payments, along with employment transitions, was presented by socio-economic characteristics outlined in the earlier section.

The second part conducted multivariate regression analysis to address Research Question 2. More specifically, it examined the transition from income support payments to employment as a dynamic process and the factors that influence it. The outcome variable was, therefore, defined for the subsample of humanitarian migrants who reported income support payments as their main income source in Wave 1. For this set of humanitarian migrants, one could either enter the labour market and report wages or salaries as their main income source or remain reliant on income support payments in Waves 5 and 6.

Given missing information on income support payments and employment across waves, 2 analytical approaches were initially considered and designated as baseline models: Approach 1 examined the dynamic processes between Waves 1 and 5, and Approach 2 investigated those between Waves 1 and 6 (see Box 2). The 2 approaches allowed for the exploration of factors associated with exit from work by year 5 (Approach 1) and a longer time frame (Approach 2). For a detailed discussion of the results derived from Approaches 1 and 2, see the main report, with supporting data presented in Appendix D.

Box 2: Outcome measures

Approach 1:

Exit to work

= 1 *if received govt income support in year* 1 *but entered the labour market in year* 5

= 0 *if received govt income support in year* 1 *and year* 5

Approach 2:

Exit to work

= 1 *if received govt income support in year* 1 *but entered the labour market in year* 10

= 0 *if received govt income support in year* 1 *and year* 10

Three additional outcome measures were analysed to strengthen the evidence base and enhance the relevance of findings for policy development (see Box 3). First, participants who received income support payments in Wave 1 but transitioned to work in Waves 5 *and* 6. Second, participants who received income support payments in Wave 1 but transitioned to work in Waves 5 *or* 6.

Third, while humanitarian migrants rely on income support payments as their main source of income upon arrival, they can also be employed at any given time due to the means testing of those payments. Accordingly, this study considered the third outcome measure with 3 possible categories:

- participants who were unemployed and received income support payments
- participants who were not in the labour force and received income support payments
- participants who were employed but received income support payments and those who were employed and reported wages/salaries as their main income source.[7]

These categories were selected based on sample size considerations to ensure reliable estimates. This exercise was conducted by waves to highlight the differential impacts over time.

The results of all extended analyses were discussed in Appendix C, with supported data presented in Appendix D.

6 There are 6 waves of data available in the BNLA study. Data in Waves 2, 3 and 4 were collected in 2014–15, 2015–16, and 2016–17.

7 These 2 outcomes were combined due to the small number of observations in the first group.

Box 3: Additional outcome measures

Approach 3:

Exit to work

= 1 *if received govt income support in W1 but entered the labour market in W5 and W6*

= 0 *if received govt income support in W1, W5 and W6*

Approach 4:

Exit to work

= 1 *if received govt income support in W1 but entered the labour market in W5 or W6*

= 0 *if received govt income support in W1, W5 and W6*

Approach 5:

Economic integration – income support reliance in W1, W5 and W6

= 1 *if unemployed and received government income support*

= 2 *if not in the labour force and received government income support*

= 3 *if employed and received government income support and employed and reporting wages/salaries as their main income source*

Methods

Part 1 presents descriptive statistics, including numbers (*n*) and percentages (%), investigating trends in reliance on income support payments (as opposed to wages, salaries or other income sources) over time, as well as transitions to employment at the 5th and 10th years of settlement, disaggregated by sex.

It also shows reliance on income support payments (as opposed to wages, salaries or other income sources) during the early settlement period, as well as transitions to employment by years 5 and 10 by socio-economic characteristics (e.g. pre- and post-arrival characteristics) to provide context and facilitate analyses in Part 2. All proportions presented in this brief were weighted to account for non-response by specific demographic characteristics over multiple waves of the BNLA study.[8]

Part 2 examines, over time, the factors influencing the likelihood of transitioning to employment (Approaches 1–4) and workforce integration and reliance on income support (Approach 5) for each wave, using statistical models. Outcome measures in Approaches 1–4 are binary, so logistic regression models were estimated (for a similar approach, see also Hansen & Lofstrom, 2011), whereas a multinomial logit model was estimated to examine the unordered choices in Approach 5 (see also Cai et al., 2008). These models were adjusted using socio-economic characteristics outlined in Figure A1.

Apart from variables that capture changes between waves, such as the number of adults and children in the household, Approaches 1–4 included variables defined from Wave 1 baseline data. This technique avoids reliance on variables from later waves, which may be influenced by the outcome itself. For example, English language study facilitated migrants' employment transition (van Kooy et al., 2025), while engagement in the labour force also contributed to English proficiency (van Kooy et al., 2024).

For ease of interpretation, the analytical results were recorded as marginal effects. In other words, it shows the marginal effects of explanatory variables on the probability of an employment transition (i.e. the change in the probability of an employment transition when an explanatory variable changes at the average values of all other variables in the model). For example, if humanitarian migrants had work experience before arriving, and their probability of employment transition was described as 0.102, it means they were 10 percentage points more likely to enter the workforce than humanitarian migrants without that experience.[9]

8 For more information on how weights were calculated, see the BNLA data user guide (Stevenson & Rioseco, 2024).

9 For binary variables, the marginal effect reflects the change in the outcome, such as the likelihood of employment transition, when the variable shifts from 0 to 1, holding all other variables at their sample means. For continuous variables, it shows the change in the probability of the outcome for a one-unit increase in the explanatory variable, holding all other variables at their sample means.

Standard errors of statistical models were clustered by migrating units (MU).[10] This is simply because there could be more than one male or female from the same MU, and they may be correlated due to observed and unobserved factors (i.e. factors not observed in the data). The significance of the results was assessed at 3 levels: 1% ($p < 0.01$: highly significant), 5% ($p < 0.05$: significant), and 10% ($p < 0.10$: marginally significant). This means that the results are statistically significant if the p value is less than 0.01, 0.05 or 0.10, respectively.

Sample selection and attrition bias

A potential problem in estimating Approaches 1–4 is the initial employment status. In other words, whether a humanitarian migrant enters the labour market depends on their initial employment status. Employment transitions over a 5- and 10-year span were analysed for migrants who were unemployed or out of the labour force at the baseline – around 90% of the sample. While it is plausible that income support payments initially supported these humanitarian migrants, they may self-select into employment over time based on observed characteristics (e.g. health status) and unobserved human capital (e.g. motivation or country-specific skills). Failing to account for non-random selection into employment (i.e. when there is a specific reason for not participating in the workforce) can bias estimates (Shin, 2022).

The sample selection bias was investigated using baseline Approaches 1 and 2. In both cases, the transition to employment was modelled as a two-step process consistent with Heckman's two-step estimator (Heckman, 1979). This method involved estimating a first-stage discrete choice model (typically a probit or logit model)[11] of initial employment status (coded as 1 for not employed, and 0 for employed). From this, the inverse Mills ratio (IMR) was calculated and subsequently included in the second-stage transition model to correct for sample selection bias (Sarkar et al., 2019).

For identification, the initial employment model should include explanatory variables (instruments) that are validly excluded from the employment transition model. Otherwise, identification would completely rely on the non-linear functional form of the IMR. In the absence of suitable identifying instruments in the BNLA study or other evidence, this analysis retained variables that were statistically significant in the initial employment status model but not in the transition model (for a similar approach, see Delaporte & Piracha, 2018). The control variables were the same as those used in the employment transition model. Furthermore, since the IMR is a constructed variable, standard errors were bootstrapped using 500 replications to ensure robust inference (see Table D9 in Appendix D).

In addition to initial employment status, there may be a problem of panel attrition in the analysis. For instance, approximately 22% of participants from Wave 1 did not participate in Wave 5 and were excluded from that wave (see Figure D3, Appendix D). Due to non-participation, it is impossible to observe their employment status in Wave 5 and, therefore, to define their employment transition. If this dropout is non-random (i.e. there is a specific reason for dropping out of the survey), the final results may not accurately reflect the entire population, as participants who left the survey differed from those who stayed (see Tables D1–D2, Appendix D).[12] This study addressed panel attrition bias in estimating employment transition probabilities using baseline Approaches 1 and 2, and the results are presented in Tables D10 and D11 in Appendix D.

The analysis used the Heckman two-step estimator (Heckman, 1979).[13] In the first step, the probability of sample retention was estimated using a logit model. From this, the inverse Mills ratio (IMR) was calculated and subsequently included in the second-stage transition model to correct for attrition bias. Furthermore, since the IMR is a constructed variable, standard errors were bootstrapped using 500 replications to ensure robust inference.

The retention equation should also include an identifying variable observed for all study participants associated with retention but not with the employment transition. Research indicates that the interview mode and the language used during the interview can predict panel attrition. For example, face-to-face interviews may reduce attrition compared to telephone interviews due to the personal interaction and rapport building (Vassallo et al., 2015). Moreover, conducting interviews in multiple languages can help retain respondents who might otherwise drop out due to language barriers (Jacobsen, 2021).

Following the same line of thought, this brief used the interview mode (self vs interviewer/interpreter) and the language used during the interview (English vs non-English) in Wave 1 as identifying instruments for retention. The validity of these identifying instruments used in the first-stage retention equation is supported by their lack

10 A MU comprises all persons who migrated to Australia as part of the same migration application as the Principal Applicant.

11 Although probit and logit models are largely similar, the logit model was selected for this analysis due to its robust feature.

12 See Cappellari and Jenkins (2004) for a discussion on sample drop-out when estimating transition probabilities.

13 For a similar method of addressing attrition bias with panel data, see Sarkar et al. (2019).

of statistical significance in the second-stage employment transition equation. This indicates that while these variables – such as survey mode and survey language – are effective in predicting panel retention, they do not directly influence the employment outcome. Their exclusion from the employment transition model satisfies the necessary condition for valid identifying instruments, reinforcing the credibility of the retention model and the robustness of the main results.

In the second step, the transition to employment was modelled using a logit specification applied only to those retained in the study. The IMR derived from the first stage was incorporated into this estimation to correct for attrition bias.

Taken together, the analysis was conducted in 4 steps:

1. Separate logistic regression models were estimated for each baseline approach outlined above.
2. Each baseline approach was estimated by sex, as women were more likely than men to rely on income support payments over time (see Figure D5, Appendix D).
3. Each baseline approach (Approaches 1 and 2) was re-estimated with adjustments for sample selection and attrition bias to investigate whether the effect sizes of baseline models changed.
4. Further analyses using additional outcome measures were conducted.

Study sample

This brief uses BNLA data from 3 approximately equidistant time points: Wave 1 (baseline data collected in 2013–14), Wave 5 (2017–18) and Wave 6 (2023), referred to as year 1, year 5 and year 10.

The study sample includes BNLA participants aged 15–59 in Wave 1. While 'working age' adults are commonly considered to be aged 15–64 years (ABS, 2024), this study restricted the sample in recognition of the presumed low likelihood that newly arrived humanitarian migrants aged over 60 included in Wave 1 will be active participants in the Australian labour market. In accordance with this hypothesis that older humanitarian migrants would be outliers, analysis showed that 98% of BNLA participants who were aged 60 and above in Wave 1 reported not being in the labour force by Wave 5, and 100% were not in the labour force by Wave 6 (van Kooy et al., 2025).

There were 2,229 participants aged 15–59 in Wave 1. Of these, 1,735 responded in Wave 5, and 1,132 of that group responded in Wave 6. The analytic sample, however, comprised 2,182 Wave 1 participants who reported income support payments as their primary source of income (as opposed to wages, salaries or other sources). In Waves 5 and 6, 1,697 and 973 of these participants, respectively, reported their main income source and were included in this study. BNLA participants aged 15–59 who did not report their main income source were treated as missing (approximately 2% in Waves 1 and 5, and 14% in Wave 6) and were generally excluded from the analysis.

Appendix B: Domains and measures

The following table includes details of demographic and other measures from Waves 1 (Year 1: 2013–14), 5 (Year 5: 2017–18), and 6 (Year 10: 2023) used in the analysis. Further information on questionnaires and other data-related information is available via the BNLA Data user guide (Stevenson & Rioseco, 2024).

Table B1: Domains and measures used in the analysis

Variable in BNLA	Description	Waves	Coded Values
Controls			
Age at arrival	Age of the respondent at the time of the interview	Wave 1	1. 15–19; 2. 20–29; 3. 30–39; 4. 40–49; 5. 50–59; 6. 60+
Sex	Whether the respondent is male or female[a]	Wave 1	0. Female; 1. Male
Married/has a partner	Whether the respondent was married or had a partner	Wave 1	0. No; 1. Yes
Religion	Religion of the respondent	Wave 1	1. Christian; 2. Islam; 3. Buddhist/Hindu/other; 4. No religion/not important/unknown
Individual			
Pre-arrival education	Whether the respondent completed up to 12 years of education or more, attained university or technical degrees, or had no education at all before arriving in Australia	Wave 1	1. None; 2. Schooling (0–12 or more years of education but without University/Technical education); 3. Post-schooling (University or technical)
Pre-arrival proficiency in speaking English	Respondent's proficiency in speaking English before arriving in Australia	Wave 1	0. Not at all/not well; 1. Well/very well
Study/job-training in Australia	Whether the respondent had undertaken any study (other than English courses) or job training in Australia prior to each survey	Waves 1, 5 and 6	0. No; 1. Yes
Study English	Whether the respondent is studying or learning English in Australia	Waves 1, 5 and 6	0. No; 1. Yes
Poor mental health	It is determined by a battery of diagnostic questions, such as meeting intrusion, avoidance and hypervigilance criteria for post-traumatic stress disorder (PTSD) or having experienced severe mental illness.	Waves 1, 5 and 6	0. No; 1. Yes
Disability	Whether the respondent reported disability or any long-term health conditions	Wave 1	0. No; 1. Yes

Variable in BNLA	Description	Waves	Coded Values
Labour force status	Whether the respondent reported being in paid work in the last 7 days (employed), whether they looked for work in the last 4 weeks (unemployed) or neither (not in the labour force)	Waves 1, 5 and 6	3. Not in the labour force; 2. Unemployed; 1. Employed
Desire for a job	Whether the respondent wants a job[b]	Waves 5 and 6	0. No; 1. Yes
Looked for work	Whether the respondent looked for work in the last 12 months	Waves 1, 5 and 6	0. Not at all/not well; 1. Well/very well
Pre-arrival work experience	Whether the respondent had paid work before arriving in Australia	Wave 1	0. No; 1. Yes
Main income source	Respondent's self-reported main source of income at the time of the survey	Waves 1, 5 and 6	0. Wages/Salary/Others; 1. Income support payments
Migration pathway	Whether the respondent came to Australia under offshore or onshore pathways[c]	Wave 1	0. Onshore; 1. Offshore
Mode of interview	Mode of interview at the time of the survey	Wave 1	3. Computer-assisted personal interview (CAPI) with an interpreter; 2. Computer-assisted personal interview (CAPI) with an interviewer; 1. Computer-assisted self-interview (CASI)
Language of the interview	Language of the interview at the time of the survey	Wave 1	0. Non-English; 1. English
Family and social support			
Adults 18 years and above	Number of adults 18 years and above in the household	Waves 1, 5 and 6	Numbers
Changes in the number of adults 18 years and above	Changes in the number of adults in the household between waves	Waves 1, 5 and 6	Numbers
Children under 18 years	Number of children under 18 years in the household	Waves 1, 5 and 6	Numbers
Changes in the number of children under 18 years	Changes in the number of children in the household between waves	Waves 1, 5 and 6	Numbers
Composition of friendship groups	Whether the respondent reported mainly having friends from their own ethnic or religious group, from mixed/other backgrounds, or no friends	Waves 1, 5 and 6	0. No friends or mostly from own ethnic/religious community; 1. Mixed/other communities
Neighbourhood			
Remoteness area	Whether the respondent lived in regional areas or major cities (derived)	Waves 1, 5 and 6	0. Regional; 1. Major city
Location	Whether the respondent lived in areas with low, medium or high levels of disadvantage[d]	Waves 1, 5 and 6	1. Low/Medium; 2. High

Variable in BNLA	Description	Waves	Coded Values
Structural			
Unemployment	Local unemployment rate at pre-arrival level[e]	Derived	Percentages
Unemployment	Unemployment rate in Wave 5 (October–December 2017 to January–March 2018)[f]	Derived	Percentages
Unemployment	Unemployment rate in Wave 6 (January–July 2023)[g]	Derived	Percentages
Driving license	Whether the respondent holds the Australian driver licence	Wave 1	0. No; 1. Yes

Notes: a BNLA collected self-reported gender, not biological sex at birth. Since 'gender' and 'sex at birth' are distinct concepts, any references to 'sex' in this context should be reported as 'self-reported gender'.

b Desire for a job was not captured in Wave 1.

c Offshore respondents were those identified by the UNHCR as refugees in need of resettlement, along with individuals who arrived through the Special Humanitarian Program. In contrast, onshore respondents were those already in Australia when they received a permanent visa.

d Measured by the Socio-economic Indexes for Areas (SEIFA), Index of Relative Socio-economic Disadvantage (IRSD) (ABS, 2023)

e The unemployment rate in the geographic area where each participant lives and was derived from ABS.

f, g Seasonally adjusted quarterly rate derived from ABS.

Appendix C: Extended analyses

Understanding self-selection effects in employment transitions

It is argued that some humanitarian migrants may delay entering the workforce in the hope of securing jobs that match their skills or expectations, particularly if they are receiving income support payments and not under immediate financial pressure. However, many begin with low-skilled jobs while relying on government income support yet still face financial hardship (Olliff, 2010). This suggests that systemic barriers – such as limited job opportunities and lack of skill recognition – may play a more significant role in shaping employment outcomes than individual choice.

Over time, those who do transition into employment tend to be a self-selected group – potentially different from those who remain reliant on government income support. These differences are not incidental; they reflect underlying disparities in demographic characteristics, as presented in Tables 3 and 4 of the report.

This study accounted for differences in the types of humanitarian migrants included in the analysis, using the method outlined in Appendix A. This helped ensure that the findings on employment transitions by the 5th and 10th years of settlement were more accurate – particularly in showing how the strength and direction of the effects may change depending on who is included. When compared with baseline estimates in Tables D3 and D4, the adjusted results remained consistent in direction and strength, suggesting that the findings are reliable and not distorted by self-selection bias (see Table D9, Appendix D).

Insights from those who stay and those who leave the BNLA study

Panel attrition in the BNLA study was relatively high, particularly by year 10. It is likely that some participants who withdrew after the baseline survey were among the key recipients of government income support or they had successfully transitioned to employment. This loss of participants may have affected the representativeness of the remaining sample, potentially leading to biased estimates of employment transitions – especially those presented in Tables D3 and D4.

This study analysed panel attrition between years 1 and 5 and years 1 and 10 of the BNLA data. It examined whether the loss of participants at the 5th or 10th year of settlement influenced the baseline results, using the method outlined in Appendix A. This helped assess whether results on employment transitions in year 5 or year 10 were affected by the fact that those who dropped out of the survey may differ in important ways from those who remained. More specifically, correcting for attrition helps ensure that the baseline results more accurately reflect the broader population, especially when designing policies to support long-term employment among humanitarian migrants.

In the employment transition model, the IMR was found to be statistically insignificant (Tables D10 and D11). This suggests that attrition does not introduce systematic bias to the estimation of the employment transition in year 5 and year 10. In other words, the characteristics influencing survey retention do not appear to correlate with the determinants of the transition itself. As a result, the primary findings from baseline Approaches 1 and 2 can be considered robust even without correction for panel attrition bias. Nonetheless, including the IMR serves as a diagnostic check and reinforces confidence in the validity of the results.

Taken together, attrition did not introduce systematic bias to the estimation of the employment transition. In other words, the characteristics influencing survey retention do not appear to correlate with the determinants of the transition itself. As a result, the primary findings from baseline approaches (Tables D3 and D4) can be considered robust, even without correction for panel attrition bias.

Understanding employment transition from income support payments: insights from alternative outcomes

To strengthen the evidence base and enhance the relevance of findings, this study considered 2 additional outcomes:

1. participants who received income support payments in year 1 but transitioned to work in year 5 *and* year 10
2. participants who received income support payments in year 1 but transitioned to work in year 5 *or* year 10 (for details, see Appendix A).

Overall, the findings are robust to the use of different outcome measures and remain consistent despite changes in sample size (see Table D12, Appendix D). In particular, being young, male, married, having studied English, undertaking other studies or job training in Australia, living in low- to medium-disadvantage areas, and having pre-arrival work experience were all significantly and positively associated with employment transition. On the contrary, having a disability and additional adult members in the family were found to be significant barriers to employment transition.

A few results were significant for the first alternative outcome but not for the second, including changes in the number of adults between year 1 and year 5 and having friends from a mix of cultural or ethnic backgrounds (see Table D12, Appendix D). Both factors showed a positive association with employment transition over time. Ideally, a larger family size can drive greater economic participation, as increased financial needs encourage more household members to seek employment (Hill, 1971). This relationship becomes apparent only when the analysis simultaneously includes data from both years 5 and 10, which reveal the link between larger family size and economic participation more clearly. More specifically, this analysis captured changes in family dynamics over time, such as children growing older and entering the workforce or shifts in household circumstances that contribute to employment transitions within the household.

Understanding income support payments and employment status: insights from each survey wave

Humanitarian migrants often rely on income support payments as their main source of income upon arrival; however, many also find employment at some point. BNLA data show that among those employed, reliance on income support payments declined notably – from 11% in year 5 to 8% in year 10 (see Table D13, Appendix D).[14] Over time, the proportion of humanitarian migrants not in the labour force decreased; however, those who remained outside the labour force continued to show a high dependence on government income support.

Accordingly, this study considered the third outcome measure with 3 possible categories:

- participants who were unemployed and received income support payments
- participants who were not in the labour force and received income support payments
- participants who were employed but received income support payments, and those who were employed and reported wages/salaries as their main income source.

This analysis was conducted by waves to highlight the differential impacts over time (for details, see Appendix A).[15]

In most cases, the results aligned with those seen across the broader Australian population (Cai et al., 2008). Starting with the findings in year 1, males were more likely than females to be in the employed-recipient or not-recipient states, and also more likely to be in the unemployed-recipient state (Table D14, Appendix D). On the contrary, they were less likely to be in the NILF-recipient state compared to their female counterparts.

Disability or long-term health conditions were found to reduce the probability of being in the employed-recipient or not-recipient state by about 6 percentage points and to increase the probability of being in the unemployed-recipient state by about 4 percentage points, compared with those without disability or long-term health conditions.

Humanitarian migrants who had studied English were 3 percentage points more likely to be in the NILF-recipient state compared to those who had never studied English. This aligns with the discussion in Part 1 that

14 Additionally, humanitarian migrants expressing a desire for work were increasingly represented in wage and other income categories, indicating stronger labour market engagement.

15 The results should be interpreted with caution due to the limited sample sizes across different categories and years.

humanitarian migrants who studied English early on were more likely to be unemployed or NILF. On the contrary, they were 3 percentage points less likely to be in the employed-recipient or not-recipient states, suggesting that those already engaged in employment were less likely to enrol in language programs, possibly due to time constraints or reduced perceived need – highlighting a link between employment status and language program participation (i.e. endogeneity bias).

Humanitarian migrants who undertook other studies or training in Australia had a lower probability of being in the NILF-recipient state compared to those who did not, indicating a potential link between educational engagement and increased labour market participation. On the other hand, humanitarian migrants with pre-arrival work experience were more likely than those without such experience to be in the employed-recipient or not-recipient states, and also more likely to be in the unemployed-recipient state. However, they were less likely to be in the NILF-recipient state compared to those without prior work experience.

Family dynamics, in terms of the number of adults aged 18 and above and young children under 18 years, play a significant role in labour force participation. Humanitarian migrants with additional adult family members or young children were more likely to be in the NILF-recipient state, and their impact was of a similar magnitude (approximately 3 percentage points). These patterns reinforce the evidence of caring responsibilities in BNLA data, especially for elderly, disabled and dependent children.

Finally, both the onshore migrant pathway and residing in less disadvantaged areas were associated with a lower likelihood of being in the NILF-recipient state. Consistent with earlier findings, humanitarian migrants who arrived through the onshore pathway were more likely to be in the employed-recipient or not-recipient states. Additionally, having friends from diverse ethnic and religious backgrounds was linked to a higher likelihood of being in the unemployed-recipient state and a lower likelihood of being in the NILF-recipient state, suggesting that broader social networks may support labour market engagement.

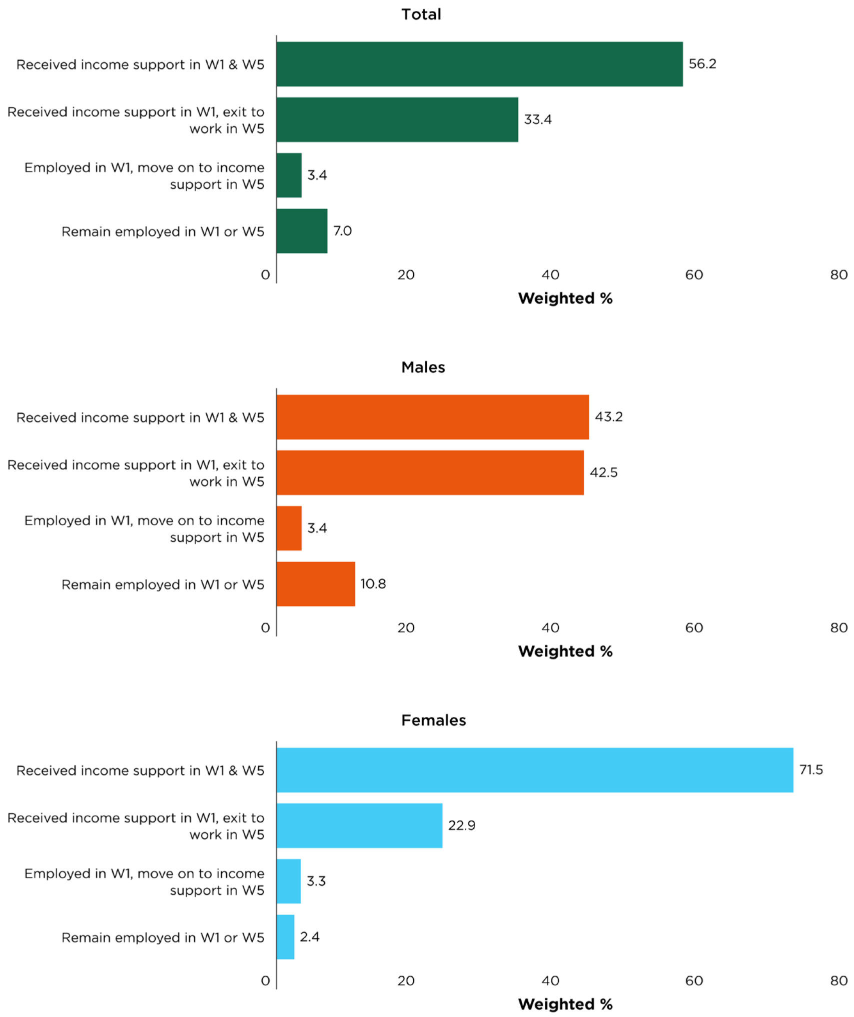
The results for year 5 mirrored those for year 1 (Table D15, Appendix D). The only exception was that individual, family and social attributes were all significantly associated with the employed-recipient and not-recipient states. These associations were in the same direction as those observed for employment transitions in year 5 (see Table D3, Appendix D), thereby reinforcing the baseline estimates for that year. Another notable exception was that pre-arrival education (i.e. up to 12 or more years of education and university/technical degrees) was associated with a higher likelihood of being in the unemployed-recipient state. This pattern further underscores that humanitarian migrants often face challenges securing jobs that align with their skills and qualifications.

The association between socio-economic characteristics and income support payments-employment state observed in year 5 persisted through to year 10 but its strength diminished over time (Table D16, Appendix D). In particular, the influence of English skills, undertaking other studies or job training in Australia, the number of children and the onshore arrival pathway were no longer relevant to the government payment-employment state. Another notable finding was the importance of pre-arrival education. Pre-arrival formal education up to 12 or more years (but without university/technical degrees) and university/technical degrees were found to be associated with a higher likelihood of being in the employed-recipient or not-recipient states. It probably suggests that the effect of education was delayed, becoming more visible as other enabling factors improved (van Kooy et al., 2024).

In addition, the results for the government payment-employment state in year 10 were broadly consistent and were in the same direction as those observed for employment transitions in year 10 (see Table D4, Appendix D), thereby emphasising the baseline estimates for that year.

Appendix D: Supplementary tables and graphs

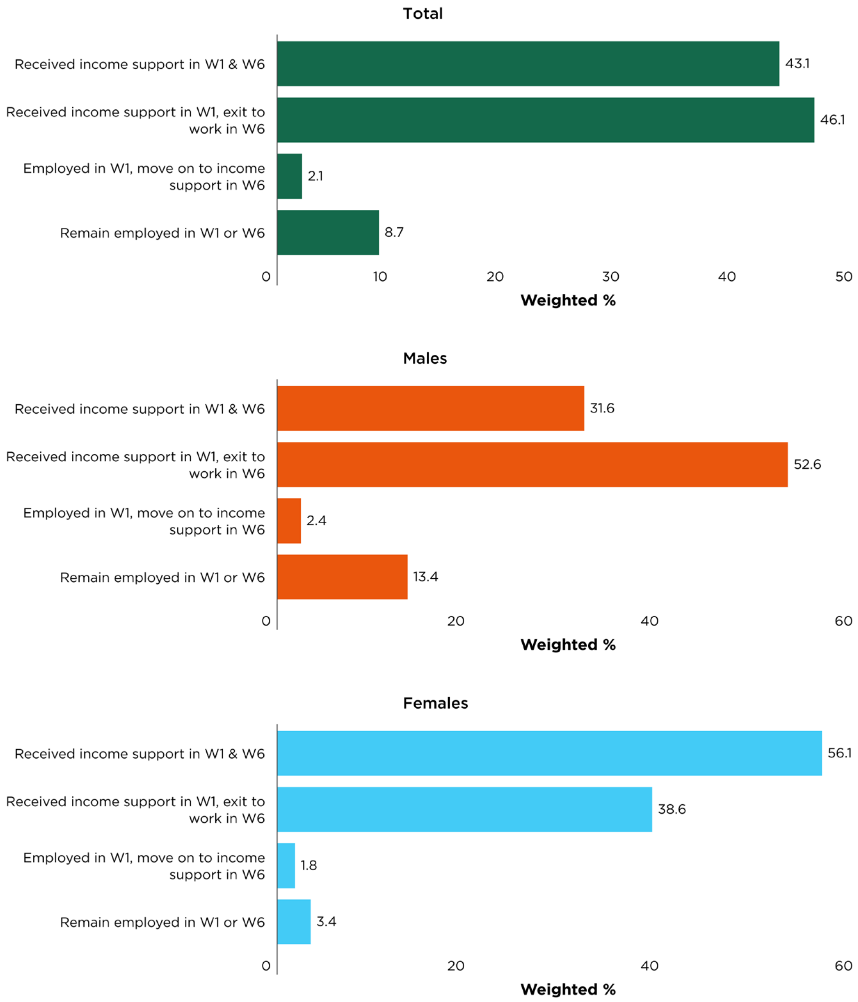
Figure D1: Transitions between income support payments-employment states between year 1 and year 5



Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in Wave 5 (n = 1,659, males = 865, females =794). Observations (n) represent the number of BNLA participants who responded to the question about their main sources of income, either income support payments or wages/salary/other (unweighted). Panel weights were applied to BNLA data.

Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

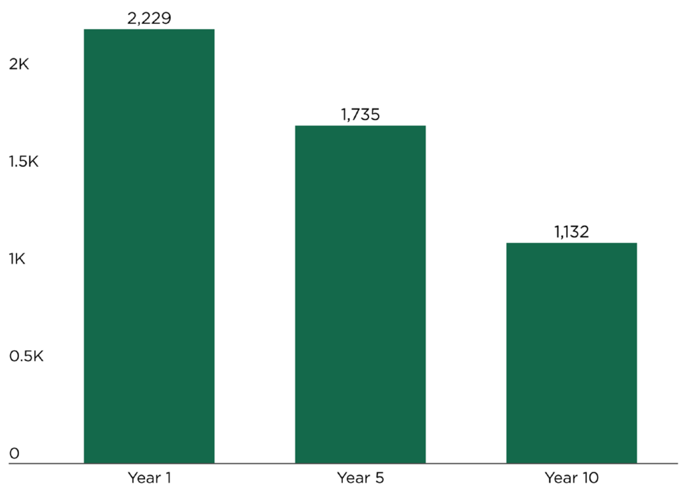
Figure D2: Transitions between income support payments-employment states between year 1 and year 10



Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in Wave 6 (*n* = 950, males = 494, females = 456). Observations (*n*) represent the number of BNLA participants who responded to the question about their main sources of income, either income support payments or wages/salary/other (unweighted). Panel weights were applied to BNLA data.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

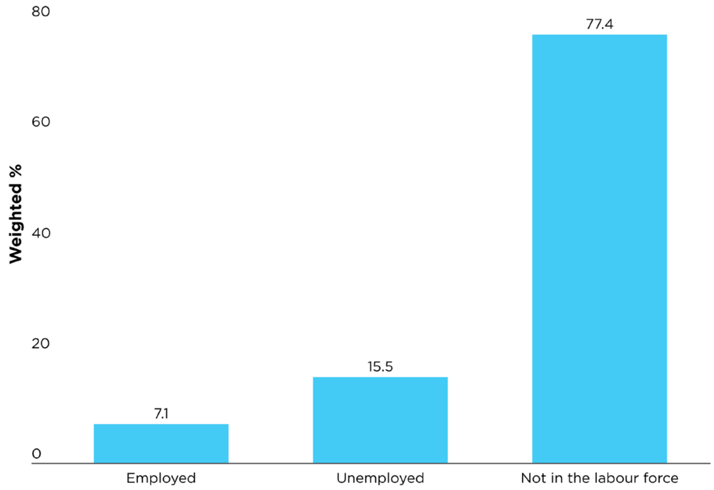
Figure D3: BNLA participants over time



Notes: Unweighted observations. BNLA participants aged 15–59 in Wave 1 and those also surveyed in Waves 5 and 6.

Source: BNLA Waves 1 (Year 1: 2013–14), 5 (Year 5: 2017–18) and 6 (Year 10: 2023)

Figure D4: Labour force status of BNLA participants in year 1



Notes: BNLA participants aged 15–59 in Wave 1 (*n* = 2,221). Observations (*n*) represent the number of BNLA participants who responded to the question about their labour force status (unweighted). Cross-sectional weights were applied to BNLA data.

Source: BNLA Wave 1 (Year 1: 2013–14)

Table D1: Distribution of demographic characteristics by BNLA participants and non-participants between year 1 and year 5

	Participants in year 1 and year 5	Participants dropped in year 5	Obs.	*p* value
Age group				
15–19	13.1	13.8	296	<0.001
20–29	27.2	36.4	652	
30–39	26.3	28.5	597	
40–49	22.7	11.5	450	
50–59	10.7	9.7	234	
Sex				
Female	47.4	39.7	1,019	0.002
Male	52.6	60.3	1,210	
Married or has a partner				
No	38.3	46.6	844	0.001
Yes	61.7	53.4	1,255	
Disability or long-term health conditions				
No	76.5	80.7	1,703	0.048
Yes	23.5	19.3	496	
Number of adults 18 yrs and above in the household				
1	29.3	49.0	751	<0.001
2	42.5	31.8	894	
3 and more	28.2	19.2	584	
Number of children under 18 yrs in the household				
0	32.5	49.6	809	<0.001
1–2	45.5	36.2	968	
3 and more	22.0	14.2	452	
Study English				
No	20.3	22.5	451	0.284
Yes	79.7	77.5	1,718	

	Participants in year 1 and year 5	Participants dropped in year 5	Obs.	*p* value
Study or job training since arrival				
No	85.6	81.2	1,878	0.016
Yes	14.4	18.8	340	
Pre-arrival speaking English proficiency				
Not proficient	79.3	70.9	1,701	<0.001
Proficient	20.7	29.1	495	
Pre-arrival education				
None	14.5	16.0	327	0.047
0–12 or more years of schooling	69.9	64.3	1,519	
University or technical	15.6	19.7	365	
Pre-arrival work experience				
No	47.1	42.1	1,018	0.053
Yes	52.9	57.9	1,196	
Total	**77.8**	**22.2**	**2,229**	

Notes: Unweighted percentage. BNLA participants aged 15–59 in Wave 1 and those also surveyed in Wave 5.
Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

Table D2: Distribution of demographic characteristics by BNLA participants and non-participants between year 1 and year 10

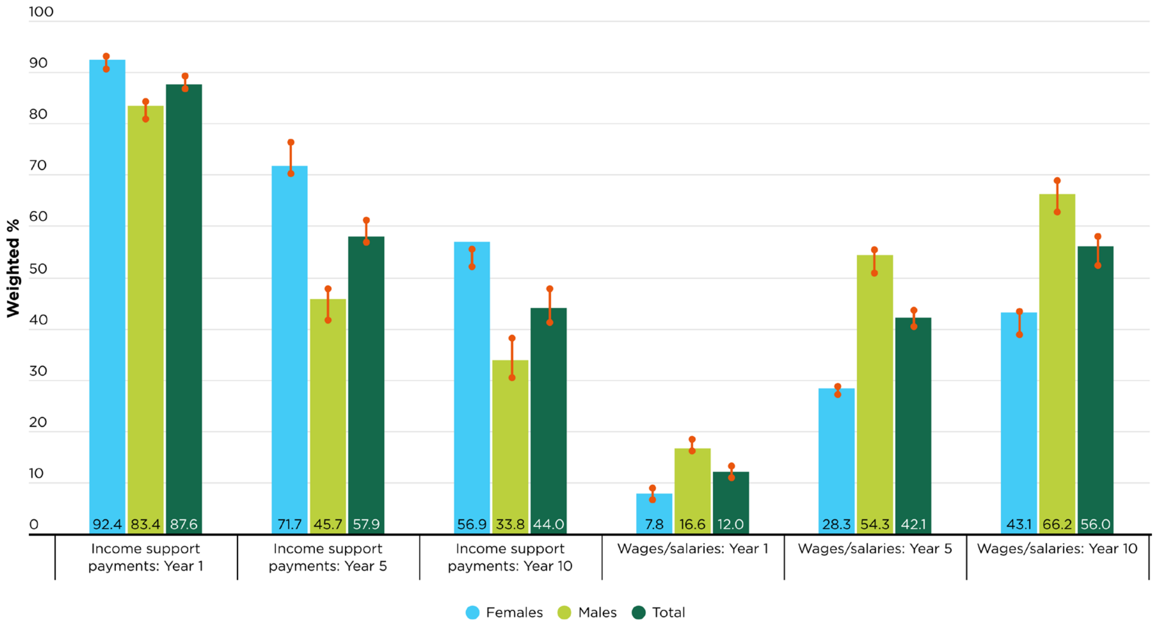
	Participants in year 1 and year 10	Participants dropped in year 10	Obs.	*p* value
Age group				
15–19	13.3	13.3	296	<0.001
20–29	26.1	32.5	652	
30–39	25.6	28.0	597	
40–49	22.9	17.4	450	
50–59	12.2	8.8	234	
Sex				
Female	48.4	42.9	1,019	0.009
Male	51.6	57.1	1,210	
Married or has a partner				
No	37.8	42.7	844	0.023
Yes	62.2	57.3	1,255	
Disability or long-term health conditions				
No	76.4	78.5	1,703	0.222
Yes	23.6	21.5	496	
Number of adults 18 yrs and above in the household				
1	28.4	39.1	751	<0.001
2	42.2	37.9	894	
3 and more	29.3	23.0	584	
Number of children under 18 yrs. in the household				
0	32.1	40.7	809	<0.001
1–2	47.3	39.4	968	
3 and more	20.6	20.0	452	
Study English				
No	19.0	22.6	451	0.038
Yes	81.0	77.4	1,718	

	Participants in year 1 and year 10	Participants dropped in year 10	Obs.	*p* value
Study or job training since arrival				
No	85.0	84.3	1,878	0.671
Yes	15.0	15.7	340	
Pre-arrival speaking English proficiency				
Not proficient	78.9	76.0	1,701	0.105
Proficient	21.1	24.0	495	
Pre-arrival education				
None	14.2	15.4	327	0.338
0–12 or more years of schooling	68.3	69.1	1,519	
University or technical	17.6	15.4	365	
Pre-arrival work experience				
No	46.7	45.3	1,018	0.514
Yes	53.3	54.7	1,196	
Total	**50.8**	**49.2**	**2,229**	

Notes: Unweighted percentage. BNLA participants aged 15–59 in Wave 1 and those also surveyed in Wave 6.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

Figure D5: Main income source over time by sex



Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in Waves 5 and 6 (n = 2,182, 1,697, and 973). Observations (n) represent the number of BNLA participants who responded to the question about their main sources of income, either income support payments or wages/salary/other (unweighted) in Waves 1, 5 and 6. Cross-sectional weights were applied to BNLA data.

Source: BNLA Waves 1 (Year 1: 2013–14), 5 (Year 5: 2017–18) and 6 (Year 10: 2023)

Factors contributing to the transition from income support payments to employment over time

Results for complete models

Table D3: Logit marginal effects of employment transition from income support payments between year 1 and year 5

Dependent variable	Exit to work in year 5			
	Baseline	Extended		
	(1)	(2)	(3)	(4)
Age 20–29	-0.202***	-0.200***	-0.197**	-0.185**
	(0.075)	(0.076)	(0.078)	(0.078)
Age 30–39	-0.331***	-0.329***	-0.329***	-0.310***
	(0.075)	(0.076)	(0.077)	(0.078)
Age 40–49	-0.433***	-0.431***	-0.415***	-0.406***
	(0.074)	(0.076)	(0.077)	(0.078)
Age 50–59	-0.545***	-0.539***	-0.534***	-0.519***
	(0.075)	(0.077)	(0.078)	(0.079)
Male	0.141***	0.120***	0.118***	0.111***
	(0.032)	(0.032)	(0.032)	(0.032)
Islam	0.072*	0.066*	0.112***	0.056
	(0.038)	(0.038)	(0.039)	(0.038)
Buddhist/Hindu/other	0.040	0.040	0.022	0.042
	(0.052)	(0.052)	(0.050)	(0.053)
No religion/not important/not stated	0.148**	0.125*	0.156**	0.117*
	(0.071)	(0.070)	(0.069)	(0.071)
Married or has a partner	0.158***	0.165***	0.159***	0.167***
	(0.039)	(0.039)	(0.040)	(0.039)
Disability or long-term health condition	-0.158***	-0.153***	-0.117***	-0.121***
	(0.037)	(0.037)	(0.040)	(0.038)
Poor mental health			-0.091***	-0.101***
			(0.033)	(0.032)
Study English	0.124***	0.127***	0.122***	0.130***
	(0.040)	(0.040)	(0.041)	(0.040)
Study or job training	0.088**	0.081*	0.058	0.083*
	(0.042)	(0.042)	(0.045)	(0.043)
Number of adults 18 years and above in the family	-0.057*	-0.050	-0.029	-0.050*
	(0.031)	(0.031)	(0.029)	(0.030)
Change in the number of adults 18 years and above	0.005	0.002	-0.001	-0.002
	(0.015)	(0.014)	(0.015)	(0.014)
Number of children under 18 years in the family	-0.047***	-0.046***	-0.048***	-0.045***
	(0.016)	(0.016)	(0.015)	(0.016)
Change in the number of children under 18 years	-0.050**	-0.046**	-0.046**	-0.044**
	(0.020)	(0.020)	(0.019)	(0.020)
Onshore arrival pathway	0.149**	0.129**	0.177***	0.129**
	(0.063)	(0.064)	(0.066)	(0.064)
Low/medium disadvantage area	0.108**	0.107**	0.105**	0.096**
	(0.044)	(0.044)	(0.045)	(0.044)

Dependent variable	Exit to work in year 5			
	Baseline	Extended		
	(1)	(2)	(3)	(4)
Pre-arrival education: 0–12 or more yrs	-0.102**	-0.106**	-0.056	-0.100**
	(0.047)	(0.048)	(0.046)	(0.048)
Pre-arrival education: University/Technical	-0.140**	-0.136**	-0.032	-0.125**
	(0.057)	(0.058)	(0.061)	(0.059)
Pre-arrival work experience	0.102***	0.095***	0.076**	0.089***
	(0.034)	(0.034)	(0.034)	(0.034)
Mixed sources of friends	0.044	0.039	0.051	0.040
	(0.031)	(0.031)	(0.032)	(0.031)
Looking for work in the last 12 months		0.077**	0.062	0.076**
		(0.038)	(0.038)	(0.038)
Unemployment rate at arrival			-0.036***	
			(0.006)	
Unemployment rate in year 5				0.361
				(0.224)
Pearson chi-square	1,300.29	1,292.93	1,290.64	1,279.13
Prob > chi^2	0.18	0.22	0.28	0.41
Observations	1,335	1,320	1,301	1,307

Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, poor mental health: no, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, and not looked for work in the last 12 months.

Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

Table D4: Logit marginal effects of employment transition from income support payments between year 1 and year 10

Dependent variable	Exit to work in year 10			
	Baseline	Extended		
	(1)	(2)	(3)	(4)
Age 20–29	-0.207***	-0.207***	-0.192***	-0.181***
	(0.059)	(0.061)	(0.065)	(0.063)
Age 30–39	-0.401***	-0.397***	-0.388***	-0.374***
	(0.062)	(0.064)	(0.070)	(0.069)
Age 40–49	-0.569***	-0.574***	-0.556***	-0.557***
	(0.063)	(0.064)	(0.070)	(0.068)
Age 50–59	-0.780***	-0.772***	-0.779***	-0.776***
	(0.056)	(0.058)	(0.062)	(0.060)
Male	0.189***	0.165***	0.153***	0.159***
	(0.046)	(0.045)	(0.047)	(0.047)
Islam	0.051	0.044	0.078	0.035
	(0.062)	(0.064)	(0.068)	(0.065)
Buddhist/Hindu/other	-0.011	-0.009	-0.045	-0.015
	(0.079)	(0.079)	(0.080)	(0.080)
No religion/not important/not stated	0.057	0.030	0.025	-0.029
	(0.094)	(0.096)	(0.091)	(0.090)

Dependent variable	Exit to work in year 10			
	Baseline	Extended		
	(1)	(2)	(3)	(4)
Married or has a partner	0.115*	0.123*	0.126*	0.132**
	(0.062)	(0.063)	(0.065)	(0.065)
Disability or long-term health condition	-0.277***	-0.280***	-0.230***	-0.236***
	(0.061)	(0.062)	(0.064)	(0.064)
Poor mental health			-0.126**	-0.135***
			(0.052)	(0.051)
Study English	0.056	0.059	0.065	0.055
	(0.066)	(0.066)	(0.067)	(0.067)
Study or job training	0.134**	0.140**	0.168**	0.177***
	(0.067)	(0.068)	(0.071)	(0.069)
Number of adults 18 years and above in the family	-0.110***	-0.099***	-0.071*	-0.093**
	(0.038)	(0.038)	(0.039)	(0.038)
Change in the number of adults 18 years and above	0.023	0.024	0.032*	0.033*
	(0.018)	(0.018)	(0.019)	(0.018)
Number of children under 18 years in the family	-0.011	-0.009	-0.018	-0.018
	(0.025)	(0.026)	(0.025)	(0.026)
Change in the number of children under 18 years	-0.004	-0.003	-0.010	-0.012
	(0.020)	(0.021)	(0.020)	(0.020)
Onshore arrival pathway	0.092	0.087	0.127	0.088
	(0.101)	(0.103)	(0.098)	(0.104)
Low/medium disadvantage area	0.218***	0.221***	0.238***	0.239***
	(0.060)	(0.060)	(0.063)	(0.060)
Pre-arrival education: 0–12 or more years	0.005	0.005	0.046	-0.010
	(0.072)	(0.074)	(0.073)	(0.076)
Pre-arrival education: University/Technical	-0.017	-0.010	0.079	-0.014
	(0.091)	(0.092)	(0.095)	(0.095)
Pre-arrival work experience	0.147***	0.139***	0.130**	0.136**
	(0.053)	(0.054)	(0.054)	(0.055)
Mixed sources of friends	0.135***	0.132**	0.117**	0.119**
	(0.051)	(0.052)	(0.051)	(0.052)
Looking for work in the last 12 months		0.115*	0.113	0.121*
		(0.069)	(0.070)	(0.070)
Unemployment rate at arrival			-0.033***	
			(0.010)	
Unemployment rate in year 10				-1.115**
				(0.490)
Pearson chi-square	689.21	694.62	723.73	692.7
Prob > chi^2	0.84	0.75	0.46	0.74
Observations	769	759	746	750

Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. **p* < 0.10, ***p* < 0.05, ****p* < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, poor mental health: no, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, and not looked for work in the last 12 months.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

Table D5: Logit marginal effects of employment transition from income support payments between year 1 and year 5

Dependent variable	Exit to work in year 5		
	Baseline	Extended	
	Age 15–59	Age 15–59	Age 15+
	(1)	(2)	(3)
Age 20–29	-0.202***	-0.200***	-0.204***
	(0.075)	(0.076)	(0.077)
Age 30–39	-0.331***	-0.329***	-0.333***
	(0.075)	(0.076)	(0.076)
Age 40–49	-0.433***	-0.431***	-0.432***
	(0.074)	(0.076)	(0.076)
Age 50–59	-0.545***	-0.539***	-0.541***
	(0.075)	(0.077)	(0.077)
Age 60 and above			-0.595***
			(0.073)
Male	0.141***	0.120***	0.103***
	(0.032)	(0.032)	(0.029)
Islam	0.072*	0.066*	0.055
	(0.038)	(0.038)	(0.034)
Buddhist/Hindu/other	0.040	0.040	0.041
	(0.052)	(0.052)	(0.047)
No religion/not important/not stated	0.148**	0.125*	0.109*
	(0.071)	(0.070)	(0.065)
Married or has a partner	0.158***	0.165***	0.137***
	(0.039)	(0.039)	(0.035)
Disability or long-term health condition	-0.158***	-0.153***	-0.125***
	(0.037)	(0.037)	(0.032)
Study English	0.124***	0.127***	0.103***
	(0.040)	(0.040)	(0.035)
Study or job training	0.088**	0.081*	0.068*
	(0.042)	(0.042)	(0.038)
Number of adults 18 years and above in the household	-0.057*	-0.050	-0.052*
	(0.031)	(0.031)	(0.028)
Change in the number of adults 18 years and above	0.005	0.002	-0.002
	(0.015)	(0.014)	(0.013)
Number of children under 18 years in the household	-0.047***	-0.046***	-0.041***
	(0.016)	(0.016)	(0.014)
Change in the number of children under 18 years	-0.050**	-0.046**	-0.042**
	(0.020)	(0.020)	(0.018)
Onshore arrival pathway	0.149**	0.129**	0.123**
	(0.063)	(0.064)	(0.060)
Low/medium disadvantage area	0.108**	0.107**	0.104***
	(0.044)	(0.044)	(0.040)
Pre-arrival education: 0–12 or more years	-0.102**	-0.106**	-0.117**
	(0.047)	(0.048)	(0.046)
Pre-arrival education: University/Technical	-0.140**	-0.136**	-0.147***

Dependent variable	Exit to work in year 5		
	Baseline	Extended	
	Age 15–59	Age 15–59	Age 15+
	(1)	(2)	(3)
	(0.057)	(0.058)	(0.053)
Pre-arrival work experience	0.102***	0.095***	0.094***
	(0.034)	(0.034)	(0.031)
Mixed sources of friends	0.044	0.039	0.031
	(0.031)	(0.031)	(0.028)
Looking for work in the last 12 months		0.077**	0.069**
		(0.038)	(0.034)
Pearson chi-square	1,300.300	1,292.900	1,435.700
Prob > chi²	0.18	0.22	0.11
Observations	1,335	1,320	1,445

Notes: The first 2 columns restricted to BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves, and the 3rd column restricted to BNLA participants aged 15 and above in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, and not looked for work in the last 12 months.

Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

Table D6: Logit marginal effects of employment transition from income support payments between year 1 and year 10

Dependent variable	Exit to work in year 10		
	Baseline	Extended	
	Age 15–59	Age 15–59	Age 15+
	(1)	(2)	(3)
Age 20–29	-0.207***	-0.207***	-0.212***
	(0.059)	(0.061)	(0.063)
Age 30–39	-0.401***	-0.397***	-0.399***
	(0.062)	(0.064)	(0.065)
Age 40–49	-0.569***	-0.574***	-0.568***
	(0.063)	(0.064)	(0.065)
Age 50–59	-0.780***	-0.772***	-0.762***
	(0.056)	(0.058)	(0.060)
Age 60 and above			-0.836***
			(0.056)
Male	0.189***	0.165***	0.147***
	(0.046)	(0.045)	(0.042)
Islam	0.051	0.044	0.041
	(0.062)	(0.064)	(0.060)
Buddhist/Hindu/other	-0.011	-0.009	0.005
	(0.079)	(0.079)	(0.072)
No religion/not important/not stated	0.057	0.030	0.025
	(0.094)	(0.096)	(0.088)
Married or has a partner	0.115*	0.123*	0.093
	(0.062)	(0.063)	(0.059)

Dependent variable	Exit to work in year 10		
	Baseline	Extended	
	Age 15–59	Age 15–59	Age 15+
	(1)	(2)	(3)
Disability or long-term health condition	-0.277***	-0.280***	-0.246***
	(0.061)	(0.062)	(0.056)
Study English	0.056	0.059	0.038
	(0.066)	(0.066)	(0.060)
Study or job training	0.134**	0.140**	0.131**
	(0.067)	(0.068)	(0.062)
Number of adults 18 years and above in the household	-0.110***	-0.099***	-0.095***
	(0.038)	(0.038)	(0.035)
Change in the number of adults 18 years and above	0.023	0.024	0.018
	(0.018)	(0.018)	(0.017)
Number of children under 18 years in the household	-0.011	-0.009	-0.005
	(0.025)	(0.026)	(0.024)
Change in the number of children under 18 years	-0.004	-0.003	-0.002
	(0.020)	(0.021)	(0.019)
Onshore arrival pathway	0.092	0.087	0.105
	(0.101)	(0.103)	(0.102)
Low/medium disadvantage area	0.218***	0.221***	0.195***
	(0.060)	(0.060)	(0.059)
Pre-arrival education: 0–12 or more years	0.005	0.005	0.004
	(0.072)	(0.074)	(0.067)
Pre-arrival education: University/Technical	-0.017	-0.010	-0.002
	(0.091)	(0.092)	(0.085)
Pre-arrival work experience	0.147***	0.139***	0.126**
	(0.053)	(0.054)	(0.050)
Mixed sources of friends	0.135***	0.132**	0.116**
	(0.051)	(0.052)	(0.048)
Looking for work in the last 12 months		0.115*	0.104
		(0.069)	(0.063)
Pearson chi-square	689.200	694.600	1251.100
Prob > chi^2	0.84	0.75	0.00
Observations	769	759	838

Notes: The first 2 columns restricted to BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves, and the 3rd column restricted to BNLA participants aged 15 and above in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. **p* < 0.10, ***p* < 0.05, ****p* < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, and not looked for work in the last 12 months.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

Results by sex

Table D7: Logit marginal effects of employment transition from income support payments between year 1 and year 5, by sex

Dependent variable	Exit to work in year 5			
	Baseline		Extended	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
Age 20–29	-0.184**	-0.121	-0.185**	-0.123
	(0.092)	(0.118)	(0.093)	(0.119)
Age 30–39	-0.319***	-0.232*	-0.320***	-0.233*
	(0.094)	(0.121)	(0.097)	(0.122)
Age 40–49	-0.412***	-0.319***	-0.413***	-0.322***
	(0.095)	(0.120)	(0.098)	(0.120)
Age 50–59	-0.621***	-0.353***	-0.619***	-0.355***
	(0.095)	(0.122)	(0.098)	(0.122)
Islam	0.199***	-0.046	0.185***	-0.041
	(0.057)	(0.040)	(0.058)	(0.040)
Buddhist/Hindu/other	0.051	0.023	0.053	0.022
	(0.071)	(0.059)	(0.071)	(0.059)
No religion/not important/not stated	0.230***	0.014	0.194**	0.014
	(0.084)	(0.093)	(0.085)	(0.093)
Married or has a partner	0.145**	0.149***	0.154**	0.154***
	(0.064)	(0.040)	(0.065)	(0.040)
Disability or long-term health condition	-0.237***	-0.064	-0.226***	-0.066
	(0.058)	(0.044)	(0.058)	(0.045)
Study English	0.171***	0.108**	0.179***	0.108**
	(0.062)	(0.043)	(0.062)	(0.043)
Study or job training	0.210***	-0.014	0.199***	-0.010
	(0.074)	(0.049)	(0.076)	(0.050)
Number of adults 18 years and above in the household	-0.042	-0.060**	-0.026	-0.057**
	(0.054)	(0.025)	(0.052)	(0.025)
Change in the number of adults 18 years and above	0.015	-0.021	0.013	-0.022
	(0.022)	(0.019)	(0.021)	(0.019)
Number of children under 18 years in the household	-0.076***	-0.010	-0.074***	-0.012
	(0.023)	(0.015)	(0.023)	(0.015)
Change in the number of children under 18 years	-0.053	-0.034*	-0.049	-0.034*
	(0.038)	(0.018)	(0.037)	(0.019)
Onshore arrival pathway	0.158**	0.028	0.138*	0.021
	(0.077)	(0.078)	(0.079)	(0.078)
Low/medium disadvantage area	0.111*	0.106**	0.116*	0.103**
	(0.063)	(0.045)	(0.064)	(0.045)
Pre-arrival education: 0–12 or more years	-0.135*	-0.072	-0.148**	-0.071
	(0.070)	(0.054)	(0.071)	(0.054)
Pre-arrival education: University/Technical	-0.232***	-0.046	-0.235***	-0.045
	(0.085)	(0.067)	(0.087)	(0.068)
Pre-arrival work experience	0.054	0.126***	0.035	0.130***
	(0.057)	(0.035)	(0.057)	(0.036)

Dependent variable	Exit to work in year 5			
	Baseline		Extended	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
Mixed sources of friends	0.068	0.025	0.052	0.028
	(0.047)	(0.035)	(0.047)	(0.035)
Looking for work in the last 12 months			0.111**	0.007
			(0.053)	(0.059)
Equality test: males vs. females	42.7		40.2	
	p=0.004		*p*=0.010	
Pearson chi-square	668.9	633.5	661.6	632.2
Prob > chi²	0.10	0.24	0.14	0.26
Observations	679	666	656	654

Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *p < 0.10, **p < 0.05, ***p < 0.01.
Reference groups: Age 15–19, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, and not looked for work in the last 12 months.

Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

Table D8: Logit marginal effects of employment transition from income support payments between year 1 and year 10, by sex

Dependent variable	Exit to work in year 10			
	Baseline		Extended	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
Age 20–29	-0.089*	-0.269**	-0.089*	-0.281**
	(0.046)	(0.122)	(0.047)	(0.121)
Age 30–39	-0.372***	-0.355***	-0.374***	-0.362***
	(0.063)	(0.123)	(0.066)	(0.122)
Age 40–49	-0.513***	-0.559***	-0.525***	-0.566***
	(0.074)	(0.114)	(0.074)	(0.112)
Age 50–59	-0.768***	-0.729***	-0.763***	-0.736***
	(0.073)	(0.109)	(0.074)	(0.108)
Islam	0.188**	-0.072	0.177**	-0.067
	(0.075)	(0.064)	(0.077)	(0.065)
Buddhist/Hindu/other	0.007	-0.049	0.010	-0.050
	(0.111)	(0.079)	(0.109)	(0.079)
No religion/not important/not stated	0.264***	-0.147*	0.246**	-0.157*
	(0.091)	(0.083)	(0.097)	(0.080)
Married or has a partner	0.287***	-0.001	0.298***	0.009
	(0.094)	(0.067)	(0.097)	(0.067)
Disability or long-term health condition	-0.274***	-0.215**	-0.276***	-0.221***
	(0.071)	(0.084)	(0.072)	(0.084)
Study English	-0.022	0.105	-0.016	0.102
	(0.090)	(0.070)	(0.091)	(0.070)
Study or job training	0.223**	0.041	0.223**	0.049

Dependent variable	Exit to work in year 10			
	Baseline		Extended	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
	(0.094)	(0.075)	(0.096)	(0.074)
Number of adults 18 years and above in the household	-0.140***	-0.086**	-0.125**	-0.086**
	(0.050)	(0.040)	(0.050)	(0.041)
Change in the number of adults 18 years and above	0.023	0.007	0.025	0.007
	(0.022)	(0.019)	(0.023)	(0.019)
Number of children under 18 years in the household	-0.040	0.007	-0.038	0.007
	(0.029)	(0.026)	(0.030)	(0.026)
Change in the number of children under 18 years	-0.015	0.002	-0.015	0.003
	(0.023)	(0.025)	(0.024)	(0.025)
Onshore arrival pathway	-0.115	0.258*	-0.093	0.227
	(0.112)	(0.150)	(0.120)	(0.151)
Low/medium disadvantage area	0.204***	0.187**	0.208***	0.188**
	(0.066)	(0.075)	(0.066)	(0.074)
Pre-arrival education: 0-12 or more years	-0.044	0.056	-0.043	0.056
	(0.087)	(0.078)	(0.090)	(0.079)
Pre-arrival education: University/Technical	-0.049	0.051	-0.047	0.058
	(0.111)	(0.103)	(0.114)	(0.104)
Pre-arrival work experience	0.165**	0.091	0.153**	0.089
	(0.075)	(0.059)	(0.078)	(0.060)
Mixed sources of friends	0.223***	0.055	0.211***	0.058
	(0.068)	(0.058)	(0.069)	(0.058)
Looking for work in the last 12 months			0.074	0.089
			(0.081)	(0.098)
Equality test: males vs. females	34.68		30.71	
	p=0.031		p=0.10	
Pearson chi-square	349.47	355.72	335.58	333.98
Prob > chi^2	0.54	0.38	0.74	0.74
Observations	389	380	380	379

Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, and not looked for work in the last 12 months.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

Robustness check

Table D9: Logit marginal effects of employment transition from income support payments between year 1 and year 5, and between year 1 and year 10, adjusted for selection effects

Dependent variable	First stage:	Second stage:			
	Unemployed/ not in the labour force in year 1	Exit to work in year 5: adjusted	Exit to work in year 5: unadjusted	Exit to work in year 10: adjusted	Exit to work in year 10: unadjusted
	(1)	(2)	(3)	(4)	(5)
Age 20–29	-0.020***	-0.237***	-0.202***	-0.219***	-0.207***
	(0.007)	(0.068)	(0.075)	(0.065)	(0.059)
Age 30–39	-0.008	-0.348***	-0.331***	-0.413***	-0.401***
	(0.006)	(0.069)	(0.075)	(0.068)	(0.062)
Age 40–49	-0.013*	-0.464***	-0.433***	-0.583***	-0.569***
	(0.007)	(0.071)	(0.074)	(0.066)	(0.063)
Age 50–59	-0.005	-0.564***	-0.545***	-0.792***	-0.780***
	(0.008)	(0.071)	(0.075)	(0.063)	(0.056)
Male	-0.025***	0.092***	0.141***	0.173***	0.189***
	(0.006)	(0.034)	(0.032)	(0.055)	(0.046)
Islam	-0.008	0.049	0.072*	0.057	0.051
	(0.006)	(0.040)	(0.038)	(0.064)	(0.062)
Buddhist/Hindu/other	0.011*	0.057	0.040	-0.009	-0.011
	(0.006)	(0.058)	(0.052)	(0.083)	(0.079)
No religion/not important/not stated	-0.002	0.143*	0.148**	0.056	0.057
	(0.008)	(0.074)	(0.071)	(0.108)	(0.094)
Married or has a partner	0.001	0.160***	0.158***	0.117*	0.115*
	(0.004)	(0.042)	(0.039)	(0.065)	(0.062)
Disability or long-term health condition	0.022***	-0.111***	-0.158***	-0.265***	-0.277***
	(0.006)	(0.038)	(0.037)	(0.065)	(0.061)
Study English	0.010**	0.163***	0.124***	0.063	0.056
	(0.004)	(0.047)	(0.040)	(0.067)	(0.066)
Study or job training		0.093**	0.088**	0.129*	0.134**
		(0.041)	(0.042)	(0.072)	(0.067)
Number of adults 18 years and above in the household		-0.056*	-0.057*	-0.108***	-0.110***
		(0.031)	(0.031)	(0.040)	(0.038)
Change in the number of adults 18 years and above		-0.003	0.005	0.024	0.023
		(0.015)	(0.015)	(0.020)	(0.018)
Number of children under 18 years in the household	0.005*	-0.036**	-0.047***	-0.011	-0.011
	(0.003)	(0.017)	(0.016)	(0.027)	(0.025)
Change in the number of children under 18 years		-0.040*	-0.050**	-0.003	-0.004
		(0.021)	(0.020)	(0.021)	(0.020)
Onshore arrival pathway	-0.061***	-0.030	0.149**	0.039	0.092
	(0.021)	(0.076)	(0.063)	(0.141)	(0.101)
Low/medium disadvantage area		0.125***	0.108**	0.219***	0.218***
		(0.048)	(0.044)	(0.064)	(0.060)

Dependent variable	First stage:	Second stage:			
	Unemployed/ not in the labour force in year 1	Exit to work in year 5: adjusted	Exit to work in year 5: unadjusted	Exit to work in year 10: adjusted	Exit to work in year 10: unadjusted
	(1)	(2)	(3)	(4)	(5)
Pre-arrival education: 0–12 or more years		-0.098**	-0.102**	0.009	0.005
		(0.050)	(0.047)	(0.078)	(0.072)
Pre-arrival education: University/ Technical		-0.131**	-0.140**	0.001	-0.017
		(0.063)	(0.057)	(0.097)	(0.091)
Pre-arrival work experience	-0.011**	0.089**	0.102***	0.138**	0.147***
	(0.005)	(0.035)	(0.034)	(0.056)	(0.053)
Mixed sources of friends		0.044	0.044	0.135**	0.135***
		(0.033)	(0.031)	(0.056)	(0.051)
Inverse Mills ratio		1.234***		0.320	
		(0.366)		(0.691)	
Driver licence	-0.010**				
	(0.004)				
Major city	0.029***				
	(0.008)				
Pearson chi-square	1,490.200	1,287.900	1,300.300	690.800	689.200
Prob > chi²	0.00	0.40	0.18	0.84	0.84
Observations	1,999	1,331	1,335	766	769

Notes: The 'unadjusted column' retains the baseline estimates (column 1) in Tables D3 and D4. BNLA participants aged 15-59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and are clustered by MU. In the second stage, standard errors were estimated based on 500 bootstrap replications. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, no driver licence and regional areas.

Source: BNLA Waves 1 (Year 1: 2013–14), 5 (Year 5: 2017–18) and 6 (Year 10: 2023)

Table D10: Logit marginal effects of employment transition from income support payments between year 1 and year 5, adjusted for attrition bias

Dependent variable	Retention effect estimates	Exit to work in year 5	
		Baseline	
		Adjusted	Unadjusted
	(1)	(2)	(3)
Age 20–29	0.049	-0.197***	-0.202***
	(0.041)	(0.076)	(0.075)
Age 30–39	0.074*	-0.318***	-0.331***
	(0.043)	(0.078)	(0.075)
Age 40–49	0.132***	-0.407***	-0.433***
	(0.044)	(0.077)	(0.074)
Age 50–59	0.056	-0.549***	-0.545***
	(0.049)	(0.077)	(0.075)
Male	0.001	0.146***	0.141***
	(0.016)	(0.032)	(0.032)

Dependent variable	Retention effect estimates	Exit to work in year 5	
		Baseline	
		Adjusted	Unadjusted
	(1)	(2)	(3)
Islam	-0.025	0.078**	0.072*
	(0.021)	(0.038)	(0.038)
Buddhist/Hindu/other	0.007	0.055	0.040
	(0.027)	(0.055)	(0.052)
No religion/not important/not stated	-0.079**	0.120*	0.148**
	(0.036)	(0.071)	(0.071)
Married or has a partner	0.043**	0.169***	0.158***
	(0.019)	(0.039)	(0.039)
Disability or long-term health condition	-0.014	-0.158***	-0.158***
	(0.020)	(0.039)	(0.037)
Study English	-0.005	0.116***	0.124***
	(0.019)	(0.041)	(0.040)
Study or job training	0.000	0.079*	0.088**
	(0.021)	(0.045)	(0.042)
Number of adults 18 years and above in the household	0.013	-0.046	-0.057*
	(0.012)	(0.030)	(0.031)
Change in the number of adults 18 years and above in the household	-0.058***	-0.009	0.005
	(0.009)	(0.019)	(0.015)
Number of children under 18 years in the household	0.041***	-0.042**	-0.047***
	(0.009)	(0.017)	(0.016)
Change in the number of children under 18 years in the household	-0.122***	-0.064***	-0.050**
	(0.012)	(0.021)	(0.020)
Onshore arrival pathway	-0.090***	0.119*	0.149**
	(0.033)	(0.067)	(0.063)
Low/medium disadvantage area	-0.006	0.105**	0.108**
	(0.021)	(0.044)	(0.044)
Pre-arrival education: 0–12 or more years	0.025	-0.091**	-0.102**
	(0.026)	(0.046)	(0.047)
Pre-arrival education: University/Technical	-0.016	-0.134**	-0.140**
	(0.033)	(0.054)	(0.057)
Pre-arrival work experience	-0.020	0.093***	0.102***
	(0.018)	(0.036)	(0.034)
Mixed sources of friends	-0.025	0.038	0.044
	(0.017)	(0.033)	(0.031)
CAPI with interviewer	0.034**		
	(0.017)		
CAPI with interpreter	-0.202**		
	(0.103)		

Dependent variable	Retention effect estimates	Exit to work in year 5	
		Baseline	
		Adjusted	Unadjusted
	(1)	(2)	(3)
English mode	-0.053**		
	(0.024)		
Inverse Mills ratio		0.229	
		(0.159)	
Observations	1,931	1,322	1,335

Notes: The 'unadjusted column' retains the baseline estimates (column 1) in Table D3. BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and are clustered by MU. In the second stage, standard errors were estimated based on 500 bootstrap replications. **p* < 0.10, ***p* < 0.05, ****p* < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, CASI, and non-English mode.

Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

Table D11: Logit marginal effects of employment transition from income support payments between year 1 and year 10, adjusted for attrition

Dependent variable	Retention effect estimates	Exit to work in year 10	
		Baseline	
		Adjusted	Unadjusted
	(1)	(2)	(3)
Age 20–29	-0.063	-0.206***	-0.207***
	(0.061)	(0.060)	(0.059)
Age 30–39	-0.029	-0.401***	-0.401***
	(0.061)	(0.063)	(0.062)
Age 40–49	0.090	-0.572***	-0.569***
	(0.061)	(0.071)	(0.063)
Age 50–59	0.073	-0.781***	-0.780***
	(0.069)	(0.061)	(0.056)
Male	0.017	0.189***	0.189***
	(0.029)	(0.050)	(0.046)
Islam	-0.073**	0.053	0.051
	(0.037)	(0.069)	(0.062)
Buddhist/Hindu/other	0.010	-0.012	-0.011
	(0.050)	(0.083)	(0.079)
No religion/not important/not stated	-0.085	0.062	0.057
	(0.057)	(0.105)	(0.094)
Married or has a partner	0.007	0.111*	0.115*
	(0.031)	(0.067)	(0.062)
Disability or long-term health condition	-0.038	-0.275***	-0.277***
	(0.031)	(0.068)	(0.061)
Study English	0.016	0.054	0.056
	(0.034)	(0.068)	(0.066)
Study or job training	0.039	0.133*	0.134**
	(0.037)	(0.070)	(0.067)

Dependent variable	Retention effect estimates	Exit to work in year 10	
		Baseline	
		Adjusted	Unadjusted
	(1)	(2)	(3)
Number of adults 18 years and above in the household	0.172***	-0.111***	-0.110***
	(0.040)	(0.043)	(0.038)
Change in the number of adults 18 years and above in the household	-0.398***	0.034	0.023
	(0.029)	(0.037)	(0.018)
Number of children under 18 years in the household	0.075***	-0.013	-0.011
	(0.019)	(0.026)	(0.025)
Change in the number of children under 18 years in the household	-0.044***	-0.003	-0.004
	(0.017)	(0.021)	(0.020)
Onshore arrival pathway	-0.073*	0.096	0.092
	(0.042)	(0.119)	(0.101)
Low/medium disadvantage area	-0.005	0.218***	0.218***
	(0.035)	(0.065)	(0.060)
Pre-arrival education: 0–12 or more years	0.019	0.004	0.005
	(0.044)	(0.074)	(0.072)
Pre-arrival education: University/Technical	0.036	-0.019	-0.017
	(0.053)	(0.097)	(0.091)
Pre-arrival work experience	-0.016	0.147**	0.147***
	(0.032)	(0.058)	(0.053)
Mixed sources of friends	-0.039	0.136**	0.135***
	(0.029)	(0.056)	(0.051)
CAPI with interviewer	0.009		
	(0.031)		
CAPI with interpreter	-0.174**		
	(0.082)		
English mode			
Inverse Mills ratio		-0.064	
		(0.181)	
Observations	1,960	769	769

Notes: The ‘unadjusted column’ retains the baseline estimates (column 1) in Table D4. BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and are clustered by MU. In the second stage, standard errors were estimated based on 500 bootstrap replications. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, no pre-arrival work experience, no friends or mostly from own ethnic/religious community, CASI, and non-English mode.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

Extended analyses: alternative approaches

Table D12: Logit marginal effects of employment transition from income support payments at different times

Dependent variable	Exit to work in years 5 and 6	Exit to work in year 5 or 6
	(1)	(2)
Age 20–29	-0.369***	-0.195***
	(0.093)	(0.042)
Age 30–39	-0.650***	-0.373***
	(0.073)	(0.045)
Age 40–49	-0.845***	-0.558***
	(0.056)	(0.050)
Age 50–59	-0.907***	-0.785***
	(0.052)	(0.056)
Male	0.186***	0.160***
	(0.050)	(0.045)
Islam	0.056	0.120**
	(0.069)	(0.061)
Buddhist/Hindu/other	0.047	0.029
	(0.096)	(0.082)
No religion/not important/not stated	0.050	0.059
	(0.109)	(0.100)
Married or has a partner	0.150**	0.182***
	(0.065)	(0.063)
Disability or long-term health condition	-0.306***	-0.224***
	(0.068)	(0.059)
Study English	0.152**	0.128*
	(0.071)	(0.066)
Study or job training	0.223***	0.207***
	(0.068)	(0.069)
Number of adults 18 yrs and above in the household	-0.103**	-0.106**
	(0.051)	(0.044)
Change in the number of adults between years 1 and 5	0.041*	0.006
	(0.023)	(0.022)
Change in the number of adults between years 1 and 10	0.009	0.024
	(0.025)	(0.024)
Number of children under 18 yrs in the household	-0.007	-0.031
	(0.027)	(0.027)
Change in the number of children between years 1 and 5	-0.067**	-0.042
	(0.032)	(0.031)
Change in the number of children between years 1 and 10	0.033	0.006
	(0.022)	(0.022)
Onshore arrival pathway	0.020	0.084
	(0.110)	(0.102)
Low/medium disadvantage area	0.267***	0.188***
	(0.085)	(0.056)
Pre-arrival education: 0–12 or more yrs	-0.102	0.000

Dependent variable	Exit to work in years 5 and 6	Exit to work in year 5 or 6
	(1)	(2)
	(0.094)	(0.072)
Pre-arrival education: University/Technical	-0.125	0.003
	(0.104)	(0.090)
Pre-arrival work experience	0.196***	0.169***
	(0.060)	(0.054)
Mixed sources of friends	0.115**	0.072
	(0.055)	(0.050)
Pearson chi-square		
Prob > chi²		
Observations	502	743

Notes: BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, and no pre-arrival work experience, and no friends or mostly from own ethnic/religious community.

Source: BNLA Waves 1 (Year 1: 2013–14), 5 (Year 5: 2017–18) and 6 (Year 10: 2023)

Table D13: Employment status by main income source over time

	Income support payments (%)	Wages/other (%)	All (%)
Year 1			
Labour force status			
Employed	2.0	47.0	7.0
Unemployed	16.0	12.0	16.0
Not in the labour force	82.0	41.0	77.0
Total	1,953	229	2,182
Year 5			
Labour force status			
Employed	11.0	70.0	36.0
Unemployed	15.0	8.0	12.0
Not in the labour force	74.0	23.0	52.0
Desire for a job			
No/unsure	59.0	52.0	58.0
Yes	41.0	48.0	42.0
Total	1,060	637	1,697
Year 10			
Labour force status			
Employed	8.0	75.0	44.0
Unemployed	7.0	6.0	7.0
Not in the labour force	84.0	19.0	49.0
Desire for a job			
No/unsure	68.0	54.0	64.0
Yes	32.0	46.0	36.0
Total	**474**	**499**	**973**

Notes: Weighted proportions and cross-sectional weights were applied to BNLA data. BNLA participants aged 15-59 in Wave 1 and those also surveyed in subsequent waves. 'Desire for a job' was not reported in Wave 1.

Source: BNLA Wave 1 (Year 1: 2013-14), 5 (Year 5: 2017-18) and 6 (Year 10: 2023)

Table D14: Multinomial Logit marginal effects of income support payments-employment status, year 1

	Unemployed and recipients	NILF and recipients	Employed and recipients/not recipients
	(1)	(2)	(3)
Age 20–29	-0.049	-0.012	0.061***
	(0.038)	(0.039)	(0.019)
Age 30–39	-0.056	0.033	0.023
	(0.040)	(0.041)	(0.019)
Age 40–49	-0.081*	0.049	0.032
	(0.042)	(0.043)	(0.023)
Age 50–59	-0.144***	0.123***	0.021
	(0.043)	(0.044)	(0.026)
Male	0.121***	-0.179***	0.058***
	(0.022)	(0.020)	(0.016)
Islam	0.084***	-0.108***	0.023
	(0.022)	(0.023)	(0.016)
Buddhist/Hindu/other	-0.037	0.065**	-0.029
	(0.024)	(0.027)	(0.019)
No religion/not important/not stated	0.078**	-0.094***	0.016
	(0.033)	(0.035)	(0.020)
Married or has a partner	0.007	-0.010	0.004
	(0.019)	(0.020)	(0.014)
Disability or long-term health condition	0.035*	0.023	-0.058***
	(0.020)	(0.021)	(0.017)
Study English	-0.001	0.034*	-0.033***
	(0.020)	(0.020)	(0.011)
Study or job training	0.025	-0.039*	0.014
	(0.021)	(0.023)	(0.014)
Number of adults 18 years and above in the household	-0.014	0.038**	-0.024
	(0.016)	(0.017)	(0.016)
Number of children under 18 years in the household	-0.018*	0.024**	-0.006
	(0.010)	(0.010)	(0.008)
Onshore arrival pathway	0.022	-0.110***	0.089***
	(0.025)	(0.029)	(0.021)
Low/medium disadvantage area	0.025	-0.037*	0.012
	(0.020)	(0.021)	(0.013)
Pre-arrival education: 0–12 or more years	0.011	-0.005	-0.006
	(0.024)	(0.025)	(0.019)
Pre-arrival education: University/Technical	0.041	-0.044	0.003
	(0.029)	(0.031)	(0.022)
Pre-arrival work experience	0.054**	-0.087***	0.033**
	(0.021)	(0.020)	(0.014)

	Unemployed and recipients	NILF and recipients	Employed and recipients/not recipients
	(1)	(2)	(3)
Mixed sources of friends	0.048***	-0.059***	0.010
	(0.017)	(0.017)	(0.011)
Observations	1,849	1,849	1,849

Notes: NILF = not in the labour force. BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, and no pre-arrival work experience, and no friends or mostly from own ethnic/religious community.
Source: BNLA Wave 1 (Year 1: 2013–14)

Table D15: Multinomial Logit marginal effects of income support payments-employment status, year 5

	Unemployed and recipients	NILF and recipients	Employed and recipients/not recipients
	(1)	(2)	(3)
Age 20–29	0.023	0.145***	-0.167***
	(0.033)	(0.054)	(0.059)
Age 30–39	0.004	0.238***	-0.243***
	(0.033)	(0.056)	(0.061)
Age 40–49	0.038	0.287***	-0.325***
	(0.037)	(0.058)	(0.063)
Age 50–59	0.003	0.466***	-0.469***
	(0.038)	(0.061)	(0.065)
Male	0.007	-0.234***	0.227***
	(0.017)	(0.022)	(0.023)
Islam	0.022	-0.029	0.007
	(0.021)	(0.031)	(0.029)
Buddhist/Hindu/other	-0.016	-0.018	0.034
	(0.023)	(0.039)	(0.038)
No religion/not important/not stated	0.097**	-0.179***	0.082
	(0.045)	(0.053)	(0.052)
Married or has a partner	-0.068***	-0.018	0.086***
	(0.019)	(0.028)	(0.029)
Disability or long-term health condition	0.034*	0.103***	-0.138***
	(0.020)	(0.028)	(0.029)
Study English	0.007	-0.116***	0.109***
	(0.024)	(0.029)	(0.029)
Study or job training	-0.045*	-0.033	0.079***
	(0.027)	(0.034)	(0.030)
Number of adults 18 years and above in the household	-0.006	0.052***	-0.045**
	(0.012)	(0.018)	(0.021)
Change in the number of adults 18 years and above between years 1 and 5	-0.019**	-0.004	0.024**
	(0.009)	(0.011)	(0.011)

	Unemployed and recipients	NILF and recipients	Employed and recipients/not recipients
	(1)	(2)	(3)
Number of children under 18 years in the household	0.010	0.012	-0.021**
	(0.007)	(0.011)	(0.010)
Change in the number of children under 18 years between years 1 and 5	0.008	0.028*	-0.035**
	(0.009)	(0.014)	(0.014)
Onshore arrival pathway	-0.042*	-0.064	0.106**
	(0.025)	(0.046)	(0.043)
Low/medium disadvantage area	0.011	-0.079**	0.067**
	(0.022)	(0.031)	(0.030)
Pre-arrival education: 0-12 or more years	0.073***	-0.071**	-0.003
	(0.018)	(0.033)	(0.031)
Pre-arrival education: University/Technical	0.089***	-0.064	-0.024
	(0.028)	(0.043)	(0.039)
Pre-arrival work experience	-0.008	-0.122***	0.130***
	(0.018)	(0.026)	(0.026)
Mixed sources of friends	0.022	-0.079***	0.057**
	(0.018)	(0.025)	(0.024)
Observations	1,331	1,331	1,331

Notes: NILF = not in the labour force. BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *p < 0.10, **p < 0.05, ***p < 0.01. Reference groups: Age 15–19, female, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, and no pre-arrival work experience.

Source: BNLA Waves 1 (Year 1: 2013–14) and 5 (Year 5: 2017–18)

Table D16: Multinomial Logit marginal effects of income support payments-employment status, year 10

	Unemployed and recipients	NILF and recipients	Employed and recipients/not recipients
	(1)	(2)	(3)
Age 20–29	-0.009	0.147**	-0.138**
	(0.036)	(0.064)	(0.064)
Age 30–39	-0.007	0.271***	-0.264***
	(0.038)	(0.068)	(0.066)
Age 40–49	0.007	0.351***	-0.358***
	(0.041)	(0.070)	(0.070)
Age 50–59	0.065	0.569***	-0.634***
	(0.055)	(0.076)	(0.069)
Male	-0.017	-0.140***	0.158***
	(0.020)	(0.030)	(0.028)
Islam	-0.019	0.019	0.000
	(0.021)	(0.044)	(0.043)
Buddhist/Hindu/other	-0.035*	0.007	0.028
	(0.021)	(0.053)	(0.053)
No religion/not important/not stated	-0.011	-0.023	0.034

	Unemployed and recipients	NILF and recipients	Employed and recipients/not recipients
	(1)	(2)	(3)
	(0.032)	(0.062)	(0.055)
Married or has a partner	-0.018	-0.051	0.068*
	(0.018)	(0.041)	(0.039)
Disability or long-term health condition	-0.001	0.206***	-0.205***
	(0.019)	(0.039)	(0.039)
Study English	0.021	-0.043	0.023
	(0.024)	(0.040)	(0.040)
Study or job training	-0.006	-0.058	0.064
	(0.025)	(0.044)	(0.042)
Number of adults 18 years and above in the household	-0.016	0.067**	-0.051*
	(0.013)	(0.026)	(0.027)
Change in the number of adults 18 years and above between years 1 and 10	0.001	-0.020	0.019
	(0.007)	(0.013)	(0.013)
Number of children under 18 years in the household	-0.006	0.010	-0.005
	(0.009)	(0.016)	(0.016)
Change in the number of children under 18 years between years 1 and 10	-0.000	0.018	-0.018
	(0.007)	(0.012)	(0.012)
Onshore arrival pathway	0.016	-0.115*	0.099
	(0.048)	(0.066)	(0.060)
Low/medium disadvantage area	-0.018	-0.093**	0.111***
	(0.019)	(0.043)	(0.043)
Pre-arrival education: 0–12 or more years	-0.011	-0.066	0.077*
	(0.029)	(0.048)	(0.046)
Pre-arrival education: University/Technical	-0.003	-0.100	0.102*
	(0.038)	(0.062)	(0.060)
Pre-arrival work experience	-0.024	-0.152***	0.176***
	(0.018)	(0.034)	(0.033)
Mixed sources of friends	0.010	-0.111***	0.101***
	(0.016)	(0.032)	(0.032)
Observations	734	734	734

Notes: NILF = not in the labour force. BNLA participants aged 15–59 in Wave 1 and those also surveyed in subsequent waves. Values are marginal effects estimated from logistic regression models. Standard errors are in parentheses and clustered by MU. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Reference groups: Age 15–19, female, Christian, not married/no partner, no disability, never studied English, not undertaken other study or job training, offshore arrival pathway, high disadvantage area, pre-arrival education: no formal education, and no pre-arrival work experience, and no friends or mostly from own ethnic/religious community.

Source: BNLA Waves 1 (Year 1: 2013–14) and 6 (Year 10: 2023)

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