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Simutation of fuel poverty in France

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The assessment of fuel poverty in mainland France is based mainly on data provided by the French national housing survey (ENL). However, the last two surveys date from 2006 and 2014. To understand the change in the number of fuel poverty households, we have developed a micro simulation tool that takes into account the three predominant factors in the notion of fuel poverty, that is, household resources, energy prices and dwelling quality. Our tool includes three multiple linear models for estimating the following: 1. disposable income; 2. energy expenditure; and 3. the probability of performing a thermal renovation. We test our model with real values for variation in energy prices and variation in disposable income and a realistic number of housing renovations. The model is calibrated to the two last ENLs, matches the data very well and closely reproduces the number in fuel poverty in the 2012/2014 period. We not only evaluate fuel poverty in France in 2018 but also study the effects of variations in the unemployment rate, energy prices and number of thermal renovations.

Key words: Fuel poverty, Simulation
JEL codes: I3, Q4

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1. Introduction

In French legislation, a 12 July 2010 law (named Grenelle II) defines fuel poverty as follows: "*a household that has difficulties obtaining the necessary energy to satisfy its basic needs due to the inadequacy of its resources or its living conditions is in fuel poverty under this Act*". In other words, a household is fuel poor (FP) when it does not have enough resources to satisfy its basic energy needs, such as a proper temperature inside, or because of bad living conditions (such as bad insulation against humidity/cold). This definition is quite restrictive because it only mentions housing costs and does not include transportation costs. We also focus on housing-related fuel poverty that does not include the cost of mobility. Some households accumulate difficulties and have dwellings with both very bad energy performance (we literally call them "energy strainers" in French) and low revenue.

Numerous indicators are used to identify the fuel-poor households (see Rademaekers et al., 2016). Four indicators are used by the ONPE[1] (2016) for its studies and in general by publications about fuel poverty. The first one is the energy effort rate (EER_3d), which should not exceed 10%[2] and is limited to the 3rd decile of the revenue per CU[3]. According to this indicator, a household is fuel poor if the two following conditions are met: the ratio (energy expenditures)/(revenue of the household) > 10% and (revenue of the household)/(consumption units) < 3rd decile. ONPE (2016) estimated that 10.4% of French households in 2013 are fuel poor according to this indicator. The second and third indicators are the French versions[4] of the LIHC (for Low Income, High Cost) indicator that considers a household fuel poor if the two conditions of low income and high energy expenditures are met. According to these indicators, a household is FP if its income falls below the relative poverty line and if its declared energy expenditure exceeds the median household energy expenditure. The relative poverty line is set at 60% of the national median income after housing costs (e.g., rent or mortgage payments) and energy costs (e.g., electricity bills) are deducted. Two versions of the LIHE indicator are used: the LIHE_m² and the LIHE_CU. In the first case, the energy expenditures are divided by the surface area of the dwelling; in the second case, the energy expenditures are divided by the consumption units. In 2013, the percentage of FP in France is equal to 13.9% when considering the LIHE_m2 and 10.4% when considering the LIHE_CU (ONPE, 2016). The last indicator that is commonly used in France to detect fuel poverty is a subjective indicator based on the feeling of the household members in terms of thermal comfort. ONPE (2016) estimated that, in 2013, 6% of French households are FP according to this cold indicator COLD_3D[5].

These indicators target partially overlapping populations (see Figure 1). Thus, Bernard and Teissier (2016) note that LIHE_CU and LIHE_m² have the largest area of recovery (approximately 2.3 million FP

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[1] ONPE (for "Observatoire National de la Précarité Energétique") is a think tank in charge of studies linked to fuel poverty.

[2] The 10% threshold is used because in 1988, when the indicator was used for the first time in the United Kingdom, 10% was twice the median of the fuel poverty ratio. In other words, 1 in 2 households in 1988 in the United Kingdom used less than 5% of its revenue to pay the energy bill. Authorities judged at this time that using twice this value, which is equal to 10%, was a good means of detecting households that had unsustainable energy expenditures regarding their revenues. EER_E3d is widely appreciated for its simplicity but has been subjected to severe criticism. For example, there is a fixed threshold of 10%. Consequently, if we wanted to be rigorous, we should take twice the median of the French fuel poverty ratio – (energy expenditures)/(revenue of the household).

[3] CU, the scale for consumption units, is the same as the OECD scale, i.e., 1 CU for the first adult in the household, 0.5 CU for other persons aged 14 years or older and 0.3 CU for children under 14 years.

[4] French version because declared energy expenditures are used instead of normative energy expenditures.

[5] This indicator of perceived cold is based on two questions from the French national housing survey, namely, "Did your household suffer from the cold during last winter? If so, why did your household suffer from cold weather?" Households considered to be in FP are those who report being cold due to at least one of the five reasons for energy poverty (insufficient insulation, long-lasting failure of the insulation, financial reasons, poor insulation and failure of the supplier due to being unpaid) and whose income per CU is less than the third decile, i.e., € 15,712 per CU.

households in common), followed by LIHE_m² and EER_3D (1.9 million households in common), then LIHE_CU and EER_3D (1.8 million households in common). On the other hand, COLD_3D targets a group of households more distant from other indicators.

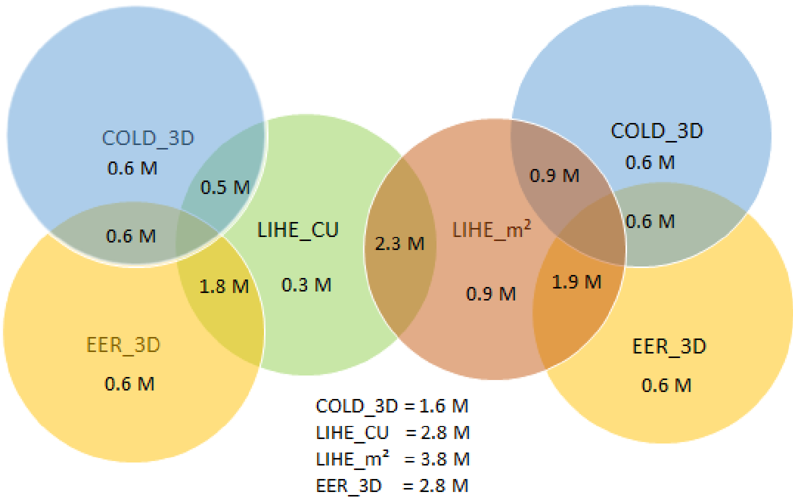

Figure 1. Overlap amongst the targets of fuel poverty indicators (ENL 2013) – Source: Bernard and Teissier (2016)

Interpretation: Of the 2.8 million FP households according to the LIHE_CU indicator, 0.5 million are FP according to indicator COLD_3D, 1.8 million are FP according to indicator EER_3D, and 2.3 million are FP according to indicator LIHE_m²

The study carried out by the ONPE in 2016 is based on the latest French national housing survey in 2013 (known as ENL2013[6]). It is worth noting that ENL2013 data collection was conducted from June 2013 to June 2014. As a result, since the energy expenditures declared by households relate to the 12 months preceding their interrogation, they concern the following period, from June 2012 to June 2014.

Since 2012/2014, the situation has changed. The three key elements of fuel poverty, namely, the price of energy, household income and dwelling energy efficiency, have undergone changes. Indeed, apart from 2016, the electricity price has increased significantly in recent years. However, electricity prices have a strong impact on the purchasing power of households. From 2013 to 2016, the commodity's price on the wholesale markets collapsed under the effect of several systemic factors: exploitation of shale gas and shale oil, slowing of global demand in a context of economic crisis, and a desire of the major producers to maintain high production rates. As a result, the regulated natural gas tariff in France has gradually decreased, reaching its lowest level since 2010 in 2016. However, agreements between the major oil and gas powers have allowed wholesale market prices to rise. Thus, prices began to rise in July 2016 and continued to rise in 2017. The beginning of 2018 was marked by a significant increase in the French Domestic Tax on Natural Gas Consumption (TICGN[7]), which was followed by a strong gas price recovery. The increases in regulated natural gas tariffs were very important during the month of July (+7.45%); October (+3.25%) and November (+5.79%) 2018. Figure 2 provides the monthly average retail prices (in euros) of domestic heating oil (per 1,000 litres delivered to home) in mainland France. The cost of one ton of wood pellets in 2018 is higher than in 2013 (see Figure 3).

[6] ENL is an acronym of « "Enquête national logement".
[7] TICGN is the acronym of "Taxe Intérieure de Consommation sur le Gaz Naturel".

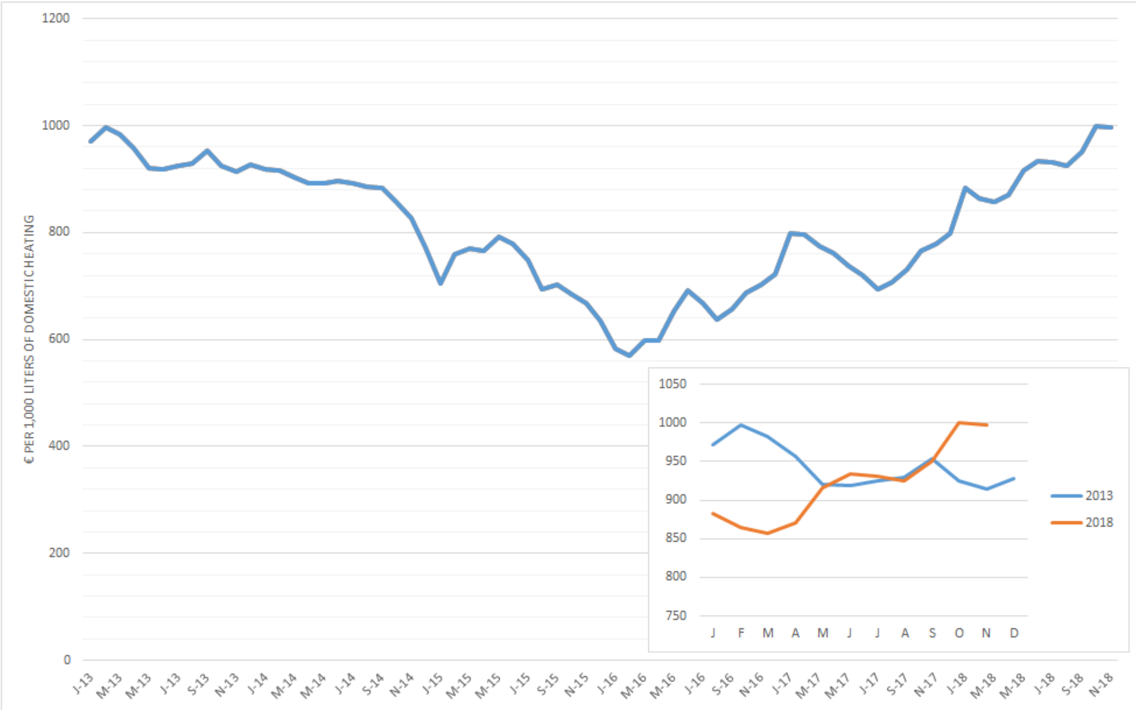

Figure 2. Monthly average retail prices (in euros) of domestic heating oil (per 1,000 litres delivered to home) in mainland France. Source: INSEE

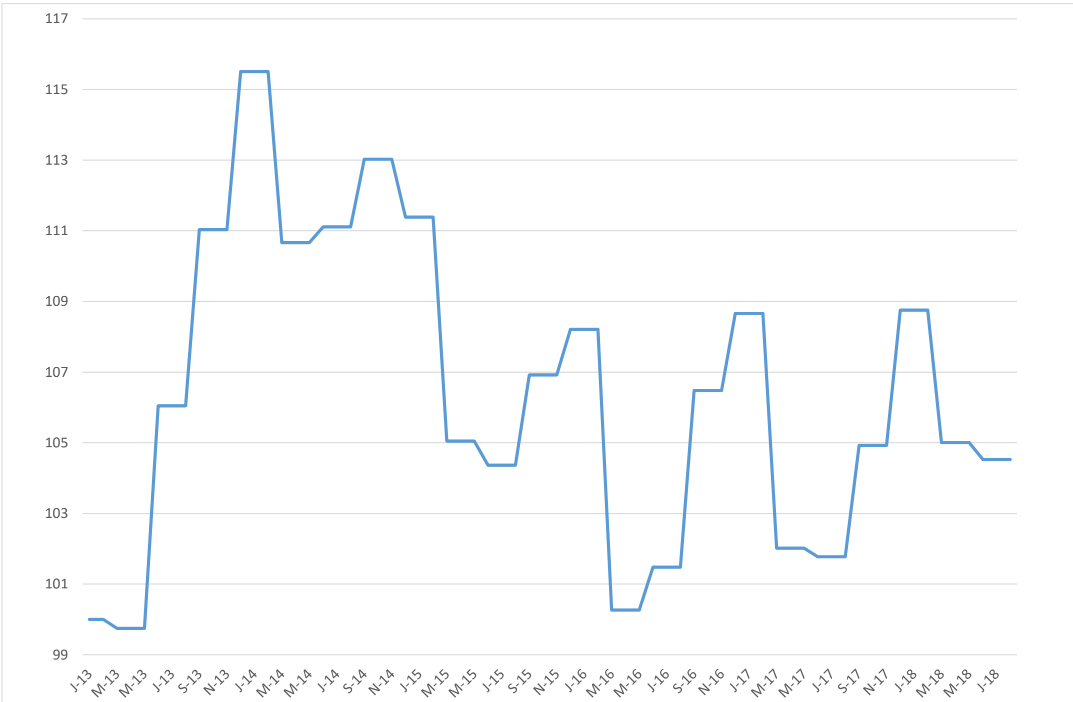

Figure 3. Evolution of the cost of one ton of wood pellets (in bulk) - Index base 100 = January 2013. Data: PEGASE - MEEM/CGDD/SOeS

According to INSEE[8], since 2014, individual purchasing power has been increasing. The unemployment rate in 2018 is lower than that in 2013 (see Figure 4).

[8] INSEE for "Institut national de la statistique et des études économiques" is the French National Institute of Statistics and Economic Studies.

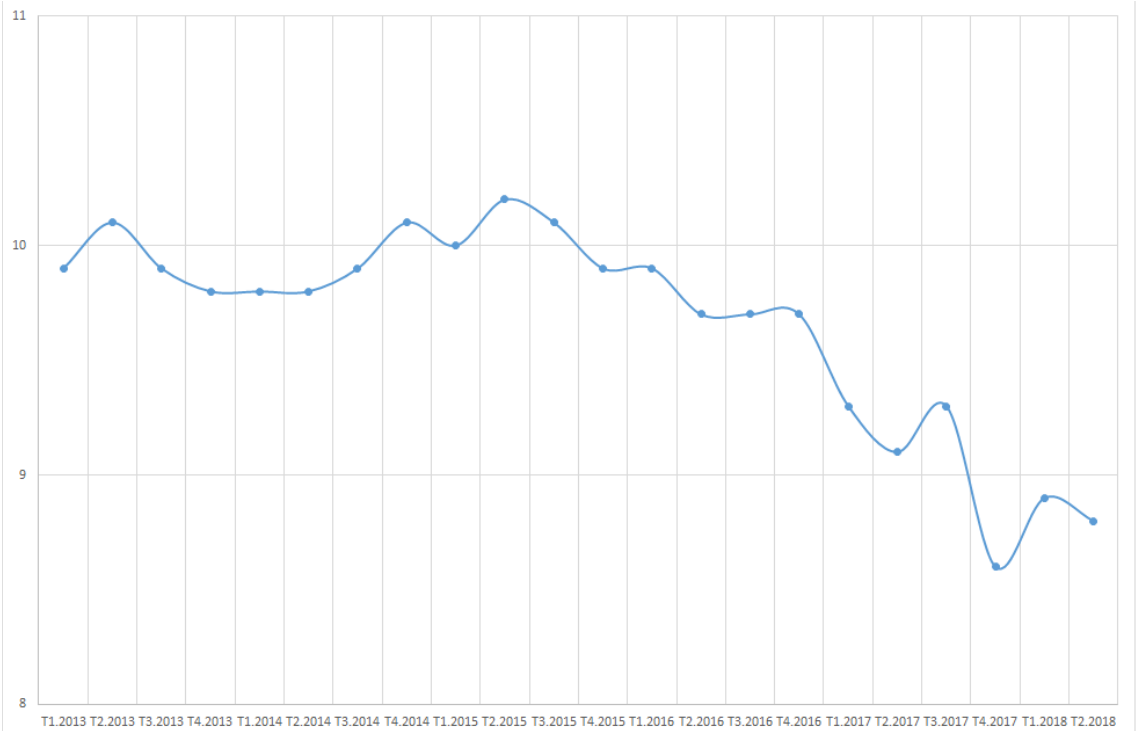

Figure 4. Unemployment rate (source: INSEE)

At the environmental conference on September 14, 2012, a goal to renovate 500,000 French housing units per year, including 120,000 social housing units and 380,000 private housing units, was announced. The ambition was strong. To achieve this goal, in March 2013, French President of the Republic François Hollande presented his investment plan for housing. This plan implements the plan for energy renovation of housing (PREH). This objective was reaffirmed in Law No. 2015-9929 of 17 August 2015 on the Energy Transition for Green Growth (LTECV). According to article 3 of this law, "*France sets itself the objective of renovating 500,000 homes per year starting in 2017, at least half of which are occupied by low-income households, and in that way aims at a decrease of 15% in fuel poverty by 2020*." Numerous public policies are in effect that provide fiscal or financial incentives to households to renovate their dwellings to improve energy efficiency. In France, eco-loans at zero rates to finance thermal renovations or the "Living better" ("Habiter mieux") programme, which is, among other things, a social energy efficiency refurbishment programme, may be given as examples. In the seven years since its launch in 2010, the "Living better" programme has helped renovate 250,000 homes and made the French people aware of the need to undertake renovations of their homes. According to the ADEME[10] (2018), in the 2014-2016 period, 5.1 million households in single-family homes carried out home improvement projects, of which at least one portion ended in 2016 (i.e., 32% of the French existing individual houses). Of these renovations, 260,000 resulted in an energy gain representing 2 or more energy classes.

Given these changes, the number of fuel poor in 2018 has changed since 2013. ONPE wishes to monitor the evolution of fuel poverty between two ENL surveys. To do so, ONPE (see Devalière et al., 2018) decides to measure the phenomenon using two of the indicators previously mentioned, namely, the EER_3D and the cold indicator. The indicator based on the EER_3D is estimated annually by the Commissioner General for Sustainable Development using the Prometheus micro simulation tool, and the threshold is no longer 10% but 8%. Prometheus is a tool that simulates individual household fuel consumption and the corresponding invoices. In the beginning (in 2013), it was based on individual

[9] https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000031044385&categorieLien=id

[10] ADEME for "Agence de l'environnement et de la maîtrise de l'énergie" is the French Environment and Energy Management Agency.

expenditure data (ENL_2006 survey) and used sources of information on household energy consumption and prices such as CEREN[11] data and the SOeS Pegase database[12] (see Thao Khamsing et al., 2016). The current Prometheus model (Clément et al., 2018) uses two databases for input: the ENL_2013 base for the household energy consumption of each household and the 2008 National Transportation and Travel Survey (ENTD_2008) for consumption of fuels from each household. Each household of the ENL is matched with a comparable household of the ENTD. The pseudo-pairing in Prometheus makes it possible to take into account the totality of the energy bill for the same household. It allows the study of fuel poverty (Housing) and of global energy vulnerability (Housing and Transport). In our mind, this model is not sufficiently detailed in the literature.

The objective of our study is mainly the description of a tool that we are developing with R to predict the percentage of fuel-poor households in France. The interest of such study is to characterize the populations most at risk to better target the population concerned and measure the extent of fuel poverty. The tool that was developed makes it possible to study the impact of policies and can help to properly design policies to attack fuel poverty. The database that we used to make our estimates and projection is the ENL2006 data collection, which was conducted from March 2006 to December 2006. We also study the impact of energy prices, unemployment rate, revenue and energy refurbishment on fuel poverty.

Section 2 describes the important steps of the program used for the simulation, such as the method used for the variation in unemployment rate in the population or the effect of a thermal renovation of the house on the energy bill. Section 3 addresses a brief description of the simulation results, characterizes the fuel-poor households in France in 2018 and performs a benchmark of the model with the values computed by the ONPE in 2016. Finally, Section 4 concludes.

2. The micro-simulation program

The micro-simulation program has been developed with R. This section, covering a description of the most important stages of the program, is summarized in Figure 5. The program is based on three main blocks, namely, income, energy prices and thermal renovations. This structure allows one to take into account the three predominant factors in the notion of fuel poverty, that is, household resources, energy prices and housing quality.

2.1. Model variables

The variables (see column 1 of Table 1) are the number of houses renovated during the simulation and the average decrease in the energy bill after the renovation expressed as a percentage. For example, minus twenty-five percent (-25%) means that a renovation on average reduced the energy bill by twenty-five percent (25%). There are also the variations in six energies – electricity, gas, heating oil, butane/propane, wood, and charcoal – and an elasticity for each of them. Then, we address the variation in percentage of the gross declared revenue of the household and the variation in assistance received from the State ("family allowances"), since the gross declared revenue we usually use for our statistics does not include such assistance. The figure includes only a computation of the net revenue used for the two versions of the LIHE indicator. We assumed in our simulations that their amounts closely followed the trend of the gross revenue of households. It is possible to set the value of the threshold to compute statistics for the initial year and for the final year. The variable

[11] CEREN for "Centre d'études et de recherches économiques sur l'énergie" is a French Centre for Economic Studies and Research on Energy.
[12] http://www.statistiques.developpement-durable.gouv.fr/donnees-ligne/r/pegase.html

“number_simulations” is the number of iterations that the R package MICE[13] used to impute missing values using the predictive matching mean method (pmm). Finally, the unemployment rate for the initial year and the final year can be lower than the initial year but also higher. We tested the model with low values (5%) and high values (25%), both of which worked well.

2.2. Input data

Because we do not have the 2013 French national housing survey (ENL2013), we use the survey conducted in 2006 (ENL2006). We perform three simulations. The first simulation from 2005/2006 to 2012/2014 compares our results with the ONPE study based on the ENL2013 (see Bernard and Teissier, 2016), the second simulation from 2005/2006 to 2017 compares our results with ONPE (see Devalière et al., 2018), and the third simulation covers from 2005/2006 to 2018.

The ENL2006 is divided into various subtables that contain specific answers from households, each table addressing a “general topic”. We will use the three main tables of the survey for the simulation. The first is the table denoted by “H”, which provides us a great deal of varied information about the households such as their income, their declared energy bill and the age of the person that is in charge of the household. The second table, denoted by “D”, is about the dwelling itself: age of insulation, surface area of the dwelling, declared age of the dwelling, and so on. Finally, there is a table that provides us specific information about potential refurbishment of the dwelling made by its residents. This table is useful to obtain information about insulation of the dwelling or the purchase of a new boiler, for example. The three tables have in common a variable we use to identify a specific profile of household (an identification variable, ID) and its associated sampling weight. The sampling weight will ensure that our results are representative of the French (households) population. Once the import is completed, we merge the two first tables (H and D) to create table “HD”, with the ID as the key for the fusion. The third table (“HR”) shows the profile of households that did a thermal renovation, but it contains almost two times fewer observations than do the first two. To avoid losing much information by doing a useless fusion, we proceed in another direction that is also quite simple (see subsection 2.3.).

2.3. Imputation of missing values for energy consumption and housing refurbishments

Many households have a missing value (“Na”), which creates many problems for our models and various statistics. While most of the tools that we use have an integrated option to not take into account “Nas”, we would like to fill holes in our database to permit using as much information as possible. Second, there is another problem: some households strongly under-declare their energy bills. For example, there is a value in the database for an electricity bill equal to 200 euros per year, which is low, and then “Nas” for the other energies or even declarations of nothing at all. Of our households, 2.11% declared zero energy expenditures. We want to correct this error, and that correction is the job of the package MICE of R. Concerning missing values, we primarily have four choices that are always debatable. First, we could suppress the lines with Na’s and suppress important information with them (we decided not to take this approach). The second option is that we could declare that a “Na” value will be simply a “0” or third choice; it could be the mean of the sample. The fourth option is to use all the information we have in the dataset to simulate the value and fill a hole in the data. We employed the last option, the predictive mean matching method[14], with MICE, a method that is closely related

[13] MICE (Multivariate Imputation by Chained Equations) is an R package used to fill missing values in a dataset, using other observations as a base for the imputation. We used the predictive mean matching method, which provides good results.

[14] The SAS website describes this method as follows: “The predictive mean matching method is an imputation method available for continuous variables. It is similar to the regression method except that for each missing value, it imputes a value randomly from a set of observed values whose predicted values are closest to the predicted value for the missing value from the simulated regression model (Heitjan and Little 1991; Schenker and Taylor 1996)”.

to multiple linear regression models but uses a random draw of the set of parameters to create variability. The advantage is that MICE does so automatically. We subtracted a part of the dataset with variables that are potentially good predictors of the energy expenditures. We then used the package to fill the holes. More specifically, we did so for the following three tables: households that do not live in a place with collective heating, households that live in a place with collective heating and rent their flat and finally households that live in a place with collective heating and own their flat. The variables we choose for the imputation with MICE are the following: age of the reference person in the household (HRP); occupancy status of the dwelling (5 modalities[15]); surface area of the dwelling; gross income of the household; type of heater (6 modalities[16]); insulation of the dwelling (5 modalities[17]); age of the dwelling (4 modalities[18]); declared bills of electricity, gas, fuel, butane/propane, wood and charcoal; and declared collective bill. Once our table "HD" is ready to be used, we use MICE again to fill missing values for the variable "Housing Refurbishments" and create another table that is a merge of table "HD" and table "HR" with the ID of the household as a key of fusion. The variables used for the imputation of missing values are age of the HRP; net revenue per CU; surface area of the dwelling; gross income of the household; type of heater (6 modalities); insulation of the dwelling (5 modalities); age of the dwelling (3 modalities); and thermal renovation.

2.4. Impact of household reference person's unemployment on gross household income

2.4.1. Gross household estimate

First, we made an estimate of gross household income considering various variables. The results of this estimation are shown in Table A.1 in appendix A.1. The most important result of this estimation is the impact of the fact that the reference person in the household is unemployed. We estimated at the 1% level of significance that having the reference person of the household unemployed reduces the household revenue by 69.7% compared to a household with the reference person employed. This finding is significant. First, we use it for the projection; the idea is to modify the percentage of fuel-poor households (and at the same time the number of employed people) by changing the value of the binary variable "unemployed" from 0 to 1 (or the opposite if we reduce the unemployment rate) and at the same time changing the binary variable "employed" from 1 to 0. Second, we use this estimation to see whether the profile of a household is far away from the mean revenue of comparable households in the data. If a household has a (declared) higher revenue than the simulated one, we consider that the revenue level is more likely to "come back" to the normal level. Thus, we will extract it and include it in a subtable that we will use for random draws and then reduce its revenue by 69.7%, the average "effect" of the unemployment. We did the same in the case where we increase the number of employed people by taking a household with revenue that is less than that of the estimated one.

2.4.2. Impact of the change in the unemployment rate on income: income forecast

We simulate the change of the unemployment rate as follows: we divide the data into 5 categories:

- Households with a revenue higher than their average profile and unemployed;
- Households with a revenue lower than their average profile and employed;
- Other households employed;
- Other households unemployed; and

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https://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_mi_sect020.htm

[15] New homebuyer; owner-occupier; usufructuary; tenant or subtenant and free accommodation.

[16] Individual heater; urban heater; collective heater; mixed heater; individual electric heater and other type of heaters

[17] Unknown insulation; Collective insulation; Recent insulation; Old insulation but enough and Old insulation, not enough.

[18] Unknown date of construction; from 1990 to today; from 1962 to 1989 and before 1961.

- All the other households (disabled, retired, staying at home).

We create new indicators of the status of the HRP (employed in projection / unemployed in projection). For that purpose, using a relation of proportionality, we compute the number of households that a variation in the classic unemployment rate represents. Let us take the example of an increase of 1 percentage point (pp) in the unemployment rate, for example, from 9% to 10%. We have in our data in 2006 4.5% of our households with an HRP indicating unemployed. Using a cross-product, increasing the unemployment rate by one point is equivalent to increasing the number of households with an unemployed HRP by $4.5 \times \frac{10}{9} = 5\%$ (we increase by 0.5 pp). Therefore, we must increase the unemployment rate in our data such that the computed percentage will no longer be 4.5% but rather 5%, which represents approximately 130,000 households that will see their variables "employed =1 / unemployed =0" becoming "employed_projection = 0 / unemployed_projection = 1". The same applies if we want to reduce the unemployment rate, simply making the opposite change.

Random draws on households that simulated income very far (above the median) from reported income (i.e., categories 1 and 2) form the basis for random draws from unemployment to non-unemployment and vice versa.

New variables for the unemployment state of the projection year (and the employment state) have thus been created**.** We integrate the unemployment state into the model that we use to estimate the revenue and compute the impact of a variation in the unemployment rate.

We compute the "delta" (called $\Delta_{simulated}revenue$) between the original simulated revenue and the simulated revenue integrating the new group of variables (those resulting from the variation in the unemployment rate). Thus, revenue for the year of projection is

$$Revenue_{projection} = (1 + \Delta_{simulated}revenue) \cdot (1 + \Delta revenue) \cdot (declared\ gross\ revenue) \quad (1)$$

and the net revenue per CU for the year of projection is

$$Net_{Revenue_{CU_{projection}}} = \frac{Revenue_{projection} + social_{helps} * (1 + \Delta social\ helps) - \left(cost\ of\ housing\ without\ energy\ bill * (1 + \Delta revenu)\right)}{Consumption\ units}. \quad (2)$$

2.5. Probability of housing refurbishments

To have a probability of renovation to make our random draws[19] for renovations in the simulation better (even slightly) than a completely random draw, we estimate a logistic model. The results presented in appendix A.2 are not very good (but are still better than random). The coefficients of the logit are overall not at all significant (not even at the 10% level), which is disappointing. The size of the dwelling, its type or the status on the job market of the person in charge of the dwelling has no impact in our case. However, the presence of moisture, construction prior to 1990, the type of heating, and past insulation are significant variables. The computed AUC on the validation set is equal to 0.68, which is barely good (over 0.8 is considered good in general). However, since an AUC in the case of a random classification is equal to 0.5, we realize much better results than would a random classification with respect to predicting households that are likely to have a thermal renovation declared. Additionally, our model classifies correctly 84% of the observations in the validation set. Once we have our logistic regression fitted, we can output the computed probability for each household. The interesting profiles will be those with a high probability of renovation but with their variable "Housing Refurbishments" equal to 0. Note that the logistic regression also takes into account the new variables – the revenue for the year of projection and the new unemployment rate. Once we have these probabilities, we divide the dataset in three parts:

- A dataset with households already renovated that we will never touch (P1);
- A dataset with households that have a "high" probability of renovating their dwelling, the false positive cases (P2); and

[19] We will create a table with households that have a "false positive" profile and do our random draw with it.

- A dataset with all the other households (P3).

We use an algorithm very similar to the one we used for the modification of the unemployment rate, but this time, the process will be much simpler. There are only two possibilities: the number of households we renovate is less than the number of households in P2, and of course the second case, where the renovated amount is massive (more than 4.5 million), and we must use P3. In both P2 and P3, we sorted the probabilities from the highest to the lowest to always select households with the highest probability of renovation. Again, the probability for the uniform random draw is the number of households we must renovate divided by the number of households in the table we use. When the number of households renovated reaches the number we desire, the loop stops. After we simulate this phenomenon, we also randomly simulate a quality of renovation.

2.6. Impact of variation in the revenue and unemployment on the average energy bill

2.6.1. Energy bill estimate

To be able to integrate the effect of a variation in the unemployment rate and the variation in revenues on the energy expenditures (to which we will also add the variation in energy prices moderated by the elasticity) in our simulation model, we fit another multiple regression model. The results of this regression are in appendix A.3. The results are satisfying overall. However, the coefficient for the thermal renovation is quite unexpected. Thus, our model states that having a thermal renovation increases the energy bill, probably because integrating this variable does not measure the impact of the renovation on the energy bill itself but more the fact that households that did a thermal renovation are on average more affluent than others are and have a higher energy bill. Regardless, we will not use this coefficient to simulate the effect of a renovation on the energy bill; instead, we will proceed in another direction, a more radical one. This model is used to integrate the effect of a variation in the unemployment rate and the revenue on the energy bill.

2.6.2. Impact of changing energy prices

Let ΔP_i be equal to the price of energy *i* for the final year minus that of the initial year and ε_i be the price elasticity of the demand for *i*; then the energy bill projection for *i* is defined by

$$energy\ bill_{projection,i} = (1 + \Delta P_i) \cdot (1 + \epsilon_i \Delta P_i) \cdot (declared\ energy\ bill\ for\ the\ energy\ i).$$

We have 7 different "new" energy bills for each household in the dataset, and we sum them all to obtain the new energy bill for the year of projection. We then compute the variation before/after for each household, denoted by $\Delta energy\ bill_{projection}$.

2.6.3. Effect of unemployment and the general increase of revenues in the population

We use our model that estimates the energy consumption for each household by integrating the new revenue of projection and the new state of the job market. We compute the variation between the new simulated revenue and the old one. Then, the new variation in the energy bill is equal to the following:

$$\Delta simulated\ energy\ bill_{projection} = \frac{\left(simulated\ energy\ bill_{\Delta revenue_{proj}, \Delta unemployment_{proj}} \cdot (1 + \Delta energy\ bill_{projection}) - simulated\ energy\ bill\right)}{simulated\ energy\ bill}.$$

We apply this variation (which takes into account the variation in prices, the elasticity, the unemployment rate change and the variation in revenues) to the declared energy bill for the initial year, which yields the value for the final year:

$$declared\ energy\ bill_{projection} = (1 + \Delta simulated\ energy\ bill_{projection}) \cdot declared\ energy\ bill.$$

2.6.4. Impact of renovation and rebound effect

The simulation of the rebound effect (or Jevons Paradox)[20] is done by the following process: if the (initial year) simulated energy consumption of the households was superior to the declared one, then we consider that the household was over-consuming and the renovation will be 100% effective. If the simulated energy consumption was below the declared energy consumption, then we consider that the household was under-consuming and a part of the gain in the energy bill amount will be used to gain in comfort. We divide the value of the gain after a renovation by two.

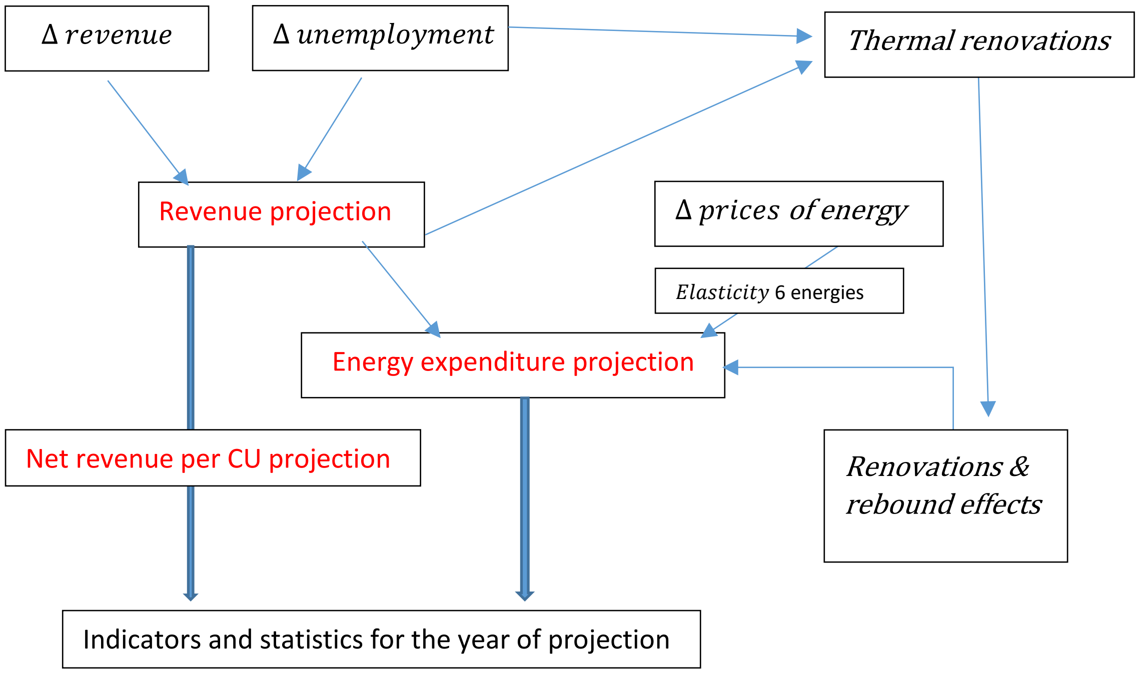


Figure 5. The main stages of the simulation process

3. Fuel poverty in mainland France in 2005/2006, 2012/2014, and 2017/2018

3.1. Calibration and benchmark of the model from 2005/2006 to 2012/2014

To have a reference for our projections, we compute basic statistics for the initial period (2005/2006) and compare our values with those obtained by Bernard & Teissier (2016). These results are satisfying (see Table B in appendix B) because these numbers are close to those of Bernard and Teissier, which means that our initial "data management" is correct. We test our model with real values (see Table 1) of variation for prices of six energies (electricity, gas, charcoal, butane, oil heating and wood), the variation in disposable income and a realistic number of renovations of housing to see whether the model evolves correctly[21]. We consider the start of the simulation is the period from March 2005 to December 2006 and its end the period from June 2012 to June 2014. These periods coincide with those of the two surveys ENL2006 and ENL2013.

We assume that there are 1,050,000 renovated housing units during those times of simulation (roughly 150,000 per year), with an average gain on the energy bill equal to 25% (using a uniform draw between 5% and 50%). Variation in the prices of energies is the percentage of variation between the prices averaged for the period March 2005 to December 2006 and for from June 2012 to June 2014.

[20] Many studies have studied the rebound effect; see, for example, Greening et al. (2000), Schipper & Grubb (2000) and Grepperud & Rasmussen (2004).
[21] Good sign of variation first, then a realistic delta of variation, especially with the fuel poverty ratio indicator.

What values should be retained for elasticities? As stressed by Nesbakken (1999), the estimates of energy price elasticity found in the literature show large variation. This variation depends on not only the model used and the statistical estimation method but also the type of data used (sample, time series, and panels), the country studied and the date of the measurements (Espey & Espey, 2004). Neenan & Eom (2009) concluded that the price elasticity of short-term residential electricity demand is between -0.2 and -0.6, with an average value of -0.3, and that long-term elasticity ranged from -1.4 to -0.7, with an average value of -0.9. For Nilsen et al. (2005) for example, price elasticities appear significantly higher in Europe than in the United States. The price elasticity values also vary according to the form of energy and the use considered. Thus, for certain uses, the use of energy can be modulated more easily than for others. This point is true, for example, for the consumption of gasoline or the use of certain domestic electrical appliances. On the other hand, heating or cooking uses, which correspond more to a necessity, will be more difficult to modulate. Therefore, in the residential sector as a whole, the elasticity values of electricity demand are generally higher than for other forms of energy; electricity has specific uses (lighting, for example) that are more easily modulated. These hypotheses are confirmed by Maddala et al. (1997), who compared the price elasticities of residential demand for electricity and natural gas. For both energies, price elasticities were estimated using the same methodology and the same database. Estimates of price elasticities of gas demand tend to be lower (in absolute value) than those of electricity demand. Rothman et al. (1994) obtain similar results by comparing electricity with other energies (oil, natural gas and solid fuels). Depending on the estimation period, the estimated elasticity values may differ due to structural changes in the economy and efforts made in energy efficiency. The foregoing considerations encourage us to be cautious about the interpretation of the identified price elasticity values of the energy demands, which are highly dependent on parameters such as the nature of the data, the choice of model and the type of demand studied.

The values of the elasticities (see Table 1) allow calibrating the model to have approximately 10.4% of fuel-poor households in 2013, with a fuel poverty ratio with a 10% threshold (10%EER_3d), and allow determining its associated statistics and those of the two LIHEs. The value for the augmentation of the revenue of households was taken from the OECD website; the value is the average of the percentage variation each year of the disposable income of households from 2006 to 2012, inclusive, and from 2007 to 2014, inclusive.

Unemployment rate values are the average of the 2005 and 2006 rates and, for the projected year/period, are the average of the 2012, 2013 and 2014 rates. The absolute value is not very important itself; the variation between the two periods is more important. In the model, increasing unemployment from 6% to 8% will have the same impact as moving from 10% to 12%.

Label of the parameter	Value of the parameter
Number of renovated households during the simulation	1 050 000
Average gain (in percent of the total energy bill) after a thermal renovation	-25%
Variation in electricity price	29%
Variation in gas price	53%
Variation in heating oil price	48%
Variation in butane price	40%
Variation in wood price	20%
Variation in charcoal price	80%
Elasticity value for electricity consumption	-0.31
Elasticity value for gas consumption	-0.28
Elasticity value for heating oil consumption	-0.24
Elasticity value for butane consumption	-0.24
Elasticity value for wood consumption	-0.24
Elasticity value for charcoal consumption	-0.24
Variation in the disposable income of households	8.9%
Variation in social aids received by households	8.9%
Threshold for the fuel poverty ratio, initial year of simulation	10%
Threshold for the fuel poverty ratio, final year of simulation	10%
Number of repetitions for the imputation with MICE	5
Unemployment rate, initial year	8.85%
Unemployment rate, final year	10.13%

Table 1: Parameters for a simulation from 2005/2006 to 2012/2014 with calibrated elasticity

Table 2 provides statistics to determine whether our model is accurate overall. With the parameter values of Table 1, we obtain in the projection a value equal to 10.4% of households being fuel poor according to the 10%EER_3d. This percentage is the value of the ONPE for the period 2012-2014; therefore, the model was "well" calibrated.

However, our model significantly underestimates the value of the LIHE_m² indicator, since the projected variation is much smaller than the actual variation. Indeed, the LIHE_m² is equal to 12.52% for the projected period, whereas the ONPE value is 13.9%. The gap between our projected value and the real value for the period June 2012/June 2014 is large and can be reduced by changing the value of the elasticities. Indeed, elasticity is an extremely important variable that can change the simulation entirely with low variation. The variation for the two LIHEs are the same in the simulation, which is normal. However, on one hand, we need the LIHE_m² to react more; on the other hand, we need the LIHE_CU to react less. Since their respective constructions are extremely close, there is a dilemma impossible to solve. We could also argue that the variations computed by ONPE are completely different with both LIHEs, which is somewhat hard to explain with two indicators that differ only by a ponderation value of energy expenditures. There is likely a change in the structure of the data that our model cannot take into account. Concerning our indicators, there is obviously a compromise to find. It might be necessary to find a proper elasticity for each indicator instead of one elasticity for the four, especially for the LIHE_m². This approach is not absurd; since the profile of the population targeted by each indicator is different, so might be their respective reaction to a rise in energy prices. However, considering zero values for the elasticity, a delta between the initial and final values of LIHE_m² equal to 0.6 instead of 1.5 for the ONPE can be observed[22]. Unfortunately, introducing a non-zero value for

[22] In this case, the LIHE_m² is equal to 12.25% for the initial period and 12.85% for the period of projection (ONPE computed 12.4% in 2006 and 13.9% in 2013).

elasticity will reduce the value, and the gap we computed will decrease and even further away from the value observed in the ONPE report. As a result, there is a structural change in the data that explains this gap.

One explanation could be that survey data collection took place at different times. That is, ENL2006 data collection was conducted from March 2006 to December 2006, and ENL2013 data collection from June 2013 to June 2014. As a result, since the energy expenditure declared by households relates to the 12 months preceding their interrogation, it relates to the following periods from March 2005 to December 2006 for ENL2006 and from June 2012 to June 2014 for ENL2013. As a result, only one winter is considered in ENL2006, while two winters are considered in ENL2013. An important explanatory factor in energy spending that our model does not take into account is the weather. According to Devalière et al. (2018), the winter in 2013 was particularly harsh, which increased the need for heating in dwellings and thus increased the energy bills paid by households that year. The authors corrected the cyclical impact of the weather. As a result, according to the 8%EER_3D, the estimated fuel poverty rate in 2013 is equal to 13.8% with this correction against 14.5% without. However, according to Météo France, the 2012/2013 winter in France was rather cool, with a significant excess of rainfall and insufficient sunshine but a not particularly severe winter. In addition, the ENL2013 covers two winters, and the winter of 2013-2014 was mild (see Météo France). Therefore, the correction made by Devalière et al. (2018) may seem excessive. Since the 2005/2006 winter weather (see Météo France) was not marked by exceptional cold spells and mild periods were particularly rare, it appears that temperature differences are not the situational factor explaining the difference in value of LIHE_m².

Fortunately, 10%EER_3D is the yardstick variable; thus, the target is naturally correct and the LIHE_CU reacts quite well. The LIHE_CU is equal to 10.17% for the initial year and 10.47% for the period of projection (2012/2014).

Projection for the period 2012-2014	**10%EER_3d**	**8%EER_3d**	**LIHE_m²**	**LIHE_CU**
Percentage of fuel poor (ONPE reports* between parentheses)	10,4% (10.4%)	13,89% (13,8% - 14,5%)	12,52% (13.9%)	10,47% (10.4%)
Average disposable income of fuel-poor households (FP) – in euros	12,178 (11,901)	13,427	16,565 (15,781)	15,142 (15,192)
Average energy expenditures of fuel-poor households	1,944 (1,925)	1,870	1,765 (1,734)	2,026 (1,966)
Average number of inhabitants of fuel-poor households	1.86 (1.94)	1.97	2.27 (2.25)	1,86 (1.81)
Average age of the household reference person (HRP) of fuel-poor households	60 (56)	59	53 (51)	59 (55)
Average disposable income for the entire population – euros			39,861 (39,266)	
Average energy expenditures for the entire population – euros			1,592 (1,584)	

*See Bernard and Teissier (2016) and Devalière et al. (2018).

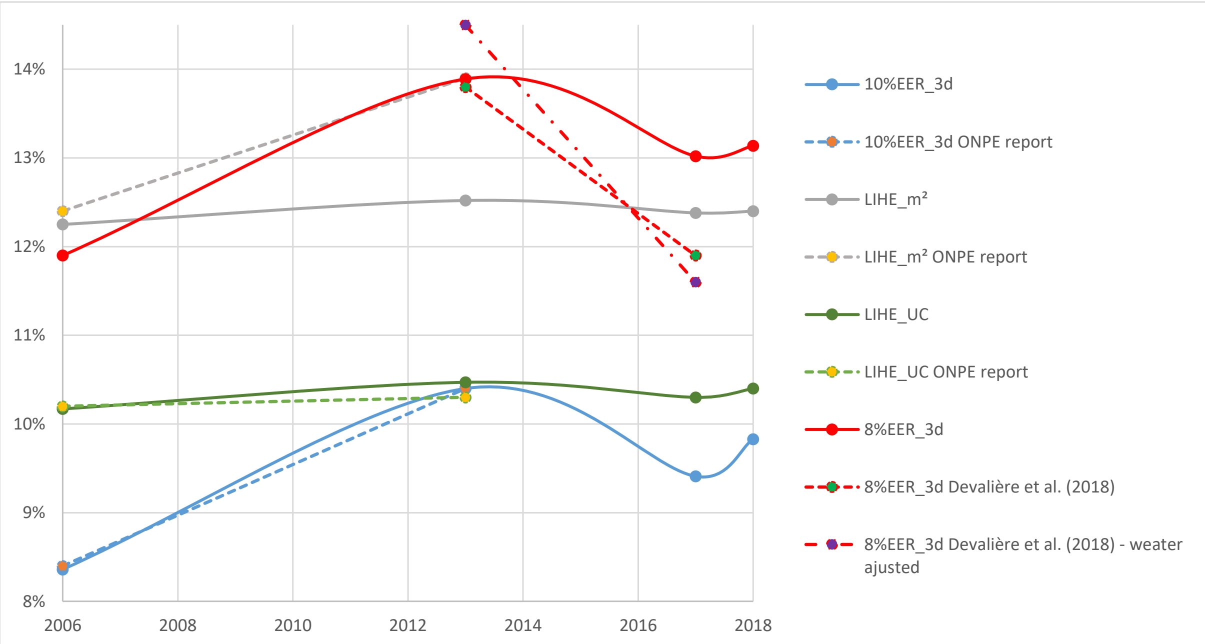
Table 2: Comparison between the projection in 2012-2014 and ONPE values

The comparison between the computed values for the projection and the ones that were observed in the ENL2013 are quite close, but we can already see a difference between our simulation and “reality”. The different parameters for the revenue and the prices of energies seem efficient overall even if not perfect. These results are good considering that the model is quite simple in its architecture. The weighted mean gross revenue for the population is almost the same as the one computed in the ONPE report (see Bernard and Teissier, 2016) and the energy expenditures. In other words, our initial treatment of the database and OECD’s computed variations in revenues are efficient for short-to-middle-term projections. Overall, the values computed are quite good, and the model provides us additional information to track four different profiles: only households that entered fuel poverty, only households that left fuel poverty, only fuel-poor households (this category also includes households that entered fuel poverty) and finally households that are not fuel poor.

The significant increase in energy prices between the two periods of 2005/2006 and 2012/2014 (see Table 1) generated an increase of the average energy expenditures of households. Combined with an increase in the unemployment rate and moderate growth in household disposable income, this increase in energy prices has led to an increase in the intensity of fuel poverty between these two periods (see Tables 2 and B).

3.2. Fuel poverty in 2017 and in 2018

The model was used to simulate the number of fuel poor in mainland France for the years 2017 and 2018. The parameters' simulation values are those listed in Table C of Appendix C. Figure 6 shows the evolution of fuel poverty defined by different indicators and calculated / simulated by different authors. While the number of households in fuel poverty increased between 2005/2006 and 2012/2014, it decreased between 2012/2014 and 2017, and it increased in 2018. In contrast to the EER indicators, the evolution of fuel poverty is small for the two LIHE indicators. This difference exists because energy prices and income changes have less impact on the LIHEs compared to the EERs, as the LIHEs use relative thresholds instead of a ratio. Indeed, with the LIHEs, the energy expenditure threshold is defined according to the national median. As a result, an increase in the price of energy implies higher expenditures for all households without structurally affecting the phenomenon of fuel poverty measured with the LIHE indicators.



Interpretation: The ONPE report corresponds to the values found in Bernard and Tessier (2016). The results of our projections are those shown by the solid line in the figure.

Projection Values	10%EER_3d		8%EER_3d		LIHE_m^2		LIHE_CU	
Percentage of fuel poor (Devalière et al., result between parentheses)	2017	2018	2017	2018	2017	2018	2017	2018
	9.41%	9.83%	13.02% (11.6% - 11.9%)	13.37%	12.38%	12,40%	10.3%	10,4%

Figure 6. Evolution of fuel poverty according to different indicators

Between 2013 and 2017, the decrease in fuel poverty rates (8% EER_3D) simulated by Devalière et al. (2018) with the CGDD-Prometheus model is much higher (2.9 pp) than that obtained by our simulations (0.9 pp). One reason for this is that Devalière et al. have corrected the 8% EER_3D indicator by -1.9 pp because they considered that the winter of 2013 was particularly harsh and that the temperatures of the winter of 2017 were mild. We have not made this correction because, as previously reported, the ENL 2013 covers two winters: the rather cool 2012-2013 winter and the mild winter of 2013/2014. The analysis below provides further explanations concerning the difference (2 pp) obtained between our results and those of Devalière et al. (2018).

3.2.1. Evolution of the disposable income of households is an essential element of the change in the fuel poverty rate

The main reason for the fuel poverty decline between 2012/2014 and 2017 is the increase in the disposable income of households associated with a decrease in consumer prices (including taxes) on natural gas, heating oil and butane. This increase results in an increase in average disposable annual income for the entire population[23] equal to €2,109 and a decrease in average energy annual expenditure for the entire population[24] equal to €14. If we retain as an indicator of fuel poverty an energy effort rate, we find that the impact of income growth between 2012/2014 and 2017 has the effect of reducing fuel poverty by 0.81 pp with the 10%EER_3D, 0.76 pp with the 8%EER_3D and 1.15 pp with the EER_3D (see Figure 7). Unfortunately, we have only the reference from ONPE to judge the value of the sensitivity of these indicators against the variation in household incomes. Thus, according to Devalière et al. (2018), between 2013 and 2017, income growth led to a 0.7 pp decrease of 8%EER_3D. Their result is close to ours. However, it is difficult to be certain because we do not know the income growth rate adopted by Devalière et al. (2018). Have they taken into account that the ENL2013 on which their study is based covers the period June 2012 – June 2014? Do they consider the variation in revenues between 2013 – 2017?

Between 2017 and 2018, the increase in household incomes[25] did not offset, and for some of them, the average increase in energy expenditures[26] is due to the increases in the prices of gas and heating oil. If the indicator 8% EER_3D is retained, then the contribution of the variation in the incomes to the evolution of fuel poverty between 2017 and 2018 is -0.17 pp (see Figure 8).

Note that the impact of the change in the unemployment rate for the two periods is lower (at most a decrease of 0.11 pp for the 8%EER_3D). We will explain this effect and the limited impact of thermal renovations on the variation in fuel poverty in 3.3.

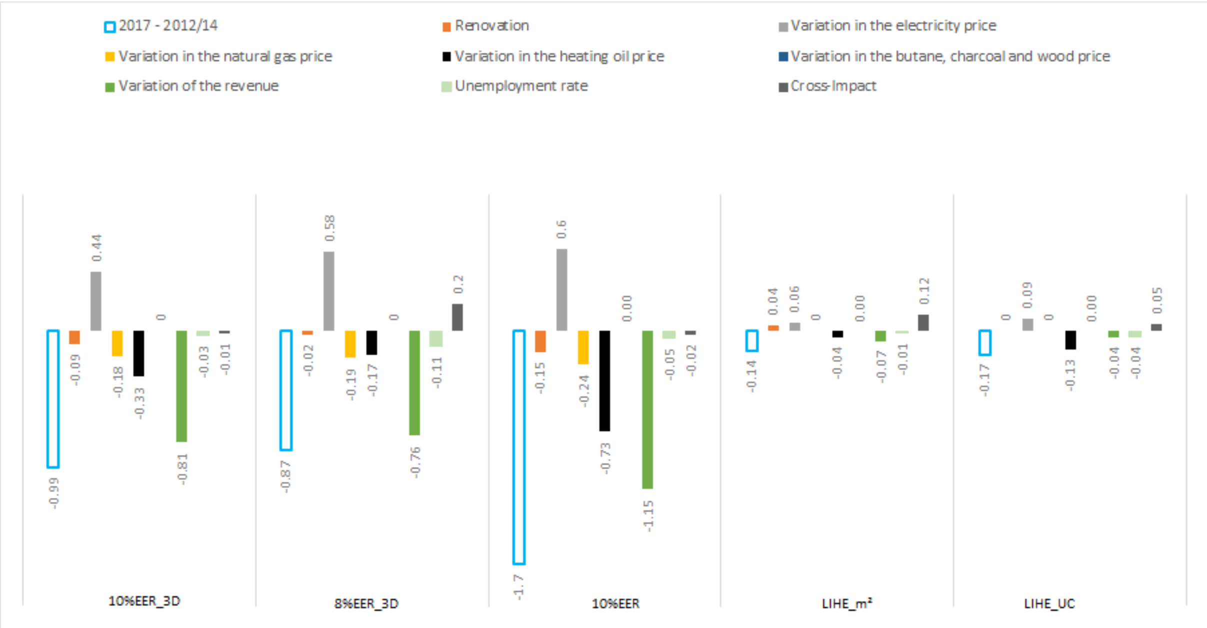
3.2.2. Impact of the evolution of energy prices on the change in the fuel poverty rate

Between 2012/2014 and 2017, the price to the consumer (including taxes) of natural gas, heating oil and butane deceased. This decline has contributed to a decrease in fuel poverty rates (see Figure 7). Thus, the impact of the decrease in the price of gas (respectively heating oil) was a variation in -0.19 pp (or -0.17 pp) of 8% EER_D. However, between the same periods, the price of electricity increased. The increase results in an increase of the 8%EER_3D of 0.58 pp. The impact of energy price changes for the consumer on the 8%EER_3D is ultimately equal to 0.18 pp. This result is higher than that in Devalière et al. (2018). Indeed, according to these authors, the impact of energy prices excluding tax on fuel poverty evolution between 2013 and 2017 is -1.3 pp. At these percentage point levels, we must add the impact of energy taxation on fuel poverty, which is estimated at 1.3 pp, yielding 0 pp. An explanation of this difference is probably that Devalière et al. consider that the ENL2013 survey only concerns the year 2013 and not the period from June 2012 to June 2014.

Between 2017 and 2018, the price of electricity did not change. On the other hand, the same cannot be said for natural gas and heating oil prices. Figure 8 provides the impact of these variations on the

[23] In 2017, the average disposable annual income for the entire population equalled €41,970.
[24] In 2017, the average energy expenditures for the entire population equalled €1,578.
[25] + 416 euros for average disposable income for the entire population compared to the value of 2017 (see Table 3).
[26] + 64 euros for average energy expenditures for the entire population compared to the value of 2017 (see Table 3).

rates of fuel poverty. Thus, if we retain 8% EER_3D, the rise in natural gas prices (respectively heating oil) has resulted in an increase in fuel poverty of 0.27 pp (respectively 0.22 pp). These effects were not offset by those related to higher incomes and lower unemployment rates. Therefore, the increase in natural gas and heating oil prices between 2017 and 2018 has led to an increase in the number of households in fuel poverty between these two years.



Interpretation: Between the two 2012/2014 and 2017 periods, fuel poverty in mainland France fell by 0.99 pp if the indicator selected is 10EER_3D. The factors that contributed to this decline are, in other words, the thermal renovations of dwellings, whose effect on fuel poverty was reflected in a decrease of 0.09 pp, the fall in the natural gas price (effect on the 10%EER_3D equal to -0.8 pp), the fall in the heating oil price (effect on the 10% EER_3D equal to 0.33 p) and especially the increase in revenue (effect on fuel poverty equal to - 0.81 pp). The effects of these factors were reduced by the impact of the rise in the electricity price (+0.44 pp)

Figure 7. According to hyperparameters evolution of fuel poverty between 2012/14 and 2017

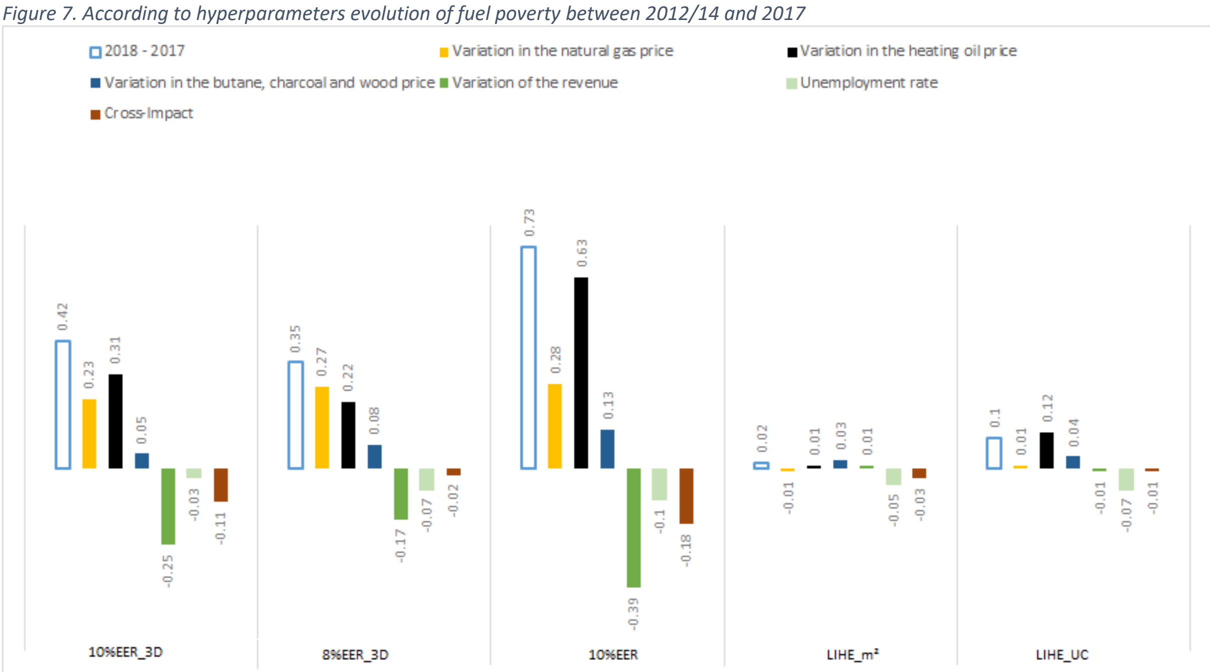


Figure 8. Evolution of fuel poverty according to hyperparameters between 2017 and 2018

3.2.3. Different types of profiles according to the fuel poverty indicator

The profile of households in fuel poverty varies according to the indicator used (see Bernard and Tessier, 2016). It is the same for households moving from one state (whether or not fuel poor) to the other. Thus, the profile of households in a situation of fuel poverty is as follows (for illustration, the figures given in appendix C are those of the simulations obtained for the year 2018).

EER_3D: These households are mostly small (for 2018, 1.86 people on average when the 10% threshold is retained, and 1.95 for an 8% threshold), with low disposable income (13,027 euros per year); the reference person is inactive (retired or unemployed; see Figure D11). Their energy expenditures for housing is on average high (2,064 euros per year against 1,536 euros per year for non-fuel-poor households). They live mainly in Ile de France; Provence-Alpe Cote d'Azur; Rhône-Alpes; Bretagne and Nord-Pas-de-Calais (Figure D21). Note that this last department is strongly affected by fuel poverty. They live mainly in dwellings of 40 m² to 100 m² built before 1961 and mainly in houses (see Figures D31, D41 and D51). These dwellings mainly have an individual boiler (see Figure D61).

LIHE_m²: Compared to the households targeted by the EER_3D and LIHE_CU indicators, the size of households in fuel poverty according to the LIHE_m² indicator is on average higher (2.28 people). These households are often younger (the average age of the HRP of fuel-poor households is equal to 53), and for more than 40%, the HRP is employed (see Figure D12). Employees are particularly affected (see D72). The disposable income is on average higher (17,758 euros per year) than are the incomes of the households targeted by the EER_3D and LIHE_CU. Energy expenditures for housing are a little less important (1,890 euros per year). Households mostly live in smaller dwellings (from 40 m² to 70 m²) and mainly buildings with more than 10 dwellings. The main regions in which these households are located are the same as those mentioned if the indicator considered is the EER_3D, but they are much more likely to live in Ile de France.

LIHE_CU: The fuel-poor households according to this indicator are close to the households targeted by the EER_3Ds (energy expenditure for their dwelling, surface area of housing, type of housing, household size, and age of the reference person). However, on average, they have disposable income (16,124) between the average of the incomes available from fuel-poor households according to the EER_3D and LIHE_m² indicators. This level is explained by the fact that they are more often employed than are households in fuel poverty according to the EER_3D.

The profiles of incoming and outgoing households in fuel poverty are consistent with those of households in fuel poverty (see Figures in Appendix D). Thus, if the indicator used is one of the LIHEs, households that become fuel poor have on average disposable income and energy expenditures higher than if the indicator used were an EERs. On the other hand, the disposable incomes and the energy expenditure for the housing of the households that leave fuel poverty according to the LIHEs are excessively weak. Among the explanations for this low income level are (1) that in our projections, a larger share of households whose reference person is disabled comes out of fuel poverty according to the LIHEs than according to the EERs. (2) There are more skilled workers coming out of fuel poverty according to the EERs than according to the LIHEs.

Households leaving energy poverty according to the EER_3Ds live mainly in dwellings of more than 70 m² and mostly from 100 m² to 150 m². The size of homes of households that come out of fuel poverty according to the LIHE_m² indicator is mostly below 100 m².

Projection for 2017 and 2018	10%EER_3d		8%EER_3d		LIHE_m²		LIHE_CU	
	2017	2018	2017	2018	2017	2018	2017	2018
Percentage of fuel poor	9.41%	9.83%	13.02%	13.37%	12.38%	12,40%	10.3%	10,4%
Average disposable income of fuel-poor households (FP) – in euros	12,550	13,027	13,836	14,205	17,488	17,758	15,808	16,124
Average disposable income of households becoming FP	14,977	16,540	17,100	18,277	19,297	21,756	19,123	20,775
Average disposable income of households leaving FP	17,993	16,540	19,266	17,262	9,565	9,698	8,885	8,174
Average disposable income of households not FP	45,027	45,585	46,181	46,735	45,428	45,871	44,975	45,435
Average energy expenditures of fuel-poor households	1,978	2,067	1,856	1,932	1,799	1,890	1,969	2,071
Average energy expenditures of households becoming FP	1,632	1,759	1,519	1,557	1,862	2,330	1,982	2,341
Average energy expenditures of households leaving FP	2,064	1,596	1,892	1,362	1,187	1,184	989	1,023
Average energy expenditures of households not FP	1,536	1,595	1,536	1,597	1,547	1,606	1,533	1,592
Average number of inhabitants of fuel-poor households	1.85	1.86	1.94	1.95	2.28	2.28	1.83	1.85
Average number of inhabitants of households becoming FP	1.97	2.03	2.25	2.28	2.2	2.26	2.03	2.16
Average number of inhabitants of households leaving FP	1.85	1.88	2.1	2.28	1.87	1.97	1.79	1.74
Average number of inhabitants of households not FP	2.36	2.36	2.36	2.36	2.31	2.31	2.36	2.36
Average age of the household reference person (HRP) of fuel-poor households	61	61	59	59	53	53	59	59
Average age of the HRP of households becoming FP	56	58	52	55	54	58	52	56
Average age of the HRP of households leaving FP	67	68	62	62	62	59	62	62
Average age of the HRP of households not FP	52	52	52	52	53	53	52	52
Average disposable income for the entire population – euros/year	41,970	42,386						
Average energy expenditures for the entire population – euros/year	1,578	1,642						

Table 3. Income, energy expenditure, and age of the household reference person and the dynamics of fuel poverty

Unemployment and fuel poverty. The percentage of households entering / leaving or being in fuel poverty in 2018 whose reference person (HRP) falls / leaves or is in unemployment is calculated (see Table 4) for the various indicators. The percentage of households that become FP and whose HRPs are unemployed is significantly lower with the LIHE_m² indicator (5.36%) than with the others (from 10.67% to 16.28%). This percentage is highest when the indicator considered is 10%EER_3D. Very few households whose HRP is unemployed are considered FP according to the 10% EER_3D (1.33%), while they number more than 10% when the LIHE_CU is considered.

Percentage of	10%EER_3D	8%EER_3D	LIHE_m²	LIHE_CU
households becoming fuel poor (FP) are households whose HRP has become unemployed.	1.6%	2.07%	2.2%	3.01%
households becoming FP are households whose HRP is unemployed.	16.28%	12.92%	5.36%	10.67%
projected fuel-poor households are households whose HRP is unemployed or has failed to work.	13.8%	13.67%	13.15%	10.59%
non-fuel-poor households in the projection are households whose HRP is unemployed or has switched without employment.	3.64%	3.24%	3.43%	3.95%
households leaving FP are households whose HRP has left unemployment.	2.88%	3.14%	0.91%	0.61%
of households leaving FP are households whose HRP is unemployed.	1.33%	7.38%	6.93%	10.97%

Table 4. Impact of unemployment on fuel poverty

The dynamics (transition from FP to non-FP status and vice versa) differ according to the indicator, and the different parameters do not have the same impact (see Tables 4 and 5).

Refurbishment and fuel poverty. While more than 86% of households leaving FP when EER_3D indicators are considered have completed thermal renovations, they are fewer than 41% when the indicator selected is a LIHE (see Table 5).

Percentage of	10%EER_3D	8%EER_3D	LIHE_m²	LIHE_CU
households leaving fuel poverty are households that have undergone any type of thermal renovation.	90.36%	86.8%	40.8%	40.95%
the households becoming fuel poor are households having carried out some thermal renovation.	0.88%	0.75%	1.69%	1.82%
of projected fuel-poor households are households that have undergone any type of thermal renovation.	7.09%	6.9%	4.61%	6.03%
of non-fuel-poor households are households that have undergone any type of thermal renovation.	7.73%	7.78%	8.1%	7.85%

Table 5. Impact of refurbishment on fuel poverty

3.3. Sensitivity of indicators to the different input variables

The sensitivity of the model to variation in a single variable is studied (see Figure 9). As expected, the fuel poverty ratios (EERs) are sensitive to a variation in energy prices, a variation in revenue and to a lesser extent a variation in the unemployment rate. Note that the impact of the change in energy prices and the unemployment rate is less important since the EER is restricted to the first three deciles of income. As previously discussed, revenues and prices of energies have a very strong impact on the fuel poverty ratio (EER), unlike LIHEs. Since LIHEs moved slightly during the simulation and are computed with variable thresholds (medians), they should not be very sensitive to variations in the model.

We remark overall that the number of houses renovated does not have a strong impact on this indicator. Why is that? It is because in the simulation, the renovation of households does not target specifically fuel-poor households but rather households that are the most likely to perform a refurbishment. The probability is computed using logistic regression on the households that already did a thermal renovation considering various variables, such as revenue, the age of insulation, the size of the dwelling, etc., and then predicting the probability of a specific household that did not declare any renovation (yet) performing a renovation in the future. Second, there is a random draw of the efficiency of the renovation; thus, the value can be very optimistic (such as -30%) or, conversely, much more modest (for example -5%). Even if fuel-poor households can be selected in the simulation to have a renovation of their dwelling, it is uncertain whether it will be enough to reduce the energy bill to the point that they will appear not fuel poor. Finally, even if the renovation value is optimistic, for example, a -30% gain on the energy bill, we consider that if the simulated energy bill for a household is lower than the real, declared value, the household is potentially under-consuming. We thus divide the value of the random draw we previously made by two to simulate the fact that a part of the gain on the energy bill will be used by the household to gain in comfort (it will consume more energy, everything else being equal). This usage is the rebound effect. Ultimately, the impact on the fuel-poor subpopulation is modest simply because many households that did a renovation are not fuel poor and a portion of fuel-poor households did not perform a deep renovation that could help them to exit fuel poverty. If the renovations targeted only fuel-poor households, then the story would be different, but this scenario is probably unrealistic. When we consider that the fuel poverty ratio is not restricted to the 3 first deciles of the revenue per CU (10%EER), the effect of renovations is wider simply because we target a larger population that appeared not fuel poor with the 10%EER_3D indicator. Refurbishing 1 million households represents 3.9% of the total number of households (25,6 million). In the simulation, 1 million households are not always renovated; this figure is occasionally lower and occasionally greater. Since the incidence of fuel poverty is 8.4% (according to 10%EER_3D with ENL206), if we make a random draw of households that we will renovate, then we can expect 8.4 percent of these 1 million households to be fuel poor. This figure is equal to 0.327% of the total population. In other words, in an ideal case where all the renovations that targeted fuel-poor households helped them to leave fuel poverty 100% of the time, the maximum reduction amount we could obtain would be 0.327 pp. Since we are not doing a random draw but rather using a logit model, the probability is different. The percentage of households that are fuel poor (initial year) in the population targeted by renovations is approximately 9.5%, slightly higher than the 8.4% national average. We can also compute the number of households that did a renovation and left fuel poverty after it – it is 13,764 households. We can also compute the number of households that stayed fuel poor even after a renovation – it is 79,264 households. Ultimately, of the 93,000 fuel-poor households that did a thermal renovation (of the 1 million total), 14.8% left fuel poverty. That is a good ratio but not enough to have caused an impressive variation in fuel poverty. The variation we have with the 10% EER_3D (0.05 pp of the whole population, but we rounded some numbers) corresponds to 13,764 households. If we want to have more-impressive numbers, then the simulation must be modified to target fuel-poor households more specifically, with a higher percentage of them leaving fuel poverty. More generally, a renovated household in the projection does not necessarily mean that the household was fuel poor at the starting date or that the household will systematically leave fuel poverty after the renovation. With both LIHEs, the interpretation is much more complicated; we have two phenomena at the same time: households leaving fuel poverty after a renovation (approximately 23,000), but since the renovation of the 1 million households lowered the median value of the expenditure per square metre (or per CU), more households are becoming fuel poor because of the movement of the median (approximately 39,000). The same applies for the LIHE_CU. To measure the absolute effect, we should keep the threshold of the initial year without computing the entire indicator again.

Concerning the unemployment rate, the random draw used to “create” (or reduce) unemployment in the database is implemented by comparing the estimated revenue of the household compare to its real value (see 2.4.3). Concerning the renovation and the simulation of the rebound effect, if the estimated value of the revenue for a given household is higher than its declared revenue, then the household is more likely to "come back" to the average situation/revenue of households with the same profiles in our data. For example, if we have one household with one couple, both with no diplomas, living in a small house in the countryside but earning 50,000 euros per year, while average similar households earn 25,000 euros per year, we consider this situation "abnormal' and that the household will have a higher probability to suffer from a rise of the unemployment rate. While this technique is quite rough, it is still better than choosing households randomly. Of course, households with a reference person who is retired or unemployed are not used for the draw if we increase the unemployment rate. To increase the employment rate (or reduce the unemployment rate, which is the same), we proceed the same way; this time, we just consider households with an estimated revenue lower than the declared revenue and only those that are unemployed. We do not know directly the unemployment rate such as the one computed by OECD; recall that we work with households and not individuals. We simply know the unemployment rate of the reference person in the household in mainland France, which is approximately 4.5% of the entire population in 2006. A rise in unemployment is made by simply using a cross product with this initial value. Increasing the unemployment rate from 9% to 10% is equivalent to increasing the "household unemployment rate" by $4.5 \times \frac{9{,}85}{8{,}85} - 4.5 = 0.508$ pp. In other words, on average, if an indicator was perfectly sensitive to unemployment rate and a newly unemployed household was necessarily becoming fuel poor, then the indicator would gain 0.508 points (increasing for example from 10% to 10.508%). With the three fuel poverty ratio indicators (10%EER_3D, 8%EER_3D and 10EER), the effect of a rise of 1 pp in the unemployment rate increases the fuel poverty ratio by 0.09, 0.1 and 0.15 pp, respectively, which are approximately 3 to 5 times lower than the "maximum effect possible". This is a fairly small effect; however, a large percentage of fuel-poor households are also employed (changing their status to unemployed does not modify the frequency of FP), and many households will not be fuel poor even if the reference person in the household becomes fuel poor; 23.6% of unemployed households are fuel poor with the 10%EER_3D in 2006 (23.9% with EER), an impressive rate that is 6 times higher than that for the entire population but is far from 100%. When we multiply the optimal "0.508" by 23.6%, we obtain a value equal to 0.12. In other words, if we take the fuel poverty ratio 3d and we expect 23.6% (on average) of newly unemployed households to fall into fuel poverty, then we obtain a theoretical gain of 0.12 pp on the indicator. We have a value of 0.09 pp for the 10%EER_3D, 0.1 pp for 8%EER_3D and 0.15 pp for 10%EER. This result is not perfect but is definitely acceptable. The difference is explained by the fact that with the EER_3D, our model probably underestimates the effect of unemployment on revenue. A value of 0.09 means that approximately 17.7% (0.508 x 0.18 = 0.09) of our households that became unemployed in the simulation are now fuel poor in the projection, a lower percentage than the average observed value of 23.6%. A better estimation of the impact of unemployment on household revenue in our multiple linear regression model might be a solution to correct the error. With the LIHE_m² and LIHE_CU indicators, the rise is equal to 0.13 pp and 0.14 pp, respectively, between the observed value for the 8%EER_3D and 10%EER. Again, with these indicators, the movement is harder to interpret because increasing unemployment not only increases the number of fuel-poor households but also reduces the median of the net revenue in the population (because it is influenced by the variation in the gross revenue) and reduces the number of fuel poor at the same time. However, the variation is significant and positive.

The rightmost histogram bars in Figure 9 show that revenue has an impact on the three fuel poverty ratios but not on the LIHEs. However, the 1% increase is not very large. For example, the rise from 2007 to 2013 was equal to 6.6%. However, the variation is much less than the fuel poverty ratio (0.02 pp against 0.15 pp for the 10%EER_3d, 0.17 pp for the 8%EER_3D and 0.18 pp for the 10%EER).

The impact of energy price changes on the evolution of fuel poverty is significant since the EER_3D indicators are used. Since the increase in the price of electricity affects all households, the change in the price of this energy will have a higher effect than the same price variation in another energy. Thus, if the indicator 8% EER_3D is retained, an increase of 10 pp in the electricity price will contribute to an increase of 0.60 pp in the percentage of fuel poverty, whereas the increase of 10 pp in the natural gas price will generate an increase of 0.24 pp.

It is possible to calculate the increase in income needed to offset the rise in energy prices. Thus, if the indicator chosen is the 8%EER_3D, then an increase in the electricity price of 10 pp should be accompanied by an increase in income of approximately 3.53 pp so that the number of fuel-poor households remains stable.

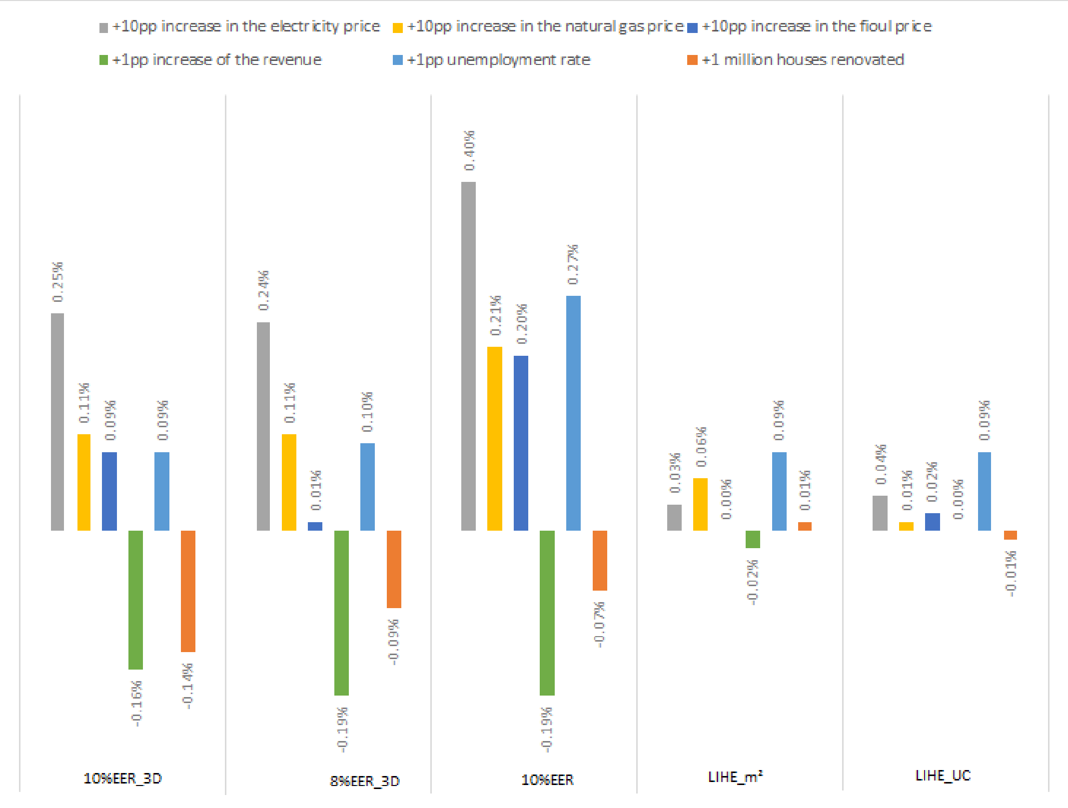


Figure 9: Impact of hyperparameters on fuel poverty

The fuel poverty ratios 8%EER_3D and 10%EER_3D seem to be the easiest to use for a projection with good reactions for the hyperparameters of the model. LIHEs are not very reactive, and using them to identify the isolated impact of a variable is more cumbersome than using the fuel poverty ratio. Consequently, projection with the EER_3d indicators is recommended – and that is exactly what Devalière et al. (2018) do.

Conclusions

This paper presents a micro-simulation model, developed from the French national housing survey, that simulates the percentage of household fuel-poor (not including the cost of mobility[27]) in mainland France. The paper makes it possible to evaluate the impact on fuel poverty of changes in the determining factors, namely, the price of energy, income, and rate of unemployment, among others.

In its latest report in November 2018, ONPE retained two new indicators of fuel poverty compared to previous studies[28]: the 8% EER_3D and the "info-energy barometer" of the French energy ombudsman. The latest barometer stated that 30% of French households reduced their heating consumption in 2017 to reduce their energy costs. This indicator, which we do not use in our study, deserves to be published

[27] An extension of our model will be to include this cost.
[28] Previously, the indicators used were 10%EER_3D, LIHE_m², LIHE_UC and COLD_3D.

annually, but it concerns a small sample of 1,500 households, which is too small, without taking their income into account.

The evolution of fuel poverty in our study is based on not only the 8% EER_3D but also the 10%EER_3D and LIHEs. The LIHEs do not change much because their construction is based on medians. Thus, with the LIHEs, an increase of 10 pp in the price of electricity or the price of natural gas has the effect of an increase in fuel poverty of at most 0.06 pp. On the other hand, with the 8%EER_3D, an increase of 10 pp in the price of electricity (respectively natural gas) results in an increase of 0.6 pp (resp. 0.26 pp) in fuel poverty. However, taking these different indicators into account is important, as they do not target the same population.

We estimate that the percentage of fuel-poor households, in 2018, according to the indicators 10%EER_3D, LIHE_m² and LIHE_UC is 17.08%. The increase in energy prices to consumers without any increase in revenue in return obviously increases this percentage.

One solution to reduce fuel poverty is thermal housing renovation, but it must be targeted to reduce the number of fuel poor households. However, on the one hand, fuel-poor households rarely have the financial means to carry out these renovations. On the other hand, renter households do not have the power to oblige their lessor to carry out these renovations. If this obligation were possible, it would probably result in an increase in rent and consequently a decrease in disposable income. In this case, the decrease in energy expenditure due to the thermal renovation should be high enough to offset the rise in rent.

Appendices

Appendix A. Multiple linear models

The tables in this appendix yield the household income estimate, the probability that a household is performing a thermal renovation and estimating a household's energy expenditure.

A.1. Gross Household income estimate

	Dependent variable: --------------------------- Log(Gross Household Income)
Age	0.043***
	(0.001)
Age²	- 0.0004***
	(0.00001)
No child	-
One child	0.167***
	(0.009)
Two children	0.254***
	(0.009)
Three children or more	0.291***
	(0.013)
Employed	-
Unemployed	-0.697***
	(0.014)
Retired	-0.143***
	(0.042)
Inactive (home)	-0.504***
	(0.046)
Inactive (disabled)	-0.562***
	(0.044)
SPC: retired	-
SPC: Farmer	-0.140***
	(0.048)
SPC: Craftsman, tradesman,	0.186***
entrepreneur, liberal profession	(0.043)
SPC: Executive,	0.383***
intellectual profession	(0.043)
SPC: Intermediate profession	0.176***
	(0.042)
SPC: Employee	-0.082*
	(0.042)
SPC: Qualified worker	0.088**
	(0.042)
SPC: Nonqualified worker	-0.061
	(0.043)
SPC: Other	-0.166***
	(0.021)
No Diploma	-
Low diploma	0.244***
	(0.008)
Medium diploma	0.425***
	(0.013)
High diploma	0.526***
	(0.012)
Declared energy expenditures	0.0002***
	(0.00000)
Ile de France Region	-
Champagne-Ardenne	-0.089***
	(0.020)
Picardie	-0.218***
	(0.018)
Haute-Normandie	-0.090***
	(0.020)
Centre	-0.136***
	(0.016)
	-0.174***

Basse-Normandie	(0.019)
Bourgogne	-0.114***
	(0.018)
Nord Pas De Calais	-0.161***
	(0.013)
Lorraine	-0.140***
	(0.016)
Franche-Comté	-0.030*
	(0.018)
Pays de la Loire	-0.128***
	(0.021)
Bretagne	-0.099***
	(0.013)
Poitou-Charentes	-0.186***
	(0.017)
Aquitaine	-0.164***
	(0.014)
Midi-Pyrénées	-0.153***
	(0.015)
Limousin	-0.169***
	(0.023)
Rhônes-Alpes	-0.099***
	(0.012)
Auvergne	-0.180***
	(0.021)
Languedoc-Roussillon	-0.174***
	(0.015)
Provence-Alpes-Côte d'Azur	-0.132***
	(0.012)
Native French	-
Naturalized French	-0.051***
	(0.014)
Not French, EU15	0.028
	(0.019)
Not French, EU new countries 2004	-0.477***
	(0.115)
Algeria, Morocco, Tunisia	-0.191***
	(0.023)
Africa	-0.317***
	(0.040)
Other or without nationality	-0.157***
	(0.029)
Intercept	***8.738****
	(0.050)
Observations	*40,396*
R^2	*0.402*
Adjusted R^2	*0.402*
Residual Std. Error	*14.328 (df = 40348)*
F Statistic	*578.009*** (df = 47; 40348)*

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.1. Gross Household income estimate

A.2. Housing refurbishment estimate

	Dependent variable:
	Housing refurbishment
Gross revenue	0.00000
	(0.00000)
Employed	-
Unemployed	-0.048
	(0.070)
Retired	-0.064
	(0.039)
Staying home	-0.105
	(0.111)
Disabled	0.099
	(0.113)
Less than 25 m²	-
From 25 to 40 m²	0.011

	(0.178)
From 40 to 70 m²	0.173
	(0.164)
From 70 to 100 m²	0.134
	(0.165)
From 100 to 150 m²	0.184
	(0.168)
More than 150 m²	0.151
	(0.175)
Detached house/farm	-
Terraced house	0.003
	(0.041)
Building with 2 flats or fewer	-0.220
	(0.147)
Building with 9 flats or fewer	-0.114
	(0.089)
Building: more than 10 flats	-0.130
	(0.083)
Precarious dwelling	-1.523
	(1.012)
Other type of dwelling	0.067
	(0.223)
Humidity detected	0.123***
	(0.045)
Noisy dwelling	-0.017
	(0.054)
Unknown date of construction	-
From 1990 to today	-0.111
	(0.085)
From 1962 to 1989	0.864***
	(0.072)
Before 1961	1.061***
	(0.073)
Individual heater	-
Urban heater	-0.754***
	(0.141)
Collective heater	-0.956***
	(0.074)
Mixed heater	0.321
	(0.240)
Individual electric heater	0.054
	(0.041)
Other types of heater	-0.289***
	(0.053)
Unknown insulation	-
Collective insulation	0.350**
	(0.151)
Recent insulation	0.692***
	(0.073)
Old insulation but enough	0.419***
	(0.071)
Old insulation, not enough	1.049***
	(0.080)
Intercept	-2.738***
	(0.193)
Observations	30,297
Log Likelihood	-12,281.260
Akaike Inf. Crit.	24,624.530
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.2. Housing refurbishment estimate

A.3. Energy expenditure estimate

	Dependent variable:
	log_depenses_energie
Gross revenue	0.00000***

	(0.00000)
Less than 25 m²	-
From 25 to 40 m²	0.082***
	(0.027)
From 40 to 70 m²	0.316***
	(0.025)
From 70 to 100 m²	0.515***
	(0.026)
From 100 to 150 m²	0.665***
	(0.026)
More than 150 m²	0.872***
	(0.027)
Detached house/farm	-
Terraced house	-0.097***
	(0.007)
Building with 2 flats or fewer	-0.205***
	(0.028)
Building with 9 flats or fewer	-0.292***
	(0.024)
Building: more than 10 flats	-0.335***
	(0.024)
Precarious dwelling	-0.254*
	(0.144)
Other type of dwelling	-0.193***
	(0.033)
Humidity detected	0.029***
	(0.008)
Noisy dwelling	-0.018**
	(0.008)
No bath nor shower	0.175***
	(0.026)
No toilets inside the dwelling	-0.070***
	(0.008)
Unknown date of construction	-
From 1990 to today	-0.055***
	(0.012)
From 1962 to 1989	0.057***
	(0.010)
Before 1961	0.114***
	(0.010)
Individual heater	-
Urban heater	-0.822***
	(0.019)
Collective heater	-0.006
	(0.009)
Mixed heater	-0.591***
	(0.031)
Individual electric heater	-0.162***
	(0.007)
Other types of heater	-0.353***
	(0.010)
Unknown insulation	-
Collective insulation	0.017
	(0.023)
Recent insulation	0.034
	(0.023)
Old insulation but enough	0.061**
	(0.024)
Old insulation, not enough	0.052**
	(0.024)
Thermal renovation	0.013**
	(0.007)
Ile_de_France	-
Champagne_ardenne	0.046**
	(0.018)
Picardie	0.075***
	(0.016)
Haute_normandie	0.023
	(0.018)
Centre	0.050***

	(0.015)
Basse_normandie	-0.002
	(0.018)
Bourgogne	0.099***
	(0.016)
Nord_pas_de_calais	-0.020*
	(0.012)
Lorraine	0.026*
	(0.015)
Alsace	0.025
	(0.016)
Franche_comte	0.030
	(0.019)
Pays_de_la_Loire	-0.107***
	(0.012)
Bretagne	-0.129***
	(0.013)
Poitou_charentes	-0.083***
	(0.016)
Aquitaine	-0.111***
	(0.012)
Midi_pyrenees	-0.030**
	(0.014)
Limousin	-0.037*
	(0.021)
Rhone_alpes	0.047***
	(0.011)
Auvergne	-0.041**
	(0.019)
Languedoc_roussillon	-0.064***
	(0.014)
Provence_alpes_cote_azur	0.004
	(0.011)
Intercept	6.372***
	(0.042)
Observations	40,396
R2	0.389
Adjusted R2	0.388
Residual Std. Error	12.850 (df = 40346)
F Statistic	523.842*** (df = 49; 40346)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.3. Energy expenditure estimate

Appendix B. Fuel poverty in 2006

	Fuel poverty ratio (10%)	BRDE m²	BRDE UC
Percentage of fuel poor households *(Bernard and Teissier, 2016)*	**8.36%** *(8.4%)*	**12.25%** *(12.4%)*	**10.17%** *(10.2%)*
Average disposable income of fuel-poor households (FP)	**10,560 euros** *(10,953 euros)*	**15,238 euros** *(14,502 euros)*	**13,636 euros** *(13,529 euros)*
Average disposable income of households not FP	39,320 euros	39,883 euros	39,552 euros
Average energy expenditures of fuel-poor households	**1,716 euros** *(1,732 euros)*	**1,503 euros** **(1,494 euros)**	**1,653 euros** **(1,653 euros)**
Average energy expenditures of households not FP	1,275 euros	1,286 euros	1,274 euros
Average number of inhabitants of fuel-poor households	**1.81** *(1.83)*	**2.28** *(2.3)*	**1.83** *(1.89)*
Average number of inhabitants of households not FP	2.35	2.30	2.36
Average age of the HRP* of fuel-poor households	**61** *(59)*	**53** *(52)*	**59** *(56)*
Average age of the HRP of households not FP	52	53	52

Table B: Statistics for the initial year 2006

Appendix C. Values of the parameters for the simulations of the energy fuel poverty of the years 2017 and 2018

Label of the parameter	**2017**	**2018**

Number of renovated households during the simulation	2 000 000	2 000 000
Average gain (in percentage of the total energy bill) after a thermal renovation	-25%	-25%
Variation in electricity price	43%	43%
Variation in natural gas price	38%	56%
Variation in heating oil price	18%	46%
Variation in butane price	39%	53%
Variation in wood price	20%	27%
Variation in charcoal price	80%	80%
Elasticity value of electricity consumption	-0.31	-0.31
Elasticity value of natural gas consumption	-0.28	-0.28
Elasticity value of heating oil consumption	-0.24	-0.24
Elasticity value of butane consumption	-0.24	-0.24
Elasticity value of wood consumption	-0.24	-0.24
Elasticity value of charcoal consumption	-0.24	-0.24
Variation in the disposable income of households	14.5%	15.5%
Variation in social aids received by households	14.5%	15.5%
Automatic computing of the double median for the fuel poverty ratio (0 or 1)	0	0
Threshold of the fuel poverty ratio, initial year of simulation	8%	10%
Threshold of the fuel poverty ratio, final year of simulation	8%	10%
Number of repetitions of the imputation with MICE	5	5
Unemployment rate, initial year	8.85%	8.85%
Unemployment rate, final year	9.40%	9.00%

Table C. Value of the parameters for the 2017 and 2018 projections

Appendix D. Evolution of fuel poverty between ENL2006 and 2018

The figures in this appendix give the profile of fuel poor households (according to different indicators) in 2006 and 2018 and the profiles of households entering and leaving fuel poverty. They show that fuel poverty indicators do not target the same households.

D.1. Fuel poverty according to the employment status of the household reference person

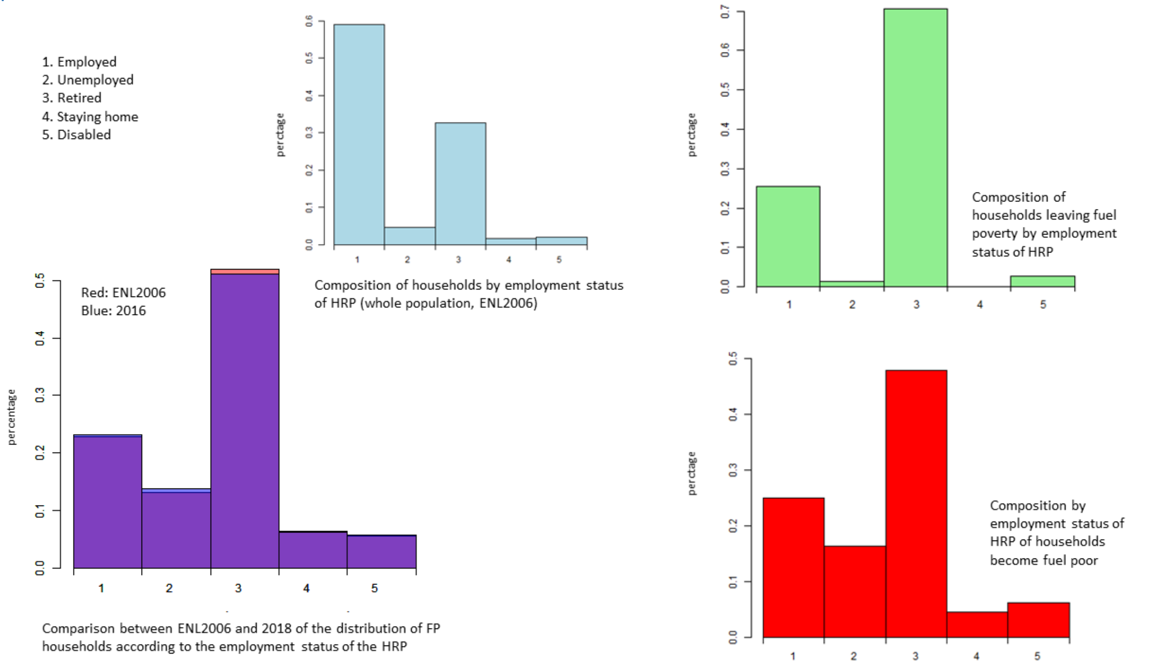


Figure D11. Fuel poverty according to the 10%EER_3D

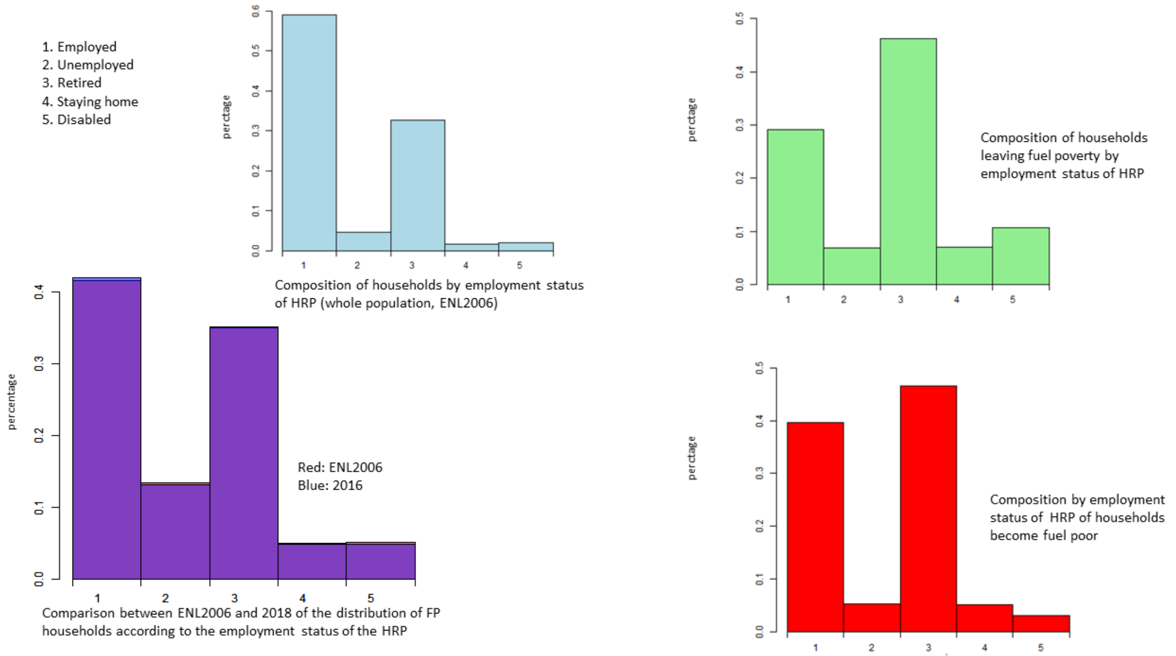


Figure D12. Fuel poverty according to the LiHE_m²

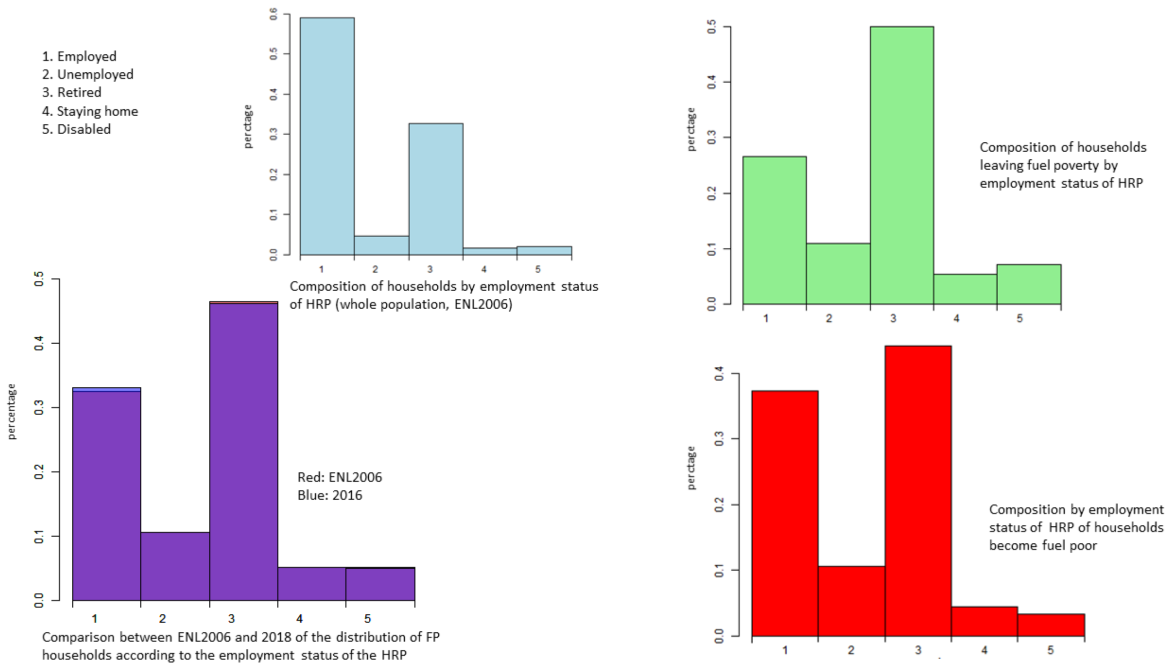


Figure D13. Fuel poverty according to the LIHE_uc

D.2. Fuel poverty depending on the residence region of the household reference person

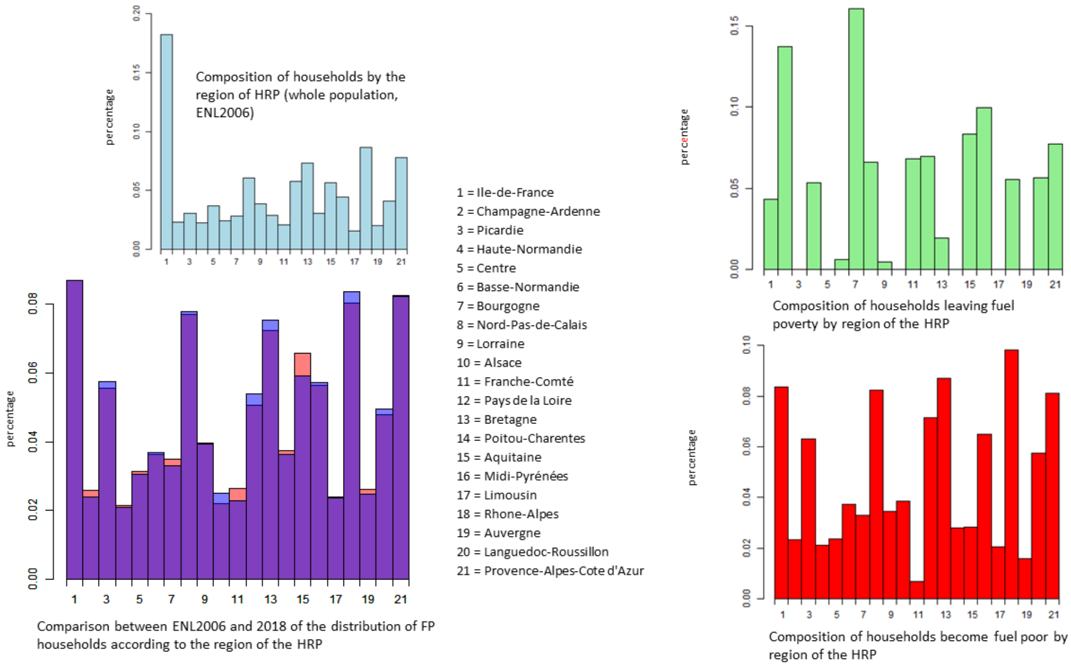


Figure D21. Fuel poverty according to the 10%EER_3D

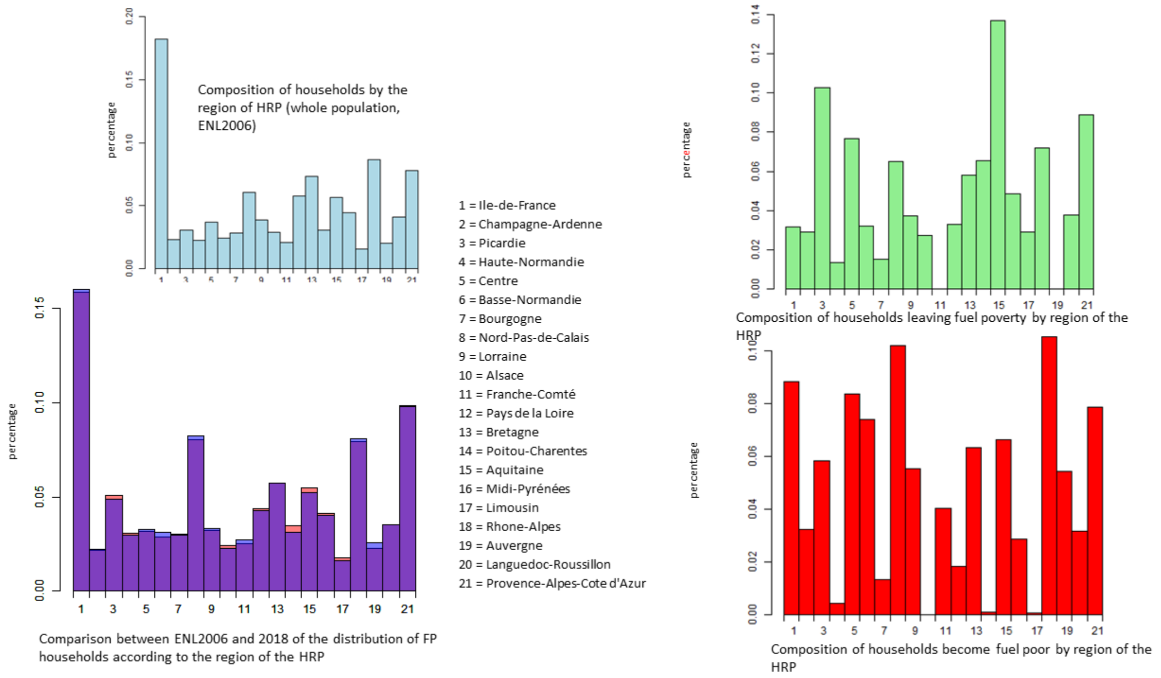


Figure D22. Fuel poverty according to the LiHE_m^2

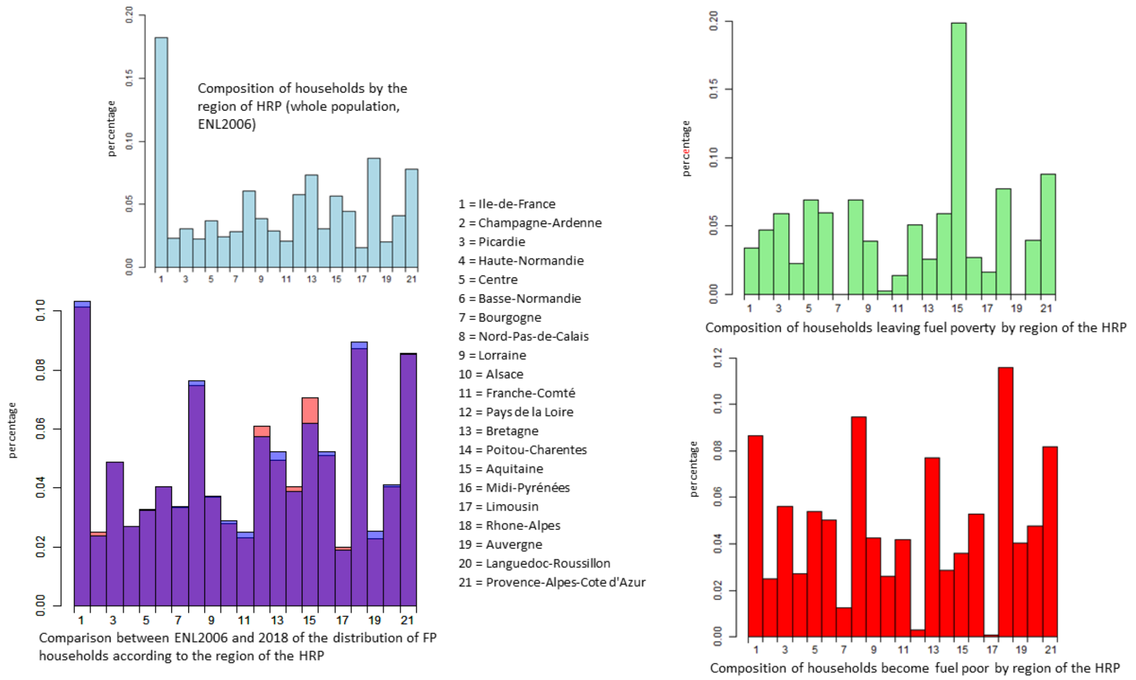


Figure D23. Fuel poverty according to the LIHE_uc

D.3. Fuel poverty depending on the dwelling surface area of the household reference person

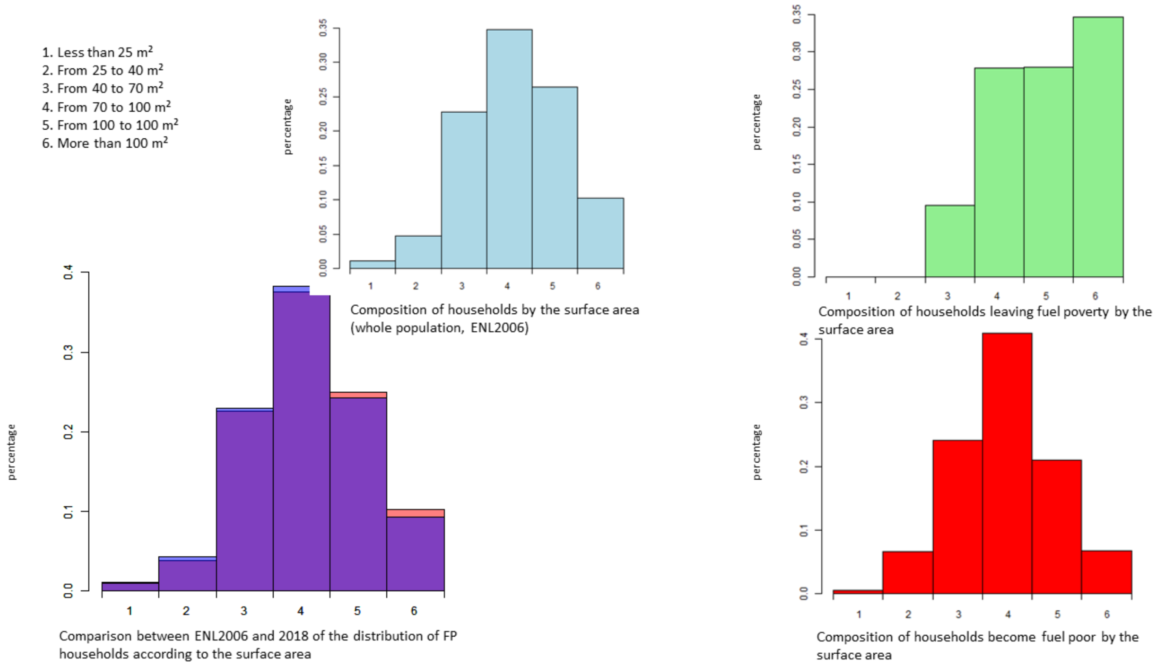


Figure D31. Fuel poverty according to the 10%EER_3D

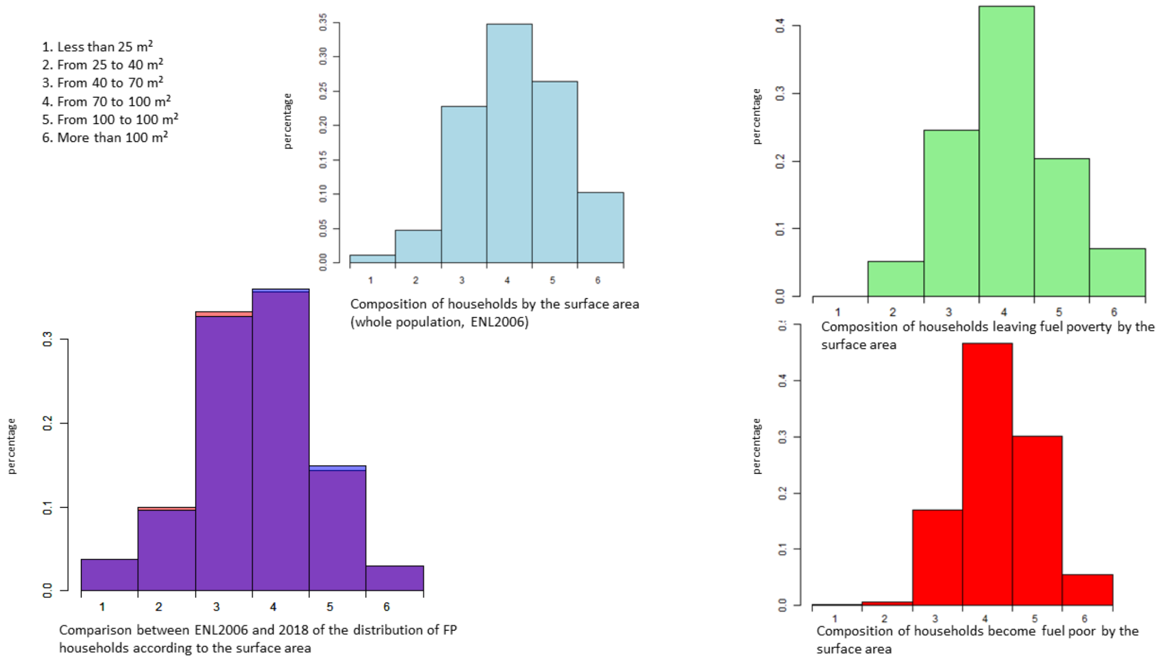


Figure D32. Fuel poverty according to the LiHE_m²

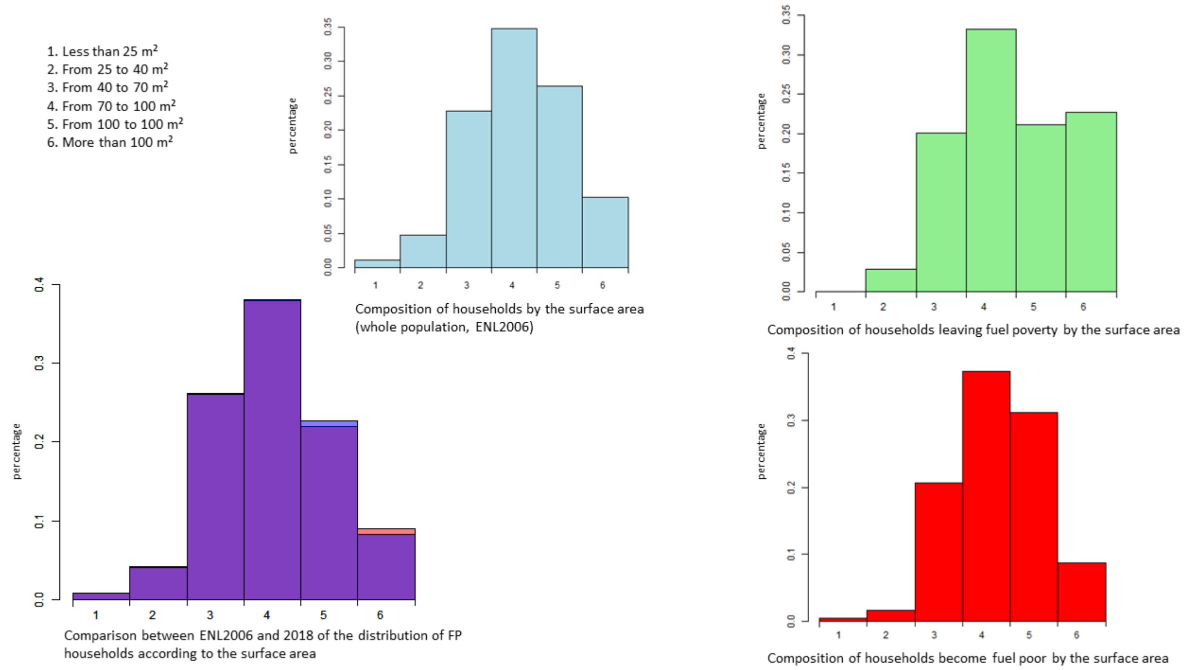


Figure D33. Fuel poverty according to the LIHE_uc

D.4. Fuel poverty depending on the dwelling type of the household reference person

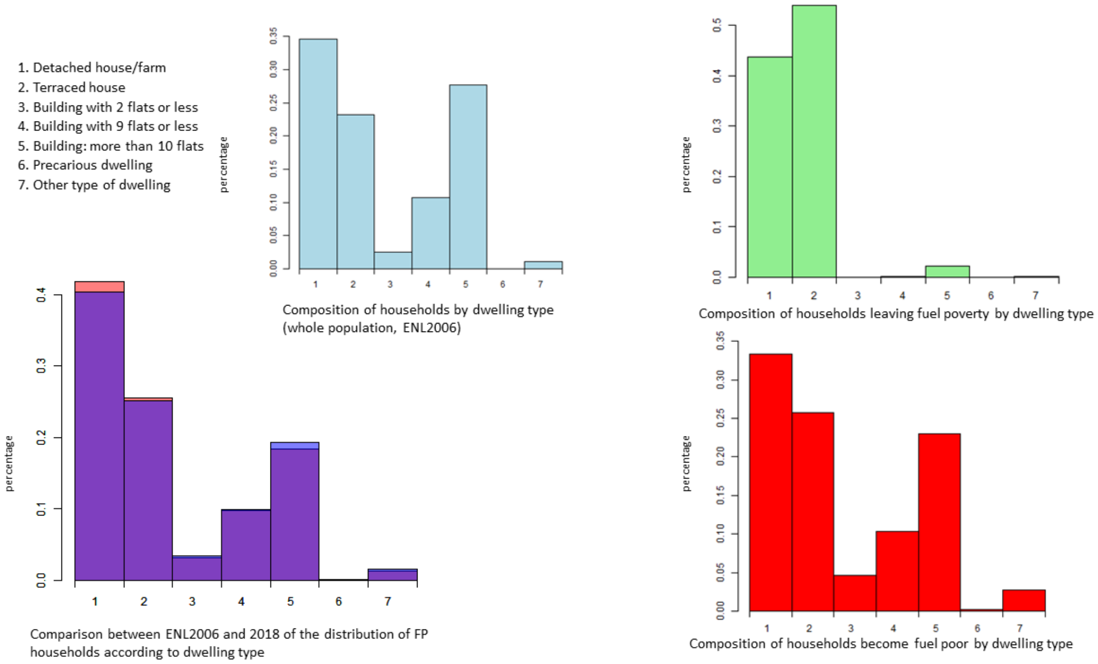


Figure D41. Fuel poverty according to the 10%EER_3D

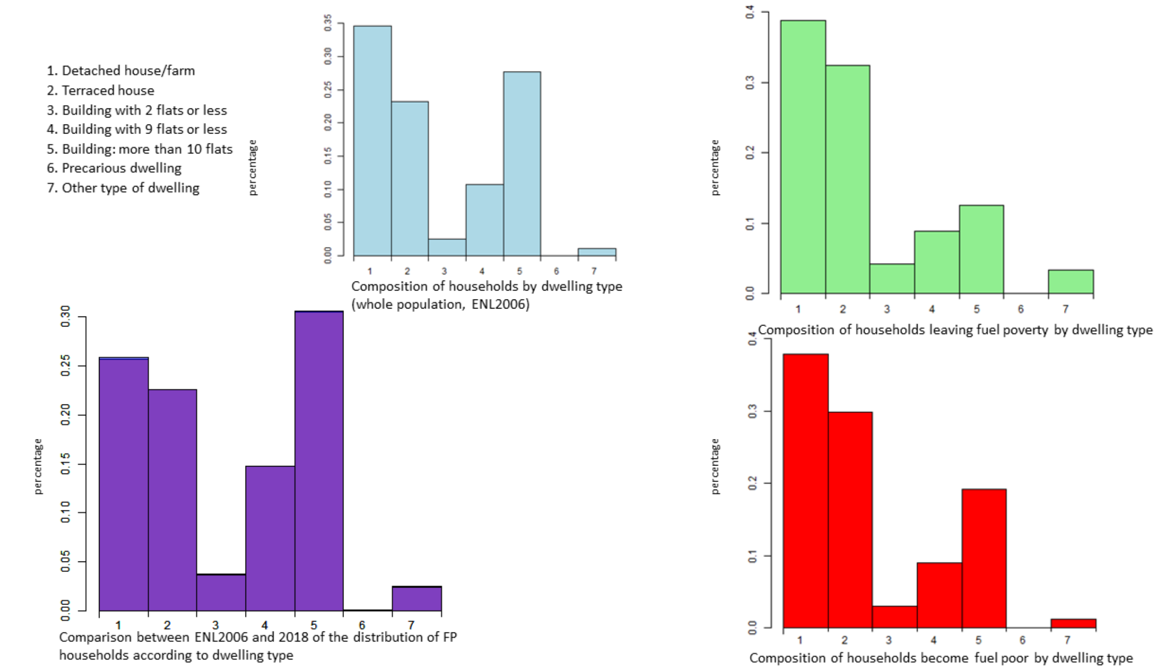


Figure D42. Fuel poverty according to the LiHE_m²

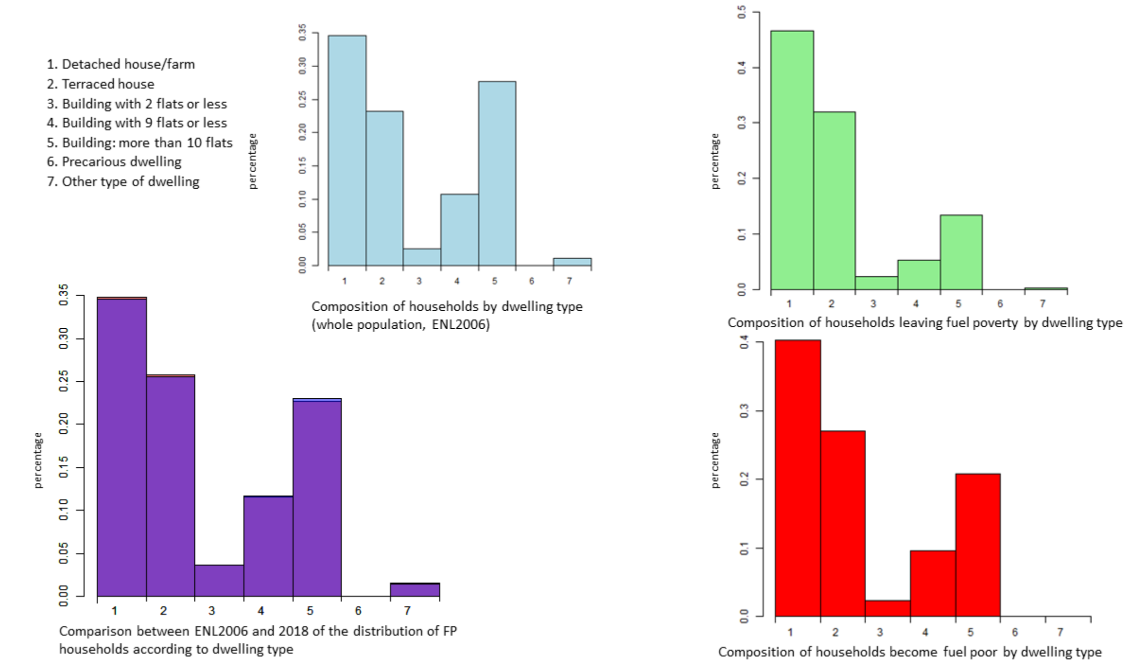


Figure D43. Fuel poverty according to the LIHE_uc

D.5. Fuel poverty depending on the date of dwelling construction of the household reference person

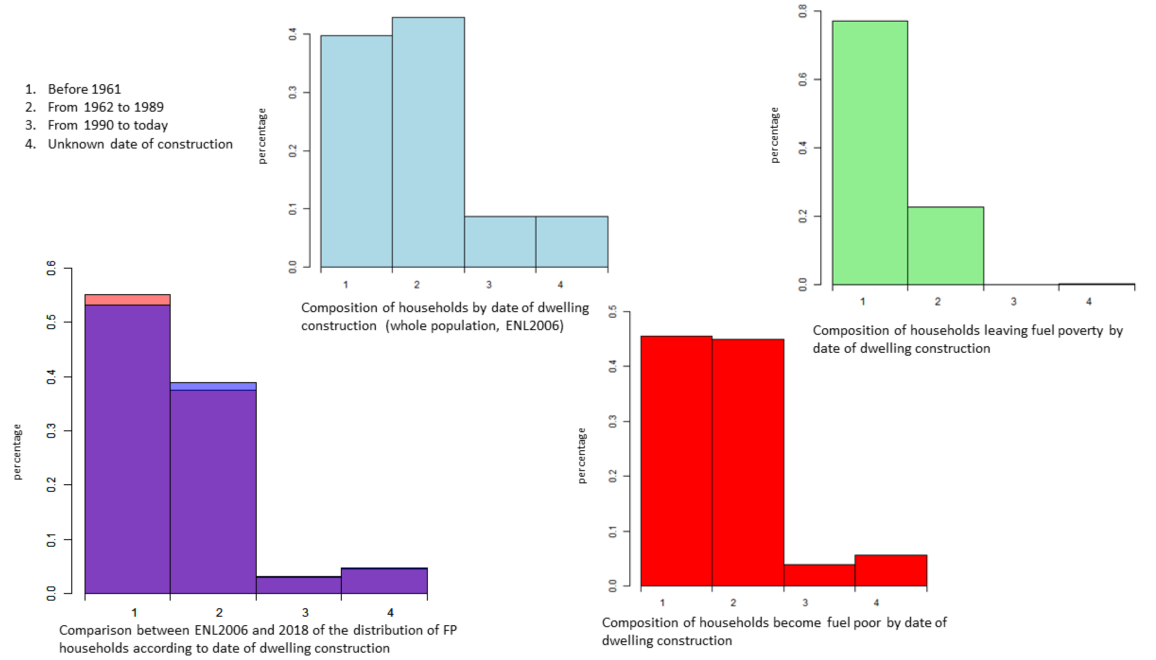


Figure D51. Fuel poverty according to the 10%EER_3D

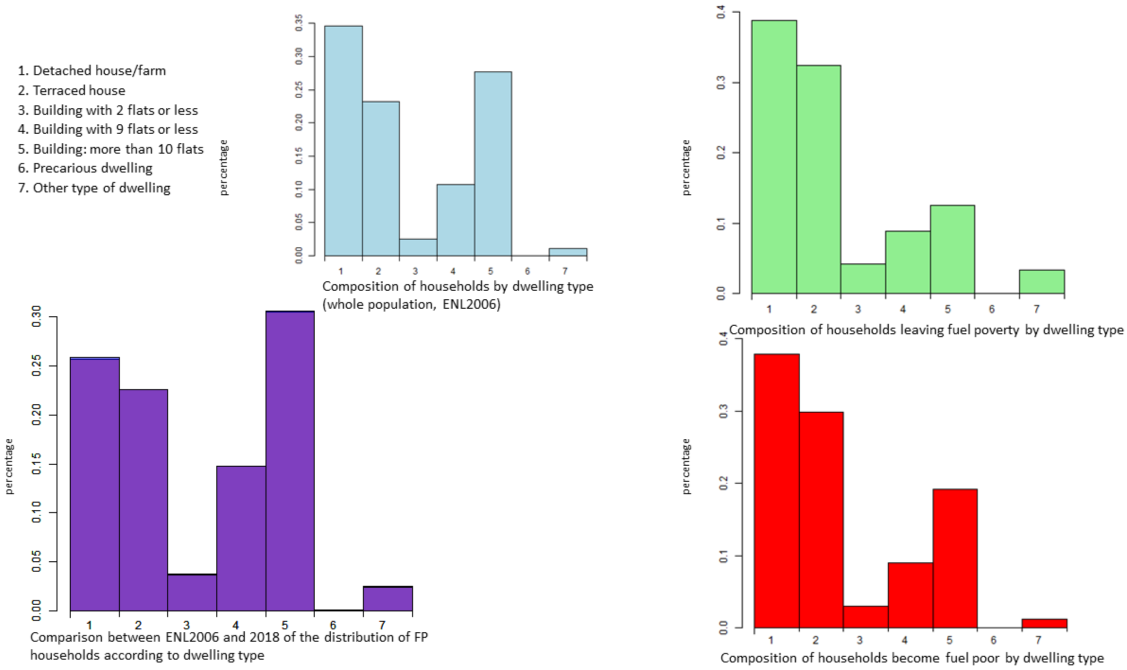


Figure D52. Fuel poverty according to the LiHE_m²

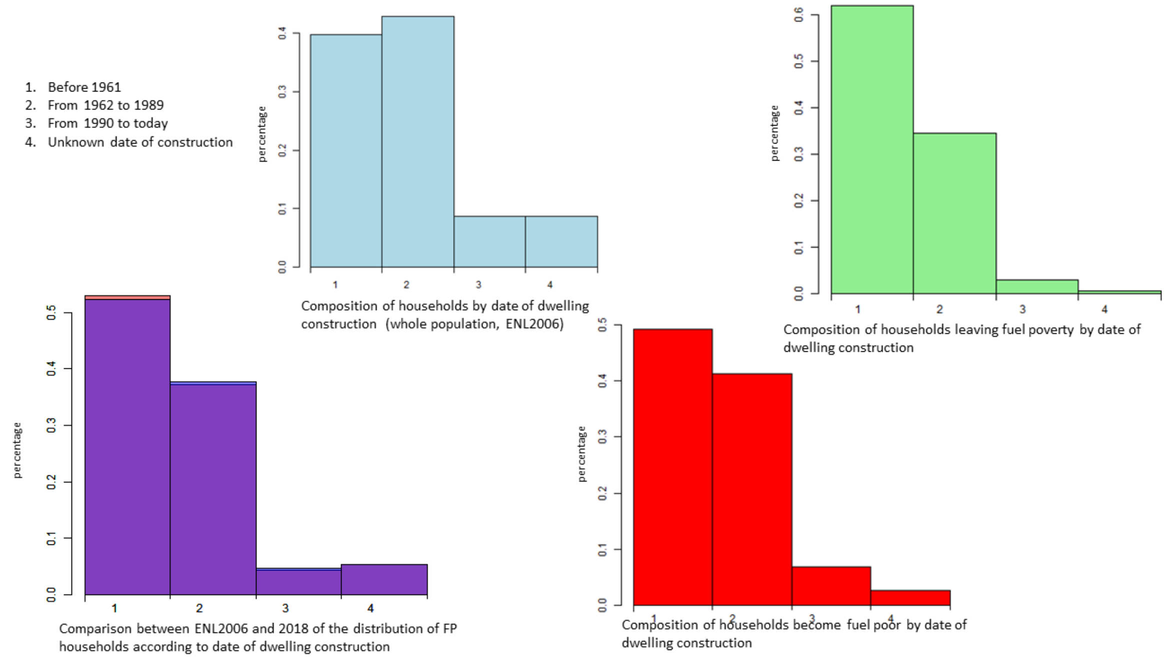


Figure D53. Fuel poverty according to the LIHE_uc

D.6. Fuel poverty depending on the dwelling heating system of the household reference person

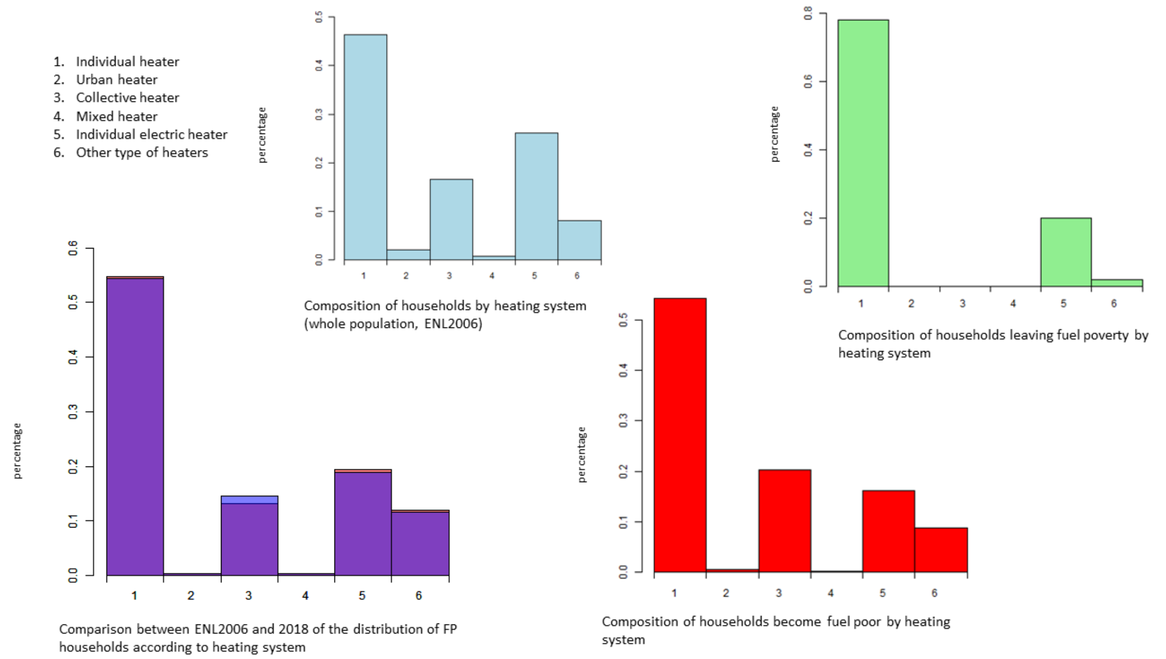


Figure D61. Fuel poverty according to the 10%EER_3D

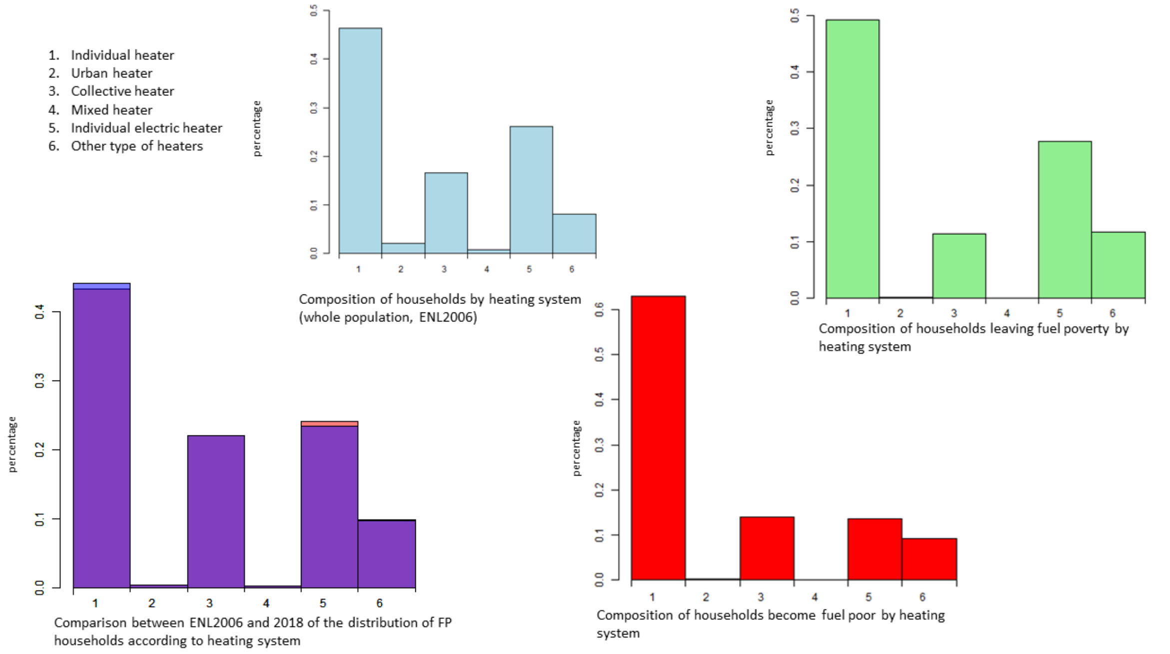


Figure D62. Fuel poverty according to the LiHE_m²

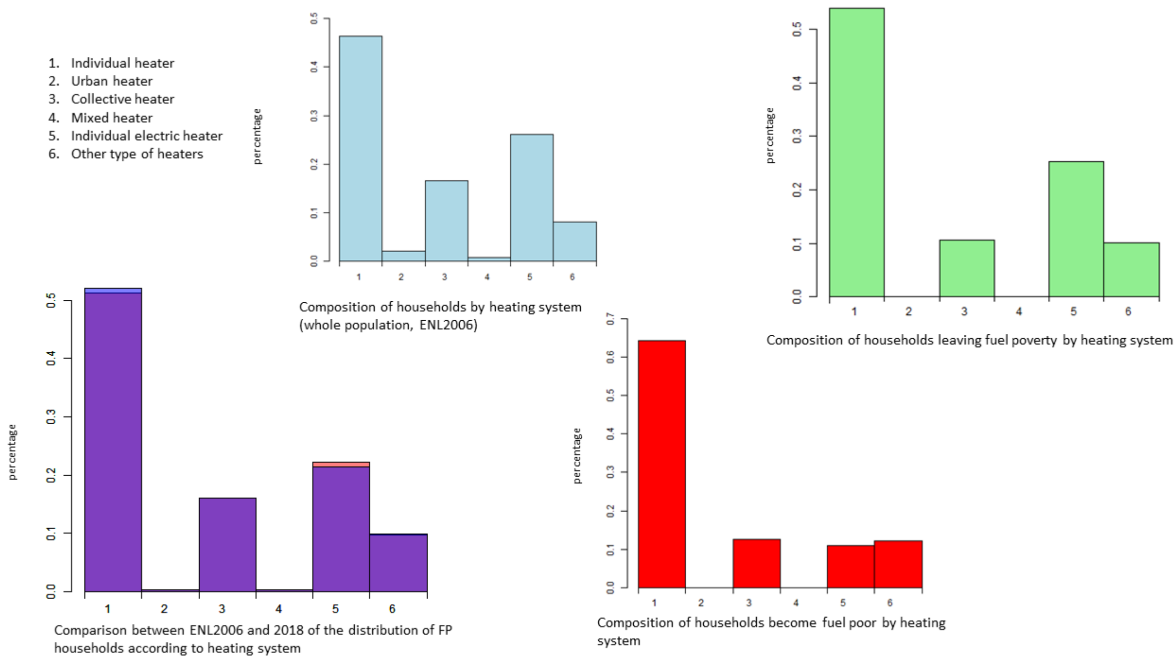


Figure D63. Fuel poverty according to the LIHE_uc

D.7. Fuel poverty according the socio-professional category of the household reference person

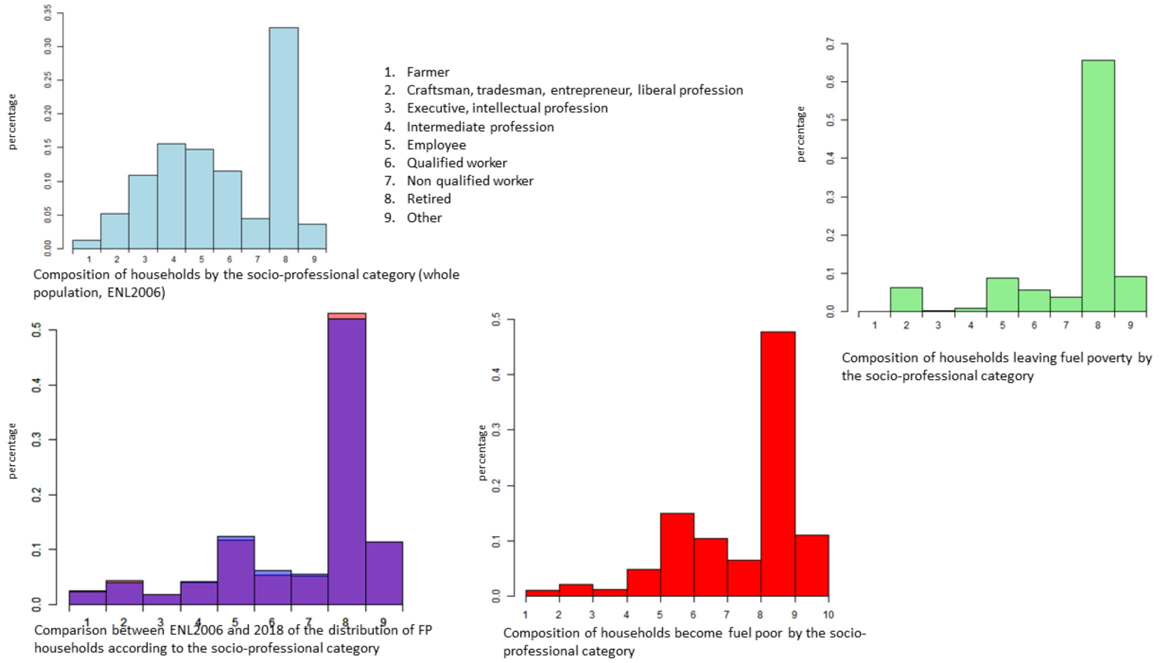


Figure D71. Fuel poverty according to the 10%EER_3D

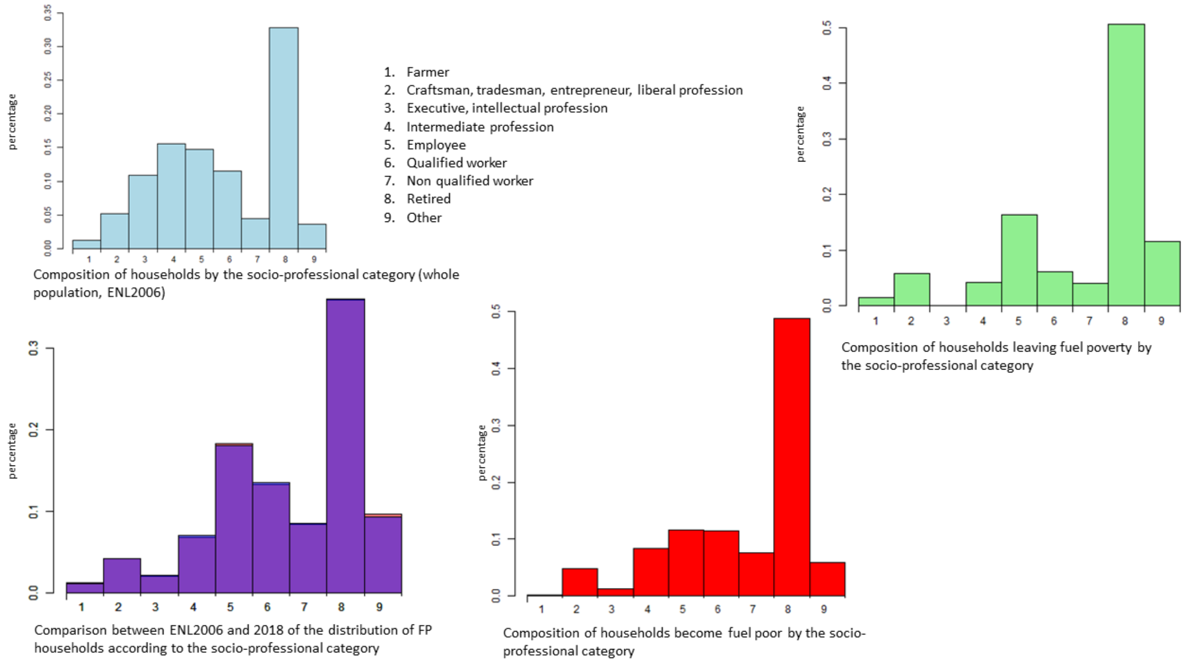


Figure D72. Fuel poverty according to the LiHE_m²

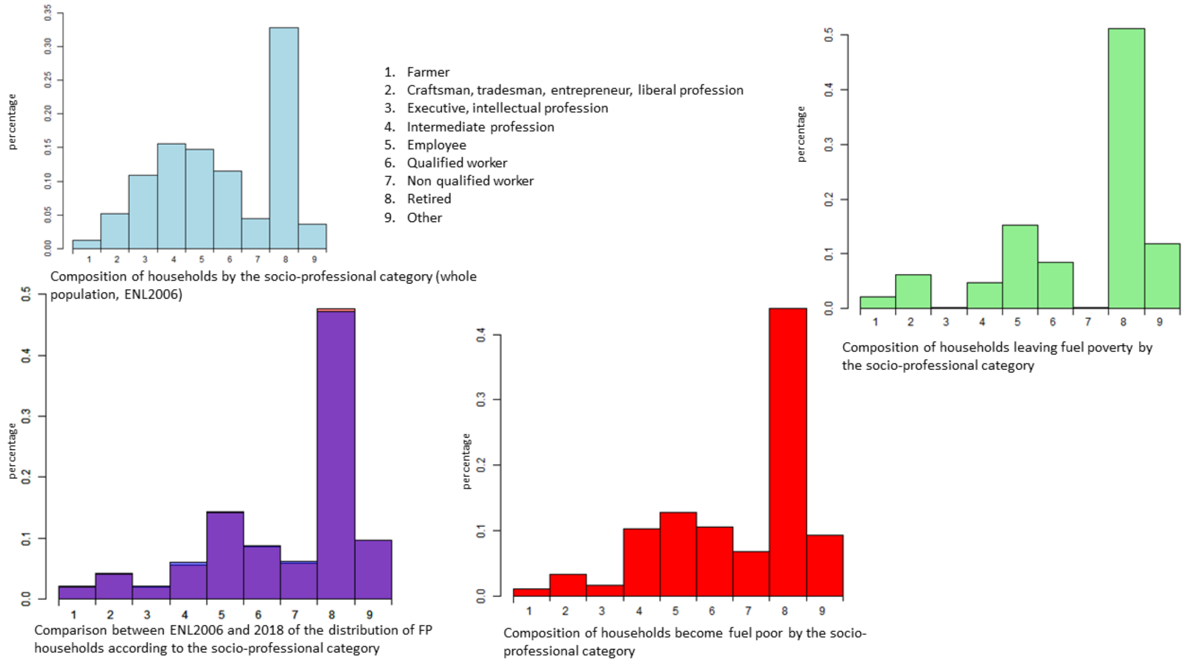


Figure D73. Fuel poverty according to the LIHE_uc

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