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Does Host Language Proficiency Among Immigrants Reduce Energy Poverty? Evidence from Australia

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Abstract

Reducing energy poverty is a critical priority for policymakers in both developed and developing nations. Immigrants are often considered a high-risk group due to their heightened vulnerability. While host language proficiency has the potential to mitigate energy poverty among immigrants by enhancing economic integration and facilitating access to essential information and services, its role remains largely unexplored. Using Australian data and addressing endogeneity concerns through a two-stage least-squares (2SLS) approach, this paper provides the first empirical evidence on the causal relationship between host language proficiency and energy poverty among immigrants. The results show that proficiency in the host language reduces the likelihood of experiencing multidimensional energy poverty by approximately 18.8 percentage points. This effect is partly driven by better access to social assistance, higher income and, to a lesser extent, stronger social capital among proficient immigrants. The findings underscore the importance of language skills in shaping energy poverty and highlight the need for language education to reduce economic disparities among immigrant populations.

JEL classification: F22, I31, C36

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1. Introduction

Lowering the share of energy-deprived households has become a priority for governments and institutions (IEA, 2023). Climate change and the upsurge of energy prices in 2021 and, especially, after the onset of the Ukrainian war have triggered interest in the topic in policy makers' agendas. Energy poverty is an issue that not only affects developing countries but also a serious concern in developed ones, insofar as households depend on energy in various forms to ensure adequate living conditions (Bonatz et al., 2019). In the economic literature, the concept of energy poverty has acquired its own status and is being studied as a stand-alone subject. This is because energy poverty is only moderately correlated with income poverty and yet negatively related to relevant economic outcomes, including self-perceived social status, productivity, health, and mortality (Lin and Okyere, 2021; Pondie et al., 2024).

International analyses systematically show that in developed countries foreign-born individuals tend to be poorer than native-born individuals across the entire wealth and income distribution (Ferrari, 2020). While some studies have explored how these differences translate into energy access and use, there is still a dearth of research regarding the determinants of energy poverty among the immigrant population. Neither housing conditions, energy financial burdens, nor income itself explain a substantial proportion of the association between ethnic origin and energy poverty (Wang et al., 2021, Iceland, 2021). Consequently, an important question arises: why is energy poverty disproportionately prevalent among certain immigrant groups? Addressing this question presents an intriguing challenge, as it has significant implications for designing policies that target economic inequalities among the immigrant population.

This paper examines an unexplored potential driver of energy poverty among immigrants: host language proficiency. While language skills can help alleviate energy poverty by enhancing immigrants' economic integration and access to essential information and services, the extent to which language proficiency influences energy poverty remains largely unexplored. Nevertheless, the host country's dominant language has been widely recognized as a crucial factor in immigrant assimilation and convergence to national living standards. Proficient immigrants are in a better position to obtain information about economic opportunities and transmit valuable information about their skills and background to employers. This notion has been supported by an array of empirical studies, which show that language proficiency is closely associated with labour market outcomes (Budría and Martínez-de-Ibarreta, 2021; Di Paolo and Mallén, 2023, Schmid, 2023). Moreover, language proficiency and social interaction with nationals are critical for immigrants' affinity with the host country's customs and social norms, enhancing educational achievement (Aoki and Santiago, 2018) and social integration (Tam and Page, 2016). In addition to income and labor market outcomes, social identity theory suggests that immigrants may feel a need to adapt their behaviors and values to foster a sense of belonging among the majority group and secure economic success within a new culture (Burke and Stets, 2009). Increased language acculturation leads to faster convergence to national standards in terms of life stability and habits (Okafor et al., 2013). Consequently, the association between host language proficiency and energy poverty may reflect the adoption of host-country values and practices centred on household preferences and consumption patterns. Moreover, poor proficiency in the host language may interfere with public services literacy and whether immigrants notice, seek out, and access local and regional information. Language barriers have been highlighted as a major constraint preventing immigrants from taking advantage of government policies and services (Pandey et al., 2020). Similarly, host language skills are expected to foster the creation of cultural bridges, communication networks, and outside opportunities (Lancee, 2010). In this context, proficient immigrants may benefit from better networks of support and consequently be less likely to suffer energy deprivation.

Using the 2007-2020 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a micro panel survey representative of the Australian population, we provide first estimates of the impact of English language proficiency on a battery of immigrants' household-level poverty indicators. The study contributes to the existing literature in three significant ways. Firstly, it enhances our understanding of the primary drivers of poverty. Although the few studies that have incorporated ethnic origin and culture as a determinant of energy poverty have observed significant differences among groups (Chaudhry and Shafiullah 2021; Wang et al., 2021; Teschner et al., 2024) the role of host language proficiency has not been researched. Our findings indicate that host language proficiency is a major determinant of energy poverty among immigrants, with an estimated effect of about -18.8 percentage points (pp) on the likelihood of energy poverty, though this impact differs among indicators. Secondly, the study extends previous research on the importance of language skills for the economic performance of immigrants by focussing on a yet unexplored domain, energy poverty. Moreover, the study is one the few to unveil the link between language proficiency and household-level outcomes. Thirdly, we investigate potential transmission mechanisms to empirically explore if income and networks of social and financial support can explain why proficient immigrants are less likely to experience energy poverty than non-proficient ones. We provide evidence that a significant portion of the language effect can be attributed to enhanced access to social assistance programs, higher income and, to a lesser extent, stronger social capital among proficient immigrants. This knowledge is expected to increase public awareness of the multifaceted determinants of energy poverty and aid policymakers in designing policies to promote convergence with national standards among the foreign population in Australia.

Australia provides an interesting case study for the question under investigation. It stands as a significant migrant-receiving nation, with approximately 29.1% of its population (7.5 million people) being born overseas, ranking it 9th globally in terms of total immigrant population (ABS, 2022a). Furthermore, Australia has prioritized the adoption of the host country's 'way of life' as a central tenet of its immigration policy. The policy shift in 1995, which elevated the English language proficiency requirement within its points-based system, underscores the implicit recognition of the importance of integration upon immigrants' arrival in Australia.[1] Against this backdrop, it becomes imperative to examine the link between assimilation and immigrants' economic outcomes across dimensions beyond the labor market. Moreover, between 2012 and 2023, electricity and gas prices in Australia exhibited a sustained upward trend, as shown by detailed sectoral data from the Australian Bureau of Statistics (ABS, 2025). Throughout most of this period, energy prices rose faster than the overall Consumer Price Index, with an accumulated increase of approximately 46% in gas prices and 12.1% in electricity prices. Recently, the war in Ukraine and the threat of an energy supply cut-off from Russia has led to record price increases in fossil fuels. The significantly larger increase in energy prices relative to household income has raised the household budget share devoted to energy expenditure and led to a prevalence of problems related to energy access and affordability (ABS, 2022b). Although our time span does not cover these latest developments, 2007–2020 period covered in this paper captures a phase of structurally high energy costs, providing a relevant backdrop for our analysis.

Methodologically, the paper presents several features. Firstly, the econometric strategy follows a two-stage-least-squares (2SLS) approach that tackles three of the main problems of identification in this kind of analysis: the endogeneity of language skills, reverse causality issues, and measurement error bias. Our instrument is à la Bleakley and Chin (2004) as it is based on the strong empirical association between immigrants' age at arrival to the host country

[1] We refer the reader to Derby et al. (2020) for a more comprehensive exploration of immigrant assimilation trends and policies in Australia.

and language proficiency. Individuals with a non-English-speaking background (NESB), that is, those coming from a non-English-speaking country, are expected to have a poorer command of English in adulthood than individuals from English-speaking countries (ESB), even though early age at arrival in the host country can compensate for this initial disadvantage. Because the language effects of early arrival only apply to immigrants whose first language is not English, the interaction between age at arrival and being an NESB immigrant is a relevant instrument. Secondly, much effort is often spent in empirical work to convincingly argue for the validity of instruments when estimating 2SLS. Nonetheless, the validity of the exclusion restriction is often questioned. To address this issue, we implement a Union of Confidence Intervals (UCI) approach that considers local violations of the exclusion restriction. By comparing the UCI estimates with the baseline 2SLS results, we can gauge the robustness of the results to changes in the degree of instrument validity (Van Kippersluis and Rietveld, 2018). We complement this analysis with a zero-first-stage (ZFS) test that provides evidence in favour of instrument validity. Thirdly, we limit the extent of omitted variable bias by controlling for potential NESB-ESB differences in terms of educational quality, individual background, parental socioeconomic status, household composition and household financial stress. Fourthly, we re-estimate the models under an alternative instrument, the linguistic distance between English and the immigrants' first language. By simultaneously considering two distinct sets of information, we assess the robustness of the results to changes in the exclusion restriction used for identification.

The rest of the paper is organised as follows. Section 2 reviews the existing literature. Section 3 describes the dataset and the measurement of energy poverty and language proficiency. Section 4 introduces the econometric approach and the chosen instrument. Section 5 presents the results by energy poverty indicator and reports plausibly exogenous estimates. Section 6 includes a large battery of robustness checks. Section 7 outlines and tests for potential transmission mechanisms running from language proficiency to energy poverty. Section 8 presents the concluding remarks.

2. Literature review

We briefly review the research on two topics: firstly, the effects of host language proficiency on economic outcomes among immigrants and, secondly, the determinants of energy poverty. At the end of the section, we outline two conclusions that serve to contextualize the present paper.

2.1 Language effects among immigrants

Economists have been curious to explore the link between host language proficiency among immigrants and various socio-economic, particularly labour-related, outcomes. This interest arises from the understanding that language proficiency can function as a buffering factor, breaking down barriers, fostering communication networks, and facilitating external opportunities. A substantial portion of this dynamic occurs within the labor market, where proficiency in the host language is linked to several positive outcomes, including increased earnings (Di Paolo and Mallén, 2023) and higher employment rates (Budría et al., 2019; Schmid, 2023). Beyond the labor market, language proficiency plays a significant role in shaping various individual outcomes, including marriage and fertility (Bleakley and Chin, 2010) and educational achievements (Aoki and Santiago, 2018). Furthermore, the prevalence and mastery of host language skills among immigrants are often regarded as indicators of social integration, triggering acculturation—the adoption of cultural patterns, behaviors, values, and norms from the native culture. Research conducted in Australia not only strongly supports the significant impact of language proficiency on labor market outcomes (To et al., 2017; Budría and Martínez-de-Ibarreta, 2021) but also hints at a notable association between language skills and various aspects of life. This includes age at first marriage, choice of partners, social interactions, and health (Guven and Islam, 2015; Tam and Page, 2016; Clarke and Isphording, 2017).

Identifying the effects of languages on socioeconomic outcomes is inherently difficult because of the endogeneity of language skills. Language abilities are often correlated with other attributes that cannot be measured, such as innate ability, the culture of the country of origin, or the motivation to learn a new language. The literature has tackled this issue through an instrumental variables strategy, originally introduced by Bleakley and Chin (2004). This approach makes use of the age at arrival of immigrants, aligning with the critical period hypothesis, which posits that there is a crucial age range during which individuals acquire languages more easily. Because the language effects of early arrival only apply to immigrants whose first language is not English, the interaction between age at arrival and being an NESB immigrant is a relevant instrument. Most of the aforementioned studies make use of this approach, although using language distance as an alternative instrument has been also successful used in the literature (Clarke and Isphording, 2017). The results do not differ significantly between the two approaches (Budría and Martínez-de-Ibarreta, 2021).

2.2 Energy poverty

Energy poverty can be defined as a household's inability to afford or access energy services needed to support adequate living conditions and human development. While translating into practice conceptual definitions of energy poverty is typically a challenge and has been the object of extensive discussion in the literature, the focus has generally been put on the inability of households to afford and have access to adequate energy services.

The literature typically distinguishes between objective (expenditure-based) and subjective (self-assessed) approaches. Because poorer households often spend higher proportions of their budget on energy-related expenses relative to higher-income households (Boardman, 1991), expenditure-based measures label a household as energy poor when the income that households spend on energy is above a specific threshold. For instance, a household may be classified as energy poor if i) its share of income spent on energy is greater than twice the national median (the *2M* indicator), ii) its share of income spent on energy exceeds 10% (the Ten Percent Rule, *TPR*), or iii) its actual energy expenditures are above the national median and, at the same time, their income net of energy costs is below the official national income poverty line (the Low Income High Costs indicator, *LIHC*). These criteria have been validated by a myriad of papers (Churchill and Smyth, 2020; Farrell and Fry, 2021, among many others).

However, while expenditure-based measures are objective and transparent, they may overlook intentional reduction in energy consumption by low-income households. If vulnerable households limit their energy consumption to prioritise other services and goods, measures based on the actual energy costs may underestimate the true prevalence of energy poverty. Moreover, low-income families can resort to energy credits and repayments to smooth their monthly energy costs over time. In this case, a low monthly energy budget may hide a chronic energy deprivation status. To overcome these limitations, applied research has relied on individuals' self-evaluations of their ability to afford and access specific energy services (Prakash et al., 2022). Following this criterion, several multidimensional energy poverty indexes have been proposed, gathering information related to basic energy services, including cooking, lighting and household appliances (Nussbaumer et al., 2012).

Using international comparable data, recent research shows that country-level factors, namely economic development, income inequality and, to a lower extent, climate conditions are also relevant determinants of household-level energy poverty (Igawa and Managi, 2022). Within countries, the causes of energy poverty are multifaceted and arise from a combination of factors, including income deprivation, high energy prices, inefficient buildings, and family needs (European Commission, 2021). Due to data availability, most studies have focused on the role of financial hardship and energy prices, showing that income constraints, coupled with high energy prices, can culminate in the difficulty to pay bills, energy debt, and even the disconnection of energy supplies (Best and Burke, 2019). Still, a recent body of literature has examined the role of other individual and household characteristics. Thus, for instance, educational achievement is negatively associated with energy poverty, mainly due to energy saving practices and a better economic situation, while households living in rural areas, single parent families, and households with dependents are also more likely to report energy deprivation due to more stringent energy consumption needs (Alem and Demeke, 2020). Furthermore, poor health conditions can hinder access to energy services and goods, altering spending priorities and consumption patterns. Energy poverty may also be influenced by issues such as cultural characteristics and parental behavior (Prakash et al., 2022).

All in all, two notable findings from these studies stand out. Firstly, in all cases, the reported effects don't operate only through the income channel, emphasizing the need to separate income poverty from energy poverty. Secondly, language effects tend to persist even after accounting for earnings, income, and education, suggesting substantial non-market returns to language skills. Despite these advancements, there is still limited understanding of how language skills relate to other economic outcomes, such as the topical issue of energy poverty.

3. Data and measures

The HILDA dataset is Australia's nationally representative household survey. With a yearly structure, each wave covers approximately 8,000 households drawn from 13 regions of the country and includes approximately 20,000 individuals. The study is based on the 2007-2020 waves of the survey. Immigrants account for about 26.2% of the sample, which comes close to its census counterpart (27.8%).[2] After retaining only immigrants and dropping observations with item non-response, the estimation sample includes 34,666 observations from 5,295 individuals across 14 years.

3.1 Energy poverty

We adopt six energy poverty measures reflecting objective (expenditure-based) and subjective (self-assessed) approaches. The objective indicators are based on the criteria outlined in Section 2.2, and include the *2M*, the *TPR*, and the *LIHC* indicators. While these three measures are used simultaneously in the paper to capture different dimensions of energy poverty, the *LIHC* indicator provides more refined information because it considers both energy costs and the relative income status of households. All energy expenditures and income variables used in the

[2] We took yearly data from the Australian Bureau of Statistics (ABS, 2022a) and calculated the yearly average for the period considered in this study, 2007-2020.

paper are transformed using the OECD equivalence scale and normalized into real terms using the yearly consumer price index.

Apart from the expenditure-based measures, we also consider two self-assessed indicators based on the household's inability to pay to heat their home because of a shortage of money (*Heat*) and pay electricity, gas, or telephone bills on time (*Arrears*). While the former indicator does not consider other energy needs such as cooling, lighting, and household appliances, the latter includes telephone bills. Despite these limitations, individuals' perceptions about energy burdens and thermal comfort provide valuable information on the household's ability to fulfil energy needs.

3.2 A multidimensional index of energy poverty

The sixth indicator used in the paper is a composite measure of energy poverty. Let *J* be a set of poverty indicators with element $j, j \in J, m = card(J)$. Let *I* be a set of individuals, with element i, $i \in I$, and EP_{ij} denote the status of the *i*th individual in the *j*th indicator. If an individual *i* is poor under indicator *j*, then EP_{ij} takes the value of one, and zero otherwise. Following the family of indexes typically described in the literature on material deprivation (see, for instance, Dhongde et al. 2019), individual *i*'s weighted energy poverty score (*EPS*) is given by $EPS_i = \left(\sum_{j \in J} w_j EP_{ij}\right) \times 100,\ \forall i \in I,$ where w_j denotes the weight assigned to the poverty indicator *j*, with $\sum_{j \in J} w_j = 1$. By construction, *EPS* ranges from 0 to 100 and represents the proportion of items in which the individual is deprived. When $\forall\ j \epsilon\ J,\ w_j = {}^{1}/_{m}$, the *EPS* corresponds to the well-known adjusted headcount ratio.

We classify an individual to be multi-dimensionally poor if $EPS_i > \overline{m}$, where $\overline{m}$ is a cut-off point. For the baseline parametrisation, we set $\overline{m} = EPS_{90}$, where EPS_{90} is the 90th percentile of the *EPS* distribution. In other words, we consider an individual to be multi-dimensionally poor (*MD* = 1) if his/her poverty score is in the top 10% of the energy poverty index. As a robustness check, we also considered alternative thresholds (5% and 20%) and obtained similar results. While it is common to assign equal weights to the indicators, we emphasise the indicators where deprivation is less common, the so-called frequency-based weighting approach (Decancq and Lugo, 2013). The weight given to an indicator is proportional to the percentage of households *not* classified as poor under that specific indicator within a particular state. In other words, $w_j = \frac{(1-n_j)}{\sum_{j \in J}(1-n_j)}$ where n_j is the proportion of poor individuals in dimension j. This choice is motivated by the idea that not having access to common items should be a more relevant determinant of deprivation than less common items. Additionally, the weights are based on the distribution of achievements in society without considering any value judgement about what the trade-offs between items should be. For greater granularity and accuracy, the weights are calculated separately for each year. There are two advantages to using this approach. Firstly, it allows the poverty of a given household to increase if their conditions do not change and the conditions of all others improve. Secondly, it adapts automatically over time, considering economic conditions and social and cultural preferences when accessing items.

Figure 1 plots the incidence of energy poverty along the income distribution. The average prevalence of expenditure-based energy poverty ranges from 2.2% (*TPR*) to 19.9% (*2M*). These figures are consistent with other studies based on Australian data (Churchill and Smyth, 2020). As we move towards higher income levels, energy poverty is generally decreasing, going from 18.1% in the lowest income decile to less than 1.0 % in the top decile if we take *MD* as a reference. Still, energy poverty is not exclusively borne by low-income households. Thus, for instance, the proportion of persons who cannot pay their bills falls below the sample average (10.8%) only among those in the top 20% of the income distribution. Similarly, the incidence of multidimensional poverty around the median household (8.2%) is close to the sample average (10.4%), whereas it is larger in the 2nd and 3rd deciles than in the bottom decile of the distribution.

-Insert Figure 1 here-

In Table 1, we examine the extent of overlap among the energy poverty indicators. The coincidences are moderate because the different parametrisations of poverty capture different realities. Only 11% and 30% of energy poor households under the *2M* indicator are also energy poor according to *TPR* and *LIHC*, respectively. In contrast, the *2M* indicator classifies as energy poor practically every household that is already poor according to other indicators (*TPR*, *LIHC*, *MD*). Similarly, a reduced fraction (<10%) of expenditure-based energy poor households cannot adequately heat their homes. In contrast, a low fraction of self-reported energy poor individuals (*Heat* and *Arrears*) are also poor according to the *TPR* (<6%) and the *LIHC* (<18%) indicators. Finally, the correlation between the two subjective measures is very modest: only 16.9% of the individuals who cannot pay bills cannot heat their houses, whereas almost 57% of those who cannot heat their homes report financial arrears.

-Insert Table 1 here-

In Table 2, we report the incidence of energy poverty by immigrant and language status. Immigrants are more likely to be energy poor, although proficient immigrants come very close to nationals. The *TPR* and *LIHC* shares of energy poor individuals practically double when we switch from proficient to non-proficient immigrants and rise by about 50% (from 9.3 to 13.2%) when we take the multidimensional index as a reference. Taken together, the figures are prima facie evidence that language skills may alleviate the disadvantaged position of immigrants.

-Insert Table 2 here-

3.3 English language proficiency

The English proficiency question on the HILDA is:

- *"Would you say you speak English…"*

with available responses ranging from 1 (*very well*) to 4 (*not at all*). We use this information to define *PR*, a dummy variable that takes the value of one if the immigrant is proficient in English (1-very well), and zero otherwise.[3] Nearly 69.3% of the immigrants in the sample report having a good command of English.

Test-based assessments of language ability are more accurate than self-appraisals. However, they are costly and mostly unavailable in large-scale surveys. Admittedly, variation in subjective assessments may reflect differences in self-perception under identical circumstances and may be influenced by social comparison or cultural norms. Such subjectivity introduces the possibility of measurement error, which could lead to an attenuation bias. Notwithstanding, the bias that may emerge from an imprecise measuring of language skills is attenuated by the use of 2SLS. Moreover, subjective questions have been widely validated in the literature and are strongly correlated with scores from objective tests designed to measure language ability in a wide range of domains (Akbulut-Yuksel et al., 2011).[4]

[3] We adopt a stringent criterion by considering only individuals who claim to be able to speak English 'very well'. An alternative classification (1-2 against 3-4) yielded similar results in the regressions stage of the paper.

[3] Even within the fields of neuroscience and cognitive psychology, only a limited number of studies include both subjective and objective measures of language proficiency. This suggests that many researchers treat them as broadly interchangeable proxies. The prevailing view is that subjective and objective indicators of language proficiency are highly correlated (Li et al., 2020) and, importantly, that results do not differ significantly depending on which measure is used in empirical models (Zhou and Privitera, 2025).

4. Models and estimators

Identifying and quantifying causal effects poses a significant empirical challenge because language skills may be endogenous. Standard estimates may be biased if language proficiency depends on non-observable individual characteristics that are also related to energy poverty. Moreover, there might be reverse causality issues if energy outcomes also influence the process of language learning. In this context, resorting to an exogenous source of variation for language ability is expected to provide consistent estimates (Dustmann and van Soest, 2002).

We follow a 2SLS procedure in which energy poverty is modelled as a function of a latent variable EP^* that is not observed, has a threshold point that determines the observed value of *EP*, and depends on observable characteristics *X*. Language proficiency, *PR*, is the treatment and is assumed to be endogenous and dependent on the instrument Z,

$$EP_{it} = \mathbb{1}(X_{it}\alpha + \theta PR_{it} + \tau Z_{it} + \varepsilon_{it} > 0) \;\; \forall\, i \in ID \qquad (1)$$
$$PR_{it} = \mathbb{1}(X_{it}\delta + \gamma Z_{it} + u_{it} > 0) \;\; \forall\, i \in ID$$

The indicator function $\mathbb{1}(\cdot)$ equals one if its argument holds, and zero otherwise. The error terms follow a standard bivariate normal distribution. For the sake of simplicity, we ignore the binary dependent nature of the outcome and treatment variables and replace Eq. (1) with its linear version. Results under a probit model were practically identical and are available upon request. The crux of our analysis is θ, the local average treatment effect (LATE) of language proficiency upon energy poverty.

4.1 Covariates

Vector X includes socioeconomic factors that are standard when accounting for economic outcomes among immigrants. These include schooling, age and dummy variables for age at arrival, marital status, parenthood, having disabled household members, and household size. We also include controls for remoteness, region of residence (the six states and two territories of Australia, reference: New South Wales), country-of-birth dummies and time fixed effects.[5] Since language proficiency can be associated with several positive labour market outcomes, namely employment and labour income, we initially remove these variables from the set of regular controls. The underlying assumption is that part of the influence of these variables on

[4] As some countries of origin are relatively infrequent, we regroup countries that represent less than 0.5% of the sample into a residual category.

energy poverty might be attributed to the host language. Notwithstanding, in Section 7 we provide sensitivity analyses when employment and income are included as additional controls.

A frequent problem when analysing household-level outcomes is that most explanatory variables are at the individual level. In this respect, we follow the literature on the socio-economic gradient of energy poverty, which typically examines how individual-level characteristics (education, marital status, gender, among other factors) of the relevant adult in the household affect energy poverty at the household level (see Section 2.2). Still, we cannot observe if individuals in the sample are solely or partly responsible for household-level outcomes, since the degree of responsibility across the adults in the household is often very fluid and dependent on the household circumstances. A second concern is the definition of the income variable included on the right-hand side of the equations. Household income is more closely related to household-level poverty than individual income. However, including household income instead of individual income may severely distort the relationship between individual-level socioeconomic profiles (e.g., gender, age) and energy poverty among those individuals who are residual earners in their households. We address these concerns in two ways. First, we assume that each adult in the household has some responsibility, either directly or indirectly, in paying bills and consider individual income rather than household income. Thus, we focus on the individual contribution to alleviate energy poverty within the household. Second, in Section 6.3, we conduct several sensitivity checks. They include i) restricting the sample to household heads, where the link between individual and household-level variables is relatively pronounced, ii) considering the English proficiency of all adults in the household, and iii) adding household income in the regressions.

Vector X also includes energy prices, given their potential impact on energy poverty. We use annual electricity and gas prices at the state level drawn from the Australian Bureau of Statistics (ABS, 2024). To avoid variable proliferation, in the regression stage we introduce just one control for energy prices, defined as the average between the price of gas and electricity.[6] Vector X also includes variables to control for macroeconomic conditions at the regional level. The economic cycle affects the chance to find and keep jobs, and it also impacts the likelihood of having a stable income source. We include controls for the regional unemployment rate, per capita GDP, and GDP growth. We also include the regional participation rate to capture competition effects in the labour market and the labour force share of part-time workers to

[6] Alternative linear combinations yielded similar results. Including separate controls for electricity and gas prices did not lead to significant improvements in the models' goodness of fit.

control for the fact that areas with a larger proportion of temporary and/or part-time workers generally have more flexibility to adapt to labour market disequilibria. We also include the share of immigrants over the total population.[7] Stigma and segregation effects may be present in the society, and these effects may depend on the relative number of immigrants (Churchill and Smyth, 2020).

Table 3 presents summary statistics by energy poverty status. We use the *MD* indicator as a reference. Relative to non-poor (*MD* = 0) individuals, the energy poor (*MD* = 1) are less likely to be English proficient, be men, have a higher education level, and be young, married, and employed. Reversely, the energy poor have lower incomes, have spent relatively more years in Australia, have more children, have family members with disabilities, be inactive, and live in smaller households. The energy poor are relatively more likely to come from Southern Europe, Maghreb and the Middle East and less likely to come from Oceania, East Asia, and North America. Moreover, energy poor individuals are more likely than non-energy-poor individuals to live in some areas of Australia, namely Victoria, South Australia, Tasmania, and the Australian Capital Territory. We do not detect relevant differences in the proportion of individuals living in major cities or inner, outer, and remote areas of the country.

-Insert Table 3 here-

4.2 Selected instrument

Figure 2 depicts average self-reported English language ability by age at arrival. ESB immigrants are essentially all fluent in English regardless of when they migrated to Australia. In contrast, age at arrival is a strong predictor of language knowledge among NESB immigrants because their migration to Australia coincides with a period of intense English exposure and there is a critical age range in which individuals learn languages more easily.

-Insert Figure 2 here-

Thus, we define the first instrument as:

$$Z_i = \max(0, \text{age at arrival}_i - 9) \times \mathbb{1}(\text{NESB immigrant}_i) \quad (2)$$

[7] This information is obtained from the Australian census of born overseas.

where 𝟙 () is the indicator function and the critical age is set to 9 years. This functional form captures the co-movement between age at arrival and English language skills displayed in Figure 2. The Kernel density of *Z* is shown in Figure 3 and is suggestive of a reasonable amount of instrument variation. We also include the density of age at $\text{arrival}_i - 9$ for ESB immigrants. Percentage variations between the two groups are minimal in the entire range of the distribution.

Age at arrival itself –included in the regressions– cannot be an instrument. Because early arrival fosters better knowledge of the host society, cultural convergence, and economic integration, this variable is potentially correlated with energy poverty and is therefore an invalid instrument. As in Bleakley and Chin (2010), we drop the dummy for NESB immigrant in the specification, for the model already includes country-of-birth dummies. Table A1 in the Appendix provides a detailed list of ESB and NESB countries and their relative frequency in the sample.

5. Results

Table 4 reports results from standard OLS regressions. Standard errors are based on two-way clusters at the individual and country of birth level. We find that English proficiency is mildly related to energy poverty. The coefficient is significant at the 5% level in most cases, and the implied effects are lie between a 0.7 and a 1.5 pp decrease in the outcome probability. These estimates are expected to be biased because of the assumptions of exogeneity of language problems and absence of measurement errors. While unobserved heterogeneity and reverse causality lead to an upward bias in the parameter estimate, measurement errors lead to a downward bias. Previous evidence on labour market outcomes and social assimilation tends to show close-to-zero OLS effects, suggesting that the later effect is substantially larger than the former (Bleakley and Chin, 2010).

Energy poverty depends negatively on several factors, including gender, schooling and marital status. Taking the *MD* indicator as a reference, the probability of energy poverty raises by 1.5 pp among women, whereas a ten-year increase in years of education is associated with a 10.0 pp decrease in the probability of poverty. The results show that being widowed and having children and household members with disabilities significantly increase the risk of poverty. There are clear geographical effects, with people living in outer regional Australia being more likely to be energy poor relative to those living in a major city. Finally, the macroeconomic variables included in the model tend to be non-significant, probably because the region and year fixed effects included in the regressions partially factor out between-regional differences and yearly fluctuations in the aggregate indicators. Nevertheless, *MD* is related to GDP and, to a lower extent, GDP growth. In contrast, immigrants living in regions with lower unemployment rates are marginally less likely to report arrears.

-Insert Table 4 here-

5.1 Does English proficiency reduce the likelihood of energy poverty?

In Table 5 we report the impact of language proficiency on energy poverty. For reasons of space, we omit the remaining covariates, noting that they do not change much relative to the OLS regression. Once endogeneity is considered, language proficiency emerges as a significant determinant of energy poverty, with an estimated effect of -18.8 pp for multidimensional poverty. The domain-specific effects range from -4.5 pp (*TPR*) to -16.0 pp (*2M*) and only in one case, *Heat*, the estimate is not significantly different from zero.[8] These figures are non-negligible if we recall the set of coefficients in Table 4 (last column), where a ten-year increase in schooling was associated with a -10.0 pp variation in the outcome probability.

-Insert Table 5 here-

To add more context, we can compare these findings with previous estimates regarding the influence of host language proficiency on various economic outcomes. For instance, research on immigrants in Australia has revealed that proficiency in the host language reduces the likelihood of unemployment by at least 9 pp (To et al., 2017) and increases the likelihood of attaining tertiary education and achieving social integration by at least 24 and 57 pp, respectively (Tam and Page, 2016). Our results indicate that the effect of host language proficiency on energy poverty is in line with its impact on other, perhaps more apparent, economic dimensions.

5.2 Relaxing the instrumental validity assumption

In this section, we examine the extent to which the results hold under local violations of the exclusion restriction. The 2SLS adopted in the paper assumes that the instrument affects the outcome variable, EP, only through treatment, PR, which amounts to a dogmatic prior that $\tau =$

[7] In encompassing tests, we implemented two widely recognized methods to control for the risk of Type I errors that arise from multiple hypothesis testing: the Holm-Bonferroni correction and the Benjamini-Hochberg (FDR) method (List et al., 2019). The resulting p-values for the English variable under the two methods were supportive of the statistical significance of the reported effects.

0 in Eq. (1) and leads to the conventional 2SLS asymptotic distribution, $\hat{\theta} \sim N(\theta, \sigma_{\theta}^2)$. Therefore, we test whether this is the case. To that purpose, we implement a ZFS test, which consists of estimating τ in a subsample for which the first stage must be zero. In applied work, identifying a ZFS sample typically requires strong priors for and substantive knowledge of the assignment mechanism. However, our framework provides us with a natural pool of individuals unsensitive to the instrument: NESB immigrants whose mother tongue is English due to their family background. Because any influence of the instrument upon the outcome variable in this group cannot be through the treatment, the estimated reduced form coefficient in Eq. (1) provides an assessment of the extent of violation. The results, in Table 6, show a non-significant estimate of the reduced form coefficient in the ZFS subsample, which is suggestive of instrument validity. This evidence is complemented with the *F*-tests for the first stage, which confirms that the ZFS subsample is insensitive to the instrument.

Next, we perform the UCI estimations, which consider local violations of the exclusion restriction (Van Kippersluis and Rietveld, 2018). This is done by producing confidence intervals on θ, the effect of language proficiency on energy poverty, for a range of models with varying values for τ. Given that the ZFS tests indicate that τ is not significantly different from zero, we allow τ to vary around zero within the range of -0.001 to 0.001. These bounds should not be regarded as small insofar as $\tau = -0.001$ represents a 1.0 pp increase in the probability of energy poverty following a ten-year increase in the age at arrival for an NESB immigrant. This effect is equivalent to, for example, one year less of schooling, considering the last column of Table 4, and it is two-thirds of the effect of being a woman. In Table 6 we present the highest upper bound and the lowest lower bound from the collection of 95% confidence intervals obtained in the assumed range of $\tau \in [-0.001, 0.001]$, and compare them with the 95% confidence bounds for 2SLS. The UCI intervals are relatively wide, and in certain instances, they include zero. This suggests that we cannot dismiss the possibility of a non-significant effect of language on domain-specific energy poverty measures (*TPR*, *Heat* and *Arrears*) when the exclusion restriction is violated. Nevertheless, the results consistently demonstrate a positive causal effect of language proficiency on the likelihood of multidimensional energy poverty (*MD*) and other domain-specific measures (*2M* and *LIHC*).

-Insert Table 6 here-

6. Robustness checks

Although the results are reasonably robust to local violations in the exclusion restriction, in this section we conduct additional sensitivity checks to limit the influence of potential confounders.

6.1 Educational quality

Differences in the quality of education NESB and ESB immigrants might be partly responsible for the observed language effects, insofar as energy poverty may be closely related to the individual values, attitudes, and economic resources gained through schooling. We address this concern in two different ways.

Firstly, the sample includes individuals who completed part of their education in Australia. Since individuals with domestic education are more likely to be proficient in English and income is a determinant of energy poverty, the coefficient associated with host language proficiency may partly reflect an economic reward of Australian education instead of a true effect of enhanced language skills. To limit this concern, in Table 7 we restrict the estimation sample to individuals who completed all their education abroad. Although the effects are smaller and lose their statistical significance in some cases, the evidence suggests that the benefits of language skills do not depend crucially on the potential reward of Australian education.

-Insert Table 7 here-

Secondly, coming from a country with higher schooling quality may help immigrants compensate the initial disadvantage that late arrival to Australia implies in terms of assimilation and the probability of energy poverty. If, for instance, NESB countries have worse education systems, the estimates reported so far may simply reflect differential assimilation patterns and not be the result of differential English-language ability. In Table 7 we examine this hypothesis by including an interaction between age at arrival and country average PISA scores, a conventional proxy of origin-country school quality. The results indicate that differences in schooling quality between NESB and ESB immigrants are not responsible for the observed language effects. Still, the interaction term between age at arrival and the PISA score shows that schooling quality tends to make up for the effects of late arrival.

6.2 Individual and parental background

Immigrants from rich countries may benefit from faster adaptation profiles due to cultural affinity with the host society, similar social norms, or strong family and economic backgrounds. If this is the case, differences in cultural and family backgrounds related to origin-country wealth may be embedded in the language effects reported in the paper. In Table 7 we extend the model to include an interaction term between age at arrival and origin-country GDP. The results suggest different speeds of adaptation depending on origin-country GDP. Still, they do not remove the significant impact of language ability on the outcome variable.

As an additional sensitivity check, we include a proxy for parental occupational status as measured by the Australian Socioeconomic Index 2006, AUSEI06 (McMillan et al., 2009). If NESB immigrants are more disadvantaged than ESB immigrants because their parents have a less favourable economic position, adding such a control is expected to remove this gap from the regression results, insofar as occupational status is related to income, job opportunities, and economic assimilation. However, the estimates show that this is not the case.

6.3 Household heads, household composition and housing stress

The impact of individual characteristics on household-level energy poverty may be obscured when household outcomes are influenced by other individuals residing in the same dwelling. This is particularly relevant among non-earners, younger family members, and immigrants living in relatively large households. We conduct three additional checks outlined in Table 7. Firstly, we narrow the sample to household heads.[9] Secondly, recognizing that migrants' language proficiency may affect their likelihood of having a native partner, as described in Guven and Islam (2015), we present results excluding individuals married to a native from the analysis. Finally, we explore a specification wherein the explanatory variables represent the average characteristics at the household level, such as the proportion of single or married members or the average age of household members. However, defining an English proficiency score at the household level presents challenges, as does identifying a suitable instrument for such an indicator. We address this by creating an indicator function that takes a value of one if at least 50% of the adults are English proficient, with the corresponding instrument based on the age-at-arrival of the adult who arrived first in Australia. In all cases, the results suggest well-defined language effects.[10]

In the next panel we include an additional sensitive check. Because financially stressed households are more likely to sacrifice aspects of their housing, including energy consumption, it is convenient to re-estimate the models adding a proxy of financial stress. A natural candidate

[8] We define the head of household as the individual who is “typically responsible for making the major household purchases”.

[9] We thank an anonymous referee for providing insightful suggestions concerning these tests and the potential influence of housing composition on the observed effects.

is the housing cost to income ratio, which is broadly regarded as an adequate measure of financial stress. Housing costs are based on rent and mortgage payments, and the ratio captures the ability of the homeowner or renters to keep up with housing-related payments. Nonetheless, such a refinement does not significantly change the results while, in line with a priori expectations, individuals with higher housing stress are more likely to be energy poor.

6.4 Linguistic distance as an alternative instrument

In Table 8 we replace the instrument used in the paper with the linguistic distance between English and the immigrant's first language. Language distance is correlated with host language proficiency and has been proposed as a valid instrument. The linguistic distance score used in the paper is based on the Levenshtein distance and the database provided by the Automated Similarity Judgment Program (Wichmann et al., 2016). Despite potential differences in terms of the population of compliers and the local treatment effect that arises when different exclusion restrictions are used, the estimates are remarkably similar to the baseline results. In the bottom part of the table, we provide an additional sensitivity check by changing the critical age (9) used for the parametrisation of Bleakley and Chin's instrument. Setting the threshold age at 7 and 11 years is innocuous for the results.

-Insert Table 8 here-

6.5 Propensity score matching

As an additional check, in Table 9 we adopt propensity score matching (PSM), which is an alternative method to eliminate the interference of confounding factors. We match subjects on the propensity score using a caliper of width equal to 0.2 standard deviations of the logit of the propensity score, in the spirit of Stuart and Rubin (2008), and report results under different PSM settings (nearest neighbour, kernel and local linear regression-based matching).[11] The results are robust to the choice of matching methods and consistent with the 2SLS findings suggesting that English proficiency reduces the probability of multidimensional poverty.

-Insert Table 9 here-

[10] The PSM setting requires a criterion to define an acceptable match. Allowing for arbitrarily bad matches, all exposed subjects will be matched, and no reduction in bias can be achieved. On the other hand, a too strict definition of acceptable match yields few matched subjects, in which case the effect estimates may be both imprecise and subject to selection bias. Therefore, the 0.2 standard deviations adopted in the paper is a working compromise.

6.6 Sample selection and endogenous attrition

The HILDA survey was first launched in 2001 and was designed to be a nationally representative study of Australian households. Although the database may be influenced by selection and attrition bias, which, over time, may limit the generalizability of the findings, in HILDA the average retention rate across waves is above 90%. Nonetheless, to tackle address this concern, we have acted following two lines. Firstly, the survey provides cross-sectional weights to overcome potential bias arising from attrition and non-response. The weights are determined through a three-step process to account for variations between the HILDA sample and the broader Australian population. This helps correct any potential biases in the HILDA sample, ensuring that specific characteristics are neither under- nor over-represented (Watson and Wooden, 2012). Table 10 presents results incorporating the individual weights. While the estimates decrease sensitively, they align with the main findings of the paper.

-Insert Table 10 here-

Secondly, we test for endogenous attrition. Although the average entry rate (individuals not in the sample in the previous period who are in the current period) and exit rate (individuals who leave the sample) are very moderate in our sample (8.9% and 7.4%, respectively), the nonrandom exit and entry of immigrants for reasons related to energy poverty is a potential concern. We can distinguish between those individuals who have joined the panel for the first time ("newcomers") and those who had been on the panel previously but have returned ("returnees"). To address this issue, we regressed a dummy equal to 1 on English proficiency, *MD* poverty (yes/no), and all the controls, and obtained coefficients equal to -0.0096 (p = 0.384) for English proficiency, and -0.0058 (p = 0.093) for energy poverty. In other words, individuals' entry in the estimation sample is not significantly related to English proficiency and energy poverty. We proceeded likewise with individuals who leave the sample and obtained similar results. Among newcomers, English proficiency was again non-significant, even though *MD* showed a negative, significant effect. This suggests that the incorporation of new panelists in the sample over the years is not completely random, with a slight tendency to incorporate people who are less likely to suffer energy poverty. These individuals may be either less difficult to contact or more ready to join the panel, although once they decide to participate, their attrition is mostly random.

7. Potential transmission mechanisms

This section explores the potential transmission mechanisms through which host-country language proficiency may influence energy poverty. The estimates reported so far may arise indirectly due to differences across individuals in key variables that are themselves affected by language skills. For example, English-proficient immigrants might be less likely to experience energy poverty simply because they earn higher incomes. In that case, the effects reported earlier would reflect indirect channels rather than a direct relationship. Since our baseline regression in Eq. (1) does not control for these indirect channels, the estimated coefficients may capture both direct and indirect effects. To address this, we extend our model by including interactions between language proficiency and several potential mediating variables.

We focus on three main channels: labor market outcomes, social and financial support networks, and household income. Table 11 presents the corresponding results. To avoid the proliferation of interaction terms, the first panel considers only the labor market channel, employment and earnings. Once these are included, the estimated effects are purged of any indirect influence through employment or income. The magnitude of the coefficients declines somewhat relative to the baseline, reaching −14.3 percentage points in the MD equation. A similar pattern is observed across the remaining indicators, suggesting that most of the language effect cannot be attributed to employment or earnings differences alone.

The lower panel of Table 11 expands the analysis to include the remaining channels. We take advantage of the information provided in the HILDA dataset to test whether the language proficient benefit from better networks of financial and social support, and whether these channels can account for the results. We distinguish between social capital (private, interpersonal networks) and social assistance programs (public, institutional support). As Putnam (1995, pp. 664–665) defines, "social capital comprises the features of social life—networks, norms, and trust—that enable participants to act together more effectively to pursue shared objectives." Communities with robust social capital are often better positioned to share information, coordinate collective action for sustainable energy use, and provide support during energy-related crises (Julsrud, 2023). We construct a social capital measure from the responses to a 10-item questionnaire in HILDA about how much support respondents were able to get from other people.[12] This variable is available in all waves of the HILDA. Respondents rate the

[11] The items are: i) I have no one to lean on in times of trouble (reverse coded); ii) I often feel very lonely (reverse coded); iii) I enjoy the time I spend with the people that are important to me; iv) I seem to have a lot of friends; v) People don't come and visit as much as I would like (reverse coded); vi) I often need help from other people but can't

sentiments they perceive about the level of support they are likely to receive from other people, including their friends and families. Support is rated on a scale of 1 (*strongly disagree*) to 7 (*strongly agree*). The measures have good reliability and internal consistency (Cronbach's alpha = 0.835). The ten items in the scale are averaged, with lower scores indicating less social support and higher scores indicating more social support. We also consider the role of social assistance programmes. Language skills may enhance access to subsidy opportunities and government allowances, which ultimately help reduce the probability of energy poverty. The underlying hypothesis is that communication skills facilitate access to relevant information from the public sector and reduce the burden of administrative tasks. We consider a battery of social benefits including a large set of allowances and non-income support payments.[13] Finally, we also introduce another explanatory variable: household income —net of public transfers.

After accounting for these indirect mechanisms, the estimated effect of language proficiency on the objective indicators of energy poverty (2M, LIHC, and MD) becomes statistically insignificant. Household income emerges as a partially significant channel, indicating that immigrants with higher language proficiency are more likely to belong to financially better-off households. This finding aligns with previous evidence linking language skills to long-term economic well-being and savings behavior (Zheng et al., 2023). In contrast, the effect of language proficiency on the likelihood of being in arrears remains statistically significant, although its magnitude is smaller than in the baseline specification. This attenuation is largely explained by the inclusion of social capital and government transfer variables, suggesting that public assistance programs and social networks help buffer the risk of payment arrears. Finally, the last column of Table 11 presents the results for the multidimensional deprivation (MD) index. The estimated coefficient for language proficiency declines from 18.8% in the baseline model to 5.1% once mediating variables are included, confirming that most of the language effect operates through income and transfer-related channels.

get it (reverse coded); vii) I don't have anyone that I can confide in (reverse coded); viii) There is someone who can always cheer me up when I am down; ix) When I need someone to help me out, I can usually find someone; and x) When something's on my mind, just talking with the people I know can make me feel better.

[13] Allowances include: Mature Age Allowance, Sickness Allowance, Widow Allowance, Special Benefit, Partner Allowance, Youth Allowance, Austudy, Abstudy, and the Community Development Program. Non-income support payments include: Family Tax Benefit Part A, Family Tax Benefit Part B, Maternity Payment, Mobility Allowance, Carer Allowance, Telephone Allowance, Maternity Immunisation Allowance, Seniors Concession Allowance, Double Orphan Pension, and Australian Government bonus payments.

Nonetheless, a direct effect persists even after accounting for a wide range of mediators. This residual effect suggests that language acquisition may shape energy consumption norms and household behaviors in ways consistent with host-country practices. This interpretation aligns with social identity theory, which posits that immigrants adapt their values and behaviors to achieve integration and success in the new cultural and economic environment (Burke & Stets, 2009). The finding that non-proficient immigrants are more likely to fall into arrears, all else equal, reinforces this interpretation. In other words, language proficiency may capture broader economic acculturation strategies that facilitate integration into the host country's energy access systems and institutional frameworks.

-Insert Table 11 here-

8. Conclusions

This paper used the 2007–2020 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey to estimate the impact of English language proficiency on energy poverty among immigrants. The paper showed that host language proficiency decreases the probability of suffering energy poverty episodes by between 4.5 and 18.8 pp depending on the poverty indicator. The results successfully passed a series of sensitivity checks aimed at addressing issues related to omitted variable bias and the influence of non-observables.

The results have both theoretical and policy implications. Firstly, they enhance our understanding of the primary drivers of poverty. While financial difficulties, energy costs, and house efficiency are commonly cited as key factors, we show that host language proficiency is a significant determinant of energy poverty among immigrants. Moreover, previous studies have identified ethnic origin and culture as factors influencing energy poverty (Chaudhry and Shafiullah 2021; Teschner et al., 2024), yet income and energy burdens alone cannot fully account for the disproportionate prevalence of energy poverty among specific ethnic and immigrant groups. This study showed that host language ability differentials are responsible for significant differences in energy poverty rates among immigrants.

Secondly, we examined the moderating role of key mechanisms linking language skills to energy poverty. While traditional theories of immigrant assimilation emphasize economic mobility through human capital accumulation and labor market integration (Chiswick & Miller, 2010; Schmid, 2023), our results indicate that these channels account for only part of the relationship. Alternative frameworks highlight structural barriers—such as social segmentation, limited social capital, and discrimination—that restrict full economic assimilation (Neumark, 2018). Our findings support this view: part of the language effect arises from improved access to social assistance programs, suggesting that proficient immigrants are better able to navigate administrative systems, understand eligibility requirements, and complete the procedural steps needed to obtain support. We also find evidence of indirect effects through enhanced social capital and household income among the language-proficient. However, part of the language effect remains even after controlling for these channels, implying that language proficiency reflects deeper processes of economic and cultural acculturation. These may include adopting local energy consumption norms, adjusting household behaviors, and better utilizing public resources. In this regard, our study complements and extends prior research suggesting that immigrants adapt their behaviors and values to achieve economic integration and social belonging within the host culture (Shayo, 2020).

In terms of policy implications, the results highlight several recommendations. They underscore the importance of providing language instruction for immigrants facing challenges with energy access and affordability. While recent studies have shown the positive effects of language education policies on labor market outcomes (Heller and Mumma, 2023) and educational enrollment and integration (Foged and Van der Werf, 2023), our findings suggest that government initiatives promoting host language fluency among immigrants could also play a crucial role in improving energy access, helping manage energy costs more effectively, and indirectly addressing factors that contribute to energy poverty. Furthermore, by decreasing information asymmetries and facilitating access to both financial and public services, host language proficiency can foster financial inclusion—a factor that recent evidence has linked to lower levels of energy poverty (Jin et al., 2024).

Another essential task of policymakers is to incorporate language barriers in identifying individuals at risk of energy poverty. While Australia boasts one of the most precise tax and transfer systems globally in terms of distributive capacity, a significant proportion of vulnerable households—roughly one in three—still fall outside its purview, highlighting the need for additional initiatives to effectively combat energy poverty (Simshauser and Miller, 2023). As suggested in this study, non-proficient immigrants may often be excluded from these initiatives due to language barriers. Hence, an integrated approach that considers factors beyond income, particularly language skills, may prove advantageous in identifying key risk groups and is expected to yield benefits in both horizontal and vertical efficiency.

In addition, the prevailing public discourse to combat energy poverty has often centered around financial interventions and energy concessions. However, as examined in this study, non-proficient immigrants are, all else being equal, more likely to suffer energy poverty, arguably due to differences in household priorities and energy consumption patterns. We argue that emergency assistance schemes in Australia should be tailored more closely to household characteristics, rather than relying on uniform lump-sum payments that overlook differences in language proficiency. Payment levels should reflect the fact that households with limited language skills often face greater barriers and may require proportionally more support. At the same time, these households could benefit from targeted interventions aimed at reducing electricity consumption—for instance, by promoting the use of energy-efficient appliances or encouraging shifts to off-peak electricity tariffs. An effective complementary strategy would involve providing recipients with information on the average electricity bills of households with comparable demographics in their area. This type of social comparison could encourage behavioral change and empower households to better manage their energy use. Moreover, initiatives tailored to the local context and culture, targeting vulnerable households similar to those implemented in the European Union (EU) through various campaigns—such as the Sun4All, TRIME, and STEP-IN projects—could prove beneficial in Australia (European Commission, 2023, for further details).

In addition, our findings suggest that language-targeted interventions could be effectively integrated with existing housing and energy assistance programs. For instance, adult English language courses (ESL) or community-based initiatives could be offered alongside schemes that provide financial support for energy bills or home efficiency improvements. Joining language learning opportunities within broader social support frameworks would allow non-proficient immigrants to simultaneously enhance their communication skills and their ability to access and manage energy-related resources. This dual approach could strengthen the effectiveness of public programs by combining immediate financial relief with the development of capabilities that promote resilience. Moreover, partnerships between local councils, energy providers, and adult education institutions could facilitate the implementation of such integrated interventions.

Finally, non-proficient immigrants may not be aware of the main features of the tariff they are on. Additional attention should be directed towards the design of energy contracts, ensuring they are reader-friendly, clear, and available in desired languages. Clear and easily understandable energy billing and contracts can empower consumers to reduce their energy consumption and, consequently, their energy bills. An effective public policy to reduce language-related barriers in access to energy services would involve providing basic information about electricity tariffs, consumer rights, and energy efficiency options in the most widely spoken languages in Australia after English. According to the latest cultural diversity census in Australia (ABS, 2021) approximately 22.2% of residents speak a language other than English at home. The most common languages are Mandarin (2.5%), Arabic (1.4%), Vietnamese (1.2%), Cantonese (1.1%), and Tagalog (0.9%). Translating essential materials into these five languages could significantly enhance understanding and access to energy services among linguistically diverse communities—many of which also face social and economic vulnerability. Additionally, as the energy bill is a key communication channel between energy suppliers and consumers, it could be used to deliver practical information on reducing energy consumption and offer customer support.

Although this study provides important evidence of the impact of English proficiency on energy poverty, it has some limitations. Specifically, it does not explore the connection between language proficiency and consumer's attitudes, preferences and behaviour towards energy consumption within the household. This is because such information is not available in the HILDA survey or other large-scale longitudinal datasets. While large consensus and empirical validations point to a positive association between language proficiency and immigrant integration, great uncertainty prevails still about the interplay between language skills and poverty in various dimensions. Hence, shedding light on this link through specifically tailored questionnaires is expected to greatly enhance our knowledge of how immigrant households make decisions about energy consumption and set their priorities. By considering behavior and spending patterns, policymakers can gain a more comprehensive understanding of households in need of consumer protection. As a second limitation, the paper offers a static view on the determinants of poverty. Expanding the analysis to account for energy poverty transitions, traps and duration should be considered in future work.

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Tables

Table 1. Overlap among energy poverty measures (%)

	2M	TPR	LIHC	Heat	Arrears	MD
2M		11.0	30.0	5.7	16.1	53.3
TPR	100.0		78.5	8.8	16.6	89.7
LIHC	100.0	28.9		9.2	18.9	94.6
Heat	35.7	5.8	17.8		56.6	37.3
Arrears	29.5	3.2	10.8	16.9		30.4
MD	99.2	17.5	51.4	11.8	32.2	

Source: HILDA 2007–2020 waves.

Table 2. Incidence of energy poverty by language proficiency and nationality (%)

		2M	TPR	LIHC	Heat	Arrears	MD
Immigrants							
	English proficient	18.3	1.7	5.2	2.9	10.5	9.3
		(38.7)	(13.0)	(22.1)	(16.9)	(30.7)	(29.1)
	Non English proficient	23.4	3.2	9.1	3.6	10.6	13.2
		(42.3)	(17.7)	(28.7)	(18.6)	(30.8)	(33.8)
Native born		18.8	1.8	5.0	3.2	14.3	10.2
		(39.1)	(13.4)	(21.8)	(17.5)	(35.0)	(30.2)

Notes: Standard deviations shown in parentheses.
Source: HILDA 2007–2020 waves.

Table 3. Summary statistics by energy poverty status

	All	Energy poor (*MD* = 1)	Non-energy poor (*MD* = 0)
Share	100	10.4	89.6
English proficient (%)	69.3	63.8	72.3
	(46.1)	(48.1)	(44.8)
Female (%)	52.4	58.0	52.0
	(49.9)	(49.4)	(50)
Years of schooling	12.9	12.1	13.2
	(2.9)	(2.8)	(2.8)
Age	49.2	55.1	48.8
	(14.6)	(14.4)	(14.3)
Age at arrival	20.8	21.3	20.5
	(12.9)	(13.4)	(12.7)
Years since migration	28.4	33.8	28.3
	(16.2)	(16.3)	(16.1)
NESB	46.5	51.7	43.5
	(49.9)	(50)	(49.6)
Single (%)	11.7	10.7	11.2
	(32.1)	(30.9)	(31.5)
Married (%)	74.3	64.2	76.6
	(43.7)	(47.9)	(42.3)
Divorced (%)	10.6	17.8	9.6
	(30.8)	(38.2)	(29.5)
Widowed (%)	3.4	7.3	2.6
	(18.2)	(26.0)	(15.9)
Have children (%)	75.5	83.6	74.7
	(43)	(37)	(43.5)
Disability in family (%)	22.7	40.9	20.2
	(41.9)	(49.2)	(40.1)
Employed	64.3	37.4	68.3
	(47.9)	(48.4)	(46.5)
Unemployed	3.1	3.9	2.8
	(17.3)	(19.3)	(16.6)

Inactive	32.6	58.7	28.9
	(46.9)	(49.2)	(45.3)
Individual yearly income	44922.4	22861.6	48714.2
	(51,881.2)	(18,516.5)	(55,182.3)
Household size (no. of adults)	2.3	2.0	2.4
	(1.0)	(0.8)	(1.0)
Remoteness (%)			
Major city	77.2	73.8	77.6
	(42.0)	(44.0)	(41.7)
Inner Regional Australia	15.2	16.1	15.1
	(35.9)	(36.8)	(35.8)
Outer Regional Australia	6.4	8.9	6.1
	(24.5)	(28.5)	(24)
Remote Australia	1.1	1.0	1.1
	(10.4)	(9.9)	(10.4)
Very Remote Australia	0.1	0.2	0.1
	(3.6)	(4.7)	(3.5)

	All	Energy poor	Non-energy poor
Region of origin (%)			
Oceania	13.9	9.9	14.5
	(34.6)	(29.8)	(35.2)
Northern Europe	33.8	37.9	35.9
	(47.3)	(48.5)	(48)
Southern Europe	8.1	13.3	6.3
	(27.3)	(33.9)	(24.3)
Eastern Europe	2.8	3.7	2.9
	(16.5)	(19.0)	(16.7)
Maghreb & Middle East	4.2	4.2	3.4
	(20.0)	(20.2)	(18.1)
South - East Asia	11.7	9.6	11.3
	(32.1)	(29.5)	(31.7)
East Asia	6.6	5.3	6.6
	(24.9)	(22.4)	(24.8)
South & Central Asia	7.7	7.8	7.4
	(26.7)	(26.8)	(26.2)
N. America	3.0	1.8	3.3
	(17.0)	(13.4)	(17.9)
Latin - America	3.0	2.5	2.9
	(17.0)	(15.7)	(16.8)
Subsaharian Africa	5.1	3.9	5.4
	(22.0)	(19.3)	(22.6)
Australian State (%)			
New south Wales	32.0	25.2	32.8
	(46.7)	(43.4)	(47.0)
Victoria	24.2	36.6	22.7
	(42.8)	(48.2)	(41.9)

Queensland	17.4 (37.9)	6.8 (25.1)	18.6 (38.9)
South Australia	8.1 (27.3)	12.3 (32.8)	7.6 (26.5)
West Australia	12.8 (33.4)	12.2 (32.7)	12.9 (33.5)
Tasmania	1.6 (12.7)	2.1 (14.4)	1.6 (12.5)
Northern Territory	1.0 (10.1)	1.0 (10)	1.0 (10.1)
Australia Capital Territory	2.8 (16.5)	3.8 (19.1)	2.7 (16.1)
Macroeconomic controls			
Participation rate	65.2 (2.3)	65.2 (2.5)	65.3 (2.3)
Share part-time workers	30.0 (2.2)	30.5 (2.4)	30.0 (2.2)
Unemployment rate	5.3 (0.8)	5.3 (0.8)	5.3 (0.8)
GDP per capita (x1000)	70.9 (9.9)	70.1 (10.2)	71.3 (10.2)
GDP yearly growth rate	1.1 (1.3)	1.0 (1.3)	1.1 (1.3)
% of immigrant people in region	26.7 (4.1)	27.0 (4.0)	26.7 (4.2)

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Notes: Standard deviations shown in parentheses.
Source: HILDA 2007–2020 waves.

Table 4. Determinants of energy poverty

	OLS					
	2M	TPR	LIHC	Heat	Arrears	MD
English language proficiency	-0.008 (0.008)	-0.007** (0.003)	-0.013** (0.005)	-0.004 (0.004)	-0.015** (0.007)	-0.015** (0.007)
Female	0.0**	0.0**	-0.0*	0.0***	0.006	0.0**

	14	00	02	12		15
	(0.006)	(0.002)	(0.004)	(0.003)	(0.006)	(0.004)
Years of schooling	-0.012***	-0.002**	-0.007***	-0.002***	-0.009***	-0.010***
	(0.002)	0.000	(0.001)	(0.001)	(0.001)	(0.001)
Age (x10)	0.001	0.000	0.001	-0.003*	-0.032***	-0.001
	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Married (*base category single)*	-0.071***	-0.017***	-0.033***	-0.024***	-0.027**	-0.052***
	(0.011)	(0.004)	(0.006)	(0.007)	(0.012)	-0.007
Divorced	-0.037	-0.005	-0.011	0.036***	0.086***	0.006
	(0.016)	(0.006)	(0.010)	(0.011)	(0.018)	(0.013)
Widowed	0.018	0.019*	0.058***	0.025	0.045**	0.049**
	(0.023)	(0.010)	(0.020)	(0.016)	(0.024)	(0.023)
Have children (yes/no)	0.087***	0.009**	0.024***	0.012***	0.049***	0.049***
	(0.009)	(0.004)	(0.007)	(0.004)	(0.012)	(0.010)
Disability in family (yes/no)	0.073***	0.011***	0.051***	0.042***	0.067***	0.080***
	(0.008)	(0.003)	(0.005)	(0.006)	(0.010)	(0.010)

Household size (OECD equivalent units)	-0.098***	-0.021***	-0.051***	0.000	0.023***	-0.049***
	(0.008)	(0.002)	(0.005)	(0.003)	(0.009)	(0.006)
Energy price	0.047	0.019	0.019	-0.002	-0.022	0.003
	(0.057)	(0.026)	(0.026)	(0.022)	(0.036)	(0.031)
Remoteness						
(base Major City)						
Inner Regional Australia	0.021**	0.004	0.003	-0.006*	0.010	0.015
	(0.010)	(0.004)	(0.006)	(0.004)	(0.010)	(0.008)
Outer Regional Australia	0.065***	0.015***	0.039***	0.005	0.027**	0.062***
	(0.016)	(0.007)	(0.013)	(0.007)	(0.016)	(0.013)
Remote Australia	0.049	0.001	0.016	0.021	-0.007	0.032
	(0.031)	(0.006)	(0.017)	(0.024)	(0.026)	(0.020)
Very Remote Australia	0.015	-0.009	0.007	-0.037**	-0.030	0.065
	(0.160)	(0.016)	(0.077)	(0.018)	(0.041)	(0.131)

	OLS					
	2M	TPR	LIHC	Heat	Arrears	MD
Oceania	-0.0	-0.0	-0.0	0.0***	0.062***	0.0*

	12	02	07	18		12
Macroeconomic controls (by year - state)						
Participation rate	0.003	0.000	0.002	-0.0002	-0.0001	-0.0001
	(0.004)	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)
Share part-time workers	0.001	0.002	-0.001	0.004**	-0.003	0.005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
Unemployment rate	0.007	-0.002	0.002	0.001	0.015*	-0.006
	(0.006)	(0.002)	(0.004)	(0.003)	(0.005)	(0.005)
GDP per capita (x10,000)	-0.001	0.005	0.002	0.006	-0.005	-0.042***
	(0.011)	(0.004)	(0.007)	(0.005)	(0.009)	(0.009)
GDP yearly growth rate	0.000	0.000	-0.001	0.001	0.001	0.003*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
% of immigrant people in region	-0.007	0.002	0.000	0.004	0.000	-0.003*
	(0.009)	(0.003)	(0.005)	(0.003)	(0.006)	(0.007)
Constant	0.289	-0.044	0.111	-0.038	0.509*	0.393

	(0.358)	(0.160)	(0.195)	(0.237)	(0.253)	(0.252)
Age-at-arrival dummies	yes	yes	yes	yes	yes	yes
Country-of-birth fixed effects	yes	yes	yes	yes	yes	yes
Australian regions fixed effects	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes
R^2	0.0888	0.0287	0.0880	0.0339	0.055	0.0884
F statistic	19.93***	4.43***	9.93***	4.23***	7.70***	15.13***
No. of observations	4,666	4,666	4,666	4,666	34,666	4,666

*Note: ID clustered robust standard errors between parenthesis, ***,**,* indicates significance at 1,5,10% level All models include set of dummies for Australian states and year (from 2005 to 2018)*

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(continuation from the previous table)

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level; * denotes significant at the 10% level; ii) standard errors, shown in parentheses, are calculated using two-way clustering at both the individual and country of birth level.
Source: HILDA 2007–2020 waves.

Table 5. Effects of English proficiency on energy poverty

	2SLS						
	2M	TPR	LIHC	Heat	Arrears	MD	MD equal weights
English language proficiency	-0.160***	-0.045**	-0.111***	-0.049	-0.121*	-0.188***	-0.186***
	(0.052)	(0.019)	(0.032)	(0.036)	(0.071)	(0.061)	(0.057)
Obs.	34,666	34,666	34,666	34,666	34,666	34,666	34,666
Obs.	34,666	34,666	34,666	34,666	34,666	34,666	

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level, ii) standard errors, shown in parentheses, are calculated using two-way clustering at both the individual and country of birth level; iii) all models include controls for gender, schooling, age,

age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, country-of-birth fixed effects, time fixed effects, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants.
Source: HILDA 2007–2020 waves.

Table 6. Determinants of energy poverty – Zero-first-stage test and plausibly exogenous bounds

	Reduced form regression					
	2M	TPR	LIHC	Heat	Arrears	MD
Max (0; age at arrival - 9) × NESB	-0.003	-0.001	0.002	0.003	-0.001	0.000
	0.007	0.003	0.006	0.004	0.008	0.007
First stage (ZFS group) F-test	2.497	2.497	2.250	1.929	1.835	2.090
p-value of F-test	0.115	0.115	0.135	0.166	0.177	0.149
Obs.	1,880	1,880	1,898	1,529	1,543	1,618
	2SLS vs Union of confidence intervals (UCI)					
English language proficiency						
2SLS 95% confidence intervals	[-0.263, -0.057]	[-0.082, 0.007]	[-0.175, -0.048]	[-0.119, 0.022]	[-0.262, 0.019]	[-0.307, -0.068]
UCI minimum and maximum bounds with τ ∈ [-0.001, 0.001]	[-0.329, -0.042]	[-0.158, 0.051]	[-0.207, -0.029]	[-0.137, 0.095]	[-0.218, 0.058]	[-0.304, -0.027]
Obs.	34,666	34,666	34,666	34,666	34,666	34,666

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level; ii) standard errors, shown in parentheses, are calculated using two-way clustering at both the individual and country of birth level; iii) all models include controls for gender, schooling, age, age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, country-of-birth fixed effects, time fixed effects, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants.
Source: HILDA 2007–2020 waves.

Table 7. Effects of English proficiency on energy poverty: sensitivity checks

	2SLS					
	2M	TPR	LIHC	Heat	Arrears	MD
Sample restricted to immigrants that took all years of education before arrival in Australia						
English language proficiency	-0.106**	-0.025	-0.077**	-0.008	-0.036	-0.099**
	(0.041)	(0.015)	(0.027)	(0.030)	(0.051)	(0.042)
Obs.	21,028	21,028	21,028	21,028	21,028	21,028
Controlling for PISA 2018 results						
English language proficiency	-0.175***	-0.082**	-0.137**	-0.014	-0.105	-0.188***
	(0.065)	(0.038)	(0.046)	(0.022)	(0.065)	(0.071)
Pisa 2018 × Max (0, age at arrival - 9)×1000	-0.014**	0.000	-0.001*	0.000	0.000	-0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Obs.	27,201	27,201	27,201	27,201	27,201	27,201
Controlling for country of origin's GDP per capita						
English language proficiency	-0.126**	-0.074**	-0.102**	-0.054	-0.147*	-0.158**
	(0.058)	(0.031)	(0.040)	(0.037)	(0.086)	(0.068)
Ln(GDP) × Max (0, age at arrival - 9)×1000	-0.274**	-0.038	-0.059**	-0.111	-0.218	-0.204*

	(0.111)	(0.063)	(0.008)	(0.071)	(0.146)	(0.121)
Obs.	30,448	30,448	30,448	30,448	30,448	30,448
Controlling for father occupational status (AUSEI06)						
English language proficiency	-0.160**	-0.045**	-0.111**	-0.047	-0.123*	-0.187***
	(0.052)	(0.019)	(0.033)	(0.036)	(0.071)	(0.061)
Obs.	34,666	34,666	34,666	34,666	34,666	34,666
Sample restricted to households heads						
English language proficiency	-0.287***	-0.062*	-0.171***	-0.046	-0.156**	-0.241***
	(0.099)	(0.034)	(0.059)	(0.048)	(0.074)	(0.083)
Obs.	23,392	23,392	23,392	23,392	23,392	23,392
Dropping individuals married to a native						
English language proficiency	-0.133***	-0.047**	-0.115***	-0.044	-0.126*	-0.191***
	(0.046)	(0.020)	(0.031)	(0.040)	(0.077)	(0.055)
Obs.	28,304	28,304	28,304	28,304	28,304	28,304
Household-level explanatory characteristics						
English language proficiency	-0.116***	-0.056***	-0.148***	-0.023	-0.048	-0.185***
	(0.038)	(0.017)	(0.033)	(0.024)	(0.030)	(0.041)
Obs.	21,765	21,765	21,765	21,765	21,765	21,765
Controlling for housing financial stress						

English language proficiency	-0.185**	-0.053*	-0.088*	-0.021	-0.080***	-0.165***
	(0.064)	(0.028)	(0.035)	(0.041)	(0.052)	(0.061)
Housing cost to income ratio ×1000	1.250***	-0.121	-0.211	0.403***	1.910***	0.633*
	(0.412)	(0.129)	(0.153)	(0.121)	(0.259)	(0.371)
Obs.	24,227	24,227	24,227	24,227	24,227	24,227

Notes: i)*** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level, ii) standard errors, shown in parentheses, are calculated using two-way clustering at both the individual and country of birth level; iii) all models include controls for gender, schooling, age, age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, country-of-birth fixed effects, time fixed effects, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants.
Source: HILDA 2007–2020 waves.

Table 8. Effects of English proficiency on energy poverty: alternative instruments

	2SLS					
	2M	TPR	LIHC	Heat	Arrears	MD
Instrument: Max (0, age at arrival - 9) x LDND distance						
English language proficiency	-0.154***	-0.039**	-0.104***	-0.047	-0.121*	-0.178***
	(0.051)	(0.015)	(0.029)	(0.037)	(0.072)	(0.058)
F statistic (first stage)	291.640 (p<0.0001)	291.600 (p<0.0001)	294.177 (p<0.0001)	212.080 (p<0.0001)	212.349 (p<0.0001)	218.640 (p<0.0001)

Obs.	34,506	34,506	34,506	34,506	34,506	34,506
Instrument: Max (0, age at arrival - 7) x I(NESB countries)						
English language proficiency	-0.163***	-0.045**	-0.113***	-0.048	-0.116*	-0.187***
	(0.051)	(0.019)	(0.032)	(0.036)	(0.070)	(0.060)
F statistic (first stage)	281.110 (p<0.0001)	281.110 (p<0.0001)	282.520 (p<0.0001)	200.604 (p<0.0001)	201.226 (p<0.0001)	207.270 (p<0.0001)
Obs.	34,666	34,666	34,666	34,666	34,666	34,666
Instrument: Max (0, age at arrival - 11) x I(NESB countries)						
English language proficiency	-0.158***	-0.045**	-0.110***	-0.050	-0.127*	-0.190***
	(0.054)	(0.019)	(0.033)	(0.036)	(0.073)	(0.062)
F statistic (first stage)	256.612 (p<0.0001)	256.612 (p<0.0001)	258.282 (p<0.0001)	181.049 (p<0.0001)	181.474 (p<0.0001)	187.500 (p<0.0001)
Obs.	34,666	34,666	34,666	34,666	34,666	34,666

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level; ii) standard errors, shown in parentheses, are calculated using two-way clustering at both the individual and country of birth level; iii) all models include controls for gender, schooling, age, age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, country-of-birth fixed effects, time fixed effects, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants.
Source: HILDA 2007–2020 waves.

Table 9. Effects of English proficiency on energy poverty: Propensity score matching (PSM)

	Propensity Score Matching (ATT)

	2M	TPR	LIHC	Heat	Arrears	MD
Matching method						
Nearest neighbour (5)	-0.031***	-0.009	-0.022***	-0.001	0.005	-0.023***
	(0.005)	(0.014)	(0.003)	(0.003)	(0.004)	(0.004)
Kernel	-0.029***	-0.009	-0.021***	-0.002	0.004	-0.022***
	(0.005)	(0.019)	(0.003)	(0.003)	(0.004)	(0.004)
Local linear regression	-0.029***	-0.009	-0.023***	-0.002	0.004	-0.024***
	(0.006)	(0.024)	(0.004)	(0.003)	(0.005)	(0.005)
Obs.	34,666	34,666	34,666	34,666	34,666	34,666
Obs.	34,666	34,666	34,666	34,666	34,666	34,666

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level; ii) standard errors are in parentheses; iii) the estimates represent the average treatment effect on the treated (ATT); iv) all models include controls for gender, schooling, age, age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants.
Source: HILDA 2007–2020 waves.

Table 10. Effects of English proficiency on energy poverty – with sample weights

	2SLS					
	2M	TPR	LIHC	Heat	Arrears	MD
English language proficiency	-0.073**	-0.015	-0.075***	-0.029	0.044	-0.098***
	(0.029)	(0.011)	(0.016)	(0.021)	(0.045)	(0.025)
Obs.	34,666	34,666	34,666	34,666	34,666	34,666

Notes: i) *** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level, ii) standard errors are in parentheses, iii) all models include controls for gender, schooling, age, age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, country-of-birth fixed effects, time fixed effects, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants; iv) The sample weights are individual weights contained in the HILDA sample,

calculated through a three-step process to address differences between the sample and the wider Australian population.
Source: HILDA 2007–2020 waves.

Table 11. Effects of English proficiency on energy poverty: potential transmission mechanisms

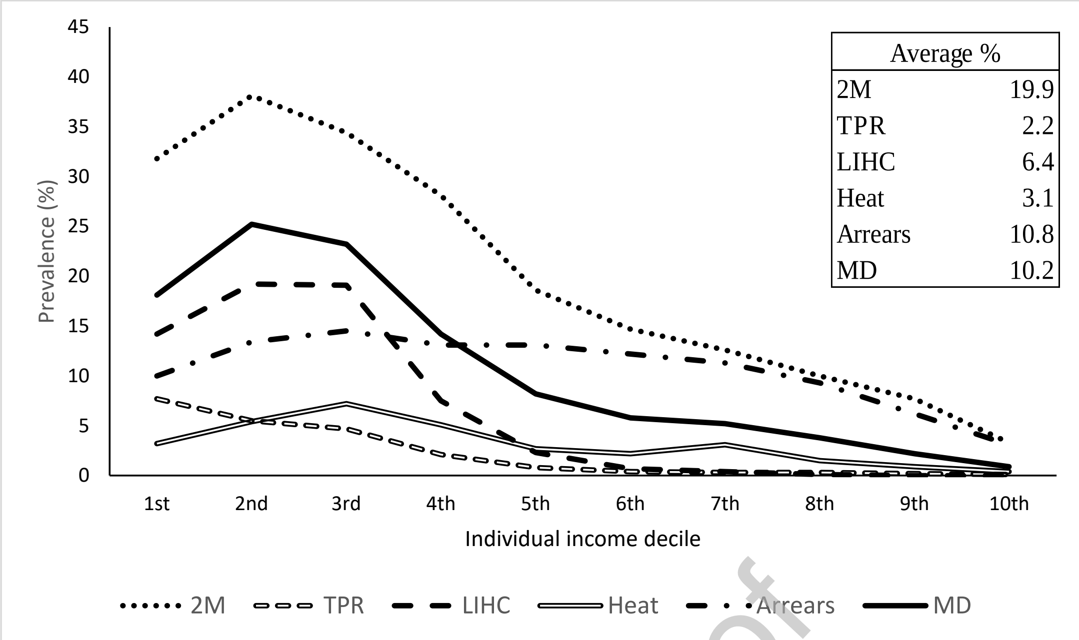
	2SLS					
	2M	TPR	LIHC	Heat	Arrears	MD
Removing income and employment channel						
English language proficiency	-0.075**	-0.028*	-0.082**	-0.048	-0.103*	-0.143***
	(0.034)	(0.016)	(0.036)	(0.037)	(0.058)	(0.060)
Interactions						
Ln(Income)×English proficiency	-0.038	-0.003	0.022	0.019	0.057*	-0.058*
	(0.028)	(0.016)	(0.028)	(0.027)	(0.034)	(0.034)
Employment×English proficiency	0.011	0.014	0.013	-0.015	-0.021	-0.021
	(0.026)	(0.011)	(0.016)	(0.015)	(0.026)	(0.027)
Removing income, employment channel, social capital and Goverment allowances channel:						
English language proficiency	-0.005	-0.002	-0.020	-0.031	-0.067*	-0.051**
	(0.037)	(0.015)	(0.024)	(0.025)	(0.035)	(0.026)
Interactions						
Ln(Income)×English proficiency	-0.011	-0.006	0.000	0.003	0.012	0.006

	(0.014)	(0.006)	(0.008)	(0.009)	(0.012)	(0.013)
Employment×English proficiency	0.032	0.052	-0.004	-0.027	-0.109	-0.099
	(0.111)	(0.491)	(0.071)	(0.076)	(0.142)	(0.027)
Social capital×English proficiency	-0.010	-0.012	0.005	0.028*	0.031*	0.018
	(0.027)	(0.011)	(0.020)	(0.015)	(0.039)	(0.024)
Ln(Government transfers)×English proficiency	0.050	0.020	0.016	0.032*	0.032*	0.041*
	(0.031)	(0.022)	(0.009)	(0.019)	(0.018)	(0.022)
Ln(Household income) ×English proficiency	-0.005	-0.071*	-0.047*	-0.034	-0.040	-0.049*
	(0.212)	(0.036)	(0.025)	(0.141)	(0.036)	(0.026)
	34,666	34,666	34,666	34,666	34,666	34,666

Notes: i)*** denotes significant at the 1% level, ** denotes significant at the 5% level, * denotes significant at the 10% level; ii) standard errors, shown in parentheses, are calculated using two-way clustering at both the individual and country of birth level; iii) all models include controls for gender, schooling, age, age at arrival dummies, marital status, parenthood, disability, household size, energy price, remoteness, region of residence, country-of-birth fixed effects, time fixed effects, regional employment rate, per capita GDP, GDP growth, participation rate, labour force share of part-time workers and share of immigrants.
Source: HILDA 2007–2020 waves.

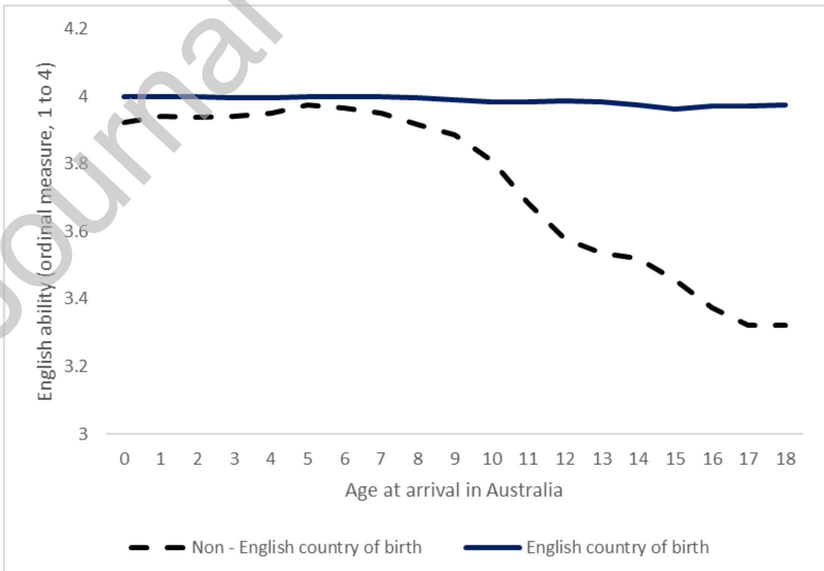
Figures

Fig. 1. Energy poverty rates along the income distribution



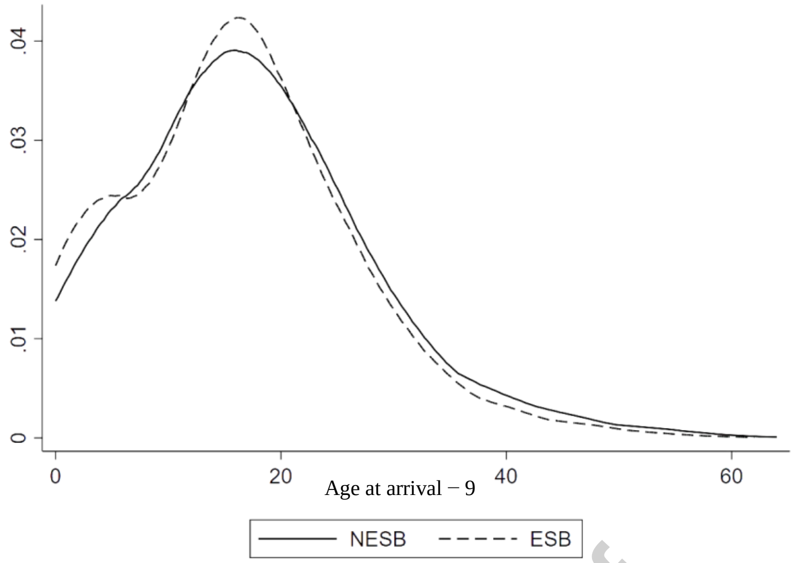
Notes: All the energy poverty measures are binary variables. *2M*: the share of family income spent on energy is greater than twice the national median; *TPR*: the share of family income spent on energy exceeds 10%; *LIHC*: family energy expenditures are above the national median and income net of energy costs is below the official national income poverty line; *Heat:* inability to pay to heat the home due a shortage of money; *Arrears*: inability to pay electricity, gas, or telephone bills on time; *MD*: the household energy poverty score is in the top 10% of the score distribution.
Source: HILDA 2007–2020 waves.

Fig. 2. English ability by age at arrival and English-speaking background



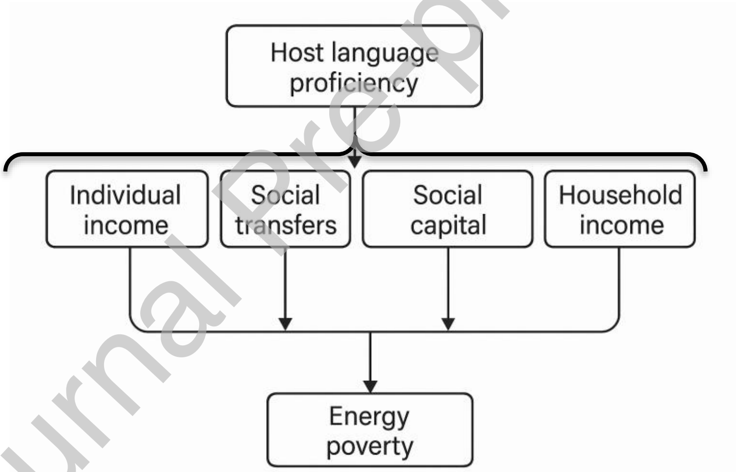
Notes: English ability levels adjusted for gender and age.
Source: HILDA 2007–2020 waves.

Fig. 3. Kernel density estimates for age at arrival in Australia – 9



Source: HILDA 2007–2020 waves.

Fig. 4. Pathways from host language proficiency to energy poverty



Source: Own elaboration.

Appendix A

Table A1. Immigrants by country of birth

ESB	no. Obs	%	NESB	no. Obs	%
United Kingdom	10,549	25.91	Philippines	1,694	4.16
New Zealand	4,388	10.78	China (exclude Hong Kong)	1,478	3.63
India	1,616	3.97	Vietnam	1,246	3.06
South Africa	1,204	2.96	Germany	1,021	2.51
United States	753	1.85	Italy	943	2.32
Fiji	606	1.49	Netherlands	908	2.23
Ireland	501	1.23	Sri Lanka	679	1.67
Canada	452	1.11	Former Yugoslavia	623	1.53
Papua New Guinea	365	0.90	Malaysia	613	1.51
Mauritius	271	0.67	Hong Kong	565	1.39
Malta	201	0.49	Lebanon	522	1.28
Zimbabwe	190	0.47	Poland	445	1.09
Singapore	182	0.45	Indonesia	397	0.98
Tonga	111	0.27	Croatia	366	0.90
Zambia	104	0.26	Greece	353	0.87
Kenya	62	0.15	Japan	315	0.77
Tanzania	53	0.13	Chile	305	0.75
Trinidad and Tobago	30	0.07	Iraq	293	0.72
Jamaica	28	0.07	Egypt	279	0.69
Solomon Islands	26	0.06	Romania	269	0.66
Ghana	16	0.04	Nepal	269	0.66
Norfolk Island	14	0.03	Taiwan	262	0.64
Marshall Islands	9	0.02	Colombia	257	0.63
Bahamas	9	0.02	Bangladesh	249	0.61
Seychelles	9	0.02	Thailand	219	0.54
Bermuda	8	0.02	France	205	0.50
Uganda	7	0.02	Russian Federation	184	0.45
Vanuatu	6	0.01	Turkey	182	0.45
Falkland Islands	6	0.01	Cambodia	175	0.43
Botswana	6	0.01	Pakistan	172	0.42
Nigeria	4	0.01	Top 30 NESB countries	15,488	38.04
Malawi	2	0.00	Rest of NESB countries	3437	8.44
Liberia	1	0.00	Total of NESB countries	18,925	46.48
Total of ESB countries	21,789	53.52			

Source: HILDA 2007–2020 waves.