

## Review

# Empowering networks: Social capital as informal insurance against energy poverty

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## HIGHLIGHTS

- Social capital buffers energy poverty in disadvantaged groups.
- Dynamic estimators (WCML, 2-stage GMM) identify true state dependence.
- Policy: strengthen community networks to curb persistence of energy poverty.

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## ABSTRACT

Research on energy poverty has mainly focused on socioeconomic and structural determinants, while the role of social capital has received much less attention. This is particularly relevant for highly disadvantaged households, for whom informal support networks may represent an important source of protection when formal policy support is limited. We draw on the Journeys Home survey, a unique longitudinal dataset of Australians experiencing severe economic disadvantage, to examine whether social capital affects the dynamics of energy poverty. To account for state dependence, we estimate dynamic models based on Wooldridge's conditional likelihood approach for binary outcomes and complementary two-step GMM specifications. Considering two complementary measures of individual social capital, we find that a one-standard-deviation increase in perceived informal support reduces the probability of experiencing energy poverty by 4.8 percentage points, while an equivalent increase in social connectedness is associated with a 2.6 percentage-point reduction. These findings suggest that social capital can complement conventional policy measures in reducing energy poverty among vulnerable households.

"I would rather walk with a friend in the dark, than alone in the light"

Helen Keller

## 1. Introduction

Energy poverty is a global constraint on basic capabilities and life chances. Globally, around 730 million people remain without electricity and close to 2 billion still lack access to clean cooking, deficits with far-reaching implications for well-being (IEA, 2024). These consequences have contributed to a growing economics literature that recognises

energy poverty as a distinct dimension of deprivation, only partially overlapping with income poverty. Recent evidence associates energy poverty with weaker human-capital formation (Wali et al., 2025), reduced employment opportunities and poorer household economic prospects (Shabbir et al., 2024), and lower overall quality of life (Lin and Okyere, 2021; Qin et al., 2022). A related strand of research documents adverse physical and mental health outcomes (McTague and Trujillo-Baute, 2025; Hashmi et al., 2025).

Research has extensively examined the socioeconomic aspects of energy poverty, with the aim of identifying households at risk and designing targeted policy solutions (del Río et al., 2025; Umair et al.,

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2024; Awan et al., 2022; Abbas et al., 2020). Most studies emphasise factors such as household income, energy prices, dwelling characteristics and demographic composition. More recently, a small but growing literature has also begun to examine whether social capital influences energy poverty using household-level data from China (Ren et al., 2023; Li et al., 2025). The underlying idea is intuitive. Individuals embedded in stronger social networks may gain access to information, material assistance and emotional support that help them cope with adverse economic shocks. However, existing evidence focuses primarily on explaining differences in the prevalence of energy poverty across households, rather than on its dynamics over time. Consequently, we know relatively little about whether social capital helps households avoid persistent energy poverty or facilitates transitions out of it. Likewise, evidence remains scarce for particularly vulnerable populations, among whom informal support networks may play a fundamentally different role.

This gap is important for both theoretical and policy reasons. Existing policy responses to energy poverty, particularly in developed countries, have largely relied on price concessions (e.g., bill discounts or rebates) and targeted income support (e.g., cash transfers). However, a significant proportion of vulnerable households fall outside the purview of policies that rely heavily on means-testing (Simshauser and Miller, 2023). For these individuals, informal support networks may constitute an additional layer of protection, enabling them to cope with temporary financial shocks and avoid prolonged episodes of energy deprivation. Conceptually, social capital may affect not only the current likelihood of energy poverty but also the ability to recover from adverse shocks, and hence its persistence.

This paper addresses these questions using the Journeys Home (JH) survey, a unique longitudinal dataset designed to follow Australians experiencing severe economic, housing, and social vulnerability (Elkins et al., 2023). This empirical setting differs markedly from the nationally representative household surveys typically used in the literature. Individuals facing homelessness, housing instability, labour market exclusion or domestic violence often depend more heavily on perceived informal support, making social capital potentially more consequential in explaining their ability to cope with energy deprivation. To capture the inherently dynamic nature of energy poverty, we estimate dynamic panel models that explicitly account for state dependence and unobserved individual heterogeneity. Our benchmark specification relies on Wooldridge's (2005) conditional maximum likelihood estimator for dynamic binary response models, while alternative GMM specifications (Arellano and Bond, 1991; Arellano and Bover, 1995) provide an additional robustness check.

The paper shows that social capital, operationalized through its cognitive dimension, plays an important role in reducing energy poverty. Specifically, a one-standard-deviation increase in perceived informal support reduces the probability of experiencing energy poverty by almost five percentage points. The estimated effects remain remarkably stable across a wide range of robustness exercises, including alternative estimators, energy poverty definitions, identification strategies and tests for reverse causality, sample selection and the potential endogeneity of social capital. The paper further shows that, within a vulnerable population, financial distress, health status and housing insecurity constitute important mechanisms through which social capital affects energy poverty outcomes.

This paper contributes to the literature in three main ways. First, it shifts attention from the prevalence of energy poverty to its dynamics. Existing studies, including the closely related works by Ren et al. (2023) and Li et al. (2025), typically model current energy poverty as a function of contemporaneous household characteristics. As a result, the estimated associations largely reflect persistent differences across households, since both energy poverty and the explanatory factors exhibit considerable inertia over time. By contrast, we explicitly account for state dependence and unobserved heterogeneity, allowing us to examine whether social capital influences *transitions* into and out of energy

poverty. This distinction is important because recent evidence shows that energy poverty is highly persistent (Drescher and Janzen, 2021; Halkos and Kostakis, 2023; Budría and Betancourt-Odio, 2025). Building on the poverty dynamics literature (Cappellari and Jenkins, 2004; Fabrizi and Mussida, 2020), we investigate whether perceived informal support and social connectedness reduce the persistence of energy poverty by facilitating exits and preventing re-entry in a developed-country setting.

Second, this study draws on a longitudinal dataset specifically designed to capture the lived experiences of individuals facing severe economic and housing insecurity, rather than relying on standard general population surveys. The study covers a population characterised by unstable living arrangements, recurrent adverse shocks, and weak attachment to formal institutions — features rarely captured in conventional household surveys. Importantly, these conditions are likely to shape both the availability of informal support and its protective value in ways that differ from the general population. Whereas most existing work draws on broad population surveys and offers static snapshots of energy poverty, we examine the dynamics of deprivation (entries, exits, and persistence) within a highly disadvantaged population. Moreover, the paper is the first to examine the mechanisms through which social capital influences energy poverty among highly vulnerable households.

Third, Australia provides a particularly informative institutional context in which to examine the role of social capital in shaping experiences of energy poverty among disadvantaged populations. Energy assistance is highly fragmented across jurisdictions, with most policies designed and implemented at the state and territory levels and substantial variation in scope, eligibility criteria, and coverage (ACIL Allen Consulting, 2018; Energy Consumers Australia and KPMG, 2021). Existing responses to energy vulnerability are largely centred on price concessions and targeted subsidies, which are unevenly distributed geographically and across population groups, and often insufficiently tailored to households facing complex or cumulative disadvantages (Chester and Morris, 2011; Willand, 2022). Moreover, access to formal assistance frequently requires self-identification, engagement with energy retailers, or prior payment difficulties—conditions that may systematically exclude individuals experiencing stigma, social isolation, or unstable housing situations (Willand, 2022). As a result, severe energy poverty in Australia is shaped not only by affordability constraints, but also by weak institutional attachment and limited informal support networks, increasing the potential relevance of social capital as a coping resource.

Moreover, recent increases in energy prices and broader cost-of-living pressures have intensified affordability concerns for low-income households (ABS, 2025; AER, 2023), amplifying the risk that short-term shocks translate into persistent deprivation. Against this backdrop, social capital may be a key resource for coping with rising energy costs and mitigating the persistence of energy poverty (Middlemiss et al., 2019; Parsell and Clarke, 2020). This combination of price volatility and reliance on informal support makes Australia a particularly relevant case for analysing how relational resources shape energy-poverty dynamics among disadvantaged groups. The Australian setting is not exceptional: it exemplifies contemporary welfare arrangements in which targeted support coexists with administrative complexity and rising cost pressures (Heller et al., 2024).

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and sets out the research objectives. Section 3 describes the data and the main variables used in the analysis. Section 4 presents the econometric framework and details the estimation methods. Section 5 reports the results, focusing on the role of social capital in shaping transitions into and out of deprivation while controlling for income and other household characteristics. Section 6 provides a large battery of robustness checks and additional exploratory analyses. Section 7 examines potential transmission mechanisms, including financial status, health and housing situation. Section 8 concludes with a discussion of the main findings, limitations, and policy

implications. The paper contains two appendices with additional results from alternative GMM specifications and assumptions, and a technical note on the calculation of residential energy prices.

## 2. Literature review

Energy poverty is commonly understood as a household's inability to secure the energy services needed to maintain adequate living conditions and support human development (Bouzarovski and Petrova, 2015). Translating this conceptual notion into operational, measurable indicators is far from straightforward and has been widely debated (Sy and Mokaddem, 2022). Nonetheless, most empirical studies converge on a core idea: energy-poor households are those that cannot obtain sufficient energy services at an acceptable cost and quality. Three strands of literature inform our study: a large body of static evidence on the determinants of energy poverty, a smaller dynamic literature on its persistence, and an emerging line of work connecting energy poverty to social capital. Section 2.1 reviews the first two strands; Section 2.2 turns to the third and outlines the existing gaps; and Section 2.3 defines social capital and explains how it is operationalized in the paper.

### 2.1. The determinants of energy poverty: from static to dynamic evidence

Cross-national research shows that household energy poverty is heavily conditioned by the broader national context, with economic development, income inequality and, in some settings, climatic conditions emerging as key risk factors (Igawa and Managi, 2022). Country differences in retail energy prices, geographical position and the reliability of access to modern energy services also help account for affordability constraints (Andreoni, 2024). Recent work highlights the importance of how energy is produced: the structure of the electricity mix, the extent of dependence on imported fossil fuels and the deployment of renewable sources all shape energy-poverty outcomes, suggesting that energy and climate policy are tightly intertwined with distributional issues (Kolati and Raghutla, 2025).

At a more disaggregated level, household characteristics emerge as a core determinant. Low income, when combined with high tariffs, increases the likelihood of arrears, energy-related debt and, in extreme cases, disconnection from supply (Memmott et al., 2024). The systematic review by del Río et al. (2025) shows that a relatively small group of factors repeatedly appears across studies: low income, low education of the household head, unemployment or low-skilled employment, large household size and the presence of children, renting rather than owning, living in older or detached dwellings, and residing in rural or disadvantaged regions. Within this broad pattern, recent empirical work documents sizeable socio-demographic gradients. For Ghana, (Crentsil et al., 2019) find strong associations between multidimensional energy poverty and income, education and gender, while Awan et al. (2022) report that labour-market participation and marital status are key correlates of deprivation in Pakistan. Using a group of South Asian countries, Behera et al. (2015) underline the role of education, through its impact on information, decision-making and the adoption of efficient energy sources. Abbas et al. (2020) obtain similar conclusions for a broader set of developing economies. Evidence from high-income settings complements these findings: drawing on Australian longitudinal data, Fry et al. (2022) emphasise the importance of employment histories and retirement status, while Prakash et al. (2022) point to cultural traits and parental behaviours. In the European context, Waldron et al. (2025) combine indicators of energy deprivation with housing-cost stress and show that private tenants are considerably more exposed to combined housing and energy hardship than owner-occupiers.

A common feature of these contributions is that energy poverty is modelled as a static outcome, with current deprivation linked to contemporaneous characteristics and the set of controls assumed to fully capture the relevant heterogeneity. This approach may be too restrictive if energy poverty is, in practice, a recurrent condition shaped by past

experiences and cumulative disadvantage. A second, more recent strand of research addresses this issue by modelling deprivation dynamically and allowing past energy-poverty status to influence current outcomes. Drescher and Janzen (2021), using German panel data, estimate sizeable state-dependence effects: having been energy poor in the previous period raises the probability of being poor again by around 4–8 percentage points. Similar models for Ethiopia, Greece and Australia reveal even larger persistence effects, of the order of 10 percentage points (Alem and Demeke, 2020; Halkos and Kostakis, 2023; Budría and Betancourt-Odio, 2025). These findings suggest that state dependence tends to be stronger in settings where vulnerability is more widespread and safety nets are weaker. However, despite these advances, there is still little evidence on whether social capital buffers the dynamics of deprivation, i.e., whether it helps prevent entries into energy poverty or shortens poverty spells.

### 2.2. Social capital and energy poverty

A third, still small but growing strand of literature links social capital to energy poverty, suggesting that social networks, trust, and community ties may operate as protective resources (Middlemiss et al., 2019). Nevertheless, empirical evidence remains limited. The studies most closely related to ours are Ren et al. (2023) and Li et al. (2025), both of which use the China Family Panel Studies (CFPS) to show that individuals with higher levels of social capital (proxied by social trust and gift expenditure) are less likely to experience energy poverty. Social capital may operate through several channels, including improved access to informal finance, more efficient information sharing, stronger reciprocal support networks, lower transaction costs in accessing resources, and healthier behavioural responses. Consistent with these theoretical arguments, Li et al. (2025) identify income, informal finance and health emerging as transmission channels.

While these studies represent an important step forward, several questions remain open. First, both papers analyse energy poverty as a contemporaneous outcome. Although Li et al. (2025) exploit the longitudinal structure of the CFPS, their empirical framework does not explicitly model state dependence or entries into and exits from energy poverty. This leaves open the question of whether social capital helps households avoid entering energy poverty or facilitates their exit once deprivation occurs. Conceptually, this distinction is important because social capital is expected to operate precisely by helping households cope with adverse shocks, making its effects more likely to emerge through the persistence of energy poverty than through its contemporaneous incidence. Second, the available evidence is based on nationally representative surveys. Whether social capital plays an effective protective role among highly disadvantaged populations (whose access to formal support mechanisms is often limited) remains largely unexplored.

### 2.3. Social capital, perceived informal support, and social connectedness

Social capital has become an influential idea across the social sciences. In Putnam's (1995, pp. 664–665) classic formulation, it comprises "the features of social life—networks, norms, and trust—that enable participants to act together more effectively to pursue shared objectives", and a growing body of evidence links it to better health (Amoah and Adjei, 2023; Pedersen et al., 2023) and to socio-economic mobility and resilience against adversity (Karnik and Peterson, 2023; Parvin et al., 2023). Yet the concept demands precision about what is being measured. At its core, social capital refers to the actual or potential resources embedded in a person's social relations (Bourdieu, 1986; Coleman, 1988; Lin, 2002), which is not the same as the relations themselves. The web of ties in which an individual is embedded, its size, density, and frequency of interaction, constitutes the social network: the infrastructure through which resources may flow, not the resources proper (Berkman et al., 2000).

For the question addressed in this paper, one further distinction is decisive. The resources a network provides can be assessed in two fundamentally different ways: by what individuals observably have (contacts, memberships, interactions, what the literature calls the *structural* dimension of social capital) or by what individuals believe they can count on (perceptions of trust, belonging, available help, what the literature calls the *cognitive* dimension) (Harpham et al., 2002; Grootaert, 2004). The two need not coincide: a person embedded in a wide network may expect little from it, while someone with few ties may draw a firm sense of security from them (Cornwell and Waite, 2009). This distinction matters for empirical purposes because theory assigns the two dimensions different roles. According to the buffering model of social support, what governs the capacity to withstand hardship is mainly the expectation that help could be mobilised if needed, i.e., a sense of security that operates even when assistance is never actually drawn upon (Cohen and Wills, 1985; Barrera, 1986). If this is so, perception, rather than network architecture, should be the primary shield against deprivation among people exposed to adverse shocks and weakly attached to formal protection, which is precisely the population studied in the present paper.

The cognitive dimension is not a residual category, for it has a measurement tradition of its own. In psychology, validated instruments have long elicited the perceived availability of support, including the Interpersonal Support Evaluation List (Cohen and Hoberman, 1983), the Multidimensional Scale of Perceived Social Support (Zimet et al., 1988), and Barrera's (1986) explicit separation of perceived from received support. A common finding is that perceived availability, rather than enacted assistance or network size, predicts resilience to stressors. In epidemiology, short cognitive social capital modules asking whether help would be available in an emergency have been validated for general-population surveys (Harpham et al., 2002; De Silva et al., 2006) and incorporated into the World Bank's integrated social capital questionnaire (Grootaert, 2004). In fact, meta-analytic evidence links individual cognitive social capital to mental health (De Silva et al., 2005). In the economics of well-being, a single-item version (whether one has relatives or friends to count on in times of trouble) is measured worldwide by the Gallup World Poll and ranks among the strongest correlates of life evaluation across countries (Helliwell et al., 2025). Closer to our setting, Australian panel research has used multi-item perceived support scales from HILDA as individual-level measures of social capital (Budría et al., 2025; Atalay et al., 2026), following earlier work employing near-identical items (d'Hombres et al., 2010; Churchill and Smyth, 2021b). In short, where the cognitive dimension has been measured, it has proved to be the facet of social capital that does the protective work.

Energy poverty research stands in contrast to this tradition. The studies that measure social capital in this field rely on composite or aggregate constructions in which the cognitive dimension is either absent or blended with structural components: Ren et al. (2023) combine neighbourhood ties, organisational participation, gift-exchange expenditure, and generalised trust into a single household index; Li et al. (2025) aggregate annual gift expenditure (labelled social support) with generalised trust in a geometric-mean index; and Australian evidence has considered trust at the community level (Churchill and Smyth, 2020) or the presence of social connections among the elderly (Fry et al., 2022). Where cognitive elements appear, they take the form of generalised trust in others at large (strangers, neighbours, officials) rather than the support a person believes she could mobilise from her own ties. To the best of our knowledge, no study has yet brought the perceived-support measurement tradition into the analysis of energy poverty by isolating individual-level perceived informal support, let alone examined its role in the dynamics of deprivation. This is the gap our measurement strategy addresses. Given the theoretical role of perceived support under hardship, it is a relevant one.

### 3. Data and definition of variables

Our empirical analysis uses data from Journeys Home (JH), a longitudinal survey that follows individuals in Australia who face heightened risks of housing instability (Wooden et al., 2012; Cobb-Clark and Kettlewell, 2021). The sample is drawn from Centrelink administrative records, the national agency responsible for income-support payments. Because benefits are administered centrally, most people experiencing severe housing difficulties—such as sleeping rough, staying temporarily with friends or relatives, or living in public or supported housing—are in contact with Centrelink and receive some form of assistance.

For internal administrative purposes, Centrelink classifies some recipients as “homeless” or “at risk of homelessness”, and JH selects random subsamples from these flagged groups. Since these flags were introduced to improve service delivery rather than to build a sampling frame, a third (and larger) stratum was added comprising unflagged clients whose observed characteristics suggest a high likelihood of housing vulnerability. As a result, the JH panel covers a broad spectrum of individuals at different levels of housing risk. The extent of disadvantage in this data becomes evident when JH respondents are compared with a nationally representative sample from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Relative to the average Australian, they have substantially lower incomes, and are more likely to be Australian-born, to have left school before completing upper secondary education, to report a long-term health condition, to be younger on average and to live without a partner (Cobb-Clark and Kettlewell, 2021).

The sampling frame comprised 139,801 individuals, from which a stratified random sample of 2992 individuals living in 36 locations was drawn. Around 62% of those sampled agreed to participate in the first wave, conducted between September and November 2011. These respondents were then followed for five additional waves at six-month intervals, resulting in six waves in total. Because our econometric specification includes a lagged dependent variable, Wave 1 is not used in the regression analysis. After excluding observations with missing information on key variables, the final estimation sample consists of 6169 individuals; 509 observations were dropped due to item non-response, corresponding to 5.7% of the original dataset.

Although retention rates are remarkably high in the JH (yearly average = 96.5%), the non-random exit and entry of individuals in panel data is a potential concern. To counteract this, the JH survey introduces longitudinal weights for each wave to align its sample more closely with the overall population, addressing any over- or under-representation of specific characteristics. This approach improves the representativeness of the JH sample with respect to its target population of vulnerable individuals and reduces potential biases arising from differential sample attrition. In Section 6.4, we conduct additional sensitivity analyses to assess the extent to which our findings may be affected by selection and attrition bias.

#### 3.1. Energy poverty

Defining and measuring energy poverty remains contested in the empirical literature (Thomson et al., 2017). While many studies rely on expenditure-based indicators (such as the share of income devoted to energy, the Ten Percent Rule, or composite measures like the Low-Income High Costs index) these metrics are not suitable for the present analysis because the JH dataset lacks information on energy bills. Moreover, consumption-based thresholds can be misleading in contexts of severe socioeconomic vulnerability, where individuals may under-consume energy, rely on credit, or reallocate scarce resources to prioritise other basic needs.

For these reasons, and in line with previous work (Prakash et al., 2022), this paper uses self-reported indicators of access and affordability. Specifically, our measurement of energy deprivation builds on three self-reported items available in every wave of the JH. Each item is

coded as a binary variable that flags whether, at the time of the interview, the respondent (*i*) lacks access to electricity (*Electricity*), (*ii*) lacks access to cooking facilities (*Cooking*), or (*iii*) has been unable to pay electricity, gas, or telephone bills on time (*Arrears*). Because each item captures a different manifestation of deprivation, the regression analysis also reports domain-specific results for the three indicators taken one at a time.

To obtain a single metric, we aggregate the items into a Multidimensional Energy Poverty Index (MEPI), in the spirit of the counting measures developed in the material-deprivation literature and applied to energy poverty in earlier work (Budría and Betancourt-Odio, 2025). Formally, we denote the deprivation domains by  $d = 1, \dots, D$ , with  $D = 3$  in our application, and  $y_{idt} \in \{0,1\}$  indicates whether individual *i* is deprived in domain *d* at wave *t*. The individual's score is defined as the weighted count of deprivations, rescaled to a 0–100 metric:

$$MEPI_{it} = 100 \sum_{d=1}^D \omega_{dt} y_{idt} \quad (1)$$

where the weights  $\omega_{dt}$  are non-negative and sum to one within each wave. In other words, the index measures the (weighted) share of domains in which the person is deprived, with 0 denoting no deprivation and 100 denoting deprivations in every domain. Under uniform weights  $\omega_{dt} = \frac{1}{D}$ , Eq. (1) collapses to the familiar adjusted headcount ratio. An individual is classified as energy poor whenever  $MEPI_{it}$  exceeds a cut-off *c*; our baseline sets  $c = 0$ , so that deprivation in any single domain suffices. In Section 6.1 we explore stricter thresholds.

Instead of weighting all domains equally, we let the data determine the relative importance of each item through the frequency-based scheme of Decancq and Lugo (2013). The intuition is that going without a service that nearly everyone enjoys signals deeper deprivation than going without one that is commonly lacking. Accordingly, each domain receives a weight proportional to the share of individuals *not* deprived in it:

$$\omega_{dt} = \frac{1 - s_{dt}}{\sum_{d=1}^D (1 - s_{dt})}, s_{dt} = \frac{1}{N_t} \sum_{i=1}^{N_t} y_{idt} \quad (2)$$

where  $s_{dt}$  is the wave-specific deprivation rate in domain *d* and  $N_t$  is the number of respondents in wave *t*. Computing the weights by wave has two implications. First, deprivation is assessed relative to prevailing standards: an individual's measured poverty can rise even if her own

conditions remain unchanged, provided the rest of the population improves. Second, the weights adjust automatically as economic conditions and social norms regarding access to these services evolve.

### 3.2. Measures of individual social capital

Following the rationale set out in Section 2.3, we measure individual social capital through its cognitive dimension using two complementary indicators: *perceived informal support* (our principal measure) and *social connectedness*. We keep them separate so that consistent results provide evidence of convergent validity, while each captures a distinct aspect—available resources versus belonging.

The first measure is based on four JH items on the support respondents expect from friends and family: (1) You often need help from other people but can't get it; (2) You have someone you can lean on in times of trouble; (3) There is someone who can always cheer you up when you are down; (4) When something's on your mind, just talking with the people you know can make you feel better. Responses are coded on a 1–5 Likert scale (1 = strongly disagree, 5 = strongly agree). We recode item (1) so that higher values indicate stronger support and construct an aggregate index ranging from 4 to 20. Fig. 1 shows the kernel density of the standardized variable: energy-poor individuals (red solid line) display lower social capital than non-energy-poor individuals (blue dashed line).

The second measure is based on a single JH item. Respondents rate their agreement with the statement 'I often feel lonely' on a scale from 1 (strongly agree) to 5 (strongly disagree). Since higher values indicate lower isolation, we label this variable social connectedness.

### 3.3. Individual characteristics and contextual controls

The vector of covariates includes a broad set of socio-economic characteristics that the literature has linked to energy poverty. At the individual level we control for employment status, personal income, gender, self-reported health, age, educational attainment, marital status, the number of children in the household and whether the respondent lives in an urban or rural area. We also exploit features of the JH questionnaire that capture forms of vulnerability that are particularly salient in this population. Specifically, we include a self-reported indicator of problems with drug or alcohol addiction, as well as two dummies recording whether the respondent has experienced physical violence and, separately, sexual violence during the previous six months. These variables are intended to proxy for severe adverse events

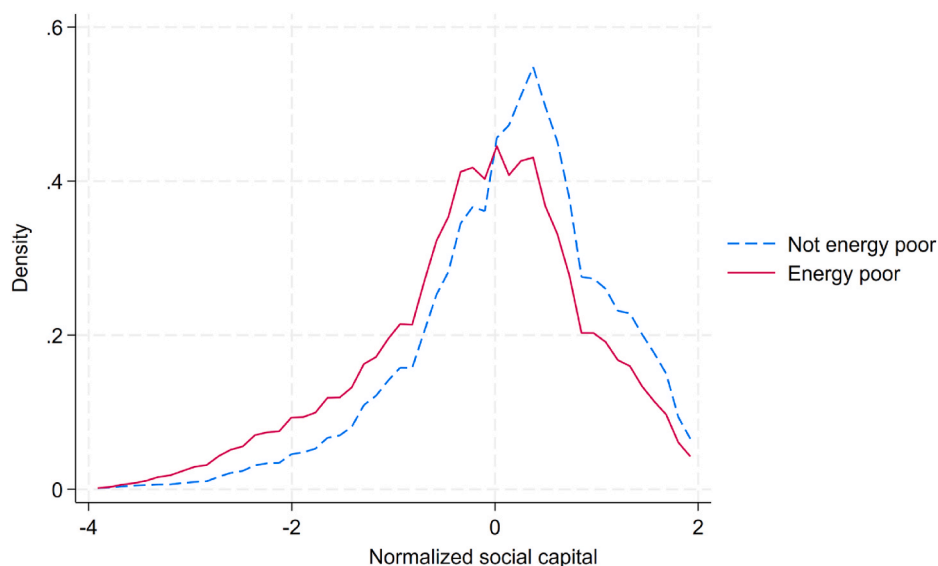


Fig. 1. Density distribution of normalized social capital by energy poverty status.

that can generate financial stress, alter social behaviours and, ultimately, constrain access to energy. A limitation is that JH does not collect detailed information on dwelling characteristics, which prevents us from directly accounting for housing efficiency and energy demand factors emphasised in earlier studies (del Río et al., 2025).

We also control for the economic environment in which individuals are embedded. To this end, the specification incorporates the annual regional unemployment rate, regional per capita GDP growth, and a full set of region and wave fixed effects, to capture both cyclical conditions and persistent regional differences in labour market opportunities. In addition, we merge state-level residential energy prices into the JH data. Since prices are observed at annual frequency while interviews occur in two within-year windows, we approximate interview-date exposure using a weighted average of adjacent annual prices; details and sources are provided in Appendix A.

Table 1 reports summary statistics for two groups defined by perceived informal support, our principal measure of social capital: individuals with values at least one standard deviation above the mean (high social capital) and those at least one standard deviation below (low social capital). The lack of electricity and kitchen facilities is notably more prevalent among those with low social capital (8.3% and 13.5%, respectively) compared to high social capital individuals (1.1% and 2.1%), and a similar pattern can be found for arrears (44.5% versus 24.9%). Consistent with these patterns, both the *MEPI* and the share of respondents experiencing at least one deprivation (*MEPI* > 0) more than double when moving from the high to the low social capital group.

The two groups also differ sharply along socio-economic dimensions. Compared to individuals with high perceived informal support, those with low perceived informal support have lower weekly income (406 vs. 511), are less likely to be employed (12.8% vs. 32.6%) or married (11.5% vs. 28.7%), and more likely to report ill health (29.6% vs. 5.3%) and have children (97.2% vs. 86.9%). They also report higher rates of physical violence in the past six months (25.8% vs. 12.1%) and alcohol/drug addiction (28.6% vs. 9.0%). Finally, there are no sizeable differences in terms of schooling, location in major urban areas and distribution among Australian regions.

#### 4. Empirical framework

To examine whether perceived informal support and social connectedness mitigate persistence in energy poverty, we estimate a dynamic probit model that accounts for state dependence using the Wooldridge conditional maximum likelihood (WCML) approach proposed by Wooldridge (2005) and further discussed by Skrandal and Rabe-Hesketh (2014). Let  $EP_{it}$  denote a binary indicator that takes the value 1 if individual  $i$  is energy poor in wave  $t$ , and 0 otherwise. The underlying latent index is specified as:

$$EP_{it}^* = \rho EP_{it-1} + \theta(\lambda SC_{it} + (1 - \lambda)SCO_{it}) + X_{it}'\beta + \gamma_{r(i,t)} + \tau_t + c_i + u_{it}, \quad (3)$$

where  $SC_{it}$  denotes the measure of social capital, and  $SCO_{it}$  is the measure of social connectedness,  $X_{it}$  is the vector of observed covariates. The terms  $\gamma_r$  and  $\tau_t$  denote region and wave fixed effects, respectively. Region fixed effects capture persistent differences across states, whereas wave fixed effects absorb common temporal shocks, including changes in aggregate macroeconomic and energy-market conditions. Unobserved individual-specific heterogeneity is captured by  $c_i$  while  $u_{it}$  denotes an idiosyncratic error term assumed to follow a normal distribution,  $u_{it} \sim N(0, \sigma_u^2)$ . In practical terms, Eq. (3) states that the probability of being energy poor today depends on three ingredients: whether the individual was poor six months earlier ( $\rho$ , the persistence parameter and our first object of interest), her current relational resources (social capital or social connectedness, depending on the specification) together with the controls in  $X_{it}$ , and a permanent individual component  $c_i$  capturing stable, unobserved traits such as ability, health endowments, or long-standing disadvantage.

To simplify notation, we write the model generically using an indicator  $\lambda \in \{0, 1\}$ , where  $\lambda = 1$  corresponds to specifications including social capital and  $\lambda = 0$  to specifications including social connectedness. The observed outcome is given by

$$EP_{it} = \begin{cases} 1 & \text{if } EP_{it}^* > 0, \\ 0 & \text{otherwise} \end{cases} \quad i \in I, t \in T_i \quad (4)$$

A well-known difficulty in estimating dynamic models of this kind is the so-called *initial-conditions problem* (Heckman, 1981). Our data do not capture individuals at the "start" of their economic lives: whether a respondent is already energy poor in the first wave is likely the result of an unobserved personal history—prior hardship, chronic disadvantage, or stable traits—rather than a random draw. If this is ignored, the model attributes to state dependence (being poor today because one was poor yesterday) what is partly the result of who was poor to begin with, thereby inflating the estimated persistence. The approach proposed by Wooldridge (2005) addresses this concern by letting the unobserved individual effect depend explicitly on the initial poverty status and on the individual's average characteristics over the panel. In this setting, individuals are compared conditional on where they started and on their long-run profiles. Hence, the coefficient on lagged poverty isolates genuine persistence rather than pre-existing differences between individuals.

Formally, we model the individual-specific effect as a function of the initial energy-poverty status and individual-specific averages of time-varying covariates (Mundlak terms):

$$c_i | EP_{i1}, Z_i, X_{i1} \sim N\left(\theta_0 + \theta_1 EP_{i1} + X_{i1}'\theta_2 + Z_i'\theta_3 + \bar{X}_i\theta_4 + \xi_i, \sigma_\xi^2\right) \quad (5)$$

$$c_i = \theta_0 + \theta_1 EP_{i1} + X_{i1}'\theta_2 + Z_i'\theta_3 + \bar{X}_i\theta_4 + \xi_i$$

where  $EP_{i1}$  denotes the initial observed status,  $X_{i1}$  are initial values of time-varying covariates,  $Z_i$  are time-constant controls,  $\bar{X}_i$  denotes within-individual means of time-varying regressors,  $\xi_i \sim N(0, \sigma_\xi^2)$ ,  $\theta_1$  and  $\theta_2$  account for the possibility that energy poverty at a given time is endogenously determined by the individual's initial conditions. This specification mitigates bias from initial conditions and separates persistence attributable to genuine state dependence from persistence driven by time-invariant unobserved heterogeneity. Simulation evidence supports the performance of this approach in short panels (Akay, 2012). Moreover, the correlated random-effects parameterisation allows for correlation between the individual-specific effect and the observed covariates, while explicitly modelling dependence on the initial outcome (Budría et al., 2023).

As a sensitivity check, we also estimate a linear dynamic panel model using difference GMM (Arellano and Bond, 1991; Arellano and Bover, 1995). A feature of this setting is that it deals with the unobserved heterogeneity with less restrictive assumptions than those stated in Eq. (5), insofar as it does not require a distributional condition on  $c_i$ . Agreement between the two estimators is therefore informative about the validity of the auxiliary assumption in Eq. (5) (Stuart and Rubin, 2008). The well-known limitations of linear models for binary outcomes (predictions outside the unit interval and the neglect of nonlinearity) are of limited consequence in this exercise, since the GMM estimates are not used for prediction but to verify the sign, significance, and magnitude of the key coefficients.

We first-difference the model to eliminate the individual effect and instrument the differenced lagged dependent variable with its lags (collapsed instrument set, maximum lag 3) to address the correlation between  $\Delta EP_{i,t-1}$  and  $\Delta u_{it}$ . Given the binary nature of  $EP_{it}$ , we interpret this GMM exercise as descriptive robustness rather than as a substitute for the dynamic probit estimates. Standard specification tests (AR (2) and Hansen) are reported, and implementation details are provided in Appendix B.

**Table 1**

Summary statistics by housing status.

|                                          | All                | Low perceived informal support (PS.Cap < Mean (PS.Cap) - std (PS.Cap)) | High perceived informal support (PS.Cap > Mean (PS.Cap) + std (PS.Cap)) |                                               | All              | Low perceived informal support (PS.Cap < Mean (PS.Cap) - std (PS.Cap)) | High perceived informal support (PS.Cap > Mean (PS.Cap) + std (PS.Cap)) |
|------------------------------------------|--------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------|-----------------------------------------------|------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------|
| No. of observations                      | 8346               | 1011                                                                   | 1496                                                                    |                                               |                  |                                                                        |                                                                         |
| Share                                    | 100.0              | 12.11                                                                  | 17.92                                                                   | Children                                      | 0.918<br>(1.337) | 0.972<br>(1.395)                                                       | 0.869<br>(1.303)                                                        |
|                                          |                    |                                                                        |                                                                         | Major urban area (Relative Freq)              | 0.774<br>(0.418) | 0.801<br>(0.399)                                                       | 0.778<br>(0.416)                                                        |
| Perceived informal support               | 14.919<br>(2.941)  | 9.245<br>(1.730)                                                       | 18.803<br>(0.782)                                                       | Alcohol/drug addiction (Relative Freq)        | 0.166<br>(0.372) | 0.286<br>(0.452)                                                       | 0.090<br>(0.290)                                                        |
| Social connectedness                     | 3.044<br>(1.271)   | 2.082<br>(1.138)                                                       | 3.877<br>(1.152)                                                        | <b>Experience of violence (Relative Freq)</b> |                  |                                                                        |                                                                         |
|                                          |                    |                                                                        |                                                                         | Physical violence last 6 months               | 0.164<br>(0.371) | 0.258<br>(0.438)                                                       | 0.121<br>(0.326)                                                        |
| <b>Energy Poverty (Relative Freq)</b>    |                    |                                                                        |                                                                         | Sexual violence last 6 months                 | 0.020<br>(0.139) | 0.035<br>(0.183)                                                       | 0.018<br>(0.133)                                                        |
| Electricity                              | 0.033<br>(0.18)    | 0.083<br>(0.276)                                                       | 0.011<br>(0.106)                                                        | Per capita GDP growth                         | 1.311<br>(1.981) | 1.237<br>(1.866)                                                       | 1.221<br>(1.933)                                                        |
| Kitchen                                  | 0.055<br>(0.227)   | 0.135<br>(0.341)                                                       | 0.021<br>(0.142)                                                        | Regional unemployment                         | 5.478<br>(0.789) | 5.485<br>(0.753)                                                       | 5.528<br>(0.743)                                                        |
| Arrears                                  | 0.319<br>(0.466)   | 0.445<br>(0.497)                                                       | 0.249<br>(0.432)                                                        | <b>Australian region (Relative Freq)</b>      |                  |                                                                        |                                                                         |
| MEPI                                     | 0.116<br>(0.182)   | 0.197<br>(0.231)                                                       | 0.077<br>(0.141)                                                        | NSW                                           | 0.203<br>(0.403) | 0.207<br>(0.405)                                                       | 0.191<br>(0.393)                                                        |
| MEPI > 0                                 | 0.361<br>(0.480)   | 0.545<br>(0.498)                                                       | 0.265<br>(0.441)                                                        | Victoria                                      | 0.211<br>(0.408) | 0.252<br>(0.435)                                                       | 0.247<br>(0.432)                                                        |
| Individual income                        | 448.8<br>(348.125) | 405.9<br>(225.176)                                                     | 511.3<br>(388.836)                                                      | Queensland                                    | 0.265<br>(0.442) | 0.265<br>(0.441)                                                       | 0.282<br>(0.451)                                                        |
| <b>Employment status (Relative Freq)</b> |                    |                                                                        |                                                                         | SA                                            | 0.071<br>(0.259) | 0.057<br>(0.233)                                                       | 0.068<br>(0.251)                                                        |
| Employed                                 | 0.226<br>(0.418)   | 0.128<br>(0.336)                                                       | 0.326<br>(0.469)                                                        | WA                                            | 0.109<br>(0.311) | 0.097<br>(0.296)                                                       | 0.105<br>(0.307)                                                        |
| Unemployed                               | 0.254<br>(0.435)   | 0.206<br>(0.404)                                                       | 0.237<br>(0.426)                                                        | Tasmania                                      | 0.052<br>(0.223) | 0.047<br>(0.213)                                                       | 0.044<br>(0.205)                                                        |
| Inactive                                 | 0.520<br>(0.500)   | 0.667<br>(0.472)                                                       | 0.437<br>(0.496)                                                        | NT                                            | 0.056<br>(0.230) | 0.054<br>(0.227)                                                       | 0.040<br>(0.196)                                                        |
| Woman (Relative Freq)                    | 0.469<br>(0.499)   | 0.397<br>(0.489)                                                       | 0.554<br>(0.497)                                                        | ACT                                           | 0.030<br>(0.170) | 0.020<br>(0.139)                                                       | 0.021<br>(0.142)                                                        |
| Ill health (Relative Freq)               | 0.118<br>(0.323)   | 0.296<br>(0.457)                                                       | 0.053<br>(0.224)                                                        | <b>Wave</b>                                   |                  |                                                                        |                                                                         |
| Age                                      | 33.150<br>(12.862) | 38.523<br>(12.855)                                                     | 29.870<br>(11.788)                                                      | Wave 1                                        | 0.187<br>(0.390) | 0.210<br>(0.407)                                                       | 0.173<br>(0.378)                                                        |
|                                          |                    |                                                                        |                                                                         | Wave 2                                        | 0.170<br>(0.376) | 0.190<br>(0.392)                                                       | 0.169<br>(0.375)                                                        |
| <b>Education level (Relative Freq)</b>   |                    |                                                                        |                                                                         | Wave 3                                        | 0.163<br>(0.369) | 0.146<br>(0.354)                                                       | 0.162<br>(0.368)                                                        |
| Tertiary education                       | 0.329<br>(0.473)   | 0.331<br>(0.471)                                                       | 0.392<br>(0.488)                                                        | Wave 4                                        | 0.164<br>(0.370) | 0.157<br>(0.364)                                                       | 0.160<br>(0.367)                                                        |
| Upper secondary                          | 0.112<br>(0.315)   | 0.112<br>(0.315)                                                       | 0.119<br>(0.324)                                                        | Wave 5                                        | 0.160<br>(0.366) | 0.148<br>(0.356)                                                       | 0.191<br>(0.393)                                                        |
| Lower secondary or less                  | 0.384<br>(0.486)   | 0.335<br>(0.472)                                                       | 0.365<br>(0.482)                                                        | Wave 6                                        | 0.157<br>(0.364) | 0.148<br>(0.356)                                                       | 0.145<br>(0.352)                                                        |
| <b>Marital status (Relative Freq)</b>    |                    |                                                                        |                                                                         |                                               |                  |                                                                        |                                                                         |
| Married                                  | 0.222<br>(0.415)   | 0.115<br>(0.319)                                                       | 0.287<br>(0.452)                                                        |                                               |                  |                                                                        |                                                                         |

(continued on next page)

Table 1 (continued)

|                       | All              | Low perceived informal support (PS.Cap < Mean (PS.Cap) - std (PS.Cap)) | High perceived informal support (PS.Cap > Mean (PS.Cap) + std (PS.Cap)) | All | Low perceived informal support (PS.Cap < Mean (PS.Cap) - std (PS.Cap)) | High perceived informal support (PS.Cap > Mean (PS.Cap) + std (PS.Cap)) |
|-----------------------|------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------|-----|------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Single                | 0.568<br>(0.495) | 0.563<br>(0.496)                                                       | 0.560<br>(0.497)                                                        |     |                                                                        |                                                                         |
| Divorced or separated | 0.200<br>(0.400) | 0.305<br>(0.460)                                                       | 0.142<br>(0.350)                                                        |     |                                                                        |                                                                         |
| Widowed               | 0.011<br>(0.103) | 0.018<br>(0.132)                                                       | 0.011<br>(0.103)                                                        |     |                                                                        |                                                                         |

## 5. Results

### 5.1. Perceived informal support, social connectedness and the socio-economic gradient of energy poverty

Table 2 reports estimates from the WCML specifications (columns 1 and 2). Experiencing energy poverty in the previous period is associated with an increase of almost 14 percentage points (pp) in the probability of being energy poor in the current period, even after controlling for a rich set of socio-economic characteristics, unobserved individual heterogeneity, and initial conditions. This effect is suggestive of substantial state dependence: past exposure to energy poverty continues to raise the likelihood of subsequent deprivation even after accounting for contemporaneous circumstances. Results from the GMM specification are similar ( $\approx 10$  pp), further supporting this conclusion. Diagnostic tests support the validity of the GMM specification, with no significant evidence of second-order serial correlation in first-differenced residuals. In addition, the Hansen test does not reject the null of valid overidentifying restrictions.

Turning to our core research question, the estimates indicate that perceived informal support acts as a significant safety net against energy poverty. In the WCML model, a one-standard-deviation increase is associated with a 4.8 percentage point decrease in the probability of being in energy poverty. This implies that, for an individual who experienced energy poverty in the previous period, such an increase in social capital substantially improves the chances of escaping energy poverty in the following wave. We find a very similar estimate (4.6 pp) in the GMM specification, which reinforces the robustness of this relationship. These findings are broadly consistent with recent evidence from China showing that social capital is associated with lower household energy poverty (Ren et al., 2023; Li et al., 2025). However, the two sets of results are not directly comparable, for these studies relate contemporaneous measures of social capital to contemporaneous energy poverty. Hence, their estimates partly reflect persistent differences between households that consistently exhibit both high social capital and low energy poverty. By contrast, our dynamic specifications explicitly control for state dependence and unobserved time-invariant heterogeneity. As a result, our estimates primarily capture the role of social capital in facilitating transitions into or out of energy poverty over time, rather than long-run cross-sectional differences across households. In this sense, our findings suggest that social capital not only correlates with lower energy poverty levels but also acts as a buffer against short-term adverse shocks, reducing the persistence of energy poverty.

When we use social connectedness in place of social capital, a similar pattern emerges. In the baseline specification, a one-standard-deviation increase in social connectedness is associated with about a 2.6 pp reduction in the probability of being in energy poverty (Table 2). The larger estimates obtained for perceived informal support compared with social connectedness are consistent with the idea that access to concrete support is more relevant for coping with temporary financial shocks than broader feelings of social integration.

To put the estimates for social capital in context, their protective association is comparable to (and in some cases stronger than) that of

other covariates commonly linked to lower energy deprivation. In the WCML specification, a one-standard-deviation increase in perceived informal support is associated with a 4.8 percentage-point reduction in the probability of being in energy poverty. This effect is substantially larger than the estimated association of log income (1.7 pp) and is almost as large in absolute value as the estimated gender differential, with women exhibiting a 5.7 percentage-point higher probability of experiencing energy poverty.

Appendix Table B reports robustness checks for the two-step difference-GMM estimates under alternative instrumenting assumptions. Allowing income and employment to be treated as endogenous leaves the estimated effects of perceived informal support and social connectedness largely unchanged in sign and order of magnitude. When perceived informal support (column 3) or social connectedness (column 7) are treated as endogenous, standard errors increase and statistical significance weakens, especially for social connectedness, which becomes insignificant. Adding a second lag of energy poverty yields an insignificant coefficient on  $EP_{t-2}$  while the coefficient on  $EP_{t-1}$  remains around 0.16, consistent with sizeable, short-run state dependence. Standard diagnostics are supportive: the Arellano–Bond test indicates significant AR(1) in first differences (as expected) but no evidence of AR (2), and the Hansen overidentification test does not reject the validity of the instrument set.

Notably, in our estimates individual income does not emerge as a statistically robust predictor of transitions into or out of energy poverty. This finding should be interpreted with caution. The JH sample consists of individuals experiencing severe socioeconomic disadvantage, implying limited variation in income compared with the general population. Moreover, our dynamic specifications identify the association between within-individual changes in income and changes in energy poverty over time, rather than cross-sectional differences between richer and poorer households. Consequently, the estimated coefficient should not be interpreted as evidence that income is unimportant for energy poverty more generally. In fact, a large body of evidence based on nationally representative datasets consistently finds household income to be one of the strongest correlates of energy poverty (Halkos and Kostakis, 2023; del Río et al., 2025). Our findings instead suggest that, among highly vulnerable individuals, relatively modest short-run changes in individual income may be insufficient, by themselves, to move households out of severe energy poverty once persistence and other structural constraints are taken into account. This interpretation is consistent with the possibility that poor housing conditions, energy inefficiency, debt burdens, or limited access to support services constrain the effectiveness of income increases in the short run, a result that is in line with earlier evidence from the JH dataset (Budría et al., 2025).

Energy prices contribute little additional explanatory power once persistence and wave and region fixed effects are included; results are unchanged when prices are separated into electricity and “gas and other household fuels” (Appendix A). Turning to household characteristics, family structure is informative: separated and widowed individuals display higher energy-poverty risks in the GMM specification, and the presence of dependent children is positively associated with multidimensional energy poverty, consistent with tighter budgets and time

**Table 2**  
The dynamics of energy poverty.

|                                                  | WCML                        |           | WCML                         |          | GMM       |          |
|--------------------------------------------------|-----------------------------|-----------|------------------------------|----------|-----------|----------|
|                                                  | Exogenous initial condition |           | Endogenous initial condition |          |           |          |
|                                                  | Model 1                     | Model 2   | Model 1                      | Model 2  | Model 1   | Model 2  |
| EP <sub>1</sub>                                  |                             |           | 0.202***                     | 0.207*** |           |          |
| EP <sub>t-1</sub>                                | 0.202***                    | 0.201***  | 0.021                        | 0.022    | 0.098***  | 0.100**  |
| Perceived informal support                       | 0.020                       | 0.020     | 0.020                        | 0.020    | 0.029     | 0.029    |
|                                                  | −0.050***                   |           | −0.048***                    |          | −0.046*** |          |
|                                                  | 0.010                       |           | 0.010                        |          | 0.008     |          |
| Social connectedness                             |                             | −0.034*** |                              | −0.026** |           | −0.027** |
|                                                  |                             | 0.008     |                              | 0.010    |           | 0.011    |
| Electricity & gas price                          | 0.004                       | 0.004     | 0.009                        | 0.010    | 0.008     | 0.007    |
|                                                  | 0.005                       | 0.005     | 0.009                        | 0.009    | 0.007     | 0.007    |
| Employed                                         | −0.010                      | −0.007    | −0.017                       | −0.015   | −0.014    | −0.016   |
|                                                  | 0.028                       | 0.028     | 0.027                        | 0.027    | 0.019     | 0.020    |
| Unemployed                                       | 0.032                       | 0.029     | 0.025                        | 0.023    | −0.009    | −0.013   |
|                                                  | 0.021                       | 0.021     | 0.021                        | 0.021    | 0.037     | 0.038    |
| Log (income)                                     | −0.018                      | −0.019*   | −0.017*                      | −0.017*  | −0.017    | −0.037*  |
|                                                  | 0.011                       | 0.011     | 0.009                        | 0.010    | 0.008     | 0.022    |
| Woman                                            | 0.065***                    | 0.059***  | 0.057**                      | 0.038*   | −0.031    | −0.055   |
|                                                  | 0.018                       | 0.018     | 0.018                        | 0.018    | 0.094     | 0.096    |
| Ill health                                       | 0.002                       | 0.008     | 0.001                        | 0.007    | 0.028     | 0.028    |
|                                                  | 0.026                       | 0.026     | 0.022                        | 0.026    | 0.024     | 0.024    |
| Age                                              | −0.001                      | 0.009*    | −0.011                       | −0.007   | −0.029    | −0.029   |
|                                                  | 0.028                       | 0.004     | 0.030                        | 0.030    | 0.041     | 0.041    |
| Age <sup>2</sup> × 1000                          | −0.001*                     | −0.001*   | −0.001*                      | −0.001   | 0.001     | 0.001    |
|                                                  | 0.004                       | 0.004     | 0.004                        | 0.004    | 0.005     | 0.004    |
| Tertiary education                               | −0.092                      | −0.097    | 0.023                        | 0.013    | 0.009     | −0.141   |
|                                                  | 0.065                       | 0.066     | 0.091                        | 0.092    | 0.024     | 0.127    |
| Upper secondary                                  | 0.02                        | 0.020     | 0.173                        | 0.165    | 0.006     | −0.006   |
|                                                  | 0.030                       | 0.030     | 0.117                        | 0.117    | 0.03      | 0.145    |
| Single                                           | −0.003                      | −0.005    | −0.029                       | −0.001   | −0.005    | 0.001    |
|                                                  | 0.030                       | 0.030     | 0.059                        | 0.029    | 0.041     | 0.043    |
| Separated                                        | 0.084*                      | 0.084*    | 0.083*                       | 0.085*   | 0.170**   | 0.146*   |
|                                                  | 0.046                       | 0.046     | 0.049                        | 0.049    | 0.077     | 0.078    |
| Widowed                                          | 0.069*                      | 0.020     | 0.005                        | −0.002   | 0.536**   | 0.473*** |
|                                                  | 0.041                       | 0.093     | 0.078                        | 0.079    | 0.253     | 0.164    |
| Log (Children)                                   | 0.086*                      | 0.081*    | 0.084*                       | 0.077    | 0.117     | 0.058*** |
|                                                  | 0.049                       | 0.049     | 0.049                        | 0.049    | 0.296     | 0.015    |
| Major urban area                                 | −0.005                      | −0.004    | −0.004                       | −0.006   | −0.005    | −0.004   |
|                                                  | 0.019                       | 0.019     | 0.030                        | 0.031    | 0.019     | 0.019    |
| Addiction problems                               | 0.034                       | 0.033     | 0.029                        | 0.031    | 0.034     | 0.03     |
|                                                  | 0.027                       | 0.027     | 0.026                        | 0.026    | 0.021     | 0.021    |
| Physical violence last 6 months                  | 0.069***                    | 0.069***  | 0.062***                     | 0.065*** | 0.004     | 0.009    |
|                                                  | 0.018                       | 0.018     | 0.017                        | 0.017    | 0.031     | 0.030    |
| Sexual violence last 6 months                    | 0.057                       | 0.050     | 0.069                        | 0.062    | 0.038     | 0.025    |
|                                                  | 0.056                       | 0.056     | 0.049                        | 0.049    | 0.055     | 0.056    |
| Per capita GDP growth                            | −0.008                      | −0.010*   | −0.006                       | −0.008   | −0.006    | −0.008*  |
|                                                  | 0.006                       | 0.006     | 0.007                        | 0.007    | 0.004     | 0.004    |
| Regional unemployment                            | 0.018                       | 0.023     | −0.003                       | 0.004    | −0.009    | −0.008   |
|                                                  | 0.031                       | 0.031     | 0.038                        | 0.038    | 0.017     | 0.017    |
| Year fixed-effects                               | Yes                         | Yes       | Yes                          | Yes      | Yes       | Yes      |
| Region fixed-effects                             | Yes                         | Yes       | Yes                          | Yes      | Yes       | Yes      |
| No autocorrelation of order 1 (Prob >  z )       |                             |           |                              |          | 0.000     | 0.000    |
| No autocorrelation of order 2 (Prob >  z )       |                             |           |                              |          | 0.361     | 0.187    |
| Valid overidentifying restrictions (Prob > chi2) |                             |           |                              |          | 0.323     | 0.353    |
| Obs.                                             | 6169                        | 6169      | 6169                         | 6169     | 6169      | 6169     |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; iii) \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001.

constraints. We also observe a clear gender gradient in Australia, with women facing higher predicted risks. Health exhibits the expected sign, with poorer health being associated with higher energy poverty, although the estimate is not precisely estimated. In this case, the direction of causality is unclear, for there is evidence to suggest that energy poverty may also influence health outcomes (Brown and Vera-Toscano, 2021). Contrary to much of the existing evidence (Awan et al., 2022; Churchill and Smyth, 2021a; Farrell and Fry, 2021), formal education does not provide a statistically discernible protective effect in this vulnerable sample. Finally, recent physical violence (past six months) is associated with higher energy-poverty probabilities in the

WCML estimates, whereas regional GDP growth and unemployment do not retain significance once region and wave effects are accounted for.

## 5.2. Dynamic patterns by socio-economic group

The estimated transition probabilities allow us to characterise the dynamics of energy poverty in terms of entries, exits, and implied long-run prevalence (Grotti and Cutuli, 2018). Specifically, we define the entry rate as  $P_{01} = \Pr \left( EP_{it} = 1 \mid EP_{i,t-1} = 0, X_i \right)$  and the exit rate as

$P_{10} = \Pr \left( EP_{it} = 0 \mid EP_{i,t-1} = 1, \bar{X}_i \right)$ . These transitions can be summarized into (i) persistence,  $P_{11} = \Pr \left( EP_{it} = 1 \mid EP_{i,t-1} = 1, \bar{X}_i \right)$ , (ii) expected spell duration in energy poverty,  $1/P_{10}$ , and (iii) the steady-state probability of being energy poor,  $\pi(\bar{X}_i) = P_{01}/(P_{01} + P_{10})$ . The remainder of this section reports these objects across socio-economic groups to highlight differences in both the risk of entering energy poverty and the ability to exit it.

Table 3 stratifies the sample by perceived informal support (and, separately, social connectedness), alongside standard socio-demographic groups, to show how energy-poverty dynamics differ across individuals. Results are reported for the WCML specification, with the GMM estimates displaying the same qualitative patterns. A clear gradient emerges by perceived informal support. Individuals with low perceived informal support (one standard deviation below the mean) face a markedly higher entry risk into energy poverty (35.1%) than those with high perceived informal support (23.3%). Exit probabilities also differ substantially: among the energy poor, the probability of leaving energy poverty is 50.8% for low perceived informal support individuals versus 63.4% for those with high perceived informal support. Taken together, these differences translate into a steady-state energy-poverty probability that is almost 15 pp lower for individuals with stronger perceived informal support. Social connectedness exhibits a closely analogous pattern. Beyond social ties, the table also reveals persistent energy poverty across all groups, and smaller but systematic socio-economic gradients: women are around 5 pp less likely to exit energy poverty than men, implying slightly longer expected spells (about 0.2 years). Differences by education are comparatively muted, while persistence tends to be higher at older ages.

## 6. Sensitivity checks

This section examines whether the paper's conclusions are robust to alternative energy-poverty classifications, obtained by varying the thresholds used to assign households to energy-poor versus non-energy-poor status, and to alternative dynamic specifications. We then investigate whether reverse causality or selection could be driving the baseline estimates. To mitigate contemporaneous feedback and reverse-causality concerns, we also proxy the stable component of perceived informal support using a time-invariant latent individual component purged of life events and wave-specific shocks. To further address endogeneity concerns, we implement an IV/2SLS strategy and assess selection on observables using propensity-score matching.

### 6.1. Measurement sensitivity

We assess the sensitivity of the results to alternative energy-poverty classifications: higher MEPI thresholds (MEPI  $\geq$  top 10% of the MEPI distribution, MEPI  $\geq$  top 5%) and alternative deprivation counts (MEPI<sup>count</sup>  $\geq$  1 item, MEPI<sup>count</sup>  $\geq$  2 items). The results are represented graphically in Fig. 2. The direction of the perceived informal support effect is unchanged, but its magnitude is smaller than in the baseline. Under the upper-decile threshold, a one-standard-deviation increase in perceived informal support reduces the predicted entry probability by about 1.4 pp in WCML and 2.1 pp in GMM, compared with 4.8 pp and 4.6 pp, respectively, in the baseline specification (see Table 3). This pattern is consistent with a substantive interpretation: at the extreme end of deprivation, entry may be more strongly shaped by binding structural constraints, such as very low and unstable resources, acute health limitations, or poor housing conditions, that informal support networks are less able to offset fully. Perceived informal support may still mitigate energy poverty at the margin, but its protective capacity appears weaker for acute than for moderate deprivation. Results for

social connectedness mirror this pattern. As a complementary measurement check, we replace the weighted MEPI with an unweighted deprivation count and obtain qualitatively similar conclusions across alternative cut-offs.

Beyond severity and scoring, a further concern is compositional: the MEPI combines domains that need not co-occur for a given individual. We therefore re-estimate the dynamic specification separately for electricity deprivation, lack of kitchen facilities, and arrears (Fig. 3). The protective role of perceived informal support (and, similarly, social connectedness) is not uniform across domains: it is most pronounced for arrears, remains visible for kitchen deprivation, and is weakest for electricity deprivation. Arrears and kitchen deprivation exhibit stronger short-run persistence than electricity deprivation, suggesting that perceived informal support matters most where hardship tends to be sustained rather than episodic. A plausible interpretation is that informal networks can more readily ease liquidity-type constraints (e.g., short-term support to avoid or clear arrears, help navigating payment arrangements, or access to shared resources), whereas electricity deprivation is more likely to reflect access and service-provision constraints that are less responsive to informal support. Overall, the domain-specific estimates reinforce the idea that social capital functions primarily as a buffer against persistent, bill-related hardship.

### 6.2. Reverse causality

The relationship between energy poverty and perceived informal support is likely bidirectional. Energy-poverty shocks may weaken perceived support through stress, stigma, and social withdrawal, but may also increase reliance on family and friends as a coping strategy (Middlemiss and Gillard, 2015); the net effect is thus ambiguous. Conversely, perceived informal support may reduce the risk of energy poverty by providing informal insurance, information, and practical assistance (Middlemiss et al., 2019). A second source of endogeneity is confounding: perceived support and connectedness are shaped by observable circumstances—income, employment, education, health—and by unobserved individual traits that also influence exposure to energy poverty (Middlemiss et al., 2019). Taken together, these channels imply that perceived informal support may be endogenous in the energy-poverty equation, and estimates could partly reflect reverse causality and selection rather than a causal effect.

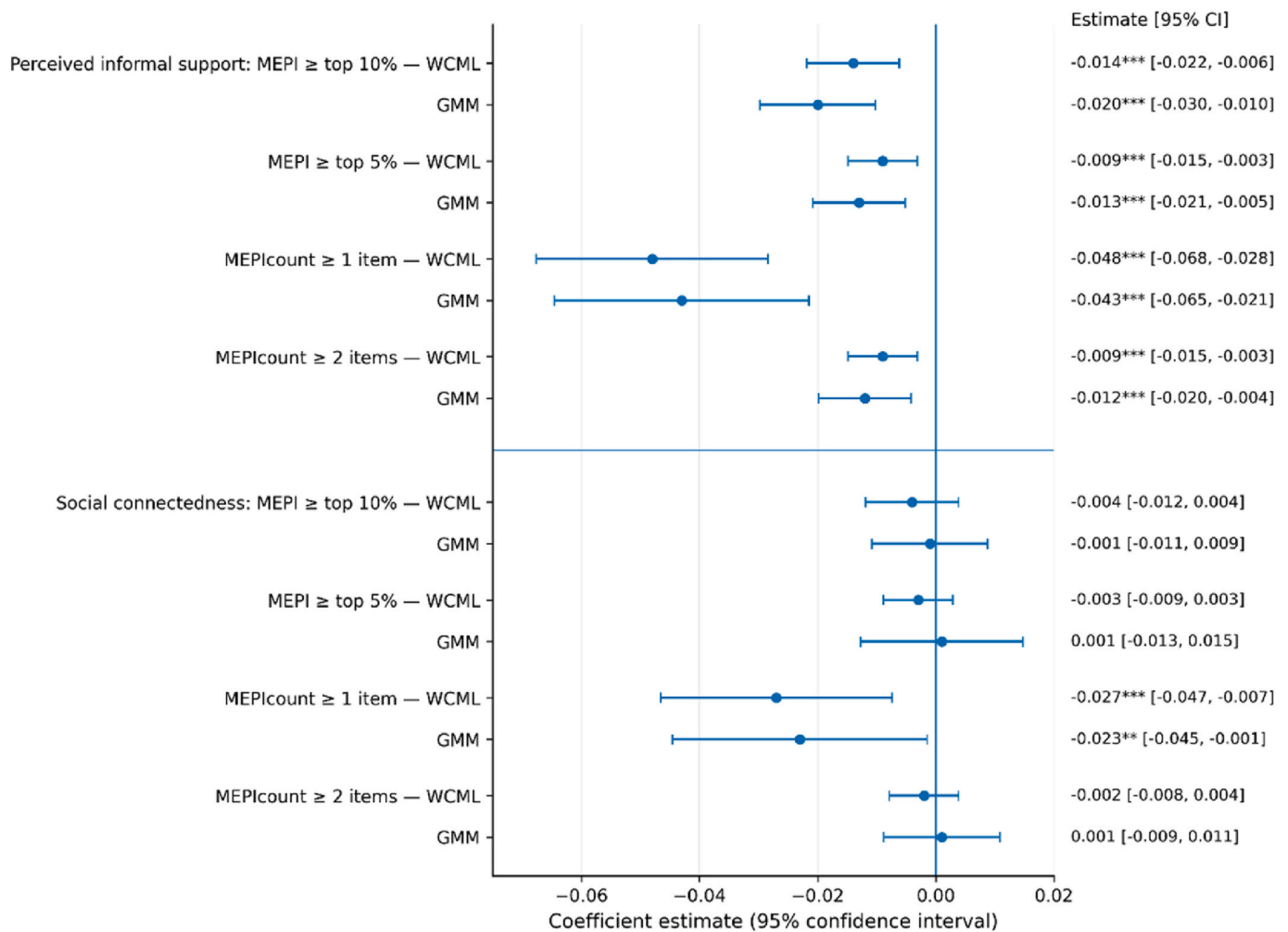
To address these issues we apply the procedure described in (Budría and Carbonell, 2019) to extract a latent, time-invariant component of perceived informal support less affected by contemporaneous life events and wave-specific shocks. This is achieved by regressing the perceived informal support score on a fourth-order polynomial of age and a vector of selected socio-economic factors, among which we include income, gender, schooling and marital status and, additionally, individual fixed effects. The fixed effects are subsequently extracted from the regression and regarded as latent social capital, a measure insulated from transient life events that primarily captures unobserved individual factors such as innate social skills, personality traits, and family background, among others.

The results, summarized in Table 4, are broadly consistent with the benchmark estimates, suggesting that enduring social connections may buffer households against energy deprivation. Point estimates are very similar across outcomes and, if anything, slightly larger in magnitude for the benchmark measure (MEPI > 0). A comparable qualitative pattern is observed for social connectedness. In GMM estimation, time-invariant variables are differenced out during the estimation process, making it impossible to separately identify their effects. To address this, we follow a two-stage procedure outlined by Kripfganz and Schwarz (2019). In the first stage, we estimate the GMM model, and in the second stage, we regress the residuals from the first stage on the time-invariant regressors (social capital and connectedness). Despite relying on different identification strategies, the results obtained from both WCML and GMM estimations are highly consistent.

**Table 3**

Energy poverty dynamic by selected groups.

|                                 |                                         | Entry probability | Exit probability | Steady state probability | Average duration |
|---------------------------------|-----------------------------------------|-------------------|------------------|--------------------------|------------------|
| Low perceived informal support  | (PS.Cap < Mean (PS.Cap) - std (PS.Cap)) | 0.351             | 0.508            | 0.409                    | 1.968            |
| High perceived informal support | (PS.Cap > Mean (PS.Cap) + std (PS.Cap)) | 0.233             | 0.634            | 0.269                    | 1.576            |
| Low social connectedness        | (S.Con < Mean (S.Con) - std (S.Con))    | 0.316             | 0.536            | 0.371                    | 1.865            |
| High social connectedness       | (S.Con > Mean (S.Con) + std (S.Con))    | 0.243             | 0.622            | 0.281                    | 1.605            |
| Income > Mean (income)          |                                         | 0.280             | 0.630            | 0.307                    | 1.585            |
| Income ≤ Mean (income)          |                                         | 0.303             | 0.577            | 0.343                    | 1.730            |
| Men                             |                                         | 0.245             | 0.622            | 0.282                    | 1.606            |
| Women                           |                                         | 0.301             | 0.556            | 0.351                    | 1.796            |
| Age > Mean (age)                |                                         | 0.332             | 0.525            | 0.387                    | 1.904            |
| Age ≤ Mean (age)                |                                         | 0.251             | 0.643            | 0.281                    | 1.554            |
| University education            |                                         | 0.278             | 0.583            | 0.322                    | 1.713            |
| No University education         |                                         | 0.268             | 0.595            | 0.310                    | 1.679            |

**Fig. 2.** Coefficient estimates for perceived informal support and social connectedness across alternative energy-poverty thresholds.

### 6.3. Two stage least squares and propensity score matching

As an additional sensitivity check, we present results from three alternative approaches that help address endogeneity concerns. First, we resort to a two-stage-least-squares (2SLS) approach that exploits exogenous variations in social capital as a source of identification. Unlike our baseline dynamic models, this approach does not account for poverty dynamics and should therefore be interpreted as complementary evidence rather than as our preferred identification strategy. The objective is simply to assess whether the estimated relationship between social capital and energy poverty remains when exploiting variation in social

capital that is plausibly predetermined. We instrument social capital using a measure of extroversion derived from the responses to a self-assessed personality test contained in the JH survey.<sup>3</sup> Extroversion, a

<sup>3</sup> In practice, we perform a principal component analysis (PCA) on responses to several personality items capturing how talkative, open, lively and warm respondents report being, and use the first principal component as our summary index. PCA is well suited for this purpose because it condenses the information contained in multiple correlated indicators into a single score while preserving most of the variance in the original variables (Ebiwonjumi et al., 2023; Kyriazos and Poga, 2023).

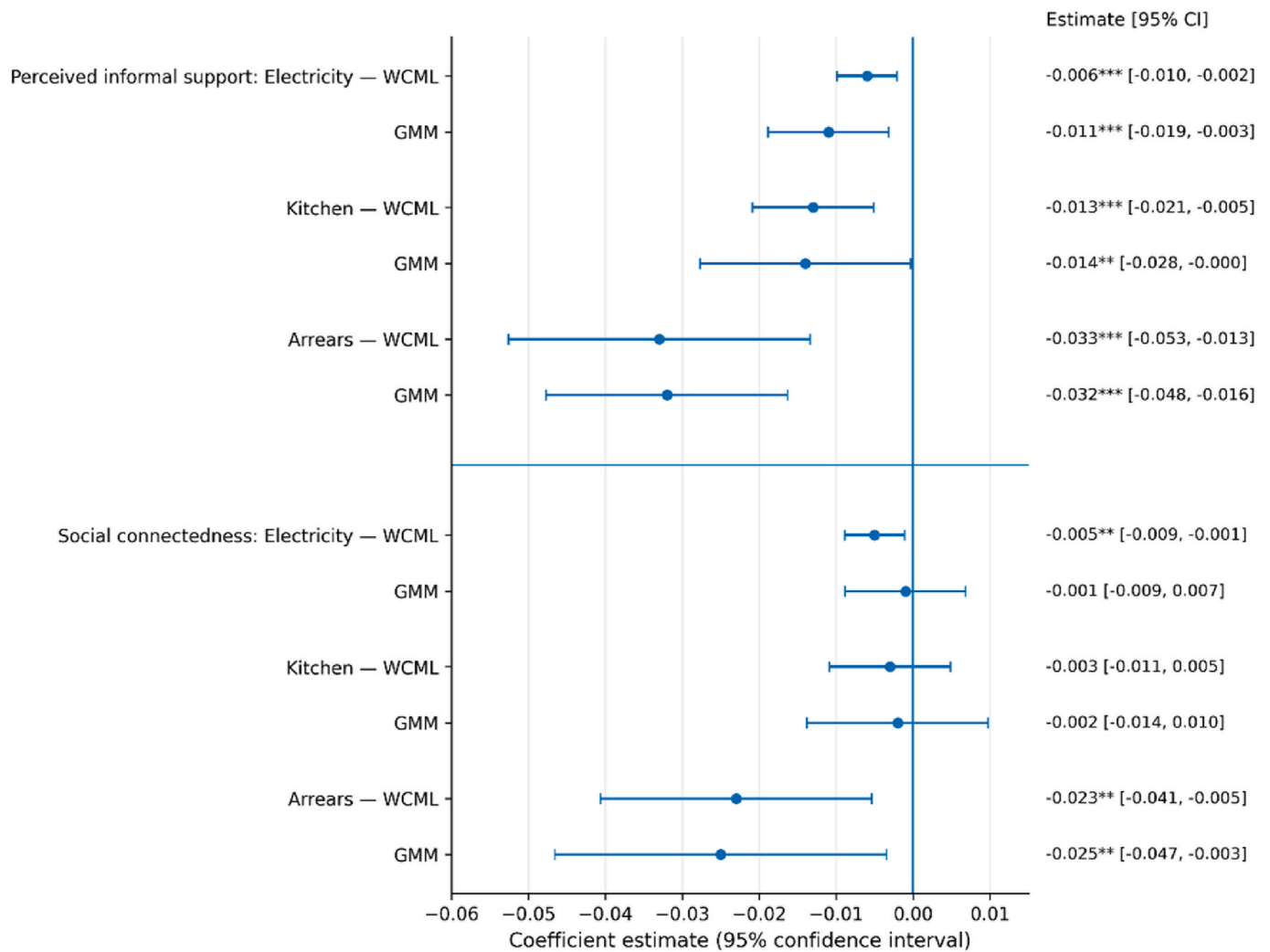


Fig. 3. Coefficient estimates for perceived informal support and social connectedness across energy-poverty dimensions.

Table 4

Energy Poverty Dynamics, alternative definitions, and time invariant perceived social capital and connectedness.

|                                             | WCML      |                |               |                                |                                 |
|---------------------------------------------|-----------|----------------|---------------|--------------------------------|---------------------------------|
|                                             | MEPI > 0  | MEPI > top 10% | MEPI > top 5% | MEPI <sup>count</sup> ≥ 1 item | MEPI <sup>count</sup> ≥ 2 items |
| Latent perceived informal support (Model 1) | -0.062*** | -0.014***      | -0.010***     | -0.061***                      | -0.011***                       |
|                                             | 0.01      | 0.003          | 0.002         | 0.01                           | 0.003                           |
| Latent social connectedness (Model 2)       | -0.054*** | -0.008*        | -0.006*       | -0.052***                      | -0.008**                        |
|                                             | 0.01      | 0.003          | 0.003         | 0.01                           | 0.003                           |
| Full set of controls                        | Yes       | Yes            | Yes           | Yes                            | Yes                             |
| Year fixed-effects                          | Yes       | Yes            | Yes           | Yes                            | Yes                             |
| Region fixed-effects                        | Yes       | Yes            | Yes           | Yes                            | Yes                             |
| Obs <sub>t-1</sub> .                        | 6169      | 6169           | 6169          | 6169                           | 6169                            |
| Obs <sub>t-2</sub> .                        | 4165      | 4165           | 4165          | 4165                           | 4165                            |
|                                             | GMM       |                |               |                                |                                 |
|                                             | MEPI > 0  | MEPI > top 10% | MEPI > top 5% | MEPI <sup>count</sup> ≥ 1 item | MEPI <sup>count</sup> ≥ 2 items |
| Latent perceived informal support (Model 1) | -0.065*** | -0.021**       | -0.016*       | -0.065***                      | -0.018*                         |
|                                             | 0.015     | 0.009          | 0.009         | 0.015                          | 0.012                           |
| Latent social connectedness (Model 2)       | -0.050*** | -0.011         | -0.005        | -0.050***                      | -0.009                          |
|                                             | 0.015     | 0.009          | 0.009         | 0.015                          | 0.009                           |
| Full set of controls                        | Yes       | Yes            | Yes           | Yes                            | Yes                             |
| Year fixed-effects                          | Yes       | Yes            | Yes           | Yes                            | Yes                             |
| Region fixed-effects                        | Yes       | Yes            | Yes           | Yes                            | Yes                             |
| Obs <sub>t-1</sub> .                        | 6169      | 6169           | 6169          | 6169                           | 6169                            |
| Obs <sub>t-2</sub> .                        | 4165      | 4165           | 4165          | 4165                           | 4165                            |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; iii) \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001.

trait characterized by a preference for outward social interaction and external stimulation (Costa and McCrae, 2000), can significantly influence the formation and maintenance of social networks (Tulin et al., 2018). Since personality traits like extroversion are largely innate and stable (John et al., 2008), they provide a consistent measure that precedes and influences social capital formation. At the same time, we acknowledge that personality traits may also affect economic outcomes through channels other than social capital, including labour market behaviour and energy poverty itself. Consequently, the exclusion restriction cannot be taken for granted, and the 2SLS estimates should be interpreted with appropriate caution, perhaps as an upper bound of the true effect. The estimates reported in Table 5 are consistent with the main findings of the paper, suggesting a sizeable negative association between perceived informal support and energy poverty. A one standard deviation increase in perceived informal support leads to a 17.1 pp decrease in the probability of multidimensional poverty, while the estimate of social connectedness raises to 38.0 pp. The first stage statistics reported in the table (the Sanderson-Windmeijer and the Kleibergen-Paap LM statistics) reject the null, indicating that the instrument is relevant and explains a non-trivial share of the variation in social capital.

Since the validity of the external instruments is often questioned in empirical research, we provide also estimates from a Lewbel 2SLS model, which does not require an external instrument because it utilizes heteroskedasticity in the data to generate internal instruments (Lewbel, 2012). In this case, the estimates are sensitively lower, suggesting that extroversion might be not a full valid instrument. This may be the case if, for instance, personality traits have a direct effect on the outcome

probability. Notably, the estimates from Lewbel 2SLS fall very close to the WCML and GMM estimates of the benchmark model, giving further support of the papers' main results.

As a complementary robustness exercise, we implement propensity score matching. Treated and control households are matched on the predicted propensity score under a caliper restriction of 0.2 SD of the logit of the score (Stuart and Rubin, 2008). We compare several matching implementations—including nearest-neighbour, kernel, and local-linear matching—to check whether results depend on the algorithmic choice. The estimates in Table 6 are stable across specifications and remain aligned with the baseline conclusion that social capital and social connectedness are linked to a lower likelihood of energy poverty.

#### 6.4. Granular controls and non-random attrition

Table 7 tests the sensitivity of the WCML estimates to the treatment of controls that may be jointly determined with energy poverty. We begin by re-estimating the model after excluding income, labour-market status, education, and health, and then consider a specification that drops the full set of socio-economic covariates. Across Columns (1) and (2), the coefficients on perceived informal support and social connectedness remain very close to the benchmark values, indicating limited sensitivity to the inclusion of these controls.

To address concerns about sample attrition, although retention in JH is very high (an annual average of 96.5%), there is still a concern that entry and exit from the survey may be systematically related to energy poverty. To assess the importance of this issue, we re-estimate the models on a balanced panel and apply the longitudinal weights supplied

**Table 5**  
Estimations under ordinary 2SLS and Lewbel 2SLS Methods.

|                                                                   | IV                 |                    |                    |                                |                                 |                    |
|-------------------------------------------------------------------|--------------------|--------------------|--------------------|--------------------------------|---------------------------------|--------------------|
|                                                                   | MEPI > 0           | MEPI > top 10%     | MEPI > top 5%      | MEPI <sup>count</sup> ≥ 1 item | MEPI <sup>count</sup> ≥ 2 items | MEPI (continuous)  |
| Perceived informal support (Model 1)                              | −0.171***<br>0.053 | −0.104***<br>0.026 | −0.097***<br>0.023 | −0.171***<br>0.053             | −0.094***<br>0.021              | −0.081***<br>0.020 |
| Social connectedness (Model 2)                                    | −0.380***<br>0.137 | −0.210***<br>0.072 | −0.211***<br>0.066 | −0.058*<br>0.027               | −0.206***<br>0.021              | −0.180***<br>0.057 |
| <i>First stage statistics model 1</i>                             |                    |                    |                    |                                |                                 |                    |
| Sanderson-Windmeijer multivariate F test of excluded instruments: | 81.670             | 83.590             | 83.810             | 81.670                         | 84.610                          | 81.750             |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| Kleibergen-Paap rk LM statistic                                   | 82.300             | 83.100             | 83.310             | 81.210                         | 84.100                          | 81.300             |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| <i>First stage statistics model 2</i>                             |                    |                    |                    |                                |                                 |                    |
| Sanderson-Windmeijer multivariate F test of excluded instruments: | 16.540             | 6.250              | 17.980             | 16.540                         | 18.160                          | 16.880             |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| Kleibergen-Paap rk LM statistic                                   | 16.620             | 272.640            | 18.070             | 16.620                         | 18.240                          | 16.970             |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| Obs.                                                              | 6169               | 6169               | 6169               | 6169                           | 6169                            | 6169               |
|                                                                   | IV LEWBEL          |                    |                    |                                |                                 |                    |
|                                                                   | MEPI > 0           | MEPI > top 10%     | MEPI > top 5%      | MEPI <sup>count</sup> ≥ 1 item | MEPI <sup>count</sup> ≥ 2 items | MEPI (continuous)  |
| Perceived informal support (Model 1)                              | −0.041**<br>0.019  | −0.040***<br>0.008 | −0.018**<br>0.007  | −0.041**<br>0.017              | −0.020**<br>0.007               | −0.023***<br>0.007 |
| Social connectedness (Model 2)                                    | −0.041<br>0.030    | −0.019<br>0.013    | −0.016<br>0.014    | −0.058*<br>0.027               | −0.018<br>0.011                 | −0.018<br>0.011    |
| <i>First stage statistics model 1</i>                             |                    |                    |                    |                                |                                 |                    |
| Sanderson-Windmeijer multivariate F test of excluded instruments: | 14.252             | 14.124             | 14.216             | 14.252                         | 14.329                          | 14.303             |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| Kleibergen-Paap rk LM statistic                                   | 600.730            | 595.842            | 599.329            | 600.730                        | 603.652                         | 602.643            |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| <i>First stage statistics model 2</i>                             |                    |                    |                    |                                |                                 |                    |
| Sanderson-Windmeijer multivariate F test of excluded instruments: | 5.529              | 5.596              | 5.596              | 5.529                          | 5.580                           | 5.57               |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| Kleibergen-Paap rk LM statistic                                   | 247.830            | 250.697            | 250.710            | 247.830                        | 250.001                         | 249.796            |
| (p-value)                                                         | 0.000              | 0.000              | 0.000              | 0.000                          | 0.000                           | 0.000              |
| Obs.                                                              | 6169               | 6169               | 6169               | 6169                           | 6169                            | 6169               |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; iii) \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001.

**Table 6**  
Propensity score matching results.

|                            | MEPI > 0           | MEPI > top 10%     | MEPI > top 5%      | MEPI <sup>count</sup> ≥ 1 item | MEPI <sup>count</sup> ≥ 2 items | MEPI (continuous)  |
|----------------------------|--------------------|--------------------|--------------------|--------------------------------|---------------------------------|--------------------|
| Perceived informal support |                    |                    |                    |                                |                                 |                    |
| <i>Matching Method</i>     |                    |                    |                    |                                |                                 |                    |
| Local Linear regression    | −0.134***<br>0.011 | −0.033***<br>0.004 | −0.026***<br>0.003 | −0.134***<br>0.011             | −0.022***<br>0.003              | −0.132***<br>0.011 |
| Kernel                     | −0.134***<br>0.011 | −0.033***<br>0.004 | −0.026***<br>0.003 | −0.134***<br>0.011             | −0.022***<br>0.003              | −0.134***<br>0.011 |
| Nearest Neighbour          | −0.134***<br>0.011 | −0.033***<br>0.004 | −0.026***<br>0.003 | −0.134***<br>0.011             | −0.022***<br>0.003              | −0.134***<br>0.011 |
| Obs.                       | 8346               | 8346               | 8346               | 8346                           | 8346                            | 8346               |
| Social Connectedness       |                    |                    |                    |                                |                                 |                    |
| <i>Matching Method</i>     |                    |                    |                    |                                |                                 |                    |
| Local Linear regression    | −0.108***<br>0.012 | −0.015***<br>0.004 | −0.011**<br>0.004  | −0.108***<br>0.012             | −0.010**<br>0.003               | −0.102***<br>0.011 |
| Kernel                     | −0.108***<br>0.012 | −0.015***<br>0.004 | −0.011**<br>0.004  | −0.108***<br>0.012             | −0.010**<br>0.003               | −0.108***<br>0.012 |
| Nearest Neighbour          | −0.108***<br>0.012 | −0.015***<br>0.004 | −0.011**<br>0.004  | −0.108***<br>0.012             | −0.010**<br>0.003               | −0.108***<br>0.012 |
| Obs.                       | 8346               | 8346               | 8346               | 8346                           | 8346                            | 8346               |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; iii) \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001.

**Table 7**  
Energy poverty dynamics. Sensitivity analysis.

|                                                                                  | WCML                       |                    |                           |                            |                    |                           |
|----------------------------------------------------------------------------------|----------------------------|--------------------|---------------------------|----------------------------|--------------------|---------------------------|
|                                                                                  | Alternative specifications |                    | With longitudinal weights | Alternative specifications |                    | With longitudinal weights |
| EP <sub>1</sub>                                                                  | 0.206***<br>0.022          | 0.230***<br>0.022  | 0.206***<br>0.028         |                            |                    |                           |
| EP <sub>t-1</sub>                                                                | 0.138***<br>0.020          | 0.139***<br>0.020  | 0.084***<br>0.020         | 0.102***<br>0.035          | 0.103***<br>0.050  | 0.109***<br>0.028         |
| Perceived informal support                                                       | −0.048***<br>0.010         | −0.054***<br>0.010 | −0.041***<br>0.011        | −0.046***<br>0.013         | −0.048***<br>0.010 | −0.040**<br>0.013         |
| Controls for income, labour status, schooling and health removed                 | Yes                        | No                 | No                        | Yes                        | No                 | No                        |
| All socio-economic controls removed                                              | No                         | Yes                | No                        | No                         | Yes                | No                        |
| Expanded set of controls (granularfinancial and health condition) <sup>(a)</sup> | No                         | No                 | No                        | No                         | No                 | No                        |
| Obs.                                                                             | 6169                       | 6169               | 4415                      | 6169                       | 6169               | 4415                      |
| EP <sub>1</sub>                                                                  | 0.210***<br>0.022          | 0.231***<br>0.023  | 0.205***<br>0.028         |                            |                    |                           |
| EP <sub>t-1</sub>                                                                | 0.139***<br>0.020          | 0.141***<br>0.020  | 0.085***<br>0.020         | 0.107***<br>0.037          | 0.104***<br>0.050  | 0.109***<br>0.028         |
| Social connectedness                                                             | −0.027**<br>0.010          | −0.035***<br>0.010 | 0.008<br>0.012            | −0.030**<br>0.012          | −0.027**<br>0.010  | −0.017<br>0.012           |
| Controls for income, labour status, schooling and health removed                 | Yes                        | No                 | No                        | Yes                        | No                 | No                        |
| All socio-economic controls removed                                              | No                         | Yes                | No                        | No                         | Yes                | No                        |
| Expanded set of controls (granularfinancial and health condition) <sup>(a)</sup> | No                         | No                 | No                        | No                         | No                 | No                        |
| Obs.                                                                             | 6169                       | 6169               | 4415                      | 6169                       | 6169               | 4415                      |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001; (a) This includes a set of 20 binary controls for: heart or circulatory condition, diabetes, asthma, chronic bronchitis, emphysema, problems with liver, arthritis, gout or rheumatism, epilepsy, kidney disease, hepatitis C, chronic neck or back problems, acquired brain injury, intellectual disability, bipolar affective disorder, (manic depression), schizophrenia, depression, cancer, post traumatic, stress disorder, anxiety disorder, pending debts and gambling problems.

with JH to mitigate potential biases due to differential non-response. The results are very similar to those from the main specification, suggesting limited sensitivity of our findings to selective attrition (Table 7, column 3).

## 7. Transmission mechanisms

In this section, we explore the potential mechanisms through which social capital may reduce the risk of energy poverty. Specifically, we consider three channels: income distress, health status, and housing insecurity.

First, perceived informal support may operate as a form of informal

insurance, whereby the expectation of receiving help prevents temporary income shortfalls from translating into bill arrears or energy deprivation. Individuals experiencing financial hardship may rely on family and friends precisely when formal sources of assistance are unavailable or difficult to access (Albers et al., 2025). Second, social capital may operate through health. According to the buffering hypothesis of social support (Cohen and Hoberman, 1983), knowing that help is available mitigates the psychological consequences of adverse events. Better health may, in turn, reduce energy poverty by lowering energy needs, improving individuals' capacity to manage household finances, and cope with financial shocks. Finally, social networks may reduce housing insecurity by helping individuals avoid unstable housing arrangements or homelessness, for example by temporarily staying with relatives or friends. This mechanism is particularly relevant in the Journeys Home sample, where nearly 19.9% of respondents experience some form of homelessness.<sup>4</sup>

To explore these channels, in Table 8 we sequentially re-estimate our baseline models while adding extensive controls capturing respondents' outstanding debts and gambling problems (*financial distress*), a large battery of binary variables capturing a large set of medical conditions, including chronic physical conditions, cognitive/neurological impairments and severe mental health disorders (*health status*) and three binary variables capturing three forms of homelessness, ranging from mild to severe (*housing insecurity*). Comparing the evolution of the estimated coefficient on social capital across specifications provides an indication of the extent to which each channel may account for the baseline association. Nevertheless, this analysis should be interpreted as exploratory rather than as a formal decomposition of causal mechanisms. Establishing the relative importance of each channel would require much richer information on the specific ways in which support from family and friends is used (for example, whether it takes the form of financial assistance, assistance in shopping, access to information and services, etc.). Such information is not collected in the Journeys Home survey, which precludes a detailed identification of the underlying mechanisms.

For perceived informal support, the WCML estimates decline from  $-0.048$  in the baseline specification to  $-0.036$  after controlling for financial distress (a reduction of around 25%), and further to  $-0.027$  once health and housing instability are also taken into account. The GMM estimates exhibit a similar pattern, falling from  $-0.046$  to  $-0.037$  in the fully adjusted specification. The larger attenuation observed after introducing the financial controls is consistent with the interpretation of perceived informal support as a form of informal insurance. By contrast, health status and housing instability appear to play a complementary, albeit more limited, mediating role. Notwithstanding, a sizeable direct association remains even after including all the set of granular controls, indicating that no single mechanism fully accounts for the protective role of social capital. This observation is confirmed in the results for social connectedness and suggest that the social capital effect may reflect broader psychosocial or behavioural mechanisms that are not directly captured in our data.

## 8. Conclusions and policy recommendations

This paper investigated a dimension of energy poverty that has received comparatively little attention: the role of perceived informal support in shaping individuals' vulnerability to energy deprivation. Methodologically, the analysis advances beyond static correlations by employing two complementary approaches—WCML and GMM

estimation—that capture true state dependence and address concerns related to unobserved heterogeneity and endogeneity. Across the main specifications considered, the evidence consistently shows that individuals with stronger social networks are substantially less likely to fall into energy poverty and experience markedly shorter spells of deprivation. A one-standard deviation increase in social capital is associated with a 4.8 pp reduction in the probability of entering energy poverty, alongside significantly shorter poverty durations. The results for social connectedness are also significant but quantitatively smaller (2.6 pp), indicating that in the context of energy poverty, knowing that help is available is more valuable than simply having a larger social network.

The robustness of the results is further reinforced by alternative definitions of energy poverty and additional econometric strategies, including 2SLS, Lewbel 2SLS, and propensity score matching. Taken together, these checks attenuate concerns that the estimated relationship is driven by spurious correlations or model artefacts. The paper further shows that financial conditions, health status and housing circumstances constitute important mechanisms through which social capital affects energy poverty outcomes.

One key implication of the analysis is that the conventional emphasis on structural or financial determinants may be overly narrow. In our specifications, once relational factors and dynamic persistence are accounted for, the marginal explanatory power of income and energy prices is substantially attenuated. Our findings should not be interpreted as implying that financial transfers or energy-efficiency programmes are unimportant. Rather, they suggest that these policies may be more effective when complemented by interventions that strengthen social networks and reduce social isolation, particularly among highly vulnerable households.

Policy frameworks would therefore benefit from incorporating strategies designed to strengthen social capital as a complement to traditional financial and housing interventions. However, the appropriate policy mix is likely to differ across population groups. For individuals experiencing housing instability or homelessness, strengthening links with community organizations, outreach services, and peer-support networks may facilitate access to emergency assistance and improve resilience to temporary financial shocks. For socially isolated older adults or people with disabilities, interventions aimed at reducing loneliness and fostering neighbourhood engagement may be particularly beneficial. Likewise, families with dependent children may benefit from school- and community-based initiatives that reinforce informal support networks and improve awareness of available assistance programmes. The Australian institutional context also suggests the need for stronger coordination across levels of government. Responsibility for energy concessions, social housing, community services, and energy efficiency programmes is currently fragmented across the territory governments, resulting in substantial differences in eligibility criteria and programme design (Simshauser and Miller, 2023). A more coordinated federal framework could promote greater consistency in support and encourage the integration of social capital considerations into existing energy poverty and social inclusion policies. Such coordination would be particularly valuable in disadvantaged communities, where overlapping economic and social vulnerabilities often require responses that cut across traditional policy domains.

Finally, this study has several limitations that warrant further investigation. First, our models assume that the effect of social capital is contemporaneous. However, changes in social capital may accumulate over time and generate longer-term effects on households' ability to cope with energy deprivation. Exploring these dynamic pathways represents an important direction for future research. Second, the Journeys Home survey is not nationally representative but instead follows individuals experiencing severe housing disadvantage who were sampled through Centrelink administrative records. While this focus is policy-relevant given the concentration of energy poverty among disadvantaged households, caution is warranted when extrapolating the magnitude of

<sup>4</sup> The categorization of homelessness is described in Budrfa et al. (2025b), ranging from situations where the individual lives in conditions below the minimum community standard for housing, such as residing in a caravan, boarding house, or inadequate housing (10.5% of the sample) to living without conventional accommodation, such as sleeping on the streets, in cars, or squatting, without voluntarily choosing that condition (2.7%).

**Table 8**

Mechanisms: sequential adjustment for financial, health, and housing-instability controls.

|                            | WCML                      |                            |                                 |                           |                            |                                 |
|----------------------------|---------------------------|----------------------------|---------------------------------|---------------------------|----------------------------|---------------------------------|
|                            | Financial distress<br>(1) | (1) + Health status<br>(2) | (2) + Housing insecurity<br>(3) | Financial distress<br>(1) | (1) + Health status<br>(2) | (2) + Housing insecurity<br>(3) |
| EP <sub>1</sub>            | 0.206***<br>0.022         | 0.157***<br>0.024          | 0.150***<br>0.024               |                           |                            |                                 |
| EP <sub>t-1</sub>          | 0.138***<br>0.020         | 0.075***<br>0.017          | 0.063***<br>0.016               | 0.102***<br>0.035         | 0.100***<br>0.029          | 0.114***<br>0.025               |
| Perceived informal support | −0.048***<br>0.010        | −0.036***<br>0.010         | −0.027***<br>0.009              | −0.046***<br>0.013        | −0.044***<br>0.012         | −0.037***<br>0.025              |
| Obs.                       | 6169                      | 5223                       | 5223                            | 6169                      | 6169                       | 6169                            |
| EP <sub>1</sub>            | 0.210***<br>0.022         | 0.167***<br>0.017          | 0.160***<br>0.017               |                           |                            |                                 |
| EP <sub>t-1</sub>          | 0.139***<br>0.020         | 0.074***<br>0.020          | 0.063***<br>0.020               | 0.107***<br>0.037         | 0.101***<br>0.029          | 0.118***<br>0.029               |
| Social connectedness       | −0.027**<br>0.010         | 0.021*<br>0.010            | 0.021*<br>0.010                 | −0.030**<br>0.012         | −0.022**<br>0.011          | −0.019<br>0.010                 |
| Obs.                       | 6169                      | 5223                       | 5223                            | 6169                      | 6169                       | 6169                            |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; \*p &lt; 0.05, \*\*p &lt; 0.01, \*\*\*p &lt; 0.001.

these effects to the broader population or to countries with different institutional, welfare and energy market settings. Third, the study abstracts from the financial strategies and economic behaviors households may employ to mitigate the impact of adverse life events, despite evidence that variables such as income and employment significantly influence how individuals navigate energy challenges (Burlinson et al., 2024). Fourth, despite employing dynamic estimators that account for state dependence, unobserved individual heterogeneity, and rich time-varying controls, time-varying unobserved factors may still influence both social capital and energy poverty. Our estimates should be interpreted as evidence of a robust longitudinal association rather than definitive causal effects. Incorporating quasi-natural experiments and exogenous variations in social capital into this line of research remains a pending challenge.

#### CRediT authorship contribution statement

**Alejandro Betancourt-Odio:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation,

Conceptualization. **Santiago Budría:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

#### Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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#### Appendix A. Energy Prices: Construction and Sources

State-level information on residential energy prices is merged into the JH data. Annual electricity prices are taken from the Residential Electricity Price Trends reports produced by the Australian Energy Market Commission (AEMC, 2013, 2014) and from the Australian Bureau of Statistics (ABS, 2012), while residential gas prices come from Oakley Greenwood Organization (OGO, 2018) and (ABS, 2017).<sup>5</sup> In Journeys Home, interviews take place in two windows each year: from September to November in waves 1, 3 and 5, and from March to May in waves 2, 4 and 6. Because price information is only available at an annual frequency rather than monthly, we approximate the energy price faced by each respondent using a weighted average of the two adjacent annual prices.<sup>6</sup> Specifically, for individual  $i$  interviewed in year  $t$ , we approximate the relevant energy price as

$$\tilde{E}_{it} = E_{t-1} + k_{it}(E_t - E_{t-1}), \quad (A1)$$

where  $E_t$  denotes the annual average energy price in year  $t$  and  $k_{it}$  is the fraction of the year that has elapsed between 1 January and the interview date. This construction treats the effective energy price as the previous year's price plus a proportion  $k_{it}$  of the year-on-year change, and allows us to exploit variation across states, over time and between individuals interviewed at different points in the year. To keep the specification parsimonious, the

<sup>5</sup> The electricity and gas series reported by the ABS are price indices designed to track changes over time within each Australian state. They are therefore not suitable for comparing absolute price levels across regions. To obtain state-level energy prices for our analysis period, we combine the ABS index information with level data from the AEMC and OGO (AEMC, 2013; AEMC, 2014).

<sup>6</sup> Alternative ways of combining electricity and gas prices led to essentially unchanged results. Adding distinct controls for electricity and gas prices did not yield any meaningful gain in model fit.

regression model includes a single price index computed as the simple average of the electricity and gas prices.

## Appendix B

**Table B1**

GMM estimator results with alternative assumptions

|                                                  | All variables strictly exogenous | Income & employment endogenous, rest weakly exogenous | Perceived informal support, income & employment endogenous, rest weakly exogenous | Two-lags model (all weakly exogenous) | All variables strictly exogenous | Income & employment endogenous, rest weakly exogenous | Social connectedness, income & employment endogenous, rest weakly exogenous | Two-lags model (all weakly exogenous) |
|--------------------------------------------------|----------------------------------|-------------------------------------------------------|-----------------------------------------------------------------------------------|---------------------------------------|----------------------------------|-------------------------------------------------------|-----------------------------------------------------------------------------|---------------------------------------|
| EP <sub>t-1</sub>                                | 0.082**<br>0.035                 | 0.085**<br>0.030                                      | 0.092**<br>0.030                                                                  | 0.160***<br>0.062<br>0.046<br>0.039   | 0.081**<br>0.035                 | 0.086**<br>0.030                                      | 0.086**<br>0.030                                                            | 0.161**<br>0.058<br>0.051<br>0.039    |
| EP <sub>t-2</sub>                                |                                  |                                                       |                                                                                   |                                       |                                  |                                                       |                                                                             |                                       |
| Perceived informal support                       | −0.044***<br>0.0103              | 0.125507<br>−0.044***<br>0.0125                       | −0.028*<br>0.0178                                                                 | −0.051***<br>0.013                    |                                  |                                                       |                                                                             |                                       |
| Social connectedness                             |                                  |                                                       |                                                                                   |                                       | −0.023**<br>0.010                | −0.029**<br>0.011                                     | −0.023<br>0.018                                                             | −0.019*<br>0.012                      |
| Full set of controls                             | Yes                              | Yes                                                   | Yes                                                                               | Yes                                   | Yes                              | Yes                                                   | Yes                                                                         | Yes                                   |
| Year fixed-effects                               | Yes                              | Yes                                                   | Yes                                                                               | Yes                                   | Yes                              | Yes                                                   | Yes                                                                         | Yes                                   |
| Region fixed-effects                             | Yes                              | Yes                                                   | Yes                                                                               | Yes                                   | Yes                              | Yes                                                   | Yes                                                                         | Yes                                   |
| No autocorrelation of order 1 (Prob >  z )       | 0.000                            | 0.000                                                 | 0.000                                                                             | 0.000                                 | 0.000                            | 0.000                                                 | 0.000                                                                       | 0.000                                 |
| No autocorrelation of order 2 (Prob >  z )       | 0.168                            | 0.919                                                 | 0.494                                                                             | 0.305                                 | 0.202                            | 0.696                                                 | 0.694                                                                       | 0.336                                 |
| Valid overidentifying restrictions (Prob > chi2) |                                  | 0.350                                                 | 0.205                                                                             | 0.606                                 |                                  | 0.322                                                 | 0.261                                                                       | 0.606                                 |
| Obs.                                             | 6169                             | 6169                                                  | 6169                                                                              | 4465                                  | 6169                             | 6169                                                  | 6169                                                                        | 6169                                  |

Notes: i) Source: JH, 6 waves; ii) Standard errors are reported below the coefficients; \*p < 0.05, \*\*p < 0.01, \*\*\*p < 0.001.

## Data availability

The authors do not have permission to share data.

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