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SICK AND COLD? EVIDENCE ON THE DYNAMIC INTERPLAY BETWEEN ENERGY POVERTY AND HEALTH

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Abstract. Energy poverty and health appear to be closely related, yet robust evidence on whether and how they mutually influence each other over time is still limited. We employ a dynamic latent class model on rich longitudinal data from the Household, Income, and Labor Dynamics in Australia Survey to uncover patterns of dynamic interdependence between energy poverty and ill-health. Our approach integrates key modelling features, such as state dependence and time-varying unobserved heterogeneity, while also revealing and quantifying mechanisms of joint dependence over time. Unlike previous studies, our model shows that although energy poverty and ill-health seem to mutually influence each other, the effect of ill-health on energy poverty appears to be comparatively larger, suggesting that ill-health might be a stepping stone to energy poverty. In addition, we identify three main types of individuals corresponding to different socioeconomic profiles and varying levels of vulnerability to changes in energy prices. These findings may indicate the need for targeted interventions rather than exclusive reliance on energy subsidies.

Keywords: energy poverty; health; dynamic latent class models; HILDA.
JEL codes: C33; C35; I31; I32.

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1 Introduction

Energy poverty is a major policy concern that affects an increasing share of the global population. Recent estimates suggest that 750 million people still lack access to electricity worldwide and more than 2 billion people lack access to clean cooking fuels (International Energy Agency, 2024). Energy poverty can be defined as the inability of a household to afford or access the energy services needed to support adequate living conditions and human development (European Commission, 2023). This includes lighting, cooking, access to technology and communication, heating, and cooling (UN Energy, 2024). Importantly, all standard definitions of energy poverty and their applications generally focus on the potential detrimental impact on individual well-being of lack of access or the inability to afford adequate energy consumption. Climate change and rising energy prices appear to have exacerbated the toll of energy poverty and its effects have been examined on different dimensions of health and well-being in several countries (Zhang et al., 2021; Pan et al., 2021; Churchill and Smyth, 2021; Pondie et al., 2024). However, evidence on the interdependence between energy poverty and health remains limited and inconclusive, as well as on the underlying mechanisms that link them over time. Without robust empirical evidence on how the relationship between energy poverty and ill-health operates dynamically at the individual level, policymakers may not be able to implement effective policies addressing these two key and interrelated aspects of an individual's life.

The main objective of this paper is to provide new evidence on the dual relationship between energy poverty and health over time using a dynamic latent class model. This empirical approach builds on recent developments in the literature on latent class models to develop a model that uncovers the underlying mechanisms driving the joint likelihood of experiencing energy poverty and ill-health. Additionally, this dynamic latent class model accounts for key features in modeling dynamic economic processes, such as state dependence and time-varying unobserved heterogeneity. This also builds on and extends emerging evidence on the bidirectional relationship between energy poverty and health (Brown and Vera-Toscano, 2021). By modelling various individual types based on different combinations of propensities to energy poverty and ill-health, we provide a novel understanding of how these factors interact and evolve over time. Furthermore, we explore the socioeconomic gradient of latent individual types and assess how fluctuations in electricity and gas prices influence them. This approach generates valuable information for designing targeted interventions that address specific vulnerabilities associated with different individual profiles.

While the literature on material hardship has traditionally focused on income poverty (Jäntti and Danziger, 2000; Meyer and Sullivan, 2023; Deaton, 2024), energy poverty has more recently emerged as a distinct area of study. This shift is driven not only by its policy relevance, exemplified by the recent energy crisis (Halkos and Gkampoura, 2021), but also by its correlations with significant negative economic outcomes, including employment (in)security (Koomson and Churchill, 2022) and low levels of education (Apergis et al., 2022). A growing body of literature has examined the relationship between energy poverty and various measures of individual health and well-being. Specifically, numerous empirical studies have found that energy (and fuel) poverty have detrimental effects on both physical and mental health, as well as on multiple aspects of public health, in both developed and developing countries (Oum, 2019; Banerjee et al., 2021; Churchill and Smyth, 2021; Nawaz, 2021; Oliveras et al., 2021; Pan et al., 2021; Zhang et al., 2021; Pondie et al., 2024). However, there is still limited understanding of the potential impact of ill-health on energy poverty, and even less on how these two factors interact, particularly over time. Brown and Vera-Toscano (2021) is one of the few studies to explore the dynamics of energy poverty and health using univariate and bivariate dynamic probit models. Yet, while their approach introduces dynamic interdependence, it does not account for potentially relevant modelling features such as individual-level time-varying heterogeneity or the inclusion of latent classes defining different propensities to experience energy poverty and ill-health. Our dynamic latent class model includes all these important attributes, while also exploring the dynamic mechanisms linking energy poverty and health.

We employ panel data from the Household, Income and Labor Dynamics in Australia (HILDA) Survey, including comprehensive information on both energy poverty and health. Australia presents an ideal case for exploring the dynamic interplay between energy poverty and health for three main reasons. Firstly, in Australia, electricity prices have almost tripled in the last decade (Proctor, 2022). Forward electricity prices for 2023 delivery in the Australian National Electric Market increased from approximately 48 dollars in 2021 to 156/MWh in 2022 (the 52-week average), peaking around 247/MWh in October 2022. The substantial rise in energy prices compared to household income has led to an increase in both the proportion of household budgets allocated to energy expenses and the prevalence of challenges related to energy access and affordability (Australian Bureau of Statistics, 2022). Secondly, despite the fragmented nature of energy assistance in Australia, which varies across jurisdictions, the existing programs mostly include price compensations and social welfare payments to cover energy bills (Willand, 2022). While these programs target low-income groups with significant reliance on means-testing (Willand, 2022), compensation rates and energy concessions may have limited relevance for individuals whose energy deprivation results from a health shock or underlying chronic conditions. Thirdly, while overall Australians are living longer and are affected by fewer communicable diseases, substantial health disparities across sub-groups of the populations appear to persist. Some groups are experiencing worsening health trends, with obesity, chronic illnesses like diabetes, and mental health disorders on the rise (Ervin et al., 2023). This surge in obesity-linked diseases and mental health challenges represents a critical public health issue in Australia (Hashmi et al., 2020) that has rarely been linked with energy poverty.

Our main findings reveal that while energy poverty and ill-health mutually influence each other over time, the effect of ill-health on energy poverty is comparatively larger, suggesting that ill-health may serve as a gateway to energy poverty. Moreover, we identify three latent "types" of individuals reflecting different propensities to energy poverty and ill-health: the 'Healthier and Wealthier' (Type 1); the 'Healthier with a Thin Wallet' (Type 2); and the 'Sicker and Wealthier' (Type 3). We further define the socioeconomic gradient of these latent types by integrating HILDA data with regional, yearly gas and electricity prices. Our analysis indicates that Type 2 individuals ('Healthier with a Thin Wallet') might be particularly vulnerable to increases in gas prices. In contrast, Type 3 individuals ('Sicker and Wealthier') appear less sensitive to price fluctuations but could face a heightened risk of falling into energy poverty as their health deteriorates.

This study offers several contributions to the literature on energy poverty and health. First, it introduces a novel econometric approach using a dynamic latent class model to examine the interplay between energy poverty and health. This methodology provides an analysis of the dynamic mechanisms liking energy poverty and health via the definition of different types, or sub-groups, of individuals presenting heterogeneous likelihoods of experiencing energy poverty and ill-health over time. Second, this model allows estimating the dynamic inter- and cross-dependencies between these two important dimensions of individual well-being. Third, we go beyond accounting for standard state-dependence and individual-level time-invariant unobserved heterogeneity typical of standard dynamic economic models by allowing the unobservable factors, potentially affecting energy poverty and health, to be correlated and vary over time. This also implies the possibility of modelling time-specific shocks that increase both the risk of illness and energy poverty. Fourth, and also differently from previous studies, we offer evidence suggesting that ill-health might be a stepping stone into energy poverty. Finally, we also provide evidence of varying levels of vulnerability to changes in electricity and gas prices based on the different types of individuals defined by our dynamic latent class model. Ultimately, this underlines the relevance of tailored health-focused interventions, rather than relying solely on more general energy subsidies.

2 Data

We exploit rich longitudinal information drawn from the Household, Income and Labor Dynamics in Australia (HILDA) Survey. This is a nationally representative panel survey of Australian households that started in 2001 and collects individual-level data of all household members aged 15 years or over. The initial sample in wave 1 consisted of 13,969 individuals from 7.862 households, whereas wave 11 added a booster sample of 5,462 individuals from 2,153 households. Given our main objective, we use a balanced sample of 3,960 individuals consistently observed between 2011 and 2021 (i.e. waves 11 to 21). A balanced sample provides significant advantages in our case: it tracks the same individuals across all periods, allowing for a more accurate analysis of the timing of relevant events. Additionally, it accounts for time-invariant individual characteristics influencing both health and energy poverty, thereby improving the accuracy of our model estimations.

2.1 Measures of Energy Poverty

As poorer households tend to allocate a larger proportion of their budget to energy-related expenses compared to higher-income households (Fry et al., 2022), we employ a Multidimensional Energy Poverty Index (MEPI) based on three income-related criteria. Specifically, a household is considered energy poor if satisfies at least one of the following three criteria: (i) its energy spending as a share of income is more than twice the national median (i.e. the 2M indicator); (ii) the share of income spent on energy is greater than 10 percent (i.e. the Ten Percent Rule, TPR); or (iii) energy expenditures are above the national median and income net of the energy costs falls below the national poverty line (i.e. the Low Income High Costs indicator, LIHC). These measures have been validated and used individually by a number of previous studies (Churchill and Smyth, 2020; Fry et al., 2022; Pondie et al., 2024). Other empirical analyses exploited alternative measures based on an individual's self-assessment of his ability to afford and access essential energy services, such as household bill arrears or the ability to heat their homes during winter (Nussbaumer et al., 2012; Prakash et al., 2022). In this paper, to minimize potential self-reporting bias that could affect our main estimates, we rely on income-based measures of energy poverty.

2.2 Measures of Health

We proxy an individual's health using alternative measures included in HILDA. Our main analysis adopts the most commonly used measure of overall health in social science, the standard 5-value self-assessed health (SAH) measure. This is based on the question "In general, how would you rate your own health?" with potential answers ranging between 'Excellent', 'Very good', 'Good', 'Fair' and 'Poor'. For the purpose of our analysis, we build a binary variable of ill-health that equals one if an individual responded either 'Fair' or 'Poor'. SAH measures of health were found to be strongly predictive of chronic health conditions across several countries (Becchetti et al., 2018) and are also correlated with other important dimensions of health such as vitality ("feeling full of energy/energetic"; e.g. Au and Johnston,2014). Despite their widespread use, it might be relevant to note that due to their nature of global measures, SAH proxies might not capture all aspects of physical and mental health equally and that may also be affected by self-perception. It should be also acknowledged that Davillas et al. (2022) found that using objective measures of both fuel poverty and individual well-being, such as biomarkers, might be more informative on the potential biological mechanisms that affect well-being through fuel poverty. However, our analysis focuses more generally on the dynamic interdependence between objective measures of energy poverty and a proxy of overall individual health. In addition, our bivariate dynamic latent class models would need binary measures of both constructs, i.e., energy poverty and health, to be estimated. In any case, as an alternative and more specific measure of health, we employ the Short Form (SF)-36 Health Survey, a validated and also widely used health instrument included in HILDA (Ware Jr (2000)). This is based on 36 questions across 8 health dimensions (general health; vitality; physical functioning; bodily pain; mental health; social functioning; role limitations due to physical health; role limitations due to emotional problems), producing an overall standardized score ranging between 0-100 increasing in good health. Due to the use of binary models in our analysis, we also included a dichotomised version of the SF-36 score in our models.[1]

[1]More specifically, we employed binary a SF-36 indicator based on a cut-off of 50. The results produced using this alternative measure of health are similar and are available on request.

2.3 Covariates

Our models encompass a wide range of individual-level characteristics that are potentially relevant to both energy poverty and health, including household income, age, gender, immigration status, years of schooling, marital status, and employment. Previous research has highlighted the importance of these variables. For instance, educational attainment is often negatively associated with energy poverty, mainly due to energy-saving practices and improved socioeconomic status. Education enhances individuals' knowledge and decision-making abilities, leading to better living conditions also through more efficient energy use (Crentsil et al., 2019). Age and gender effects may also emerge from life cycle patterns, household dynamics, health, and risk-taking behaviour (Abbas et al., 2020; Fry et al., 2022). As expected, income and labor market status are often significantly correlated with energy deprivation (Churchill and Smyth, 2020), with this relationship being especially pronounced in developing countries (Awan et al., 2022). However, HILDA does not include detailed information on dwelling characteristics, including size, age, thermal insulation, floor area, and heating systems, which prevents us from accounting for specific efficiency factors (Ntaintasis et al., 2019). However, this information might not be central to our analysis that focuses on the dynamic relationship between energy poverty — defined through objective measures — and health, while incorporating latent states, within- and between-state dependence, and time-varying unobservables. In addition, we account for broader socioeconomic variables, such as income and education, which can serve as proxies for dwelling characteristics.

2.4 Descriptive Statistics

Descriptive statistics of key variables are reported in Table 1. Notably, 13 per cent of the individuals reported poor health, while 17 per cent were classified as multidimensionally poor. The joint prevalence of energy poverty and ill-health was around 3.3 per cent. The sample has an average age of 45.6 years, with 19 per cent identified as immigrants (that is, born outside Australia) while the majority of individuals are married and employed.

Table 1. Variable descriptions with sample statistics for pooled data.

Variable	Description	Mean	S.D.
health	1 if subjective health status is bad, 0 otherwise	0.13	-
MEPI		0.17	-
female	1 if female 0 otherwise	0.56	-
age	Individual age	45.57	10.52055
foreign	1 if foreign 0 otherwise	0.19	-
divorced	1 if divorced 0 otherwise	0.08	-
single	1 if single 0 otherwise	0.14	-
widowed	1 if widowed, 0 otherwise	0.01	-
years of edu.	completed years of education	13.34	2.375584
unemployed	1 if unemployed, 0 otherwise	0.02	-
inactive	1 if other economically inactive, 0 otherwise	0.14	-
log income	Log of total household income	121.93	90.28638

3 Empirical Approach

The analysis of health dynamics often relies on models used to study movements across a poverty threshold (Jenkins, 2000). Here, we extend this general approach to examine transitions into and out of energy poverty. More specifically, in the following subsections we present three approaches to model the dynamics of energy poverty and health with increasing complexity, highlighting the relevance of each additional modelling feature. The first approach is a standard Static Random Effects (SRE) model. In this setting, health and energy poverty are treated as independent, potential dynamics are disregarded, and individual-level unobserved heterogeneity is assumed to be time-constant. The second approach is based on a Dynamic Random Effects (DRE) model, which controls for potential dynamics by including the lagged value of the dependent variable among the other regressors, yet it still ignores joint relationships between health status and energy poverty. Finally, we employ a more comprehensive bivariate Dynamic Latent Class Model (DLC). This approach allows to simultaneously take into account dynamics and time-varying unobserved heterogeneity, while also allowing health and energy poverty to be jointly related (Li Donni, 2019). The latter feature permits modelling the plausible dual relationship between an individual's health and energy poverty statuses by enabling them to mutually affect each other over time.

3.1 Static Random Effects Model

Suppose we observe two binary indicators for an individual i , denoted by h_{it} and ep_{it}, for each time period t, with $t = 1, \ldots, T$. Specifically, ep_{it} indicates whether an individual is energy-poor, while h_{it} refers to self-reported health status. Following previous studies on the empirical association between ill-health and socioeconomic status at old age (Salas, 2002), we modelled health status as a function of a set of lagged variables and time-constant individual characteristics:

$$ep_{it} = 1(\alpha_{ei} + \boldsymbol{\beta}_e \boldsymbol{x}_{it-1} + \boldsymbol{\gamma}_e \boldsymbol{z}_i + \epsilon_{eit} > 0) \tag{1}$$

$$h_{it} = 1(\alpha_{hi} + \boldsymbol{\beta}_h \boldsymbol{x}_{it-1} + \boldsymbol{\gamma}_h \boldsymbol{z}_i + \epsilon_{hit} > 0) \tag{2}$$

where 1(.) is the indicator function, $\boldsymbol{x}_{it-1}$ is a vector of lagged values of time-varying characteristics, $\boldsymbol{z}_i$ is a vector of time-constant individual characteristics, and $\alpha_{\cdot i}$ and $\epsilon_{\cdot it}$ represent a time-invariant individual-specific term and an idiosyncratic error component, respectively.

Estimation of parameters α, β and γ in equations (1)-(2) is implemented by running three separate logit or probit models, where the subject-specific parameters αs may be treated as random. This assumes that the individual-specific effect α_i are normally distributed and uncorrelated with the explanatory variables.

However, this approach is relatively limited in scope since it ignores potential time-varying heterogeneity (e.g. α_i are treated as fixed), while treating h_{it} and ep_{it} as independent, whereas in practice they are likely to be related to each other over time. Finally, SRE also assumes that past health and energy poverty statuses have no effect on subsequent periods.

3.2 Dynamic Random Effects Model

An approach which relaxes the latter assumption is the DRE model. This accounts for potential dynamic interdependencies across consecutive time periods by including the lagged value of the dependent variable on the right-hand side of equations (1)-(2) as follows:

$$ep_{it} = 1(\alpha_{ei} + \boldsymbol{\beta}_e \boldsymbol{x}_{it-1} + \boldsymbol{\gamma}_e \boldsymbol{z}_i + \delta_e ep_{it-1} + \epsilon_{eit} > 0) \tag{3}$$

$$h_{it} = 1(\alpha_{hi} + \boldsymbol{\beta}_h \boldsymbol{x}_{it-1} + \boldsymbol{\gamma}_h \boldsymbol{z}_i + \delta_h h_{it-1} + \epsilon_{hit} > 0) \tag{4}$$

where δs are the well-known state dependence parameters, indicating how persistently an individual experiences the same condition over time. Since lagged values of dependent variables now appear among the regressors, estimation should deal with the initial conditions problem (Heckman, 1981) , which arises as the h_{hit} (or ep_{fit}), measured during the first time period, might be correlated with the random parameter α_{hi} (or α_{ei}). This correlation reflects the fact the initial observation period and the distribution of y_j, measured during subsequent periods $1, \dots, T$, depend simultaneously on observable and unobservable factors. To deal with this issue, two (correlated) equations for h_{ij0} and h_{ijt} are estimated, by assuming α_i is normally distributed. Therefore in this case, a DRE probit model is employed (Stewart, 2006, 2007).

However, the DRE model does not take into account that subjective health or an individual's energy poverty status may be correlated with some common time-varying unobservable factors. For example, some individuals may be more prone to experience energy poverty and/or ill-health due to a series of unobserved characteristics. If this unobserved propensity is not systematically constant over time, the assumption that the subject-specific parameters α_i are time-constant may not be valid, making the estimated parameters potentially biased.

Moreover, the DRE, together with the SRE, treat subjective health and energy poverty as independent. A simple solution would be to include among the regressors (e.g. in (4)) the lagged values of the other outcomes (e.g. ep_{it-1} in h_{it}), and assume that they are not correlated with either fixed or time-varying components. However, this would be a restrictive approach which would also potentially bias our estimates of interest if unobserved heterogeneity is not properly taken into account.

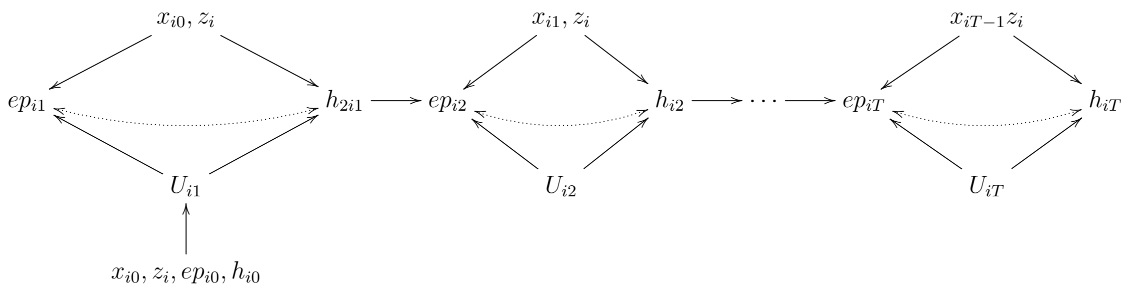
3.3 Dynamic Latent Class Model

An alternative and more flexible way to deal with this important issue consists of jointly modelling the probability of experiencing energy poverty and reporting ill-health by allowing the subject-specific parameters to be time-varying. In the next section, we describe how this could be achieved in practice by devising a DLC model with time-variant heterogeneity (Bartolucci and Farcomeni, 2009; Li Donni, 2019).

Essentially, the DLC model relies on two main assumptions: i) unmeasured time-varying heterogeneity U can be modelled by using a discrete distribution of latent states ξ_c collected in U, with $c = 1, \dots, k$ following a first-order Markov chain; and (ii) the latent states make *ep* and h conditionally independent to each other, given the full set of observable explanatory variables (that also include energy poverty and health status in past periods).

The structure of DLC model can be depicted in Figure 1. This can be summarized by the following set of equations.

FIGURE 1. Path diagram of the DLC model



The first set of equations describes the relationship between the two main statuses of interest, health and energy poverty. Let us assume that the random variables $\epsilon_{\cdot it}$ are independent error terms with standard logistic distributions. Conditional on observed individual characteristics $\widetilde{\boldsymbol{z}}$ which collect time-fixed $\boldsymbol{z}_i$ and one period lagged time varying $\boldsymbol{x}_{it-1}$ covariates, there are three possible sources of correlation between the unobservable determinants of health status and energy poverty.

First, the correlation between observations over time is captured by individual-specific effects distributed as a latent discrete variable U following a first order Markov chain. We assume that the Markov process is homogeneous, meaning that the transition probabilities between these latent states (e.g., from a "low propensity" state to a "high propensity" state of energy poverty) remain constant over time. This information is captured by a vector of parameters, one for each latent state and corresponding binary outcome, capturing time-varying heterogeneity in the individuals' propensities to suffer from energy poverty and ill-health, correspondingly. In other words, these parameters capture the persistence of being energy-poor and experiencing ill-health that is due to individual unobserved heterogeneity.

The second potential source of correlation is related to state dependence, which occurs when health status and being energy-poor in past periods predict current (i.e. present-period) energy-poverty and health statuses. This type of correlation is captured by including lagged values of the outcome variables in each equation describing health (h_{it}) and energy poverty (ep_{it}). This implies modelling state dependence within and between outcomes. State dependence *within outcomes* provides information on the extent to which a specific outcome depends on its past (previous-period) value, e.g. individuals who experienced energy poverty in the previous period (that is, at *t-1*) may (or may not) experience it again in the current period (that is, at time t). Equally, state dependence *between outcomes* can be used to explain patterns of dependency between different outcomes over time. In particular, if being energy-poor in the past increases the probability of suffering from ill-health at present, this could be interpreted as a potential stepping-stone effect, which operates from energy poverty to health.

Third, *time-specific* shocks (the dotted line Figure 1) may affect both outcomes in any given period. These shocks may not be captured by $\boldsymbol{x}_{it}$, $ep_{i,t-1}$, $h_{i,t-1}$, or by the subject-specific parameters making energy poverty and health status residually correlated. Such correlated period shocks could be the result of an unexpected health deterioration that, while occasional, might influence the likelihood of experiencing energy poverty in a specific time-period t.

Equations (3)-(4) can then be written as the following system:

$$e_{eit} = 1\big(\sum_{c=1}^{k} \alpha_{eit}(\xi_c)d_{eit} + \boldsymbol{\beta}_e\boldsymbol{x}_{it-1} + \boldsymbol{\gamma}_e\boldsymbol{z}_i + \delta_e ep_{it-1} + \tau_e h_{it-1} + \epsilon_{eit} > 0\big), \tag{5}$$

$$h_{hit} = 1\big(\sum_{c=1}^{k} \alpha_{hit}(\xi_c)d_{hit} + \boldsymbol{\beta}_h\boldsymbol{x}_{it-1} + \boldsymbol{\gamma}_h\boldsymbol{z}_i + \delta_h h_{it-1} + \tau_h e_{it-1} + \epsilon_{hit} > 0\big)$$

where $d_{\cdot it}(\xi_c)$ denotes a dummy variable defining whether the ith unit belongs to the latent state ξ_c of the Markov chain at time t and $\boldsymbol{\alpha}_{\cdot it}$ is a vector of subject-specific parameters $\alpha_{\cdot it}$. Note that αs, δs and τs capture the first and second sources of correlation described above. In particular, the random intercepts describe how unobserved heterogeneity might affect each outcome, while δs and τs measure state dependence and cross-effects between subsequent periods and outcomes, respectively.

The third source of correlation is accounted for by including in 5 the association between ep_{it} and h_{it}. Since $\epsilon_{\cdot it}$ follows a logistic distribution, residual association is parameterized by a log-odds ratio λ (Bartolucci and Farcomeni, 2009). This means that if an individual is energy-poor, the likelihood of an adverse health outcome is λ times that of the likelihood of an adverse health outcome if she is not energy poor. That is, when $\lambda = 1$ energy poverty and health status are not associated conditional on U, while when $\lambda > 1$ ($\lambda < 1$) energy poverty is associated with a higher (lower) likelihood of an adverse health outcome. Hence, this association parameter may reflect those time-specific shocks that increase both the risk of illness and energy poverty.

The second set of equations of the DLC model aim at describing the underlying process of the time-varying unobserved heterogeneity in the first and subsequent periods of time. This is described as follows:

$$p(\boldsymbol{\alpha}_i = \boldsymbol{\xi}) = p(\boldsymbol{\alpha}_{i1} = \boldsymbol{\xi}_c) \prod_{t=2}^{T} p(\boldsymbol{\alpha}_{it} = \boldsymbol{\xi}_{\bar{c}} | \boldsymbol{\alpha}_{i,t-1} = \boldsymbol{\xi}_c) \tag{6}$$

where $p(\boldsymbol{\alpha}_{i1} = \boldsymbol{\xi}_c)$ represents the initial probability and $p(\boldsymbol{\alpha}_{it} = \boldsymbol{\xi}_{\bar{c}} | \boldsymbol{\alpha}_{i,t-1} = \boldsymbol{\xi}_c)$ represents the $k(k-1)$ transition probabilities, which are collected in a $k \times k$ matrix $\boldsymbol{\Pi}$. Note that, given the first-order assumption on the Markov chain, transition probabilities depend only on the previous time period and describe how the unobservable factors captured by c evolve over time.

Notice that the initial probabilities do not only depend on ep_{i1} and h_{i1}, but also on the explanatory variables. This is achieved in practice by employing a multinomial logit parameterization:

$$p\big(\boldsymbol{\alpha}_{i1} = \xi_c | \boldsymbol{x}_{i0}, \boldsymbol{z}_i, ep_{i0}, h_{i0},\big) = \frac{\exp(\boldsymbol{\alpha}_c + \boldsymbol{\beta}_c\boldsymbol{x}_{i0} + \boldsymbol{\gamma}_c\boldsymbol{z}_i + \delta_c ep_{i0} + \tau_c h_{i0})}{1 + \sum_{j=2}^{k} \exp(\alpha_j + \boldsymbol{\beta}_j\boldsymbol{x}_{i0} + \boldsymbol{\gamma}_j\boldsymbol{z}_i + \delta_j ep_{i0} + \tau_j h_{i0})}, \tag{7}$$

with $j = 2, \dots, k$. Estimated coefficients in (7) are particularly relevant, as they capture how individual-level conditions affect the probability of being in a specific state in the the first period. In this sense, these parameters capture the effect of observable characteristics on the unobserved heterogeneity. Notice that the $c-1$ logit parameters in (7) do not impose any parametric restriction on the distribution of U and explicitly deal with the initial condition problem.

The individual log-likelihood, namely the probability of observing a specific pattern of ep and h given an unobserved state over T periods of time, can be described as follows:

$$\ell_i(\boldsymbol{\theta}) = \log\Bigg\{\sum_{\boldsymbol{\alpha}_{i1}} \dots \sum_{\boldsymbol{\alpha}_{iT_i}} \Bigg[p(\boldsymbol{\alpha}_{i1} = \boldsymbol{\xi}_c | \boldsymbol{x}_{i0}, \boldsymbol{z}_i, ep_{i0}, h_{i0}) \prod_{t=2}^{T_i} p(\boldsymbol{\alpha}_{it} = \boldsymbol{\xi}_{\bar{c}} | \boldsymbol{\alpha}_{i,t-1} = \boldsymbol{\xi}_c) \times \times \prod_{t=1}^{T_i} p(ep_{it}, h_{it} | \boldsymbol{\alpha}_{it}, \boldsymbol{x}_{it-1}, ep_{i,t-1}, h_{i,t-1})\Bigg]\Bigg\}$$

with $\boldsymbol{\theta}$ collecting the full set of model's parameters. Since ℓ involves unobervables, its estimation is implemented by an Expectation-Maximization (EM) algorithm. Details on estimation and implementation of this algorithm can be found in (Bartolucci and Farcomeni, 2009).

The share w_c of individuals in the population belonging to the unobserved group c can be recovered via Bayes's formula and backward recursion by using for each individual i at time t the posterior distribution of U. Subsequently, the posterior weight w_c for each latent state is obtained as follows:

$$w_c = \frac{1}{N} \sum_{i=1}^{N} \Bigg[\frac{1}{T} \sum_{t=1}^{T} p\big(\boldsymbol{\alpha}_{it} = \boldsymbol{\xi}_c | \boldsymbol{x}_{it-1}, \boldsymbol{z}_i, ep_{it-1}, h_{it-1}, ep_{it}, h_{it}\big)\Bigg], \text{ with } c = 1, \dots, k \quad (8)$$

4 Main Results

This section presents the estimated parameters from (i) the Static Random Effects (SRE) logit model; (ii) the Dynamic Random Effects (DRE) probit model based on the Heckman approach to deal with the initial conditions (Heckman, 1991); and (iii) the bivariate Dynamic Latent Class model with time-variant heterogeneity (DLC). Before presenting the results for multidimensional energy poverty (MEPI), we first examine one of the energy poverty indicators, 2M. To maintain brevity and facilitate comparison across models, we present only marginal effects. The full set of estimated coefficients is provided in the Appendix.

4.1 Marginal Effects

Table 2 and 3 report the average marginal effects of the univariate static and dynamic random effects models (SRE and DRE). Estimated coefficients reveal that individual characteristics do not differ substantially in magnitude and sign across the two models. Moreover, they suggest that state dependence plays a crucial role, as experiencing ill-health and energy poverty in the past increases the likelihood of facing these issues in subsequent periods. Unobserved heterogeneity is accounted for by the Intra-class Correlation Coefficient (ICC). The ICC measures the total unexplained variation attributed to the individual effect conditional on the observed explanatory variables.

Estimates suggest that unobservable heterogeneity in the SRE model accounts for 40% and 68% of the unexplained variation in energy poverty and health. Interestingly, unobserved heterogeneity appears to be relatively more important with an ICC twice as high. However, these figures are smaller in the DRE. In particular, the unobservable individual-specific factors account for 12% of the overall heterogeneity for energy poverty, while the ICC drops to 26% in the case of subjective poor health. These differences suggest modelling state dependence is crucial to understand the dynamics of health and energy poverty, since the relevance of individual-specific unobserved heterogeneity in the DRE is smaller than that of the SRE model.

Table 2. Estimated average marginal effects of the SRE models.

	Energy poverty	Health
x_i		
age	0.0007**	0.0026***
female	0.0028	-0.0002
foreign	-0.0284***	-0.0094
x_{it-1}		
years of edu.	-0.0147***	-0.0115***
divorced	0.053***	0.0104
single	0.0277***	0.0228***
widowed	0.0337	0.0137
unemployed	0.0709***	0.0165**
inactive	0.083***	0.0418***
log income	-0.0005***	-0.0001***

However, the DRE model does not provide information around the underlying structure of the unobserved heterogeneity, which is also assumed to be time-constant. This is the reason why relying on a more flexible model, like the DLC may provide a clearer overall picture of the relationship between energy poverty and poor health.

Importantly, the DLC model requires the identification of an adequate number of latent states. In the literature on latent variable and finite mixture models, the most frequently used criteria are the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Usually, the model with lowest BIC and AIC is preferred, as the lowest AIC or BIC suggests the best balance between fitting the data well and avoiding unnecessary complexity. Table 4 reports model selection criteria. The model with one latent state, assuming the existence of no time-varying unobserved heterogeneity, shows the highest values of both AIC and BIC. Conversely, three latent states appear adequate to capture the underlying differences between individuals which systematically affect the probabilities of experiencing energy poverty and reporting ill-health in our sample.

Table 3. Estimated average marginal effects of the DRE models.

		Energy poverty		Health	
		Eq. $t > 0$	Eq. $t = 0$	Eq. $t > 0$	Eq. $t = 0$
x_i					
	age	0.0005**	0.0018***	0.0015***	0.0016***
	female	0.0018	0.0139	-0.0026	0.0068
	foreign	-0.0231	-0.0176	-0.0077	-0.0043
x_{it-1}					
	years of edu.	-0.0134	-0.0051	-0.0067	-0.0083
	divorced	0.0600***	-0.0122	0.0063	0.0025
	single	0.0268***	-0.0130	0.0169***	0.0210**
	widowed	0.0379	-0.0443	0.0092	0.0240
	unemployed	0.0836***	0.0037	0.0118	-0.0053
	inactive	0.0931***	0.0584***	0.0305***	0.0346***
	log income	-0.0003	-0.0023	-0.0001	-0.0001
y_{t-1}					
	energy poverty	0.1034***			
	health			0.0595***	

Standard errors for the reported statistical significance are obtained using bootstrap method based on 600 replications. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

The pattern emerging from comparing this selection criteria indicates that, realistically, the effect of an individual's unobserved characteristics on the probabilities of experiencing energy poverty and ill-health are not time-constant and that these two processes may be jointly related over time.

Table 4. Model selection criteria for the DLC model.

k	#par	Log-lik.	BIC	AIC
1	45	-26965.93	54304.64	54021.86
2	62	-25811.62	52136.84	51747.23
3	81	-25269.81	51210.63	50701.63
4	102	-25224.34	51293.66	50652.69

Table 5 reports the average marginal effects (AME) of the most comprehensive model, namely the DLC. State dependence *within* outcomes is reported in the last two rows of the first group of columns. As shown in the table, the coefficients are all positive and statistically significant, indicating that having previously experienced a specific condition has a positive effect on the probability of experiencing it in the subsequent time period. In particular, suffering from energy poverty in the current year increases the probability of experiencing the same condition in the subsequent period by 11 percentage points. As for ill-health, the corresponding effect is still highly statistically significant but relatively smaller in size, at around 7 percentage points.

Interestingly, we also observe state dependence *between* outcomes. In particular, conditional on unobservable factors, individuals who have reported experiencing ill-health in the previous period increases the probability (by about 3 percentage points) of reporting energy poverty in the subsequent period compared to those who were not in ill-health. A similar effect is observed for the relationship between previous energy poverty status and subsequent health status, indicating that the occurrence of energy poverty at *t-1* is associated with a relatively higher probability ill-health at time *t*. Interestingly, the first effect (from ill-health to energy poverty) is larger than the second (from energy poverty to ill-health), potentially suggesting a stepping-stone effect operating from ill-health to energy poverty, although its corresponding quantitative effect is only a relatively modest-size.

TABLE 5. Estimated average marginal effects of the DLC model.

		Eq. $t > 0$		Eq. $t = 0$	
		Energy poverty	Health	Pr(U=2)	Pr(U=3)
x_i					
	age	0.0011***	0.0010***	-0.0030**	0.0019***
	female	-0.0043	-0.0014	0.0050	-0.0239
	foreign	-0.0287***	-0.0169*	0.0164	0.0168
x_{it-1}					
	years of edu.	-0.0068***	-0.0008	-0.0095	-0.0094**
	divorced	0.0433***	0.0159*	-0.0180	0.0023
	single	0.0486***	0.0418***	-0.1353***	-0.0411**
	widowed	0.0146	-0.0072	-0.0629	0.1313
	unemployed	0.0715***	0.0170	0.0483	0.0975**
	inactive	0.0683***	0.0445***	0.0231	0.0347
	log income	-0.0002***	-0.0001***	-0.0016***	0.0000
y_{t-1}					
	energy poverty	0.1114***	0.0105**	0.3403***	0.0044
	health	0.0293***	0.0768***	-0.1659***	0.6242***

Standard errors for the reported statistical significance are obtained using bootstrap method based on 600 replications. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

4.2 Latent States

We now turn our attention to the second source of correlation related to unobserved time-varying heterogeneity and captured by the latent states. From the estimated intercept one can recover the conditional average probability, reported in Panel A of Table 6, describing the joint propensity of an hypothetical individual in each latent state of experiencing energy poverty and poor health. An individual in the latent state 1 has the lowest probability of being energy-poor and sick. In contrast, individuals in latent states 2 and 3 have the highest probability of being energy-poor (about 40 %) and sick (about 50%), respectively. These groups suggest the presence of three hypothetical Types: the "Healthier and Wealthier" (Type 1) and the "Healthier with a thin wallet" (Type 2), and the "Sicker and wealthy" (Type 3).

In the population there are, on average, 60% of Type 1 individuals, and 24% and 16% of Types 2 and 3, respectively. Differently from the random effects model assuming time-invariant individual heterogeneity, in the DLC model individuals are assumed to freely move from one state to another. Transition probabilities are reported in Panel B of Table 6. It is interesting to note that the vast majority of individuals in the sample are expected to persistently remain in the same state. Comparing the elements below the diagonal of the transition matrix with those above, it is apparent that transitions are more likely from Types 2 or 3 to Type 1, whereas a relatively large share of individuals (about 3 %) shift from state 1 or 3 to state 2. Transitions between states emerge more clearly from Figure 2, which plots the expected share of the population in each latent state. Interestingly, the number of individuals in states 2 and 3, which correspond to the hypothetical Types 2 and 3, tends to constantly increase over time, whereas the corresponding share for Type 1 decreases. This is not surprising, as individuals in the sample naturally age, leading to a shift toward poorer health status (Type 3). Additionally, the consistent increase in energy prices in Australia over time has heightened the risk of energy poverty (Type 2), causing more people to face this challenge.

TABLE 6. Conditional average probabilities and transition probabilities.

Panel A: Conditional Average Probabilities				
		Latent states		
		1	2	3
Pr(ep=1—U=j)		0.0670	0.3933	0.1604
Pr(h=1—U=j)		0.0343	0.0543	0.5034
Panel B: Transition probabilities				
		1	2	3
	1	0.9743	0.0202	0.0055
t-1	2	0.0373	0.9523	0.0104
	3	0.0133	0.0105	0.9762

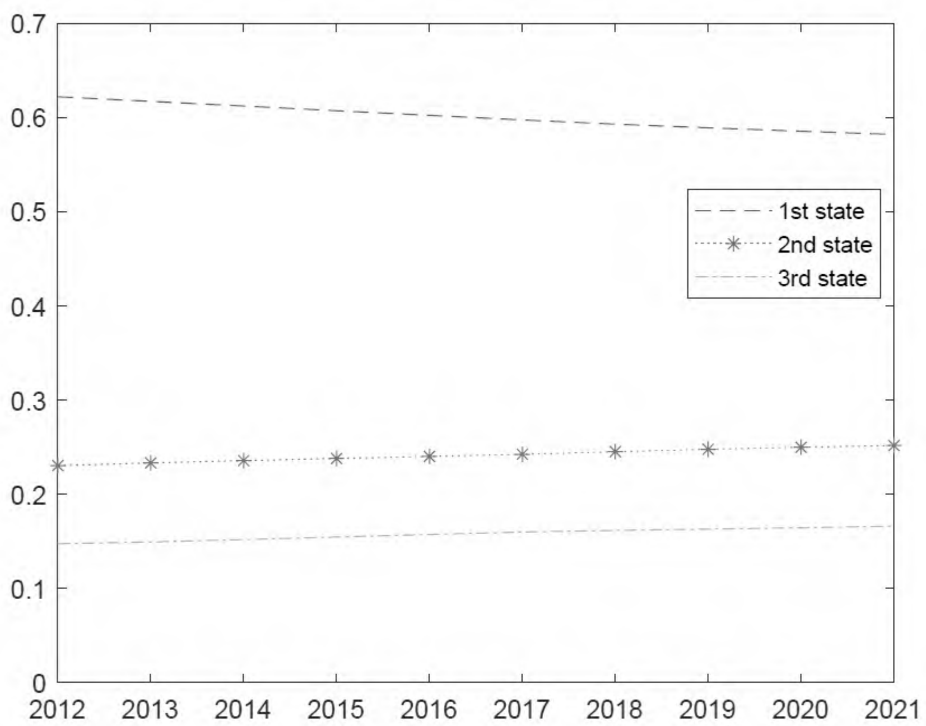


FIGURE 2. Estimated average probability of each latent state at every year.

4.3 Robustness

For robustness, we also estimated the DLC model with a different measure of energy poverty, as defined by the MEPI. Specifically, we define an individual as energy poor if he/she is poor in at least one of the TPR, 2M and LIHC dimensions. Again, three classes appear to appropriately capture the underlying unobserved time-varying heterogeneity. Table 7 reports the estimated average marginal effects of the DLC model.

TABLE 7. Estimated average marginal effects of the DLC model for a general index of energy deprivation.

		Eq. $t > 0$		Eq. $t = 0$	
		Ind. energy poverty	Health	Pr(U=2)	Pr(U=3)
x_i					
	agem	0.0008**	0.0009**	-0.0032**	0.0027***
	female	-0.0033	-0.0071	0.0033	-0.0203
	foreign	-0.0154*	-0.0239***	0.0041	0.0131
x_{it-1}					
	years of edu.	-0.0015	-0.0070***	-0.0098	-0.0074
	divorced	0.0195**	0.0494***	-0.0153	-0.0061
	single	0.0392***	0.0568***	-0.1470***	-0.0370*
	widowed	-0.0088	0.0375	-0.1085	0.1381
	unemployed	0.0170	0.0792***	0.0369	0.0966**
	inactive	0.0474***	0.0831***	0.0103	0.0287
	log income	-0.0001	-0.0002	-0.0015***	-0.0001
y_{t-1}					
	ind. energy poverty	0.0127**	0.0826***	0.3017***	0.0255
	health	0.0790***	0.0367***	-0.1694***	0.6101***

Standard errors for the reported statistical significance are obtained using bootstrap method based on 600 replications. * Significant at 10%. ** Significant at 5%. *** Significant at 1%.

4.4 Socioeconomic Gradient of Latent States and Energy prices

With the aim of providing further information about the relevance of the latent states defined via our bivariate Dynamic Latent Class model, we present results from two additional analyses. First, we show average marginal effects obtained from a multinomial logit model that includes a dependent variable with three categories corresponding to the three types of individuals defined by the latent states and a series of socioeconomic variables as controls. The results are shown in Table 8. We find that Type 1 ("healthy-wealthy") individuals are more likely to be single (an increase of around 16 percentage points, pp, in the probability of being Type 1); slightly more educated (around a 2.2 pp increase per additional year of education); and less likely to be foreign born (around 2.1 pp), unemployed (5.7 pp) or inactive (8.4 pp) and present higher levels of income, with a 1 percent increase in income raising the probability of being Type 1 by 0.2 pp. Type 2 ("healthier but with thinner wallets") tend to be female (around 1.7 pp); slightly more foreign born (around 1.1 pp); and are less likely to be single and divorced (around 16.1 and 3 pp), unemployed and inactive (2.8 and 1.6, respectively), marginally less educated and, as expected, with lower levels of income. As for Type 3 ("sicker and wealthier"), it correlates positively with age (3.9 pp), inactivity and unemployment (10 and 8.5 pp, correspondingly); widowhood and divorce (4.1 and 1.7 pp); and negatively with schooling (1.3 pp) and income. Age appears to have statistically significant marginal effects across all three types, although the magnitude of these effects is small.

Table
8. Estimated average marginal effects of being in an observed state.

	Pr($U = 1$)	Pr($U = 2$)	Pr($U = 3$)
age	-0.0012***	-0.0027***	0.0039***
female	0.0007	0.0177***	-0.0185***
foreign	-0.0214***	0.0114**	0.0101**
yearseduc	0.0218***	-0.0085***	-0.0133***
divorced	0.0128	-0.0300***	0.0172***
single	0.1585***	-0.1442***	-0.0143**
widowed	-0.0572**	0.0161	0.0411***
unemployed	-0.0567***	-0.0284**	0.0851***
inactive	-0.0841***	-0.0165***	0.1006***
log income	0.2090***	-0.1729***	-0.0360***
log electricity price	0.2887***	-0.3315***	0.0427*
log gas price	-0.5380***	0.6019***	-0.0639***

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Second, we match the individual HILDA records with annual electricity and gas prices at the state level drawn from the Australian Bureau of Statistics (Australian Bureau of Statistics, 2024). The average price of gas and electricity during the sample period was 0.012 and 0.266 per kWh, respectively. This allows us shed light on both the socioeconomic gradient of the latent states and whether these are affected by changes in energy prices differently. The results in Table 8 show that a one percent increase in electricity prices (that is, a modest increase) is associated with a higher likelihood of being Type 1 (around 0.29 pp) as well as a lower probability of being Type 2 (around 0.33 pp). The correlation between Type 3 and electricity prices is positive, but smaller in size and only weakly significant. Interestingly, the relationship between latent types and gas prices appears to be different. A 1 percent increase in gas prices is associated with a 0.53 pp decrease in the likelihood of being Type 1 and a 0.60 pp increase in the likelihood of being Type 2. Although the estimated marginal effects are of modest size and should be interpreted with caution, two potential policy takeaways appear to emerge from these findings. First, since Type 2 is considered a group at risk of energy poverty (being relatively healthy but more likely to experience energy poverty), the results indicate they might be so due to increases in gas prices. A possible implication of these results is that, if a significant portion of energy subsidies are directed toward electricity, this group may still suffer from energy poverty. Second, these findings, coupled with the ones from our main estimates, may suggest that although the group with poorer health (Type 3) should not be as sensitive to electricity and gas prices, a health deterioration could eventually push them into energy poverty. This might still underline the need for (preventive) health-linked interventions rather than general energy subsidies. Overall, these results suggest the need for targeted interventions accounting for different vulnerabilities emerging from the distinct types of individuals.

5 Conclusions

This paper provides new evidence on how energy poverty and ill-health mutually influence each other over time using a novel econometric approach based on a dynamic latent class model and rich panel data from HILDA. Employing a dynamic latent class model provides several distinct advantages in this case. First, it allows an examination of the potential mechanisms linking energy poverty and health by exploiting individual-level heterogeneity in the data. This can be achieved via the identification of unobserved (latent) sub-groups or types exhibiting different propensities to energy poverty and ill-health. In addition, it is possible to establish whether individuals may switch type over time as a consequence of changes in their risks of facing either energy poverty or an illness. Second, we extend the scope of standard dynamic economic models by not only accounting for state-dependence and individual-level unobserved heterogeneity but also allowing unobservable factors influencing energy poverty and health to be correlated and vary over time. This further enables the modelling of time-specific shocks that may simultaneously increase the likelihood of energy poverty and ill-health. Third, by integrating energy prices into HILDA, we also offer an exploratory analysis of the socioeconomic gradient of the different (latent) types of individuals as well as their sensitivity to electricity and gas prices. None of these analyses could be achieved via standard (dynamic) econometric models. As such, this study contributes directly to the growing literature on the determinants of energy poverty as well as the emerging stream of studies exploring the link between health and energy poverty.

Our analysis of the dynamic interplay between energy poverty and health reveals statistically significant within- and between-state dependence. Specifically, suffering from ill-health or energy poverty increases the likelihood of experiencing the same condition during the subsequent period. Moreover, living in energy poverty also raises the risk of ill-health in the following period, whereas poor health also increases the likelihood of falling into energy poverty. However, since the effect of ill-health on energy poverty appears to be quantitatively larger, this suggests that health deterioration may serve as a stepping stone into energy poverty. In addition, our dynamic latent class model identifies three latent types corresponding to distinct socioeconomic groups: the "Healthier and Wealthier," the "Healthier with a Thin Wallet," and the "Sicker and Wealthier." Our findings show that individuals in the "Healthier with a Thin Wallet" group are particularly vulnerable to rising gas prices, whereas the "Sicker and Wealthier" group, while less sensitive to energy price fluctuations, faces heightened risks of energy poverty if their health further deteriorates. Importantly, our estimates are systematically compared with the ones produced by static and dynamic random effects models that do not account for state dependence or time-varying individual-level heterogeneity, respectively. Overall, these findings might underline the need to jointly address energy poverty and health dynamics, while considering the socioeconomic profiles and vulnerability gradients of affected populations.

Our findings build on previous research while offering new insights into the relationship between energy poverty and health over time. Earlier studies have predominantly examined the effects of energy poverty on health (Zhang et al., 2021; Pan et al., 2021;

Churchill and Smyth, 2021; Pondie et al., 2024), consistently reporting significant associations. We extend this perspective by showing that the relationship also operates in the opposite direction: ill-health significantly increases the likelihood of experiencing energy poverty, and this reverse effect appears to be stronger. Previous evidence from bivariate dynamic probit models reported by Brown and Vera-Toscano (2021) found no cross-dependency between health and objective measures of energy poverty. We argue that incorporating individual-level time-varying heterogeneity and latent classes, which capture differing propensities to experience energy poverty and ill-health, might be essential to uncovering the patterns identified in our analysis.

Despite the novel contributions of this study, some limitations should be acknowledged. First, the main health measure employed in our analysis, while a widely used indicator of overall health, may reflect potential biases due to the self-reported nature of the data. Nonetheless, self-assessed measures of overall health have been found to be a strong predictors of chronic conditions as well as important health-related aspects of life such as vitality, making it a good proxy for overall health (Au and Johnston, 2014; Becchetti et al., 2018). Furthermore, the binary version of this measure was instrumental for the implementation of our binary dynamic latent class model, which requires binary dependent variables for both health and energy poverty. Estimates using a more specific and validated measure of health — a dichotomised version of the SF-36 Health Survey— produced similar results, suggesting that our main estimates are robust to alternative health measures. Second, the absence of detailed information on housing characteristics in HILDA, such as insulation quality or heating systems, prevents us from fully capturing the role of energy efficiency in mitigating energy poverty. However, given the focus of our analysis on dynamic relationships and individual heterogeneity, the inclusion of such information is unlikely to dramatically alter the main results. Lastly, while the study identifies broad dynamic patterns between health and energy poverty, we employ data from a representative sample of the Australian population, which may limit the generalisability of findings to other regions with different socioeconomic and policy contexts. Nonetheless, it might be reasonable to assume that these results would apply to other developed countries with similar socioeconomic composition and access to energy.

From a policy perspective, our findings shed light on the potential relevance of targeted policy interventions. For instance, for the "Healthier with a Thin Wallet" group, policies addressing rising gas prices, such as subsidies or incentives to switch to more affordable and efficient energy sources, might be crucial. Conversely, for the "Sicker and Wealthier" group, health-focused preventive measures could play a vital role in reducing the likelihood of these individuals falling into energy poverty. Overall, the evidence produced here suggests that general energy subsidies alone may not suffice. A more tailored approach combining energy assistance with health-related interventions might be needed to address the distinct vulnerabilities of these groups more effectively.

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