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Behaviours, technologies and markets: the influence of the (p)rebound effect, the energy efficiency gap and refurbishment market heterogeneity on energy demand dynamics

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Keywords

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Abstract

The modelling of long-term energy demand dynamics is of prime interest for energy policy design and energy infrastructure planning. The two main modelling approaches (bottom-up and top-down) of dynamics demand simulation have well-known drawbacks: a lack of behavioural realism for the first and a lack of technological explicitness for the second. The main challenge of our work is to build a simulation model of residential energy demand dynamics that is both realistic regarding household behaviour and the overall housing refurbishment market while ensuring a sufficient level of technological precision.

The following elements of realism have been implemented in our bottom-up model, ranging from end-users to the provision chain:

- **Household energy use**: people do not use energy as it is usually described in engineering models, rather they adopt energy saving practices when the energy service price is high (prebound effect), and relax their efforts when energy efficiency is improved (rebound effect).
- **Household investment in energy efficient technologies**: investment decisions are not solely based on techno-economic analyses but also on non-energy benefits (e.g. comfort or estate value), capital constraints and individual preferences.
- **Refurbishment markets**: information problems lead to energy-efficiency barriers, including the low visibility of energy efficient equipment prices (which are notoriously heterogeneous within the market). Moreover, price and efficiency dynamics depend on technology diffusion (technological learning).

This model has been applied to two “Factor 4” scenarios – one that is technologically driven (diffusion of energy efficient and low-carbon technologies) while the other is economically driven (high carbon tax) – to analyse how an enhanced integration of realism influences simulated energy dynamics. Results highlight the fact that it can dramatically change the dynamics of consumption, making it a crucial point for policy makers and utilities.

Introduction

The study of energy consumption dynamics at a national scale is of prime interest for both energy suppliers (for infrastructure planning) and policymakers (in order to know how to reach targets of energy consumption reduction and what the cost would be of the transition).

To conduct such studies in a quantitative way and to improve the understanding of energy consumption dynamics, many models have been developed during the last few decades, helped by increasing computational capacities. These models have been created for various purposes: the detailed description of the energy system (defined here as the energy supply and demand infrastructures), the economic optimization of the energy system and the forecasting of energy demand or foresight studies.

As there is no "perfect" model which could give insightful answers to all possible questions concerning the energy system [Hourcade et al., 2005], various models have been developed for specific applications. Many model typologies have been proposed to classify this "jungle" of models (e.g. [IPCC, 1995; Swan and Ugursal, 2009; Crassous, 2008; Mundaca et al., 2010]). However, most of these typologies are specific to a single part of the whole chain of energy services provision. For instance, Swan and Ugursal classify only the ways to calculate energy consumption for a given state of energy system whereas Crassous's typology deals mainly with the ways to represent economic growth in energy-economy-environment models. However, these typologies share the distinction between two large families of models: those coming from engineering sciences (mainly physics and thermodynamics) and those based on economic relationships and theory. Engineering models have the ability of finely describe the energy system but suffer from a lack of microeconomic and macroeconomic realism, whereas economic models possess the opposite characteristics [Hourcade et al., 2005]. This observation led to the development of so-called "hybrid models" which were first established two decades ago (e.g. CIMS [Rivers and Jaccard, 2005] or IMACLIM [Crassous, 2008]), trying to use each type of model for its specific topic (i.e. technological description or economic interactions) and making them communicate through common variables.

In a sense, because they are based on historical observation or on decision theory, economic models generally have a better ability to simulate realistic energy consumption dynamics than engineering models. However, because of their poor representation of technologies – especially demand-side technologies – economic models have difficulties to represent the effect of a large market penetration of energy efficient technologies in demand sectors (i.e. a significant deviation from historical trends). Thus there is still room for improvement of the energy consumption dynamics modelling at the scale of a sector (such as the residential sector in our case).

These background elements drove us to the following research question: how does the way of modelling the provision chain of energy efficiency (i.e. from energy use at the consumer level to the energy efficiency providers) change the simulated dynamics of energy consumption? In order to answer this question for the French residential energy sector, we have developed a model called BEUS (*Buildings Energy Use Simulation)* which is based on an engineering description of dwelling stock but also contains specific modules for simulating more realistic energy demand dynamics. These modules target the description of actual energy consumption, of households' investments in energy efficient technologies and of energy efficiency market.

Section 1 provides a description of the main parts of our model, section 2 describes the scenarios we used to observe the influence of the model parameters and shows the simulated results for these scenarios, and section 3 proposes a discussion on these results and on the model itself.

Buildings Energy Use Simulation (BEUS) model

OVERVIEW AND MODELLING CHOICES

The aim of BEUS model is to simulate realistic final[1] energy consumption dynamics of the French residential sector. Residential energy end-uses are split into 4 categories: space heating (SH), domestic hot water (DHW), cooking and other (mostly electric appliances and lighting). As space heating represents about two thirds of dwellings' energy consumption and because it has the highest short-term variability (Figure 1), it can be considered as the most responsible for the past residential energy consumption dynamics. Based on this observation, most of the BEUS development efforts have been dedicated to this end-use. In fact, the whole energy efficiency provision chain is only represented for this end-use whereas other end-uses are considered constant in the future. This assumption may be considered as questionable for electric appliances when looking at the historical trend. However, recent European energy policies (and especially the eco-design directive) have taken ambitious measures to control the increasing consumption of electric appliances, which is the justification for our simplifying assumption.

BEUS models the French residential energy consumption by extrapolating the modelled energy consumption of a sample of 913 households with individual space heating systems. The description of this sample comes from a survey conducted by EDF R&D in 2009 [Cayla et al., 2010; Cayla, 2011; Cayla et al., 2011]. Households are described by the technical characteristics of their construction (shell and windows insulation, construction period, location), their space- and water-heating systems (type), and by socio-economic characteristics (e.g. income, family type). Energy bills of these households have been collected. A statistical analysis has been conducted to split these bills by end-uses following the CEREN methodology [Cayla et al., 2010].

As thermal regulations on new dwellings is very strict and should lead to Near Zero Energy Buildings in 2020 [Grenelle, 2009], the share of energy consumption coming from new dwellings should be small in the future even if post-2010 buildings should represent about 30 % of dwelling stock in 2050. That is why it has been chosen – in a first step – to model only existing buildings in BEUS.

ENERGY USE

On the basis of the technical characteristic of dwellings, climates, SH and DHW systems, Energy Performance Certificates[2] (EPC) are calculated for each dwelling of the sample used in BEUS. However, previous works have shown that these normative calculations of energy consumption can be extremely different from actual energy consumption of households, even on average (e.g. Haas and Biermayr, 2000; Cayre et al., 2011; Allibe, 2012). These observations reveal the gap between the

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[1] I.e. the energy which is paid and consumed by households in their dwelling.

[2] Energy Performance Certificates indicate the performance of a dwelling with a label (A to G) in terms of energy consumption and carbon emissions. The energy consumption of a dwelling is calculated following a public algorithm provided by authorities [MECSL, 2008], which takes into account the thermal performance of dwelling shell, the efficiency of space heating and domestic hot water systems, as well as the local climatic conditions.

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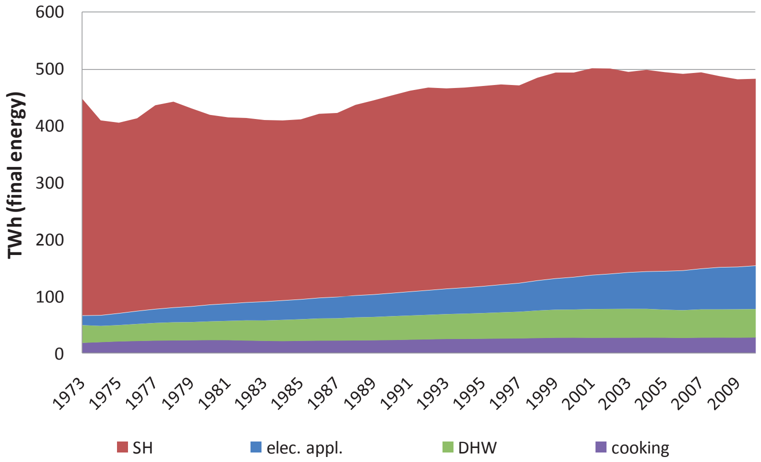

Figure 1. Energy consumption of French residential sector since 1973 by end-use [CEREN, 2011].

estimation of a dwelling's performance and a dwelling's actual energy consumption. The two main explanations of this gap seem to be [Laurent et al., 2013]:

- Behaviours: a daily use of systems by households which may be significantly different from the "normal" daily use in thermal calculation methods (e.g. 19 °C in the whole dwelling, during the whole heating period).
- Technical discrepancy: a difference between the actual energy efficiency of dwelling elements (shell, systems) and the assumed performance in the engineering model (e.g. thermal regulations may not be respected in all buildings).

The "prebound effect" is a concept that has recently been developed by Sunikka-Blank and Galvin (2012). It refers to the fact that actual energy consumption in mid- to low-performance housing is generally lower than expected by thermal calculation (e.g. Energy Performance Certificates), revealing that households' thermal comfort is constrained in low thermal performance dwellings. This situation explains why a thermal comfort increase occurs when improving thermal energy performance (rebound effect), hence his name (prebound effect).

An increase in thermal comfort (by changing daily use of heating systems and ventilation) after a dwelling retrofit – a phenomenon known as (direct) "rebound effect" (e.g. [Greenings et al., 2000; Haas and Biermayr, 2000; Sorrell et al., 2009]) – is known and has been measured for approximately two decades. By lowering the energy savings compared to those calculated by engineering models, this phenomenon highlights the importance of taking into account households' behaviours when a realistic quantification of energy dynamics must be achieved.

In BEUS, these two phenomena are represented by a modelling of the intensity of use (I) – a concept developed by Wirl (1988) – which is defined as the ratio between actual energy consumption (C_r) and theoretical energy consumption (C_{th}) (Equation 1).

Equation 1:

$I = C_r / C_{th}$

With *I* the intensity of use, C_r the actual energy consumption, and C_{th} the theoretical energy consumption (i.e. calculated by an engineering model).

To model the intensity of use depending on its main determinants a multi-linear regression has been conducted on the basis of the data from the 2009 survey. Results of this analysis show [Allibe, 2012] that following variables have a significant explanatory power ((Pr>|t|)<0,1) on the intensity of use: thermal insulation, heating system efficiency, climate, energy price (Pe), heated surface and household income (Y). By combining these variables, an aggregated indicator has been defined: the Theoretical Budget Share (TBS) dedicated to space heating (Equation 2). This indicator is used in BEUS to model intensity of use, as shown by Figure 2 (which also illustrates prebound and rebound effects under our formalism).

Equation 2:

$TBS = (C_{th} \times Pe) / Y$

With *TBS* the theoretical budget share dedicated to space heating, C_{th} the theoretical energy consumption, *Pe* the price of heating energy and *Y* the household's income.

This modelling provides a clear relationship between the economics and energy consumption. The effect of energy prices and taxes at national level and of income evolutions is straightforward. For energy services other than space heating (e.g. water heating, cooking and electric appliances), some preliminary research has been conducted but no clear relationship between the intensity of use and available variables has been demonstrated. Thus, their intensity of use has been considered as a constant over the simulation period.

INVESTMENT IN ENERGY EFFICIENCY

In BEUS, households have to refurbish technical elements of their dwelling at the end of their lifetime. "Revealed lifetimes" of technologies are calculated in order to be consistent with the observed number of refurbishments by technology in 2008 [Laurent et al., 2011]. Five types of dwelling refurbishments are modelled: internal shell, roof, external walls, windows and space heating systems (with three possible energies: electric-

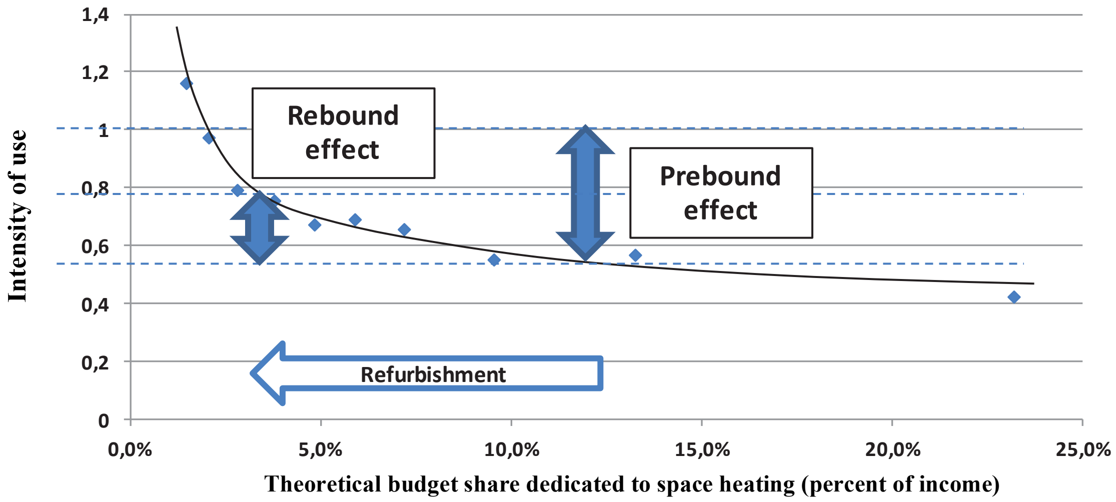

Figure 2. Illustration of prebound and rebound effects in the framework of the intensity of use modelling (own illustration). NB: Points represent the average intensity of use of each theoretical budget share decile of our sample.

ity, fossil fuels and wood). For each type of refurbishment, three performance options are available: basic, medium and optimum. For instance, for boilers, a standard boiler is "basic" whereas a low-temperature boiler is "medium" and a condensing boiler is "optimum". More technical details on this energy efficiency market segmentation can be found in the paper of Laurent et al. (2011). Each technical option is characterised by a price (from OPEN survey [OPEN, 2009]) and a performance (attributed following values of the French EPC [MECSL, 2008].

Usually, the techno-economic modelling of households' investment in energy efficiency is based on the choice of highest net present value (NPV in Equation 3) among available technical retrofitting options.

Equation 3:

$$NPV = \sum_{i=1}^{n} \frac{Rt_i}{(1+a)^i}$$

With *NPV* the net present value, Rt_i the cash flow at year *i*, and *a* the discount rate.

However, observations show that even if most efficient technological options may be more profitable, they do not consume all of the market shares when introduced into the retrofitting market. Such observations led to the definition of the concept of an "energy efficiency gap" [Jaffe & Stavins, 1994], which can be explained by various Energy Efficiency Barriers (EEBs) such as aversion to risks (inherent to almost every innovation), capital constraints (lower income household may have difficulties to pay for additional cost of energy efficiency), transaction costs (e.g. difficulty to find a retailer for new technologies) or information problems (landlord/tenant dilemma, asymmetric information between households and energy efficiency providers) [Jaffe et al., 2004]. These EEBs are generally modelled in techno-economic models by using high discount rates (e.g. [Train, 1985]), which allow to simulate realistic (relatively small) market shares for most energy efficient technological options (having higher initial costs but lower long-term costs).

In BEUS, a different position has been taken: the average discount rate is set to 12 % – a relatively low value when compared to the literature – and energy efficiency barriers are modelled explicitly by additional initial costs (added to investment costs). The average value is derived from the 2009 survey where households are asked how much they wish to save on their energy bill to choose a new efficient heating system [Cayla, 2011]. It is made in BEUS by adding to each technological option a non-technological cost expressed as a percentage of investment costs. The section "Model calibration and energy efficiency barriers estimation" describes how these costs are calculated.

Moreover, it has been observed that all households do not have the same discount rate when they make their purchase decision (e.g. [Hausman, 1979]). On average, the wealthier a household is, the lower its discount rate, reflecting decisions which are more oriented towards the long term. This observation is taken into account in BEUS by attributing discount rates depending on income quintiles (Equation 4). For tenants, discount rates should depend on the landlord's income because only landlords are in the position to decide major refurbishment actions for the building. However, as no information on landlord's income is available in the survey, discount rates have been set to the average value (12 %) for every tenant. As purchasing decisions in terms of energy efficient refurbishments directly affect long-term energy consumption dynamics, our modelling of discount rates depending on income adds another step toward more realism in energy consumption dynamics modelling.

Equation 4:

$$DR_i = 0.12 \times 0.6^{i-3}$$

With DR_i the discount rate of quintile *i* (*i*=5 being the less wealthier quintile).

Households don't make their purchase decisions based solely on techno-economic optimization but also take Non-Energy Benefits (NEB) into account (e.g. [Amann, 2006; Ürge-Vorsatz et al., 2009]). In BEUS, the following NEBs have been taken into account:

- **Thermal comfort**: the intensity of use (I) is used as a proxy for thermal comfort. Thermal comfort valuation is considered as null for intensity of use below 0.3 and the maximum valuation is given for values of intensity of use above 1.3. This maximum valuation has been set to a value of €1,000 per year following results of Jaccard and Dennis (2006). Thus, if a refurbishment makes it possible to reach the maximum level of comfort (intensity of use >1.3) then the household will virtually receive €1,000 per year in our model.
- **Loss of dwelling surface**: when internal insulation is installed in a dwelling, its added thickness lowers the net floor area which has an estate value. Estate values have been attributed to dwellings depending on the type of town in which they are located (rural, small towns or peri-urban towns, towns with a high density of inhabitants) on the basis of market surveys.
- **Increased estate value**: Based on the work of Banfi et al. (2008), increased estate values have been attributed to external wall insulation as well as new windows and new windows with increased energy performance.
- **Inconvenience during retrofitting**: during refurbishments targeting the internal parts of dwelling shell, inhabitants can't stay in the refurbished rooms. This inconvenience is a significant barrier to shell refurbishment [van Oel et al., 2009]. It is taken into account as a loss of few weeks of rent (or virtual rent for owners), which depends on the estate value of the dwelling. Basic performance (respectively medium and optimum) makes the household lose one week (respectively two and three weeks) of rent.

Finally, it is important to take into account the fact that all households do not perceive technologies in the same way (e.g. [Claudy et al., 2011]). For instance, some persons will prefer space heating made by HVAC whereas some other will prefer technical solutions based hot water emitters. This phenomenon is modelled in BEUS by adding a random term to the LCC. This term has a normal distribution centred on 0 and its standard deviation is a parameter of the model.

REFURBISHMENT MARKET

As it has been written before, long-term energy consumption dynamics fundamentally depend on the market share of the most efficient technologies in the refurbishment market. This market is made of demand (households) and supply (energy efficiency providers). First parts of this section – and a large part of literature on energy efficiency – solely focus on demand-side whereas supply side is often poorly modelled in techno-economic models. Indeed, technologies are generally modelled with a single average price and the evolution of this price is more often subjected to modeller's decisions than to a dedicated mechanism (e.g. technological learning).

A fundamental parameter of the modelling of a market is its heterogeneity [Rivers and Jaccard, 2005]. If a market is notoriously heterogeneous, then a technology that is not the best on average will nevertheless secure a portion of market shares. Conversely, in a perfectly homogeneous market, only the best technological option will be chosen by economic agents (known as the "winner takes all" situation).

In BEUS, a particular effort has been made to depict the "supply-side" of the market, both concerning its heterogeneity and its dynamics. Firstly, the price of technologies is not modelled solely by an average value but by a distribution, reflecting the fact that significantly different prices can be found for the same performance level of a technology [Laurent et al., 2011]. Price distributions are based on research conducted at EDF R&D as well as data from the OPEN survey [OPEN, 2009]. When households compare different technological options of refurbishment, they pick up a price for each technology in the prices distributions (more details on this topic can be found in the paper of Laurent et al. (2011)).

Secondly, technological learning has been implemented to model the evolution of the price of technologies depending on how many units are installed. Learning rates have been taken from studies and literature reviews of Weiss and his collaborators [Weiss et al, 2010], ranging from 5 % to 30 %. By using technological learning, the model takes into account the "history" of the market of each technology.

By representing demand- and supply-side heterogeneity in the refurbishment market, the development of the BEUS model tried to bridge the gap between techno-economic models and econometric models (such as residential modules of CIMS, IMACLIM or NEMS).

MODEL CALIBRATION AND ENERGY EFFICIENCY BARRIERS ESTIMATION

Others energy efficiency barriers (EEB) than those described before are calculated by comparing modelled market shares to observed ones. The OPEN survey [OPEN, 2009] provides market shares for each technology and each performance level. Simulations have been made with various additional costs reflecting EEBs.

In order to calibrate the model, it has been assumed that there is no EEB for "basic" technologies, which should be the default technological options of the market (e.g. facelift without insulation). Various combinations of additional costs for "medium" and "optimum" options have been tested to match observed market shares. The choice of additional cost combination was made by minimizing the distance between simulated market shares and observed ones (Equation 5).

Equation 5:

$$\min((MS_{med\ obs} - MS_{med\ sim})^2 + (MS_{opt\ obs} - MS_{opt\ sim})^2)$$

With MS_{obs} and MS_{sim} are observed and simulated market shares, MS_{med} and MS_{opt} the market shares of "medium" and "optimum" technological options.

Results of this calibration process reveal EEBs ranging from -20 % of investment costs (for "medium" internal insulation) to 160 % (for "medium" and "optimum" external wall refurbishment), with an average of 48 %. These results provide the first measures of EEBs for the French dwellings refurbishment market.

This calibration was carried out on 2008 data and it may be of particular interest to repeat the process on other historical data in order to ascertain certain tendencies concerning the evo-

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lution of these barriers over time. Without such results, EEBs have been assumed to be constant over time. Because of the magnitude of EEBs (approximately half of investment costs), the modelling of a dedicated evolution mechanism (such as technological learning for investment costs) appears to be an interesting new field of research.

Scenarios and results

COMMON ASSUMPTIONS

The two scenarios described below are simulated over the 2010–2050 period. Following assumptions have been made concerning the evolution of context variables during this period:

- Future fossil fuels prices evolution is derived from the Word Energy Outlook 2011 [IEA, 2011]. The retail prices variations are indexed on international prices variation at 70 % for gas and 90 % for domestic fuel. Future electricity prices evolutions come from the "50 % nuclear in 2030" scenario of the study of Union Française de l'Electricité [UFE, 2011] and its extrapolation to 2050. Wood prices are considered as a constant over time (extension of the French historical trend).
- Performances and revealed lifetimes of technologies are constant over time. This assumption reflects the fact that the technological learning is applied only on technologies prices.
- Climate warming is taken into account. However, this warming is expected to be significantly higher during summer than during winter [Planton and Durand, 2011]. That is why the average temperature increase during the heating period is assumed to increase "only" by 1.5 °C until 2050 (compared to the average 3 °C increase.
- The carbon content of modelled energies is constant over time.
- Households' income is assumed to grow by 1.5 % per year until 2050.
- Non-space heating systems are not changed during the 2010–2050 period. Some DHW systems may however be upgraded if the heating system also makes hot water (i.e. for most of gas and fuel boilers).

VARIATIONS OF INTENSITY OF USE IN A BAT SCENARIO

In this scenario, market shares are entirely determined by the modeller (i.e. the "investment" module is disabled). The two core assumptions of this scenario (inspired from the study of Trainsel et al. (2010)) are:

- Only "optimum" options are chosen by households when they refurbish the shell of their dwelling (wall, roof, windows).
- 50 % of heating systems progressively switch to wood boilers, and the other 50 % to electric heat pumps.

In order to illustrate the importance of the proper modelling of energy use, three variants of energy consumption calculation have been simulated:

- **EPC**: for each refurbishment, normative energy consumption reductions (i.e. those calculated by the French EPC) are applied to actual energy consumption (neither prebound effect nor rebound effect).
- **Constant intensity of use**: in this case, normative energy consumption reductions are multiplied by the households' intensity of use, which was observed in the 2009 survey. These intensities of use are held constant over the simulation period (i.e. no rebound effect occurs).
- **Modelled intensity of use**: in this case, intensity of use follows the relationship of Figure 2. Thus, rebound effect is taken into account, as well as some technical discrepancies (e.g. effective efficiency is lower than normative efficiency of refurbished dwellings parts).

Simulation results (Figure 3) show the evolution of space heating energy consumption of French residential sector under these assumptions. First, it is to note that two variants which take intensity of use into account show significantly higher energy consumption in 2050 than the EPC simulations (i.e. with normative energy savings). It illustrates the magnitude of the prebound effect, i.e. the impact of thermal comfort constraint on potential actual energy consumption reduction compared to normative approach. Secondly, the modelled intensity of use simulation shows higher energy consumption than if the intensity of use is held constant. It highlights the importance of rebound effect, even in a context of rising energy prices which compensate the service price reduction coming from improved efficiency. Indeed, the rebound effect would have been larger if energy prices had been held constant during the simulation period.

VARIATIONS OF ENERGY EFFICIENCY MARKET HETEROGENEITY IN A CARBON TAX SCENARIO

In this scenario, market shares are calculated by taking into account energy efficiency barriers, non-energy benefits and market heterogeneity. The two core assumptions of this scenario (inspired from the study of Giraudet (2011)) are:

- The extension of the French tax credit on energy efficient technologies until 2020 at its 2010 level.
- A considerable carbon tax starting at €200/tCO$_{2eq}$ in 2010 and increasing to as much as €1,000/tCO$_{2eq}$ in 2050.

In order to illustrate the importance of the proper modelling of market heterogeneity, three variants of market heterogeneity have been simulated under the aforementioned assumptions:

- **Technology and climate (TC)**: the only heterogeneity of the market comes from the various technological combinations of dwellings as well as the variety of external temperatures (climate). Discount rates are the same among the population, technology prices are only modelled by the average price and the heterogeneity of preferences is neglected.
- **Technology, climate and investment rationale (TCIR)**: On top of previous heterogeneities, this variant adds the variety of discount rates among the population (depending on households' income). Technology prices and households preferences are modelled as in the previous variant (TC).

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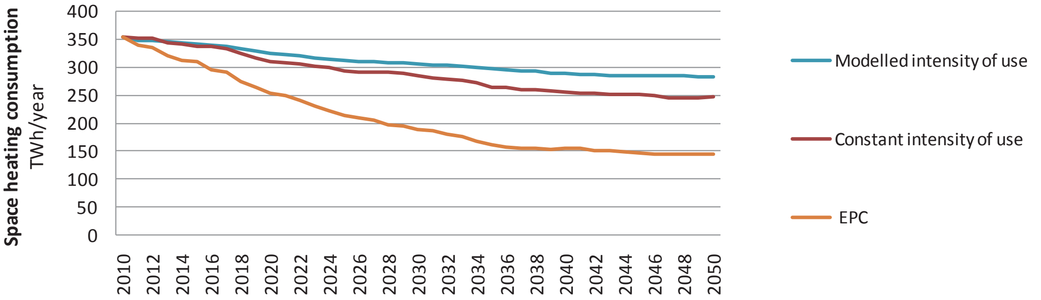

Figure 3. Simulated space heating consumption for the BAT scenario depending on the variant way of modelling the intensity of use.

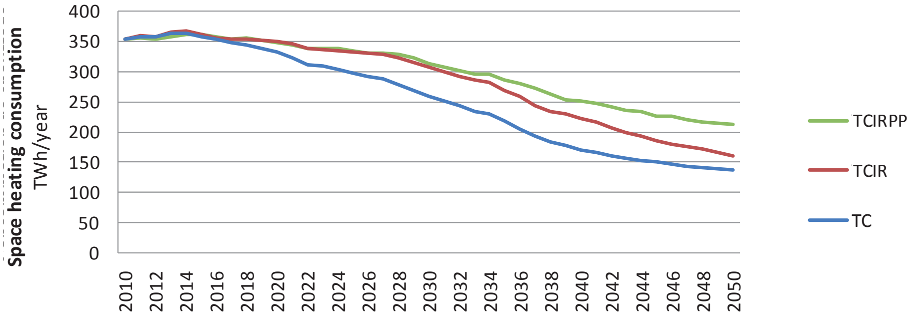

Figure 4. Simulated space heating consumption for the carbon tax scenario depending on the variant way of modelling the heterogeneity of energy efficiency market.

- **Technology, climate, investment rationale, prices and preferences heterogeneity (TCIRPP)**: in this variant, all sources of heterogeneity are taken into account, especially technology prices and households' preferences (with a standard variation of €200 for the random term).

Simulation results (Figure 4) clearly show that the more market heterogeneity is introduced in the model the more inert the energy system is. Indeed, under the same constraint for the three variants, the first (with low heterogeneity) presents an asymptote whereas it is not visible for the variants with higher market heterogeneity. These results illustrate the fact that in a heterogeneous market, low-performance options can be selected even under a considerable constraint. It may be explained by the existence of some contexts where these options will appear as the best ones (combining short-term decisions, low technology price and preference for these technologies).

Discussion

By using observed values (energy consumption, market shares and technology prices) instead of theoretical or average values, the BEUS model provides original results that diverge significantly from more simple or conventional modelling approaches (which are illustrated by the first variants of the two scenarios). It should be noted that there are still shortcomings of the model which merit further development (e.g. a better description of the landlord/tenant dilemma or of the learning effect on the performance of certain technologies, a model of energy efficiency barriers dynamics …). This is the reason for which its results should not necessarily be analysed in their absolute values but rather by their relative values by the comparison of the various simulated scenarios. This remark is common to every forecasting/foresight model but is important to keep in mind.

Results can be interpreted as showing that the prebound effect is significantly larger than the rebound effect. However, it is particularly important to note that the prebound effect is not an effect per se but the illustration of a comfort constraint, which may not be taken into account in purely technical models (i.e. not based on real energy consumptions but only on engineering calculations). It illustrate only the error that can be made in the quantification of energy efficiency potential of households daily heating behaviours (and observed space heating consumptions) are not taken into account.

The results also highlight that it may be far more difficult than expected by normative calculations (e.g. EPC) to reach large reduction factors concerning energy consumption. At most, a factor between two and three can be attained. However, the respective parts of the rebound effect and technical discrepancies are difficult to estimate, thus why further research is merited in order to know how to limit their effects on an increase in energy consumption. In the context of the fight against climate change, our results tend to show that energy efficiency will not be sufficient to reach a Factor 4[3] (at least on space heating consumption where a strong rebound effect takes place). Thus, they reinforce the need for lowering the average space heating carbon content, which can be achieved by avoiding fossil fuels (e.g. wood, heat pumps with low carbon content electricity).

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[3] As decided by the French Government in 2005 [POPE, 2005].

The significant market heterogeneity and its consequences on energy consumption dynamics may be an argument in favour of more regulation in the refurbishment market. However, this market is made of numerous small companies in France that are not used to following thermal regulations compared to bigger companies of the "new buildings" market. Moreover, it is to note that even today, after almost four decades of thermal regulations in new buildings, a significant part of newly built houses do not respect current thermal regulation in France [OPECST, 2009]. That is why a constraining regulation of the dwellings refurbishment market may take a long time before it is effectively efficient.

Household behaviours are described here as depending only on the techno-economic context. However, it is also clear that other drivers of behavioural change can have a significant impact on short and long-term energy dynamics, such as behavioural change techniques stemming from cognitive sciences (e.g. goal settings or default option [Wilson and Dowlatabadi, 2007]). The integration of knowledge from these fields into a techno-economic model is however notoriously difficult. These two approaches could be considered as complementary in the research for a better description of energy consumption dynamics.

Conclusion

By its application on two Factor 4 scenarios, the inclusion of prebound effect, rebound effect, energy efficiency barriers and energy efficiency market heterogeneity in the residential energy consumption dynamics analyses highlights the fact that energy efficiency may have a significantly lower impact than expected by basic techno-economic models: in terms of magnitude as well as in pace. The findings additionally suggest that households are both adaptable to changing contexts in term of service price and that the investments contexts are significantly diverse, which is a source of inertia in the energy consumption dynamics.

On a climate-policy point of view, simulation results strongly suggest that energy efficiency will not be sufficient to reach Factor 4 target. Thus, dramatic decreases of the energy carbon content appear even more necessary than previously anticipated.

Results highlight the need for further research in the ways to limit the rebound effect, technical discrepancies and the diffusion of low-performance technologies. Indeed, the combination of these three phenomena has a dramatic impact on simulated energy consumption dynamics and totally changes the magnitude of expected demand response to policy signals.

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Glossary

NEB	Non-Energy Benefit
EEB	Energy Efficiency Barrier
EPC	Energy Performance Certificate
TBS	Theoretical Budget Share (dedicated by households to space heating)
BEUS	Buildings Energy Use Simulation model

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