# *Beyond average energy consumption in the French residential housing market: a household classification approach*

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## Overview

Residential and tertiary sector represents about 45% of global energy consumption in France and 21% of $CO_2$ emissions in 2012. This sector consumes more energy than any other sector in the country (31% for transport, 21% for industry and less than 3% for agriculture) and within the sector, the residential part accounts for 60%. As such residential sector is considered as a key driver for energy efficiency programs (insulation, smart metering...) and more globally for energy policy. Energy consumption in private houses stems from three main usages : space heating (70% of the total expenditures), hot water and cooking (15%) and specific electricity use[1] (15%). Moreover in order to offer a comparable set of energy efficiency measure on buildings, the promotion for energy efficiency in residential building is mainly based on conventional and modeled consumption that does not take into account thoroughly and narrowly the household's characteristics and actual behaviors. In the new environment marked by the growing importance of Green House Gases (GHG) emissions, fuel poverty and energy efficiency in the different national agendas, the comprehension of energy demand factors appears to be crucial for the effectiveness of energy policies. We consider these latter could be improved by targeting specific households groups rather than searching to follow a single energy consumption level target. This article explores the scope of having a disaggregated energy consumption market to design policies aimed at curbing residential energy consumption or lowering its carbon intensity. Using a clustering method based on CHAID methodology, we find that the different levels of energy consumption in the French residential sector are related to socio-economic, dwelling and regional characteristics. Then we build a typology of energy consuming households where targeted groups (fuel poor, high income and high consuming households) are automatically and separately identified through a simple and transparent set of characteristics. This classification represents an efficient tool for energy efficiency programs and for energy poverty policy but also for potential investors such as banks which could provide specific and tailor made financial tools for different groups of consumers. Furthermore, this approach is helpful to design an energy efficiency score that could reduce the uncertainty on rebound effect for each household group and reduce the asymmetry of information on expost outcome for energy efficiency investments.

## Methods

In this paper we use the Chi Square Automatic Interaction Detection (CHAID) method developed by G; V. Kass (1980) to analyze the energy annual consumption of French households in the residential sector. The CHAID method stems from the popular data mining technique AID (Automatic Interaction Detection) and is mostly used in survey datasets for segmentation analysis. This technique of tree growing (also known as "hierarchical splitting", "partitioning", "group dividing" or "segmentation") is widely used in strategic marketing for partitioning data into homogeneous groups in terms of response variable. The different phases of the methodology are sequenced as follow: (1) We determine the key predictors of mean and median energy consumption levels. They might be of socio-demographic or dwelling characteristics and localization or exogenous factors such as climate and unobserved effects. In order to do so, we use both multiple correspondence analysis and logistic regression. (2) We undertake CHAID to hierarchized and group energy consumption levels with respect to the key predictors in order to start a household typology for their energy consumption. (3) We test the value of emerging archetype (changing the dependent variable and/or key predictor variables). (4) We feed the archetypes into the complete dataset and enriched the profile analysis (with frequency and MCA tests). (5): We analyze specified group (coupling key leverages for successful efficiency programs) and present the findings and the policy implications.

## Results

Firstly we describe the group resulting from the CHAID algorithm and analyze the segmenting variables that feed the model. Secondly we set the focus on two selected pen portraits : the fuel poor households and the "high income high energy consuming households". Thirdly we display the groups in a two dimension plan in order to realize a

[1] This usage is growing at a very high rate as household and houses are more and more connected and the appliances evolve toward high technology and multimedia services

market segmentation for residential housing. This method highlights potential rebound or back-fire effect as well as windfall effect. Finaly we investigate the benefits for using a scoring method in order to reduce ex-post uncertainty for energy efficiency investment. Our study estimate 18 sub-groups in houses and 20 sub-groups for flat housing. Income quintile appears to be the first segmentation node in three of the main groups out of four which confirms us the strong relationship between income and energy consumption even in a non-linear approach. The household's family type is also a splitting factor in every main group but at different level of the tree. It is rather straightforward as the number of active occupant (couple with children or no child, single parent or person) in the household determines the gap between the global budget and the level of heating space required but also the level of comfort needed. In flats, household (income and family type), dwelling (construction date) and location (urban density) characteristics play a significant role in explaining different levels of energy expenses across households. In gas heated flats where income appears to be the second node, urban density play a major role in gas expenses levels. Indeed gas heated flats are fuelled from collective systems and the access to a gas infrastructure is crucial but unequally distributed between dense cities and more rural areas. It is also interesting to note that construction date is a key splitting factor only for gas heated groups. One of the reasons might be because the global age of the house or flat determines also the technology of the heating system when it is gas fuelled as it is part of the building infrastructure whereas electric heating is more used as flexible equipment and is not necessarily attached to walls. Finally, tenure and occupation regime only appear to be a significant node in electric heated houses. In our group analysis, we saw that it is one of the key factors to identify fuel poverty in house as we observed that there was a fuel poverty group (hitting the 10% effort rate) among rented electric heated houses.

## Conclusions

Main identified drivers for energy consumption are related to the house's characteristics: heating fuel or equipment type; dwelling type and size; and construction date. The income is crucial in the level of energy consumed. Nonetheless, household other characteristics also play a significant role: the location's choice (urban density), the family type and the tenure (for electricity), are significant factors to estimate household energy consumption. Although, there isn't significant evidence (yet) of a learning effect through seniority influence for energy consumption (age or seniority doesn't feed the model). Access to gas is a key to lower electricity bill but it is does not prevent from fuel vulnerability or even poverty in the case of very poor and constrained households as we found fuel poverty cases (using the threshold indicator) among gas heated households in houses.

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