# Determinants, Persistence and Dynamics of Energy Poverty: An Empirical Assessment Using German Household Survey Data*

Katharina Drescher† Benedikt Janzen‡

January 3, 2021

**Abstract**

Energy affordability receives increasing attention in developed countries. We examine the determinants, persistence and dynamics of energy poverty by employing a dynamic random-effects probit model on three waves of German household panel data. While households that are energy poor under an expenditure-based indicator in one period are 19.8 percent more likely to be energy poor in the subsequent period, persistence of self-reported energy poverty is significantly lower. Next, we employ an identification function and multinomial logistic regression to distinguish between chronic and transient energy poverty. Our findings suggest that energy poverty is mostly a transitory state. Differences between the determinants of energy poverty duration states can be mainly attributed to household composition, population density, labor force status, energy efficiency measures and in particular the heating system in place.

**Keywords:** Energy poverty, fuel poverty, energy affordability

**JEL Codes:** Q48, I32, D63

*We are thankful for helpful comments and suggestions from Doina Radulescu as well as participants at the 12th SAEE Workshop and the 5th AIEE Energy Symposium.

†Statistics Austria; Email: katharina.drescher@statistik.gv.at

‡University of Bern, KPM Center for Public Management; Email: benedikt.janzen@kpm.unibe.ch

# 1 Introduction

According to Eurostat data from 2018, 2.7 percent of German households were not able to keep their homes adequately warm, 3.0 percent of Germans were in arrears on their bills and 13.4 percent faced poor housing conditions, such as a leaking roof, damp walls, foundation or floors, or rot in window frames. These living circumstances are often linked to energy poverty, which refers to a state of experiencing difficulties to reach adequate levels of domestic energy services. Research has shown the adverse effects of energy poverty which include decreasing physical and mental health, and a reduction in children's educational opportunities (Roberts et al., 2015). Due to these associated negative welfare effects, energy poverty is gaining attention. Moreover, the climate crisis has put energy affordability into political focus. Since the energy transition is accompanied by rising energy prices, low-income and energy poor households must be given special consideration when implementing policy measures. Notably, energy poverty is a multidimensional problem that therefore requires a multidimensional analysis. Against this background, the European Union has recently introduced four primary indicators to capture the extent of the different aspects of energy poverty: arrears on utility bills, low absolute energy expenditures, high share of energy expenditure on income, inability to keep the house adequately warm. Due to the growing recognition of energy poverty in developed countries an increasing number of studies is carried out to understand the extent and roots of energy poverty. Most studies employ cross-sectional data and do not consider the dynamics of energy poverty. Static identification of the energy poor in a certain period provide an incomplete picture of energy poverty, leaving out the question whether these households are persistently or only temporarily experiencing difficulties reaching an adequate level of domestic energy services. Spending a high share of their disposable income on domestic energy services forces households to decide between reducing either energy expenditures or the spending on other essential goods and services such as food and education. These trade-offs create negative feedback loops that traps households in energy poverty and poverty in general (Lapsa et al., 2020). The above mentioned negative welfare effects are expected to be even more severe when energy poverty is experienced persistently. A proper distinction between different energy poverty duration states is also crucial for policy making, since policy measures might differ for transitory and chronic energy poverty. While short-term measures like energy vouchers can help to temporarily reduce energy poverty, long-term measures such as promoting energy efficient housing are needed to lift households permanently out of energy poverty. Furthermore, if energy poverty is mostly a transient state, chronic energy poor households will consume most of the resources devoted to prevent entries into energy poverty.

We contribute to current literature by investigating not only the determinants, but also the dynamics of energy poverty in Germany using longitudinal household survey data. More precisely, we first identify the characteristics that increase the probability of being energy poor by using a random-effects probit model. We show that households that are energy poor in one period are between 6 and 19 percent more likely to be energy poor in the subsequent period depending on the energy poverty indicator chosen. Second, we investigate if energy poverty is mostly a transient or chronic state by applying a spells approach. We find that the majority of energy poor households face energy poverty only temporarily. Third, we examine the driving factors of both transient and persistent energy poverty using a multinominal logistic regression. Our results suggest that chronic energy poverty can be mainly attributed to household composition, labour force status, energy efficiency and the heating system in place. We employ two different metrics to account for the many facets of energy poverty, one based on actual household expenditures and the other based on perceived energy poverty.

The paper is structured as follows. Section two reviews the related literature. Section three describes the data. Section four explains the empirical strategy. Section five shows the results. Section six concludes.

## 2 Related Literature

Starting with Boardman (1991), there is a well-established body of literature on the extent of energy poverty in the UK and Ireland (Boardman, 2010; Liddell et al., 2012; Moore, 2012). Recently there is a growing number of country-level studies examining the prevalence of energy poverty in other European countries (Meyer et al., 2018; Aristondo & Onaindia, 2018; Karpinska & Śmiech, 2020b) as well as comparative cross-country studies for the European Union (Thomson & Snell, 2013; Bouzarovski & Tirado Herrero, 2017; Recalde et al., 2019). Although the literature has mostly focused on Europe, there are also country-level studies for other developed non-European countries like Japan (Okushima, 2016, 2017) or the US (Teller-Elsberg et al., 2016; Bednar & Reames, 2020).

In the case of Germany, Frondel et al. (2015) use data from the German Residential Energy Consumption Survey to estimate that in 2012 households at poverty risk allocated 5.5% of their income to power. Heindl (2014) applies different definitions of energy poverty on German household data and obtains a great variety of results depending on the choice of poverty line. Neuhoff et al. (2013) study the distributional implications of the German energy transition using data from the German Income and Expenditure Survey from 1998 to 2010. They forecast that in 2013 households allocate 2.5% of their consumption expenditure to electricity. The effect is even more pronounced for income poor households.

However, significantly less studies focus on the household-level determinants and features of energy poor households. Empirical findings on socio-economic and socio-demographic factors as well as housing conditions that determine the probability of energy poverty are rather limited. Using self-reported data to calculate the extent of energy poverty in Ireland Healy & Clinch (2004) identify key social groups at risk of being energy poor. They conclude that the long-term ill and lone-parent families are among the most energy vulnerable households. More recently, Legendre & Ricci (2015) identify characteristics of French households that are pushed below the income poverty line after domestic energy expenses, showing that tenure type, employment status and roof insulation influence the probability of being fuel vulnerable. Mohr (2018) uses data from the 2009 US Residential Energy Consumption Survey to look for differences in predictors of energy poverty in colder states versus warmer states. Using Australian longitudinal household-level data Churchill & Smyth (2020) find a positive impact of ethnic diversity on household energy poverty. As far as we know the only other study that is concerned with factors influencing the likelihood of energy poverty in Germany is Heindl & Schuessler (2019), who employ a survey of 1,903 German households in 2015. They identify income, energy expenditure, employment status and housing conditions as important determinants of experiencing energy poverty in Germany.

Most studies on energy poverty are carried out in a static context using cross-sectional data, mainly due to a lack of suitable longitudinal micro-level data. Only few studies consider the dynamics of energy poverty in a developed country. Phimister et al. (2015) use longitudinal data to explore the dynamics of energy poverty and its interaction with income poverty in Spain. They show that there is a greater movement out of expenditure-based energy poverty relative to subjective energy poverty and income poverty. Chaton & Lacroix (2018) employ a mover-stayer model to show that energy poverty in France is mostly a transitory state. Karpinska & Śmiech (2020a) assess energy poverty persistence in Poland using panel data spanning from 2014 to 2017.

Apart from providing an update on the current extent of energy poverty in Germany, we contribute to the literature and the ongoing debate on energy poverty in several ways: First, research on the determinants on energy poverty in Germany is rather scarce. Second, making use of the longitudinal structure of the GSOEP, we provide first evidence on the dynamics and persistence of energy poverty in Germany. Third, employing consensual as well as expenditure-based metrics on energy poverty, we identify differences and similarities in the determinants and dynamics of perceived and measured energy poverty.

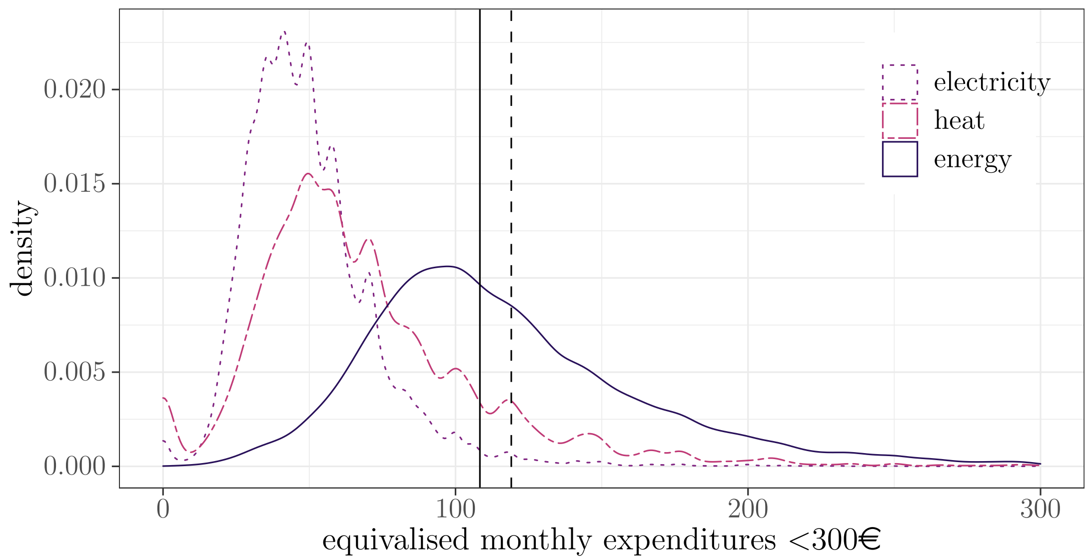
# 3 Data

The data used in this paper stem from the German Socio-Economic Panel (GSOEP), which is a nationally representative household panel study for Germany that started in 1984. The survey is conducted annually, with the latest available data being from 2018. Micro data from the GSOEP allow for an in-depth analysis of energy poverty in Germany. As opposed to many other household-level surveys, the GSOEP combines longitudinal information on income, consumption expenditures, housing conditions (including heating type) and household preferences. It also covers consensual energy poverty, as indicated by the household's ability to keep its home adequately warm, and allows computing expenditure-based energy poverty indicators for the same household. The main advantage of the GSOEP is that it allows us to analyse energy poverty dynamics. Studies on energy poverty in Europe mostly rely on two databases, the Household Budget Survey (HBS) and the EU Statistics on Income and Living Conditions (EU-SILC). While the EU-SILC includes information on income, poverty, social exclusion and housing conditions, the HBS is the only viable option to assess expenditure-based measures. Combining these two household surveys allows for a static identification of risk factors of subjective and objective energy poverty as well as energy poverty trends, however, the analysis of energy poverty dynamics is not possible[1].

We restrict our sample to the period covering 2016 and each year thereafter (i.e., waves 33 to 35) since a survey question on consensual energy poverty was only introduced in 2016 (wave 33). Only once in 2015 (wave 32) households were asked to state the type of energy they use for heat, hot water, and cooking, an information which is crucial for our analysis of energy poverty. Therefore, we exclude all households that were either not observed in 2015 or moved into a new dwelling after 2015. All in all, we obtain a balanced sample from 2016 to 2018 covering 9,032 households. Applying the above mentioned selection criteria, our sample size decreases significantly over time from 12,518 observations in 2016, to 10,475 households

[1]See Thomson et al. (2017) for a detailed discussion on the availability of data to assess energy poverty in the European Union.

Figure 1: (a) PDF of electricity, heating and energy expenditures (b) income profiles and average monthly expenditures on domestic energy services, pooled sample 2016-2018




*Note: Dashed horizontal line represents the mean value of the distribution, while the solid horizontal line represents the median value.*

| | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Average income (€) | 766.28 | 1083.18 | 1306.20 | 1484.92 | 1688.54 | 1900.93 | 2135.88 | 2452.79 | 2927.97 | 4543.67 |
| Electricity cost (€) | 46.43 | 48.14 | 48.05 | 47.97 | 48.83 | 49.56 | 50.52 | 50.73 | 52.58 | 59.70 |
| Heating cost (€) | 58.59 | 61.58 | 64.47 | 65.25 | 67.22 | 69.51 | 69.07 | 68.88 | 74.61 | 87.57 |
| Total energy cost (€) | 105.02 | 109.72 | 112.51 | 113.22 | 116.05 | 119.07 | 119.59 | 119.62 | 127.19 | 147.27 |
| Share of income spent on energy (%) | 13.71 | 10.13 | 8.61 | 7.62 | 6.87 | 6.26 | 5.60 | 4.87 | 4.34 | 3.24 |
| Energy Use Intensity (€/sqm) | 1.44 | 1.31 | 1.20 | 1.15 | 1.15 | 1.13 | 1.04 | 1.01 | 1.02 | 1.03 |

in 2017 and 9,032 households in 2018. Panel attrition might bias our estimates if the attrition is systematically related to the outcome being investigated and therefore non-random. In the case of the GSOEP, determinants of panel attrition are well documented for each survey wave[2]. Results of logit models for the probability of re-interviewing a household suggest that panel attrition was mostly related to interview characteristics, while socio-economic and socio-demographic characteristics only play a secondary role in explaining a households refusal to participate in the survey.

In our data, households separately provide information on heating and electricity costs depending on the tenure status. While tenants provide current average monthly costs, owners state their yearly expenditures on the respective domestic energy service. Yearly costs are divided by twelve to get an approximation of current average monthly expenditures of

[2]e.g. Siegers et al. (2020) for wave 35

owner-occupied dwellings. We define average monthly energy expenditures as the total sum of average monthly spending on electricity and heating. We deflate disposable household income and energy expenditures using the OECD square root scale which divides household income and consumption expenditures by the square root of household size (oecd, 2013)[3]. Due to economies of scale in consumption the needs of a household grow disproportionately with each additional member. Accounting for differences in household size and composition by adjusting household income and consumption expenditures according to an equivalence scale is standard procedure in the literature. Panel (a) of Figure 1 shows the distribution of monthly equivalised expenditures on electricity, heating, and energy services in the period from 2016 to 2018. Based on our pooled sample of 27,096 observations, the median equivalised total expenditure on energy services is 108.3 Euro, while the mean equals 118.9 Euro. For the calculation of expenditure-based poverty indicators we compute median and mean values for equivalised energy expenditures and income in every given year.

Panel (b) of Figure 1 shows income profiles and average monthly expenditures on domestic energy services in each decile. Average monthly energy expenditures are the highest in the tenth income decile. However, Energy Use Intensity (i.e. energy use per sqm) is the lowest, which indicates energy inefficiencies in lower income deciles. While absolute energy expenditures increase with income, the share of income spent on energy decreases. Low income households spend substantially more of their income than higher income households. On average, households in the lowest income decile spend 13.71 % of their disposable income on domestic energy services, while the share of energy expenditure relative to disposable income is on average 3.24% in the highest decile.

[3]The weights obtained using the square root scale are close to the weights of the OECD-modified equivalence scale. Using the square root equivalence scale we do not differentiate between the needs of adult household members and children. However, compared to the OECD-modified equivalence scale we give less weight to each additional household member, an assumption which we find more plausible with regard to domestic energy services like space heating and cooking

## 3.1 Measuring Energy Poverty

A significant share of the literature on energy poverty focuses on the conceptual identification and the development of suitable statistical indicators (Hills, 2012; Heindl & Schüssler, 2015; Castaño-Rosa et al., 2019; Herrero, 2017). As laid out by Thomson et al. (2017) three general methods to measure energy poverty can be found in the literature, i) the expenditure-based approach, which determines energy poverty on the basis of household's actual energy expenditure, often relative to income, ii) the consensual-based approach, which is based on self-reported inability to secure a certain level of domestic energy services and iii) the direct approach, which attempts to measure if actual energy consumption is sufficient to achieve an adequate standard of living. While the former two methods are rather easy to implement, the latter faces significant practical obstacles due to unavailability of data. Although the expenditure-based approach alone is already a suitable metric for energy poverty it has some significant limitations. It does not compromise the actual energy needs of households and might therefore omit households that underconsume energy due to financial constraints. Therefore, consensual measures are a useful addition to the expenditure-based metrics to identify households that are self-rationing their energy use. In addition, they allow us to capture wider elements of energy poverty, such as social exclusion and material deprivation (Bradshaw, 2000).

In Germany currently no commonly agreed definition of energy poverty exists. Hence, an official measure of energy poverty has not been defined. However, on the European level the Energy Poverty Observatory (EPOV) suggests four primary indicators to capture the extent of energy poverty, which we partly employ in our analysis (Thema et al., 2020). We use an expenditure-based energy poverty measure that is based on monthly household expenditures on domestic energy services relative to household income, with a household considered energy poor if the share of income spent on energy is greater than twice the national median [4]. The

[4] As shown in Panel (a) of Figure 1, equivalised monthly energy expenditures follow a right skewed distribution, which makes the use of the median value for calculating expenditure-based energy poverty indicators preferable to the mean value. Due to the positively skewed distribution, mean energy expenditures

Table 1: Income profiles and energy poverty rates according to different indicators, 2016-2018

| | Expenditure-based | | | | Consensual | | | |
|---|---|---|---|---|---|---|---|---|
| | 2016 | 2017 | 2018 | 2016-2018 | 2016 | 2017 | 2018 | 2016-2018 |
| D1 | 47.29 | 56.04 | 60.00 | 53.34 | 7.16 | 5.70 | 8.50 | 7.04 |
| D2 | 18.09 | 22.38 | 25.69 | 22.78 | 3.27 | 4.50 | 4.47 | 4.25 |
| D3 | 13.87 | 14.62 | 14.36 | 13.89 | 2.71 | 2.66 | 3.12 | 2.59 |
| D4 | 8.64 | 8.37 | 7.85 | 8.11 | 1.11 | 1.10 | 2.05 | 1.44 |
| D5 | 4.23 | 5.85 | 4.37 | 4.70 | 1.09 | 1.01 | 0.96 | 0.88 |
| D6 | 3.07 | 3.93 | 3.35 | 3.90 | 0.53 | 0.76 | 0.71 | 0.89 |
| D7 | 2.65 | 1.46 | 1.50 | 1.72 | 0.52 | 0.73 | 0.64 | 0.86 |
| D8 | 1.48 | 0.81 | 1.42 | 1.20 | 0.49 | 0.58 | 0.44 | 0.54 |
| D9 | 0.95 | 0.66 | 0.21 | 0.52 | 0.47 | 0.33 | 0.62 | 0.44 |
| D10 | 0.24 | 0.22 | 0.50 | 0.33 | 0.49 | 0.45 | 0.10 | 0.33 |
| All | 11.00 | 11.50 | 10.98 | 11.16 | 2.01 | 1.79 | 2.02 | 1.94 |

median share of energy expenditures in income is relatively constant over our sample period with 6.3 percent in 2016, 6.2 percent in 2017 and 6 percent in 2018. In addition to that we employ a subjective indicator of energy poverty, that labels households as energy poor if they self-report difficulties keeping their home comfortably warm in the colder months [5]. In contrast to the expenditure-based metric outlined above, the consensual indicator implies a very narrow definition of residential energy uses and does not consider all end-uses of energy but only warmth.

Table 1 shows the evolution of energy poverty rates per income decile according to the expenditure-based and consensual approach from 2016 to 2018. Even though the energy burden is higher in low income deciles, total energy poverty is not exclusively borne by low income households. While it suggests that income plays an important role in energy poverty it also indicates that energy poverty is distinct from income poverty. Over the course of our relatively short observation period, energy poverty rates remain fairly stable with on average 11.16 percent of households living in energy poverty according to the expenditure-based indicator and 1.94 percent according to the consensual indicator. Total energy poverty rates did not change significantly from 2016 to 2018, however, energy poverty rates in the lowest income decile increased from 47.29 percent (7.16 percent) in 2016 to 60 percent (8.5 percent)

are affected by high values in the distribution tail.

[5] Some households report that they do not heat their dwelling during colder months due to non-financial reasons. We do not consider these households as being energy poor.

Table 2: Summary statistics, pooled sample 2016-2018

| | Description | Frequency |
|---|---|---|
| *(a) Socio-demographic* | | |
| Household type | Couple without children | 0.312 |
| | Single parent | 0.099 |
| | One-person household | 0.235 |
| | Couple with children | 0.337 |
| | Other | 0.016 |
| Migration Background* | =1 if direct migration background | 0.156 |
| Region | =1 if household is located in rural area | 0.345 |
| *(b) Socio-economic* | | |
| Education* | No degree | 0.097 |
| | Lower secondary degree | 0.069 |
| | Upper secondary degree | 0.546 |
| | Tertiary degree | 0.289 |
| Labor Force Status | (Self-)Employed | 0.608 |
| | Non-working | 0.094 |
| | Retired | 0.298 |
| Owner | =1 if housing is owner-occupied | 0.506 |
| *(c) Housing conditions* | | |
| Thermal Insulation | =1 if housing is thermally insulated | 0.629 |
| Construction Year | Built before 1949 | 0.315 |
| | Built between 1949 and 1979 | 0.301 |
| | Built after 1979 | 0.383 |
| Housing Type | Detached | 0.359 |
| | Semi-detached | 0.172 |
| | Apartment building | 0.469 |
| Heating Type | Gas | 0.470 |
| | Oil | 0.241 |
| | Electricity (i.e. night storage) | 0.045 |
| | District Heating | 0.162 |
| | Other (i.e. heat pump, biomass, liquid gas, coal) | 0.079 |
| *(d) Environmental behaviour* | | |
| Renewable Energy | =1 if housing has additional renewable energy source | 0.137 |
| Climate change concerns | =1 if household is seriously concerned about climate change | 0.337 |

*of household head

in 2018. Only 6.4 percent of households that are energy poor under the expenditure-based measure report an inability to keep their home warm during colder months. Conversely, 21.2 percent that report difficulties in heating their dwelling spent twice the median share of their income on domestic energy services. The small overlap between both metrics in our sample suggests that both indicators indeed cover different aspects of energy poverty in Germany.

## 3.2 Variables

Descriptions and descriptive statistics for the explanatory variables used in this paper are presented in Table 2. We select our covariates based on the existent literature on energy poverty and residential energy consumption.

First, we add socio-demographic and socio-economic characteristics that potentially influence the chances of experiencing energy poverty in Germany, such as household composition, ethnicity, educational qualification, labor force status and the type of area the household resides in. We do not include gender in our analysis due to the structure of the data we use. The expenditure-based energy poverty metric is based on household income, therefore neglecting the distribution of income within a household. Thus, energy poverty among women can only be clearly visible for single parents and women living alone. The gender effect would be therefore significantly downward biased and mostly captured by the household composition. In our sample 86.2 percent of single parent households and 61.4 percent of one-person households are female headed.

Empirical evidence suggests that race and ethnicity positively impact household energy demand, which makes these households more vulnerable to energy poverty (Bednar et al., 2017; Belaïd, 2016). Therefore we add a dummy indicating if the household head has a direct migration background. Educational level and labor force status are included as a proxy for household income and social status. Apart from income potential, educational attainment might also impact the probability of adopting energy-saving behaviour (Chaton & Lacroix, 2018). Since retired or unemployed persons are likely to spend more time at home than the (self-)employed we expect labor force status to not only influence household income but also domestic energy needs. Following the literature (Healy & Clinch, 2004; Boardman, 2010; Legendre & Ricci, 2015) we also include a dummy that equals unity if the dwelling is owner occupied. There are different channels how renting an apartment impacts residential energy demand and therefore energy poverty, including differences in bill payment responsibilities and behavioural differences between renters and owners (Best et al., 2020). Also, due to split incentives and asymmetric information landlords might underinvest in energy efficiency measures which negatively affects renters' energy costs (Melvin, 2018).

Second, we introduce variables relating to housing conditions such as the construction year of the building, housing type and whether the dwelling has thermal insulation or not. We form three groups indicating the construction period of the building. Regulations that aimed at improving energy efficiency of buildings and heating systems were first introduced in 1976, which is why we expect chances of experiencing energy poverty to be lower for households that live in buildings built after the laws came into force. We also include dummy variables indicating if the dwelling has thermal insulation. In our pooled sample 62.5 percent of the properties are thermally insulated. One of the main independent variable of interest is a factor variable indicating the primary energy source used for heating. As noted by Legendre & Ricci (2015) the heating system equipment is one of the key factors in explaining energy vulnerability. Operational energy cost per kWh vary drastically across heating systems usually depending on the input price of the energy source and its efficiency in converting the energy input into heating capacity. For example, while the efficiency of electric heating is near to 100 per cent (all the electrical energy does get converted to heat) the input price of electricity is rather high compared to other energy sources. Nearly half of all households in our sample use gas (49.5 percent) as their primary energy source for heating, followed by oil (24.2 percent) and district heating (16.3 percent). The distributions of housing characteristics in our pooled sample are comparable to the ones reported by other representative studies for Germany (Loga et al., 2015; BDEW, 2019).

Third, we include variables that allow to analyse the impact of pro-environmental behaviour and preferences on the chances of experiencing energy poverty. To proxy for pro-environmental preferences we add a dummy that is equal to unity if the household head reports that he or she is seriously concerned about climate change. DellaValle (2019) argues that households might engage in inefficient energy consumption behavior that increases their risk of experiencing energy poverty, because they are being disengaged with climate change mitigation. Longhi (2015) and Belaid & Garcia (2016) show that environmentally friendly behaviour and attitudes are positively correlated with lower per capita energy expenditures. Households that use additional renewable energy technologies have on average lower energy expenditures. Therefore we include a dummy variable that indicates if a household produces additional electricity using renewable energy technologies (i.e. solar panels).

Lastly, we include state fixed effects to control for differences in grid usage charges across federal states as well as wave fixed effects to control for unobserved wave-specific characteristics.

# 4 Empirical Strategy

First, we apply a dynamic random effects probit model to identify the determinants of fuel poverty. Second, we distinguish between energy poverty duration states based on a spells approach in order to understand energy poverty dynamics. We then investigate the driving factors of being chronic and transient energy poor.

## 4.1 Dynamic Random Effects Probit Estimator

To identify the driving factors and the persistence of energy poverty, we employ a dynamic panel data model with random effects, which is commonly used in research related to state dependencies in income poverty or unemployment (Biewen, 2009; Stewart, 2007). Only recently Alem & Demeke (2020) employed a dynamic random effects probit model to estimate energy poverty persistence in Ethiopia. The dependent variable of interest $y_{it}$ represents a binary response of household $i$ at time $t$. Note however, that we have multiple non-exclusive binary responses depending on the indicator chosen. The latent index form of our model can be summarised as follows:

$$y_{it} = \mathbf{1}[y^*_{it} > 0] \tag{1}$$

$$y^*_{it} = \gamma y_{it-1} + x'_{it}\beta + u_i + \epsilon_{it}, \qquad i = 1, ..., N; t = 1, ..., T \tag{2}$$

where $y^*_{it}$ is the latent dependent variable and the error term $\epsilon_{it}$ follows a normal distribution. We include the lagged dependent variable $y_{it-1}$, which denotes household $i$'s energy poverty status at time $t-1$. Therefore, the coefficient $\gamma$ captures state dependence in energy poverty. Static panel models for energy poverty impose the restriction that $\gamma = 0$, a restriction we assume to be unrealistic given evidence in our raw data. We therefore assume that households that are energy poor in any period are more likely to experience energy poverty in the subsequent period. $x'_{it}$ is a vector of covariates including information on socio-economic and socio-demographic factors as well as housing conditions and environmental behaviour. Instead of estimating a pooled probit model, we allow for cross-correlation between the composite error term in different periods for the same households by including $u_i$. If we take the initial state of our dependent variable $y_{i0}$ as exogenous we will obtain inconsistent estimators because it is likely to be correlated with $u_i$ and the subsequent outcomes $y_{it}$, particularly if T is small. As suggested by Wooldridge (2005, 2010) the individual specific term $u_i$ can be modelled as

$$u_i = \alpha_0 + \alpha_1 y_{i0} + \bar{x}'_i \alpha_2 + v_i, \qquad v_i \sim N(0, \sigma^2), \tag{3}$$

where we include the within-means of our strictly exogenous covariates based on all periods, $\bar{x}'_i = T^{-1} \sum_{t=1}^{T} x'_{it}$. Then the response probability for $y_{it}$ is given by

$$Pr(y_{it} = 1 \mid x'_i, u_i, y_{i0}, y_{i1}, ..., y_{it-1}) = \Phi(\gamma y_{it-1} + x'_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \bar{x}'_i \alpha_2 + v_i), \tag{4}$$

where $\Phi(.)$ denotes the normal cumulative distribution function. The latent index model can be easily derived by substituting eq. (3) in eq. (2), which leads to:

$$y^*_{it} = \gamma y_{it-1} + x'_{it}\beta + \alpha_0 + \alpha_1 y_{i0} + \bar{x}'_i \alpha_2 + v_i + \epsilon_{it}, \tag{5}$$

where the coefficient $\gamma$ represents true state dependence of energy poverty of households. By estimating independent dynamic random effects probit models, we explicitly allow the coefficient to vary across the different indicators. It allows us to identify the determinants of energy poverty separately for each indicator and enables us to draw a more detailed picture of the energy poor households. If we would estimate the model considering a household to be energy poor regardless of the indicator chosen we would have to assume that the variables influencing the perception of energy poverty are similarly affecting the probability of having a high share of energy costs.

## 4.2 Indicator Function and Multinomial Logit

In a second step, we follow the literature on income poverty dynamics and distinguish between chronic and transient energy poverty based on the count of periods that households spend in energy poverty (Baulch & Hoddinott, 2000; Finnie & Sweetman, 2003; Biewen, 2006; Foster, 2009; Foster & Santos, 2013). For the identification of energy poverty duration states we employ an identification function $\psi_\tau(y_i; z)$ which determines if household $i$ with measure $y$ (i.e. share of energy expenditures in income) is chronic, transient or never energy poor given poverty line $z$. We define a duration line $\tau \in (0, 1]$, which represents the threshold for chronic energy poverty. Let $d_i$ be the fraction of periods $t$ where $y_{it} < z$ relative to all periods T. Then

$$\psi_\tau(y_i; z) = \begin{cases} 2, & \text{if } d_i \geq \tau, \\ 1, & \text{if } 0 < d_i < \tau, \\ 0, & \text{if } d_i = 0. \end{cases} \tag{6}$$

We set $\tau = 1$, so that household $i$ is considered to be chronically energy poor ($\psi_\tau(y_i; z) = 2$) only if $y_{it} < z$ for all $t$. Transient energy poor households ($\psi_\tau(y_i; z) = 1$) spend at least one but not all periods in energy poverty. Therefore, households are identified as never energy poor ($\psi_\tau(y_i; z) = 0$) if $y_{it} > z$ for all $t$. Despite its simplicity there is a serious shortcoming to the counting approach, since it does not consider the depth of energy poverty. Small movements of households around the energy poverty line or even fluctuations of the energy poverty line itself might lead to spurious entries and exits into energy poverty. We employ a simple discrete choice model to explore the differences between transient and chronic energy poor households. The response probability of our multinomial logit model is given by

$$Pr(y_{ij} = \psi \mid x_i') = \frac{e^{x_i'\beta_\psi}}{1 + \sum_{k=1}^{2} e^{x_i'\beta_\psi}}, \qquad \psi = 0, 1, 2, \tag{7}$$

where never energy poor ($\psi = 0$) is used as the base category. $x_{it}'$ is the same vector of covariates employed in the previous section.

# 5 Results

## 5.1 Energy Poverty Persistence

Average partial effects of our dynamic random effects probit models based on different energy poverty metrics are shown in Table 3. Columns 1 and 3 display the results if we estimate the models given by equation (2), i.e. taking the initial condition $y_{i0}$ as exogenous. Columns 2 and 4 employ the conditional maximum likelihood estimator given by equation (5), i.e. specifying a distribution of heterogeneity conditional on the energy poverty status of a household at the beginning of our panel. Due to the above mentioned initial conditions problem, we refer to the latter estimation model in the following interpretation.

Even though the overlap between the expenditure-based energy poverty and consensual energy poverty is rather small, our results suggest that the driving factors only differ in size and significance. While many of our covariates significantly impact expenditure-based energy poverty, fewer factors significantly influence subjective energy poverty. More importantly, the size of the effects are much stronger for the expenditure-based metric. This can be mostly attributed to higher prevalence of expenditure-based energy poverty in Germany.

We find evidence on state dependencies in energy poverty. Facing energy poverty in one period significantly raises the probability of being energy poor in the subsequent period. Without controlling for the initial condition our results indicate that the chance of being expenditure-based energy poor increases by 37.3 percent and of being consensual energy

Table 3: Regression Results: Dynamic Random Effects Probit

| | Expenditure-based | | Consensual | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Expenditure-based$_{t-1}$ | 0.373$^{***}$ | 0.198$^{***}$ | | |
| | (0.013) | (0.015) | | |
| Expenditure-based$_{t=0}$ | | 0.131$^{***}$ | | |
| | | (0.013) | | |
| Consensual$_{t-1}$ | | | 0.210$^{***}$ | 0.065$^{***}$ |
| | | | (0.023) | (0.016) |
| Consensual$_{t=0}$ | | | | 0.071$^{***}$ |
| | | | | (0.017) |
| Household type | | | | |
| *Couple without children* | Ref. | Ref. | Ref. | Ref |
| *Single parent* | 0.070$^{***}$ | 0.072$^{***}$ | 0.012$^{***}$ | 0.010$^{***}$ |
| | (0.010) | (0.010) | (0.004) | (0.004) |
| *One person hou*$_{\_--sehold}$ *0.067*$^{***}$ | 0.064$^{***}$ | 0.005$^{**}$ | 0.004$^{**}$ | |
| | (0.007) | (0.007) | (0.002) | (0.002) |
| *Couple with children* | −0.020$^{***}$ | −0.018$^{***}$ | −0.001 | −0.001 |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| *Other* | 0.011 | 0.012 | −0.001 | −0.001 |
| | (0.015) | (0.015) | (0.005) | (0.005) |
| Migration background | 0.031$^{***}$ | 0.028$^{***}$ | 0.001 | 0.001 |
| | (0.008) | (0.008) | (0.002) | (0.002) |
| Region | 0.013$^{***}$ | 0.015$^{***}$ | 0.003 | 0.004$^{*}$ |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| Education | | | | |
| *No degree* | 0.020$^{**}$ | 0.018$^{**}$ | −0.001 | −0.002 |
| | (0.008) | (0.008) | (0.002) | (0.002) |
| *Lower secondary degree* | 0.016$^{**}$ | 0.013$^{*}$ | −0.003$^{*}$ | −0.003$^{*}$ |
| | (0.007) | (0.007) | (0.002) | (0.002) |
| *Upper secondary degree* | Ref. | Ref. | Ref. | Ref |
| *Tertiary degree* | −0.032$^{***}$ | −0.030$^{***}$ | −0.001 | −0.001 |
| | (0.004) | (0.004) | (0.002) | (0.002) |
| Labour Force Status | | | | |
| *(Self-)Employed* | Ref. | Ref. | Ref. | Ref |
| *Non-working* | 0.101$^{***}$ | 0.095$^{***}$ | 0.011$^{***}$ | 0.010$^{***}$ |
| | (0.011) | (0.010) | (0.003) | (0.003) |
| *Retired* | 0.045$^{***}$ | 0.043$^{***}$ | −0.002 | −0.002 |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| Owner | −0.008 | −0.007 | −0.010$^{***}$ | −0.010$^{***}$ |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| Thermal insulation | −0.023$^{***}$ | −0.021$^{***}$ | −0.006$^{***}$ | −0.006$^{***}$ |
| | (0.004) | (0.004) | (0.002) | (0.002) |
| Construction Year | | | | |
| *Built before 1949* | Ref. | Ref. | Ref. | Ref |
| *Built between 1949 and 1979* | −0.009$^{**}$ | −0.007 | 0.001 | 0.001 |
| | (0.004) | (0.004) | (0.002) | (0.002) |
| *Built after 1979* | −0.017$^{***}$ | −0.016$^{***}$ | −0.001 | −0.001 |
| | (0.004) | (0.004) | (0.002) | (0.002) |
| Housing Type | | | | |
| *Detached* | Ref. | Ref. | Ref. | Ref |
| *Semi-detached* | −0.016$^{***}$ | −0.015$^{***}$ | −0.003 | −0.003 |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| *Apartment building* | −0.035$^{***}$ | −0.033$^{***}$ | −0.002 | −0.002 |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| Heating Type | | | | |
| *Gas* | Ref. | Ref. | Ref. | Ref |
| *Oil* | 0.020$^{***}$ | 0.019$^{***}$ | 0.006$^{***}$ | 0.006$^{***}$ |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| *Electricity* | 0.048$^{***}$ | 0.042$^{***}$ | 0.011$^{**}$ | 0.010$^{**}$ |
| | (0.012) | (0.011) | (0.005) | (0.005) |
| *District heating* | 0.009 | 0.009 | 0.004$^{*}$ | 0.004 |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| *Other* | 0.006 | 0.006 | 0.002 | 0.002 |
| | (0.008) | (0.008) | (0.003) | (0.003) |
| Environmental Behaviour | | | | |
| *Renewable energy* | −0.015$^{***}$ | −0.014$^{**}$ | −0.003 | −0.002 |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| *Climate change concerns* | −0.005 | −0.004 | 0.001 | 0.001 |
| | (0.004) | (0.004) | (0.001) | (0.001) |
| State fixed effects | Yes | Yes | Yes | Yes |
| Wave fixed effects | Yes | Yes | Yes | Yes |
| Number of obs. | 18064 | 18064 | 18064 | 18064 |

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, standard errors in parentheses.

poor by 21 percent if the household was energy poor in the previous period. These estimates of persistence are likely to be upward biased. If we correct for a household's energy poverty state at the beginning of our sample period, the coefficients of interest decrease significantly and the coefficient for initial poverty status is highly significant. The results suggest that being energy poor in the previous period increases the probability of facing energy poverty in the subsequent period by 19.9 percent under the expenditure-based metric and by 6.5 percent under the consensual indicator.

The household composition seems to be a driving factor of energy poverty independent of the indicator chosen. Being a single parent or living alone significantly increases the chances of facing energy poverty. In general living with a partner lowers the risk of falling into energy poverty due to higher household income possibilities, cost sharing and economies of scale in domestic energy services. Our regression results support our assumption that migration background positively impacts the probability of expenditure-based energy poverty. However, it does not affect consensual energy poverty.

Households living in rural areas have a higher probability of experiencing energy poverty, since they experience higher energy costs than households living in urban areas. The rural-urban price differential in energy costs can be mainly attributed to differences in grid access fees which are substantially higher in rural areas, because fewer households have to bear the costs for the infrastructure (Roberts et al., 2015). In the case of electricity network fees households also have to bear the costs of the expansion of renewable energy sources, since they are mostly built in rural areas.

Owning the property significantly reduces the likelihood of being unable to keep the home adequately warm. However, the coefficient is not significant in the case of expenditure-based energy poverty. We assume that most of the effect was captured by our covariates relating to housing conditions. Educational attainment influences expenditure-based energy poverty. As expected, the likelihood of being energy poor is decreasing with higher levels of education. In contrast, we do not find strong evidence that educational levels impact self-reported energy poverty. The labour force status plays a key role in explaining energy poverty. If the household head is non-working the probability of being affected by energy poverty increases by 9.5 percent according to the expenditure-based metric and by 1 percent according to the consensual metric. While retirees are significantly more likely to suffer from expenditure-based energy poverty, being retired has no impact on self-reported energy poverty.

We do not find evidence that moral disengagement with climate change increases the probability of facing energy poverty. The coefficient is slightly negative for expenditure-based energy poverty, however, it is not statistically significant.

### 5.2 Chronic versus Transient Energy Poverty: Distribution and Determinants

Applying the identification function, we now distinguish between three energy poverty duration states: never, transient and chronic energy poor. Table 4 reports the distribution of energy poverty duration states under the expenditure-based and consensual metrics. Based on the expenditure-based measure 1305 households in our sample (14.4 percent) face energy poverty at least once and 418 households (4.6 percent) experience energy poverty in all three periods. Based on the consensual metric 345 households in our sample (3.8 percent) are classified as transient energy poor and only 38 households (0.4 percent) are labeled as chronic energy poor. Even though we find evidence of energy poverty persistence, the majority of households are only temporarily energy poor.

Table 5 shows the composition of energy poverty states under different indicators by

Table 4: Distribution of energy poverty duration states under different indicators

| | Expenditure-based | | Consensual | |
|---|---|---|---|---|
| Energy poverty duration state | Share of households | Number of households | Share of households | Number of households |
| Never | 0.809 | 7,309 | 0.958 | 8,649 |
| Transient | 0.144 | 1,305 | 0.038 | 345 |
| Chronic | 0.046 | 418 | 0.004 | 38 |
| Total | 1 | 9032 | 1 | 9032 |

Table 5: Distribution of energy poverty duration states under different indicators by family type in 2016

| | Expenditure-based | | | Consensual | | | All |
|---|---|---|---|---|---|---|---|
| | Never | Transient | Chronic | Never | Transient | Chronic | |
| Couple without children | 0.326 | 0.264 | 0.234 | 0.319 | 0.178 | 0.105 | 0.313 |
| Single parent | 0.085 | 0.169 | 0.127 | 0.093 | 0.212 | 0.395 | 0.099 |
| One person household | 0.192 | 0.335 | 0.502 | 0.223 | 0.336 | 0.316 | 0.227 |
| Couple with children | 0.381 | 0.201 | 0.122 | 0.347 | 0.258 | 0.184 | 0.343 |
| Other | 0.016 | 0.031 | 0.014 | 0.018 | 0.014 | 0.000 | 0.018 |

family type in 2016. Whereas single parents make up 8.5 percent of the never expenditure-based energy poor sample population, they comprise 16.9 percent of the transient poor group and 12.7 percent of the chronic energy poor households. This pattern is even more striking when looking at subjective energy poverty, where 21.2 percent of the transient and 39.5 percent of the chronic energy poor households are identified as single parents. One-person households are significantly overrepresented in the group of the consistently expenditure-based energy poor where they make up 50.1 percent of the population, while their sample population share equals 22.7 percent.

Table 6 shows the distribution of energy poverty duration states by heating type. Looking at expenditure-based energy poverty the share of households that use electricity as their main heating type is nearly twice as high for transient energy poor households and more than three times as high for chronic energy poor households compared to the never energy poor. According to the subjective indicator, 36.4 percent of the chronic energy poor households use district heating as their main heating system compared to 16.2 percent of the total sample population.

The results from the multinomial logistic regression presented in Table 7 confirm the implications derived from the distribution table. Certain socio-economic, socio-demographic and housing characteristics differently impact energy poverty duration states. In particular we identify one-person households to be more vulnerable to chronic expenditure-based energy poverty than to transient energy poverty (Table 6, column (1) and (2)). Results for consensual energy poverty imply that single parents are especially likely to be trapped in

Table 6: Distribution of energy poverty duration states under different indicators by heating type in 2016

| | Expenditure-based | | | Consensual | | | All |
|---|---|---|---|---|---|---|---|
| | Never | Transient | Chronic | Never | Transient | Chronic | |
| Gas | 0.486 | 0.407 | 0.390 | 0.477 | 0.322 | 0.342 | 0.470 |
| Oil | 0.232 | 0.282 | 0.289 | 0.242 | 0.243 | 0.184 | 0.241 |
| Electricity | 0.038 | 0.064 | 0.122 | 0.043 | 0.096 | 0.105 | 0.045 |
| District heating | 0.160 | 0.188 | 0.139 | 0.157 | 0.278 | 0.342 | 0.162 |
| Other | 0.084 | 0.060 | 0.060 | 0.081 | 0.061 | 0.026 | 0.079 |

energy poverty (Table 6, column (3) and (4)). However, for the case of consensual energy poverty, most of our results for chronic energy poverty are non-significant, which is probably due to the small number of observations that are classified as chronic energy poor under the consensual indicator (n=38)

Our results suggest that households with migration background are more likely to suffer from chronic expenditure-based energy poverty than from transient energy poverty. Our findings show that households that are located in rural areas are more likely to be trapped in expenditure-based energy poverty. We attribute this to the higher energy burden in less densely populated areas. As noted by Roberts et al. (2015) rural households also fail to properly adjust to increasing energy prices due to a lack of heating system choice which limits their chances of exiting energy poverty. Additionally rural housing stock is more likely to be energy inefficient which further increases the chances of rural households to face chronic energy poverty. However, most of this effect should already be captured by our covariates relating to housing conditions.

Educational attainment has a significant impact on expenditure-based energy poverty dynamics, whereas educational levels do not seem to significantly influence self-reported energy poverty dynamics. Labour force status is an important driver of energy poverty dynamics. Unemployment especially raises the probability of chronic energy poverty under both the expenditure-based and consensual metric. While retirees are in general at risk of energy poverty there is no large difference between their risk of being transient or chronic expenditure-based energy poor. In contrast, being retired does only have little influence on the risk of being transient energy poor under the consensual indicator. This result might be attributed to one of the main critiques of subjective energy poverty indicators. As noted by Thomson et al. (2017) households may not identify themselves as energy poor, because they do not want to admit that they live in energy poverty.

As in the case of our previous analysis thermal insulation plays an important role in energy poverty. Having proper thermal insulation reduces the likelihood of experiencing transient energy poverty, but it even stronger reduces the probability of facing energy poverty constantly under both, the expenditure-based and consensual-based indicator.

When looking at the primary heating source of the household, differences between chronic and transient energy poverty according to the expenditure-based metric become apparent. While using oil as main energy source similarly increases the chances of experiencing transient and chronic energy poor, using electricity as main heating source locks households in expenditure-based energy poverty. Furthermore, using district heating as the primary energy source increases the chances of temporarily being financially constrained due to high expenditures on domestic energy services.

Having an additional renewable energy source significantly decreases the risk of chronic expenditure-based energy poverty, but does not significantly influence transient energy poverty. Due to the low operational costs of an additional renewable energy source households might have lower monthly energy expenditures, which prevents them from constantly experiencing energy poverty. We again find no evidence that moral disengagement with climate change does significantly alter the chances of experiencing energy poverty. However we have to note that part of this effect might already be incorporated in variables related to educational attainment of the household head.

Table 7: Regression Results: Multinomial Logit

| | Expenditure-based | | Consensual | |
|---|---|---|---|---|
| | never vs. transient | never vs. chronic | never vs. transient | never vs. chronic |
| Household type | | | | |
| *Couple without children* | Ref. | Ref. | Ref. | Ref |
| *Single parent* | 0.982*** | 0.870*** | 0.907*** | 2.111*** |
| | (0.112) | (0.200) | (0.191) | (0.606) |
| *One person household* | 0.760*** | 1.467*** | 0.621*** | 1.000* |
| | (0.087) | (0.141) | (0.167) | (0.593) |
| *Couple with children* | −0.442*** | −1.023*** | 0.029 | 0.553 |
| | (0.101) | (0.198) | (0.180) | (0.664) |
| *Other* | 0.458** | −0.506 | −0.275 | |
| | (0.210) | (0.462) | (0.483) | |
| Migration background | 0.440*** | 0.687*** | 0.067 | −0.672 |
| | (0.112) | (0.197) | (0.184) | (0.690) |
| Region | 0.201** | 0.317** | −0.014 | 0.488 |
| | (0.087) | (0.146) | (0.153) | (0.479) |
| Education | | | | |
| *No degree* | 0.532*** | 0.412** | 0.365* | −0.804 |
| | (0.123) | (0.208) | (0.199) | (0.820) |
| *Lower secondary degree* | 0.540*** | 0.560*** | 0.109 | −1.012 |
| | (0.110) | (0.172) | (0.205) | (0.761) |
| *Upper secondary degree* | Ref. | Ref. | Ref. | Ref |
| *Tertiary degree* | −0.794*** | −1.049*** | −0.168 | 0.082 |
| | (0.093) | (0.172) | (0.154) | (0.419) |
| Labour Force Status | | | | |
| *(Self-)Employed* | Ref. | Ref. | Ref. | Ref |
| *Non-working* | 1.329*** | 2.248*** | 0.794*** | 1.102*** |
| | (0.097) | (0.157) | (0.145) | (0.405) |
| *Retired* | 0.769*** | 0.979*** | −0.265* | −0.032 |
| | (0.080) | (0.137) | (0.157) | (0.483) |
| Owner | −0.169* | 0.019 | −0.627*** | −2.302*** |
| | (0.088) | (0.145) | (0.166) | (0.665) |
| Thermal insulation | −0.350*** | −0.625*** | −0.609*** | −0.763** |
| | (0.068) | (0.114) | (0.120) | (0.356) |
| Construction Year | | | | |
| *Built before 1949* | Ref. | Ref. | Ref. | Ref |
| *Built between 1949 and 1979* | −0.149* | −0.549*** | −0.159 | 0.242 |
| | (0.081) | (0.135) | (0.141) | (0.423) |
| *Built after 1979* | −0.382*** | −0.682*** | −0.141 | 0.265 |
| | (0.083) | (0.141) | (0.143) | (0.437) |
| Housing Type | | | | |
| *Detached* | Ref. | Ref. | Ref. | Ref |
| *Semi-detached* | −0.404*** | −0.441*** | −0.211 | −1.922* |
| | (0.107) | (0.166) | (0.222) | (1.063) |
| *Apartment building* | −0.544*** | −1.263*** | 0.019 | −0.988** |
| | (0.098) | (0.167) | (0.178) | (0.462) |
| Heating Type | | | | |
| *Gas* | Ref. | Ref. | Ref. | Ref |
| *Oil* | 0.412*** | 0.502*** | 0.547*** | 0.132 |
| | (0.083) | (0.141) | (0.157) | (0.500) |
| *Electricity* | 0.704*** | 1.437*** | 1.128*** | 1.071* |
| | (0.145) | (0.197) | (0.215) | (0.599) |
| *District heating* | 0.184* | 0.209 | 0.502*** | 0.376 |
| | (0.103) | (0.190) | (0.164) | (0.478) |
| *Other* | 0.034 | 0.076 | 0.507** | −0.244 |
| | (0.142) | (0.241) | (0.255) | (1.071) |
| Environmental Behaviour | | | | |
| *Renewable energy* | −0.165 | −0.681*** | −0.630** | |
| | (0.119) | (0.241) | (0.292) | |
| *Climate change concerns* | −0.055 | −0.189 | −0.015 | −0.144 |
| | (0.070) | (0.122) | (0.123) | (0.372) |
| Intercept | −1.875*** | −3.265*** | −3.372*** | −4.097*** |
| | (0.171) | (0.298) | (0.314) | (0.828) |
| Number of obs. | 8897 | 8897 | 8897 | 8897 |

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$, standard errors in parentheses.

# 6 Conclusion and Policy Implications

The climate crisis has put energy affordability into political focus. Lessening the burden of energy transition for low income households has become an increasingly important policy objective in Europe. Therefore, understanding not only the determinants, but also the dynamics of energy poverty is imperative.

This paper contributes to the rather limited literature on energy poverty dynamics in a developed country. We employ two measures of energy poverty to address the multidimensional nature of energy poverty: the expenditure-based approach and the consensual approach. The overlap between the two metrics is rather small. However, when examining the determinants of energy poverty, the results of our dynamic random-effects probit model suggest that the driving factors only differ in size and significance. Especially, the household type, educational attainment, labor force status, thermal insulation and heating system have a strong impact on expenditure-based energy poverty. Moreover, being energy poor in one period significantly raises the likelihood of energy poverty in the subsequent period. Although there is evidence of state dependence, we find that energy poverty is mostly a transitory state when differing between chronic and transient energy poverty. Under the expenditure-based approach, almost 15 percent of households face energy poverty at least once, and around 4.6 households percent suffer from energy poverty in all three periods. With regard to the consensual metric, the share of households labeled as energy poor is much smaller. Importantly, certain socio-economic, socio-demographic and housing characteristics differently impact energy poverty duration states. Particularly, single parents, one person households and unemployed are at a higher risk of being trapped in energy poverty. Moreover, thermal insulation and the heating type can significantly impact the probability of chronic energy poverty.

Our results have important policy implications. Generally, alleviating transient and chronic energy poverty require different policy responses. Short-term measures like direct subsidies for energy costs might reduce entries into energy poverty. However, for reducing chronic energy poverty long-term measures such as improving energy performance of housing, installing thermal heat pumps or solar panels is the most appropriate response. However, renters usually do not have influence of such investments and landlords do not benefit from them. Alternative measures have to be discussed to overcome the split incentives between landlords and tenants.

Notably, there are some shortcomings of the paper. Since we only have three waves available, a sufficient analysis of energy poverty dynamics is rather limited. Short panel duration might prevent us from observing sufficient movements in and out of energy poverty. However, examining the poverty movements of households for a longer period of time is crucial for a better understanding of fuel poverty. In addition, we do not approach energy poverty in a gender-specific way, as we would get biased results due to the data and estimation method we use. Generally, research on energy poverty lacks a gender-sensitive analysis, although fuel poverty is not at all gender-neutral. In general, having richer longitudinal data on households energy need and usage will help to study energy poverty in more detail. In light of the growing policy interest in energy poverty in the EU, this analysis is to be conducted in other European countries using similar micro panel data. As well, comparative cross-country studies might be useful to study the impact of different national policies on energy poverty dynamics.

# References


Alem, Y., & Demeke, E. (2020). The persistence of energy poverty: A dynamic probit analysis. *Energy Economics*, 104789.

Aristondo, O., & Onaindia, E. (2018). Counting energy poverty in spain between 2004 and 2015. *Energy Policy*, *113*, 420–429.

Baulch, B., & Hoddinott, J. (2000). Economic mobility and poverty dynamics in developing countries. *The Journal of Development Studies*, *36*(6), 1–24.

BDEW. (2019). Wie heizt Deutschland? BDEW-Studie zum Heizungsmarkt. `https://www.bdew.de/media/documents/Pub_20191031_Wie-heizt-Deutschland-2019.pdf`.

Bednar, D. J., & Reames, T. G. (2020). Recognition of and response to energy poverty in the united states. *Nature Energy*, 1–8.

Bednar, D. J., Reames, T. G., & Keoleian, G. A. (2017). The intersection of energy and justice: Modeling the spatial, racial/ethnic and socioeconomic patterns of urban residential heating consumption and efficiency in detroit, michigan. *Energy and Buildings*, *143*, 25–34.

Belaïd, F. (2016). Understanding the spectrum of domestic energy consumption: Empirical evidence from france. *Energy Policy*, *92*, 220–233.

Belaid, F., & Garcia, T. (2016). Understanding the spectrum of residential energy-saving behaviours: French evidence using disaggregated data. *Energy Economics*, *57*, 204–214.

Best, R., Burke, P. J., & Nishitateno, S. (2020). Factors affecting renters' electricity use: More than split incentives. *The Energy Journal*, *42*(5).

Biewen, M. (2006). Who are the chronic poor? an econometric analysis of chronic poverty in germany. *Research on Economic Inequality*, *13*(1), 31–62.

Biewen, M. (2009). Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition. *Journal of Applied Econometrics*, *24*(7), 1095–1116.

Boardman, B. (1991). *Fuel poverty: from cold homes to affordable warmth.* Pinter Pub Limited.

Boardman, B. (2010). *Fixing fuel poverty: challenges and solutions. earthscan.* London.

Bouzarovski, S., & Tirado Herrero, S. (2017). The energy divide: Integrating energy transitions, regional inequalities and poverty trends in the european union. *European Urban and Regional Studies*, *24*(1), 69–86.

Bradshaw, J. (2000). Poverty and social exclusion in britain.

Castaño-Rosa, R., Solís-Guzmán, J., Rubio-Bellido, C., & Marrero, M. (2019). Towards a multiple-indicator approach to energy poverty in the european union: A review. *Energy and Buildings*, *193*, 36–48.

Chaton, C., & Lacroix, E. (2018). Does france have a fuel poverty trap? *Energy Policy*, *113*, 258–268.

Churchill, S. A., & Smyth, R. (2020). Ethnic diversity, energy poverty and the mediating role of trust: Evidence from household panel data for australia. *Energy Economics*, *86*, 104663.

DellaValle, N. (2019). People's decisions matter: understanding and addressing energy poverty with behavioral economics. *Energy and Buildings*, *204*, 109515.

Finnie, R., & Sweetman, A. (2003). Poverty dynamics: empirical evidence for canada. *Canadian Journal of Economics/Revue canadienne d'économique*, *36*(2), 291–325.

Foster, J. E. (2009). A class of chronic poverty measures. *Poverty dynamics: interdisciplinary perspectives*, 59–76.

Foster, J. E., & Santos, M. E. (2013). Measuring chronic poverty. *Poverty and Social Exclusion: New Methods of Analysis. Routledge*, 143–165.

Frondel, M., Sommer, S., & Vance, C. (2015). The burden of germany's energy transition: An empirical analysis of distributional effects. *Economic Analysis and Policy*, *45*, 89–99.

Healy, J. D., & Clinch, J. P. (2004). Quantifying the severity of fuel poverty, its relationship with poor housing and reasons for non-investment in energy-saving measures in ireland. *Energy Policy*, *32*(2), 207–220.

Heindl, P. (2014). *Measuring fuel poverty: General considerations and application to german household data* (Tech. Rep.). SOEPpapers on Multidisciplinary Panel Data Research.

Heindl, P., & Schuessler, R. (2019). A deprivation-based assessment of energy poverty: Conceptual problems and application to germany. *ZEW-Centre for European Economic Research Discussion Paper*(19-036).

Heindl, P., & Schüssler, R. (2015). Dynamic properties of energy affordability measures. *Energy Policy*, *86*, 123–132.

Herrero, S. T. (2017). Energy poverty indicators: A critical review of methods. *Indoor and Built Environment*, *26*(7), 1018–1031.

Hills, J. (2012). Getting the measure of fuel poverty: Final report of the fuel poverty review.

Karpinska, L., & Śmiech, S. (2020a). Breaking the cycle of energy poverty. will poland make it? *Energy Economics*, 105063.

Karpinska, L., & Śmiech, S. (2020b). Conceptualising housing costs: The hidden face of energy poverty in poland. *Energy Policy*, *147*, 111819.

Lapsa, M. V., Brown, M. A., Soni, A., & Southworth, K. (2020). *Low-income energy affordability: Conclusions from a literature review* (Tech. Rep.). Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States).

Legendre, B., & Ricci, O. (2015). Measuring fuel poverty in france: Which households are the most fuel vulnerable? *Energy Economics*, *49*, 620–628.

Liddell, C., Morris, C., McKenzie, S., & Rae, G. (2012). Measuring and monitoring fuel poverty in the uk: National and regional perspectives. *Energy policy*, *49*, 27–32.

Loga, T., Stein, B., Diefenbach, N., & Born, R. (2015). Deutsche wohngebäudetypologie: Beispielhafte maßnahmen zur verbesserung der energieeffizienz von typischen wohngebäuden. *Institut Wohnen und Umwelt GmbH (IWU): Darmstadt, Germany*, 18.

Longhi, S. (2015). Residential energy expenditures and the relevance of changes in household circumstances. *Energy Economics*, *49*, 440–450.

Melvin, J. (2018). The split incentives energy efficiency problem: Evidence of underinvestment by landlords. *Energy Policy*, *115*, 342–352.

Meyer, S., Laurence, H., Bart, D., Middlemiss, L., & Maréchal, K. (2018). Capturing the multifaceted nature of energy poverty: Lessons from belgium. *Energy research & social science*, *40*, 273–283.

Mohr, T. M. (2018). Fuel poverty in the us: evidence using the 2009 residential energy consumption survey. *Energy Economics*, *74*, 360–369.

Moore, R. (2012). Definitions of fuel poverty: Implications for policy. *Energy policy*, *49*, 19–26.

Neuhoff, K., Bach, S., Diekmann, J., Beznoska, M., & El-Laboudy, T. (2013). Distributional effects of energy transition: impacts of renewable electricity support in germany. *Economics of Energy & Environmental Policy*, *2*(1), 41–54.

oecd. (2013). *Oecd framework for statistics on the distribution of household income, consumption and wealth.* OECD Publishing Paris.

Okushima, S. (2016). Measuring energy poverty in japan, 2004–2013. *Energy policy*, *98*, 557–564.

Okushima, S. (2017). Gauging energy poverty: A multidimensional approach. *Energy*, *137*, 1159–1166.

Phimister, E., Vera-Toscano, E., & Roberts, D. (2015). The dynamics of energy poverty: evidence from spain. *Economics of Energy & Environmental Policy*, *4*(1), 153–166.

Recalde, M., Peralta, A., Oliveras, L., Tirado-Herrero, S., Borrell, C., Palència, L., … Marí-Dell'Olmo, M. (2019). Structural energy poverty vulnerability and excess winter mortality in the european union: Exploring the association between structural determinants and health. *Energy Policy*, *133*, 110869.

Roberts, D., Vera-Toscano, E., & Phimister, E. (2015). Fuel poverty in the uk: Is there a difference between rural and urban areas? *Energy policy*, *87*, 216–223.

Siegers, R., Belcheva, V., & Silbermann, T. (2020). *Soep-core v35: Documentation of sample sizes and panel attrition in the german socio-economic panel (soep)(1984 until 2018)* (Tech. Rep.). SOEP Survey Papers.

Stewart, M. B. (2007). The interrelated dynamics of unemployment and low-wage employment. *Journal of applied econometrics*, *22*(3), 511–531.

Teller-Elsberg, J., Sovacool, B., Smith, T., & Laine, E. (2016). Fuel poverty, excess winter deaths, and energy costs in vermont: Burdensome for whom? *Energy Policy*, *90*, 81–91.

Thema, J., Vondung, F., Thomson, H., Bouzarovski, S., Thema, J., & Vondung, F. (2020). *Epov indicator dashboard: Methodology guidebook* (Tech. Rep.). Wuppertal Institut für Klima, Umwelt, Energie GmbH.

Thomson, H., Bouzarovski, S., & Snell, C. (2017). Rethinking the measurement of energy poverty in europe: A critical analysis of indicators and data. *Indoor and Built Environment*, *26*(7), 879–901.

Thomson, H., & Snell, C. (2013). Quantifying the prevalence of fuel poverty across the european union. *Energy Policy*, *52*, 563–572.

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of applied econometrics*, *20*(1), 39–54.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.