Global sensitivity analysis of an energy-economy model of the residential building sector

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Abstract

In this paper, we discuss the results of a sensitivity analysis of Res-IRF, an energy-economy model of the demand for space heating in French dwellings. Res-IRF has been developed for the purpose of increasing behavioral detail in the modeling of energy demand. The different drivers of energy demand, namely the extensive margin of energy efficiency investment, the intensive one and building occupants' behavior are disaggregated and determined endogenously. The model also represents the established barriers to the diffusion of energy efficiency: heterogeneity of consumer preferences, landlord-tenant split incentives and slow diffusion of information. The relevance of these modeling assumptions is assessed through the Morris method of sensitivity analysis, which allows for the exploration of uncertainty over the whole input space. We find that the Res-IRF model is most sensitive to energy prices. It is also found to be quite sensitive to the factors parameterizing the different drivers of energy demand. In contrast, inputs mimicking barriers to energy efficiency have been found to have little influence. These conclusions build confidence in the accuracy of the model and highlight occupants' behavior as a priority area for future empirical research.

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1. Introduction

Numerical energy-economy models used for energy and climate policy assessment carry considerable uncertainty. First, just like any other model, they are incomplete representations of a real-world system. This indeterminacy generates irreducible uncertainty. More specifically, the energy-economy systems they represent involve human behavior, the laws of which cannot be established

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with the same robustness as in natural sciences. Uncertainty increases further if one considers that energy-economy models are forward-looking tools for decision-making. As such, they are subject to future states of the world, which are unknown by nature.

Such deep, polymorphic uncertainty emphasizes the need to submit energy-economy models to sensitivity analysis. Though essential for transparency, sensitivity analysis can be a daunting task when models are based on non-linear relationships and involve large numbers of parameters, which is an important characteristic of energy-economy models. This difficulty is reflected by the dominant use until recently of the "One-At-a-Time" (OAT) method of sensitivity analysis (Saltelli and Annoni, 2010), in which model parameters are varied locally one after the other but never together at the same time. This technique does not allow modelers to explore the full space of uncertainty nor interactions between model inputs.

The heterogeneity of energy demand in buildings epitomizes the uncertainty associated with energy supply and demand system modelling and thereby the difficulty of sensitivity analysis. Building energy demand involves the use of a variety of technologies (e.g., heating, ventilation and air-conditioning systems, insulation techniques), a building stock that is heterogeneous in terms of its architecture and surrounding climate, and building users whose characteristics vary with respect to their tenancy status, preferences or income. Representing such a disaggregated system expands the sources of uncertainty in the associated models. Individual occupant behaviors, which are to a large extent unobservable, can only be mimicked by tentative functional forms, parameterized with incomplete data. Yet the multiplicity of technologies and agents imposes a large number of parameters. This context reinforces the so-called curse of dimensionality (Bellmann, 1957) that hampers sensitivity analysis. Accordingly, sensitivity analysis is typically rare in energy-economy models of the building sector (Mundaca et al., 2010; Kavgic et al., 2010). This is unfortunate: reducing energy demand in buildings is considered by scientists of the IPCC (Levine et al., 2007) and many policy-makers as the most cost-effective option to mitigate climate change; therefore substantiating this claim and designing practical ways to address it calls for reliable models.

In this paper, we assess an innovative model of dwelling energy demand, Res-IRF[1], using a sensitivity analysis technique, the Morris method, that is appropriate for the degree of complexity of the model (Iooss, 2011; Saltelli et al., 2008). Res-IRF has been developed at CIRED to assess the long-term impact of energy efficiency policies on energy demand for space heating in French households (Giraudet et al., 2012, 2011). The purpose with the development of

[1] "Res-IRF" stands for the "Residential module of IMACLIM-R France". IMACLIM-R France is a recursive general equilibrium model of the French economy developed at CIRED (Bibas et al., 2012). Linking Res-IRF and IMACLIM-R France allows for the clearing of energy markets and energy prices to be determined endogenously. This process is described in Giraudet et al. (2011). In the present paper, Res-IRF is run with no link to IMACLIM-R France.

Res-IRF was to improve decision criteria for technical and behavioral change compared to existing models (see Mundaca et al. (2010) and Kavgic et al. (2010) for a review). This materializes through the endogeneization of each of the different drivers of energy use: the intensive margin of energy efficiency investment (*at what level to invest?*), the extensive one (*whether or not to invest?*) and dwelling occupants' behavior. In addition, the model incorporates representations of some barriers to energy efficiency, such as heterogeneity in consumer preferences, landlord-tenant split incentives and slow diffusion of information. Up to now, its operation had been assessed through preliminary OAT sensitivity analysis and comparison with other models (see AppendixA), but never submitted to in-depth sensitivity analysis.

The Morris method of sensitivity analysis, also known as the Elementary Effects method, has been introduced by Morris (1991) and developed in particular by Campolongo et al. (2007). It can be seen as a randomized OAT design. For each input, elementary effects are computed from different points in the input space. The mean and standard deviation of the elementary effects give a measure of importance of the input and its interactions with other inputs. This method reconciles the low computational cost of OAT techniques with the global focus of more advanced variance-based methods like the Sobol method (Saltelli et al., 2008).

Application of the Morris method is growing in various fields of science. In particular, it is widely used in building simulation analysis, as reviewed by (Tian, 2013). In contrast, it is much less used in the energy-economy field, which our model is closest to. The application of the Morris method to the IMAGE model (Potting et al., 2002; Campolongo and Braddock, 1999; Van Der Sluijs et al., 2005) is the only example we are aware of.

The sensitivity analysis reported here was done in two steps. First, we perform Monte Carlo simulations to quantify overall uncertainty in the model. This allows us to assess the global range of uncertainty of the main output of our model. However, it is unsufficient to determine where the uncertainties come from among the varying inputs. This motivates the use of the Morris method in a second step to identify the most important parameters.

Section 2 of this paper presents the Res-IRF model. Section 3 details the approach for the sensitivity analysis. Section 4 presents the results. Section 5 interprets the results and discusses the reliability of the model. Section 6 concludes.

2. An overview of the Res-IRF model

Res-IRF is a bottom-up simulation model of energy demand in the French residential sector[2]. A comprehensive description of the guiding principles, struc-

[2]The model is finely detailed with technological and microeconomic representations. As such, it can be seen as a hybrid energy-economy model (Hourcade et al., 2006). The models to which Res-IRF is closest are CIMS, the Canadian Integrated Modeling System (Jaccard

ture and input data needs of the Res-IRF model can be found in Giraudet et al. (2012). AppendixB of the present paper updates that description with some recent model developments. In this section, we will present the model broadly, emphasizing on its innovative aspects and with the main objective of making the following sensitivity analysis understandable. Then, the 12 inputs that are subsequently found to be most influential in the sensitivity analysis (see Table 4 in section 4.4) are explicitly referred to with letters in the text.

2.1. Motivation

Before describing Res-IRF, it is worth mentioning the context in which it was developed. At a fundamental level, energy demand for heating in existing dwellings can be decomposed into three drivers: the extensive margin of energy efficiency investment (*how many dwellings are retrofitted*); the intensive one (*how energy efficient are these retrofits*); and dwelling occupants' behavior (*how do occupiers set their heating thermostat?*). State-of-the-art energy-economy models typically endogenize the intensive margin of energy efficiency investment, keep the extensive one exogenous and hold occupants' behavior constant.

A specific challenge to the modeling of energy demand is the representation of the alleged barriers to energy efficiency. Since the pioneering contribution of Jaffe and Stavins (1994) on the "energy efficiency gap", a large body of literature in economic and social sciences has been looking at barriers that misalign private investment in energy efficiency with its socially optimal level. These barriers include landlord-tenant split incentives and information spillovers. The most recent reviews of the literature on this subject conclude that neither the empirical existence of the barriers to energy efficiency nor their theoretical implications are well established (Gillingham et al., 2009; Allcott and Greenstone, 2012). This lack of knowledge is reflected in a perfunctory representation of the barriers in energy-economy models, which typically represent them collectively with abnormally high discount rate values[3].

Against this background, Res-IRF introduces two modeling innovations. First, it offers greater detail than just using high discount rates in the representation of the barriers to energy efficiency. Second, it endogenizes all three drivers of energy use in existing dwellings. Linking investment and capital utilization allows model users to assess the rebound effect, that is, increases in energy service consumption in response to energy efficiency investment. This issue receives much attention in policy discussions. Furthermore, policy-makers in some countries have defined annual retrofitting targets. Endogenizing the volume of retrofits in Res-IRF allows model users to assess the contribution of policy instruments to meeting such targets. These modelling innovations however lead to the creation of new sources of uncertainty, as the next subsections describe.

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and Dennis, 2006; Mau et al., 2008) and the residential module of NEMS, the U.S. National Energy Modeling System (Wilkerson et al., 2013).

[3]"Abnormal" here means any value higher than 7%, which is the value recommended by the U.S. Office of Management and Budget for private cost-benefit assessment (OMB, 2013).

2.2. Driving forces

At the aggregate level, energy demand is determined as the product of an extensive output, the dwelling stock (split into existing dwellings, constructed before the initial year 2008, and new dwellings, constructed after), measured in square meters, and an intensive output, the specific energy use of the dwelling stock, measured in $kWh/m^2/year$. Three exogenous input trajectories influence model outcomes: population growth (modified by *input E*), GDP growth and energy prices (modified by *inputs A and G*). Overall, population and GDP growth determine the dwelling stock, and energy prices drive energy efficiency improvements in both new and existing dwellings.

The number of new dwellings constructed each year is determined to satisfy the housing demand. This is turn depends on population growth, the average number of inhabitant per household (decreasing exogenously to match past trends, using *input H*), and the demolition of existing dwellings, which follows a a constant annual rate. The floor area per dwelling remains constant in existing dwelling, while in new dwellings it increases with GDP growth.

2.3. Technological detail

Res-IRF focuses on the use of electricity, natural gas, fuel oil and fuel wood for space heating (*input F* is used to calibrate the initial energy use according to energy carriers). The dwelling stock comprises single-family dwellings, multi-family dwellings and social housing. The technical characteristics of building envelopes and heating systems are not represented explicitly. Rather, the energy performance of existing dwellings takes one of seven discrete values, corresponding to the labels set out by the French Energy Performance Certificate. Energy efficiency improvements are realized through transitions to higher energy labels and through fuel switches. The performance of new dwellings takes one of three discrete values, corresponding to the minimum requirements of the French building codes of 2005, 2012 and 2020 (as currently anticipated for the latter). The heating energy carrier and efficiency level of new constructed dwellings are chosen simultaneously.

Representing energy efficiency improvements through energy label transitions facilitates the simulation of microeconomic decisions as discrete choices. It however also creates parametric and empirical uncertainty. As a given transition could in reality be realized through different combinations of building envelope and heating system measures, its cost is hard to specify and likely to be dispersed over a range of possible values.

2.4. Microeconomic detail

Homeowners use discrete choice functions on the intensive margin of energy efficiency investment based on life-cycle costs of the different options. The life-cycle cost of each transition in energy label is given by the sum of investment costs (a matrix modified by *input J*) and discounted energy operating costs specific to this label. Logit functions allocate market shares across the seven different energy labels according to their respective life-cycle costs. A heterogeneity parameter controls for the spread in market share allocation. Investment costs decline with cumulative investment through learning-by-doing (through *input D*). The computation of life-cycle energy operating costs assumes myopic[4] expectations of energy prices.

Res-IRF adds several innovative features to this otherwise standard modeling framework. First, unlike most other models, in which abnormally high discount rates are used to represent all barriers to energy efficiency, the Res-IRF model considers discount rates with split incentives only. Owner-occupiers in single-family dwellings are assumed to have normal discount rates (*input I*); homeowners who rent out their dwelling are assumed to have a higher than normal discount rate. Likewise, owner-occupiers of multi-family dwellings, who are not the sole decision-maker when it comes to the renovation of the whole dwelling are assumed to discount the future more sharply than owner-occupiers of single-family dwellings. Second, the life-cycle costs of each energy label factor-in some intangible costs, which are calibrated (using *input K*) so as to allow logit functions to replicate the energy label choices observed in 2008 (matrix modified by *input L*). As such, intangible costs can be interpreted as including all possible barriers to energy efficiency other than landlord-tenant split incentives. The impact of barriers is assumed to decrease over time with cumulative investment as a consequence of information spillovers. The introduction of intangible costs in the model and the mechanism by which they decrease come from the CIMS model (Jaccard and Dennis, 2006; Mau et al., 2008)[5].

The extensive margin of investment corresponds to annual constructions of new dwellings and annual retrofits of existing dwellings. While the former derives directly from exogenous inputs in the model, the latter is determined endogenously. For a representative homeowner-dwelling bundle, a logistic function (calibrated with *input C*) is used to deduce the retrofitting rate from the average net present value of retrofitting. The average net present value is calculated as the difference between the average life-cycle cost of upgrading the dwelling and the life-cycle cost of staying in its current energy label. Beforehand, the average life-cycle cost (including intangible costs) of a retrofitting project is weighted by the market share of each possible energy label transition, determined by logit functions, as described above. This simulation framework is equivalent to assuming that homeowners have a heterogeneous preference for the utility derived from energy services (e.g., some are more sensitive to cold than others) and that this heterogeneity is normally distributed across the population. In this view, the logistic curve mimics the cumulative distribution function of the preference parameter.

Lastly, in both new and existing dwellings, the utilization of newly installed

[4]It means that investors consider the energy price to be constant over time, equal to its value at the time of investment.

[5]As discount rates in CIMS are not used to mimic split incentives only, intangible costs cannot be interpreted as representing the same barriers in the two models.

capital adjusts after investment. The underlying idea is that dwelling occupants optimize the consumption of energy services (using *input B*), in the case of this work the heating temperature. Improvements in the energy efficiency of the dwelling typically decrease the marginal cost of heating, hence increasing the quantity of heating consumed via a rebound effect. This is represented in Res-IRF as an iso-elastic response of the demand for energy service, measured as the ratio between effective energy use and the conventional one disclosed by the energy label, to the energy efficiency of the dwelling, measured as the conventional energy expenditure, that is, the conventional use disclosed by the label valued at current energy prices (see AppendixB for further detail).

3. Sensitivity analysis approach of Res-IRF

First, we perform Monte Carlo simulations to quantify overall uncertainty in the model. This allows us to assess the global range of uncertainty of the main output of our model, but is unsufficient to track where the uncertainties come from among the varying inputs. Therefore, in a second time, we use the Morris method to identify the most important parameters. A preliminary step for both exercises is to assign probability distributions to the inputs of the model. These three steps are described in more detail below.

3.1. Variables of interest

In this work, we focus on uncertainty in *national energy use for space heating*[6], the main output of interest of the model. We compare it to its value in a reference scenario[7] at two points in time, 2020 and 2050. Separating short- and long-term effects is important for inputs like the learning rate, which parameterizes a dynamic process. As such the learning rate may be more influential in the long-term than in the short-term.

We use the term input to name any factor that is given a numerical value in the model. Model inputs fall into three categories:

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[6]Energy demand in the model is computed in final energy and then converted in primary energy, which is the metric used by French policy-makers to set energy savings targets, energy performance certificates and building codes. For electricity, a 2.58 conversion rate is applied, following governmental recommendations. This heterogeneity across fuels opens room for energy label upgrades that are not driven by energy efficiency (strictly speaking, improvements to the building envelope or heating system) but only by fuel switch (which is also endogenous to the model). In the present analysis, we focus on energy efficiency improvements. Therefore, to neutralize the effect of fuel switch, we assume that fuel prices follow a parallel evolution. That is, we disregard the uncertainty stemming from relative fuel prices.

[7]As the motivation of the work is to assess the fitness of the model for the purpose of increasing behavioral detail, we do not assess uncertainty around policy scenarios. Still, estimates of the sensitivity of the model to energy prices give insights into its sensitivity to energy taxes. Likewise, sensitivity to variation in investment costs gives insights into sensitivity to different levels of subsidies.

- Exogenous input trajectories (EI) representing future states of the world: energy prices, population growth and GDP growth[8].
- Calibration targets (CT), which are empirical values the model aims to replicate for the reference year 2008. They include hard-to-measure aggregates such as the reference retrofitting rate and the reference energy label transitions.
- All other model parameters (MP), which reflect current knowledge on behavioral factors (discount rates, information spillover rates, etc.) and technological factors (investment costs, learning rates, etc.)

For each model input in the sensitivity analysis, we make specific assumptions about the mean (which is the value used in the reference scenario), the probability distribution function and the range of values explored. Some factors cannot be manipulated as a simple scalar input and they are assessed through indirect inputs, as detailed in AppendixC. AppendixD provides a complete description of the 71 model inputs, by input type.

3.2. Monte Carlo simulations

1,500 Monte Carlo simulations are run. In each simulation, each input value is drawn pseudo-randomly from its probability distribution function. We use Latin Hypercube Sampling (McKay et al. 1979) to efficiently cover the input space. The probability density function of each input is divided into 1,500 regions of equal density. The sampling procedure then ensures that draws occur once in each region. Inputs are drawn from a uniform distribution within each region.

The number of simulations is large enough for us to compute the mean and standard deviation of the output distribution generated, hence get an aggregate view of the magnitude of uncertainty in the model. It is however not large enough for us to compute statistically significant standardized regression coefficients (used to rank inputs by importance), so this motivates the use of the Morris method in a second step.

3.3. The Morris method

Sensitivity analyses are generally divided into local and global approaches (Confalonieri et al., 2010, and references therein). Local sensitivity analyses, also known as “One At a Time” (OAT) techniques, are based on the estimation of partial derivatives (Campolongo et al., 2011). Partial derivatives are only informative at a global scale if some linearity and additivity conditions are met,

[8] AppendixC.1 details how exogenous inputs are handled. Each energy price trajectory is parameterized by two random inputs: the short-term price (in 2008) and the long-term price (in 2050). The energy price evolves linearly between these two values over the 2008-2050 period. For the population and GDP trajectories however, only one input is used (a random growth input corresponding to a percentage increase growing over time).

which is rarely the case in energy-economy models (Saltelli and Annoni, 2010). In contrast, global sensitivity analyses evaluate the effect of a factor while all others vary as well. This allows modelers to efficiently explore the multidimensional input space. The global approach includes screening methods (mainly the Morris method), regression-based methods (computation of standard regression coefficients) and variance-based methods (mainly the Sobol method (Sobol, 1993)).

The Morris method can be thought of as an enhancement on the "perfunctory" OAT method (Morris, 1991; Saltelli and Annoni, 2010). It was developed in 1991 by Morris and went through some refinements with Campolongo et al. (2000) and Ruano et al. (2012). It is increasingly used[9], for applications in hydrology (Braddock and Schreider, 2006; Matthews et al., 2006), chemistry (Campolongo et al., 2007), agronomy (Richter et al., 2010), biophysics (Cooling et al., 2007), building thermal simulation (Garcia Sanchez et al., 2014) and energy-economy modeling (Campolongo and Braddock, 1999).

The Morris method can be summarized as follows. Consider a model with k random input variables $Y = f(X_1, ...X_k)$. Each model input $(X_i)_{i\in\{1,...,k\}}$ varies across a uniform distribution in $[0,1]$. In the Morris method, each input varies across p selected levels[10]. The region of experimentation is then a k-dimensional p-level grid. An elementary effect for variable i is defined by:

$$EE_i(X_1, ..., X_k, \triangle) = \frac{f(X_1, .., X_i \pm \Delta, ..X_k) - f(X_1, ..., X_k)}{\pm\triangle}$$

p is chosen to be even and $\triangle$ equals $p/(2(p-1))$ for symmetry considerations. For each input variable, there are $p/2$ possible values below 0.5 and $p/2$ corresponding values $(+\triangle)$ above 0.5. This configuration leads to $p^k/2$ different elementary effects per input[11]. The finite distribution of elementary effects corresponding to the i-th input factor is called F_i. Then G_i is the equivalent distribution of *absolute values* of elementary effects.

The sensitivity measures proposed by Morris are the estimated mean μ and standard deviation σ of F_i (Morris, 1991). Campolongo et al. (2011) propose a third measure, μ^*, the estimated mean of G_i. Any significant difference between μ and μ^* indicates a non-monotonic influence of the underlying input on the output.

Estimating μ^*, μ and σ requires sampling elementary effects from both F_i and G_i. One *efficient random sampling strategy* is to build r *trajectories* of

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[9] The number of citations of Morris' original paper in Thomson-ISI Web of Knowledge has grown steadily from below 10 per year until 2003 to more than 100 in 2013.

[10] The normalized inputs are then converted from the original hypercube to their actual distribution as follows: if F_{Xi} is the cumulative distribution function, the corresponding value for the level j ($j/(p-1)$ in $[0,1]$) is $F_{Xi}^{-1}((j-0.5)/p)$. The method works best when p is even. In our analysis, p is set to 8.

[11] Each input X_j with $j \neq i$ may take the p values of the grid. For X_i, half of possible values below 0.5 give the same EE as corresponding values $(+\triangle)$ above 0.5.

$(k+1)$ points. As each trajectory gives k elementary effects, the computational cost of the experiment is $r(k+1)$. The construction of the trajectories requires several steps of randomization which are detailed in Morris (1991).

A decisive advantage of the Morris method is that it is "computationally cheap" (Herman et al., 2013). Around 50 simulations per input are needed, while the Monte Carlo regression requires 1,000 and the Sobol method 10,000[12] (Iooss, 2011). Nonetheless, the measure of importance μ^* compares favorably with those used in variance-based methods to rank inputs according to their influence (Campolongo et al., 2007; Tang et al., 2007; Confalonieri et al., 2010). Furthermore, the Morris method allows one to handle unstable models that may crash when inputs are too different from their reference value. Unlike the Sobol method, it is possible to drop an elementary effect calculation without affecting the full design.

Ex ante, the Morris method seemed well-suited to the size and non-linear nature of Res-IRF. We set the number of trajectories at $r = 80$, which, when applied to 71 inputs, led to $80 \times (71 + 1) = 5,760$ simulations. The computational cost incurred was low[13]. *Ex post*, the Morris method proved appropriate: Results (presented below) showed that the non-linearities found in the model were such that no further analysis was necessary.

4. Results

4.1. Global uncertainty

The aggregate value of energy use is the result of complex dynamics driven by different forces. On the one hand, the growth of population and GDP increases the total dwelling surface area hence drives energy use up. On the other hand, the retrofitting dynamics (stimulated by high energy prices) drives it down. In parallel, rising energy prices[14] decrease the energy demand through energy service elasticity. Overall, Figure 1 shows that median output value for residential sector energy demand over all Monte Carlo simulations falls steadily from 378 TWh in 2008 to 344 TWh in 2020 (-9%) and 288 TWh in 2050 (-24%). In the baseline (with inputs set at their mean value), the number of dwellings increases from 24 million in 2008 to 33 million in 2050, with respective total floor area of 2.2 Gm^2 and 3.0 Gm^2. Then, in the baseline, the decrease in energy consumption per area is more pronounced than the decrease in total energy use, from 175 $kWh/m^2/year$ to 96 $kWh/m^2/year$.

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[12] Those numbers can be considered as rather low. In Herman et al. (2013) for example, the number of simulations is 6,000.

[13] Res-IRF is coded in the Scilab language. The script is approximately 2000 lines of code long. Running Res-IRF on a standard computer with CPU of 2.6 GHz and 4 Gb of RAM takes approximately one minute.

[14] Energy prices are always rising in our inputs uncertainty configuration (see AppendixC.1 and Table D.6): the maximum possible 2008 energy price is equal to the minimum 2050 energy price, and the energy price evolves linearly between these two values over the 2008-2050 period.

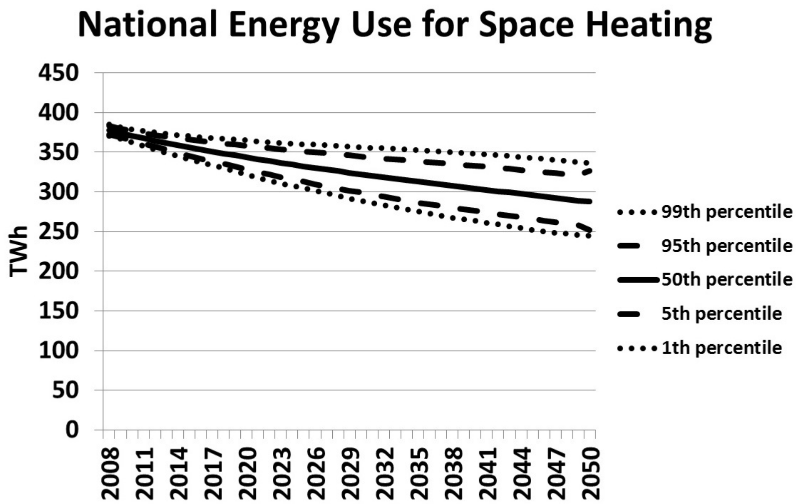


Figure 1: Global variations of national energy use for space heating

Overall, uncertainty in national energy use for space heating in 2050 is ±13% at the 95% confidence level. Uncertainty increases over time: while the mean is decreasing, the standard deviation of the output distribution is increasing in absolute value.

One may expect a decrease in uncertainty due to an exhaustion of the potential for retrofitting. Yet one can also think of several reasons why uncertainty increases over time, mostly linked to the structure of the model and the definition of the input space. First, the parameterization of uncertainty in exogenous inputs involves larger differences among these inputs in the long run than in the short run (energy prices cover a wider range in 2050 than in 2020 for example). Second, inputs linked to the calibration process could lead to diverging output trajectories. Further, these differences could be accentuated by the propagation of the uncertainty attached to inputs that parameterize the dynamics of the model, e.g., learning and information rates.

4.2. Important inputs

In Figure 2, inputs are ranked on the horizontal axis according to their influence on the output in 2020, measured as their μ^* value on the vertical axis. We see that uncertainty is concentrated among a handful of inputs. A similar observation can be made for the long-term output (not reported here). Such a concentration is quite common in sensitivity analysis (Saltelli et al., 2008). In the following discussion, we focus on the 10 most important inputs for each of the two outputs examined, energy use in 2020 and 2050 (Tables 1 and 2). To get a more tangible value of importance, we also compute ν^*, the ratio between μ^* and the output value in the reference scenario. A value of 2% for ν_i^* means that a change of $\triangle$ (which is close to 0.5) of input i (assumed to be uniformly

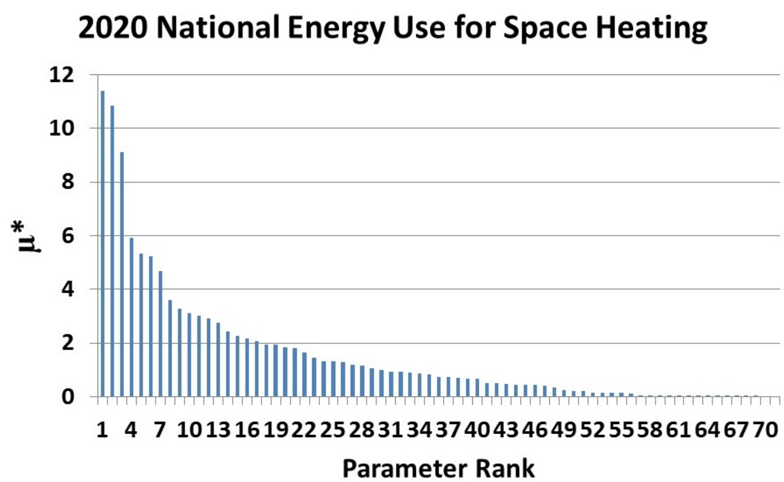


Figure 2: Input influence on national energy use for space heating to 2020

Table 1: Inputs most influential on national energy use for space heating to 2020 (EI: exogenous input; CT: calibration target; MP: model parameter)

Rank	Input	Input type	μ^*	ν^*
1	2008 Retrofitting Rate	CT	11.40	3.1%
2	2050 Energy Price	EI	10.85	2.9%
3	Energy Service Elasticity	MP	9.12	2.5%
4	Household Density Growth	MP	5.91	1.6%
5	2008 Electricity Use	CT	5.31	1.4%
6	Discount Rate for Intangible Cost Calibration*	MP	5.23	1.4%
7	2008 Energy Label Transition Shares	CT	4.68	1.3%
8	Discount Rate for Owner-occupied Existing Single-family Dwelling*	MP	3.59	1.0%
9	Population Growth	EI	3.27	0.9%
10	2008 Natural Gas Use	CT	3.10	0.8%

Inputs with a * are nonlinear (see further)

Table 2: Inputs most influential on national energy use for space heating to 2050 (EI: exogenous input; CT: calibration target; MP: model parameter)

Rank	Input	Input type	μ^*	ν^*
1	2050 Energy Price	EI	27.12	7.3%
2	Energy Service Elasticity	MP	17.87	4.8%
3	2008 Retrofitting Rate	CT	15.77	4.3%
4	Learning Rate	MP	13.43	3.6%
5	Population Growth	EI	12.19	3.3%
6	2008 Energy Price	EI	11.87	3.2%
7	Household Density Growth	MP	10.62	2.9%
8	Retrofitting Costs Breakdown*	MP	10.58	2.9%
9	Discount Rate for Intangible Cost Calibration*	MP	9.03	2.4%
10	2008 Energy Label Transition Shares	CT	8.13	2.2%

Inputs with a * are nonlinear (see further)

distributed in [0,1]) leads, *on average*, to a 2%/△ increase in the output value, as compared to its value in the reference scenario.

Three inputs consistently stand out as being most influential: the 2050 energy price[15], the 2008 retrofitting rate and the energy service elasticity. The 2050 energy price is an exogenous input, which is mostly influential in the long-term. The 2008 retrofitting rate is the target against which the retrofitting function is calibrated. It proves to be most influential in the short-term. The energy service elasticity is a model parameter.

After these three most influential inputs, the learning rate proves to be influential in the long-term, which is consistent with it parameterizing an accumulation process. The 2008 energy price has a significant impact in the long-term, but hardly any impact in the short-term. This perhaps counter-intuitive outcome is in fact due to the calibration of the retrofitting function, as will be shown further on in the analysis. The discount rate used to calibrate intangible costs is influential in both the short- and long-term. The discount rate parameterizing the investment behavior of owner-occupiers of existing singe-family dwellings (the biggest category of decision-makers) is influential in the short-term.

The breakdown of retrofitting costs (see AppendixC) is among the top ten most influential inputs in the long-term. Part of its influence is absorbed by the variations of intangible costs in the short-term. In the long-term, as the latter vanish, the variations of investment costs become more visible.

[15] The fact that the 2050 energy price has an impacts on the 2020 energy use as well is directly linked to the way uncertainty over energy price is modelled. Two random energy prices (2008 and 2050) are chosen, and the energy price evolves linearly between these two values over the 2008-2050 period. Then, for a given 2008 energy price value, a higher value of 2050 energy price involves a higher energy price in 2020.

The 2008 Energy label transition share input is also influential. Together with the influence of the 2008 retrofitting rate, this emphasizes the importance of calibration targets. The population growth and the household density growth, which are directly linked to the floor area of new dwellings to be built each year, are also significant. Finally, two dwelling stock calibration targets are important: the 2008 demand for electricity and natural gas.

4.3. Robustness of the ranking

Two questions arise: is computing 80 elementary effects per input enough to get reliable estimates of μ^*? Would the ranking change if we had more trajectories? To answer these questions, we compute the position factor index defined by Ruano et al. (2012):

$$PF_{r_i \to r_j} = \sum_{l=1}^{k} \frac{|P_{l,i} - P_{l,j}|}{0.5 \times (P_{l,i} + P_{l,j})}$$

where $P_{l,i}$ is the position of input l when $r = r_i$.

The $PF_{r_i \to r_j}$ index measures the difference between rankings obtained with samples of size r_i and r_j. The paramaters found to be most sensitive are given higher weight in the index. A low value of PF (e.g. less than 2) means that the ranking is robust to an increase in the sample size. However, the PF value may increase as sample sizes increase. Thus in the present analysis, we consider a ranking to be stable when PF indices of a parameter tested over a range of sample sizes are all found to have low values.

As shown in Table 3, the position factor indices are found to be consistently low. They are even below 1 when the number of trajectories is shifted from 70 to 80. Whatever the shift examined, the indices tend to be higher when applied to the long-term output as compared to the short-term one. This seems quite logical because as the time horizon gets further away, the chances are greater that an input will become influential and thus change its ranking. Overall, the sensitivity analysis suggests that the ranking obtained in the previous section is robust[16].

Table 3: Position Factor Index

Number of Elementary Effects	30 to 40	40 to 50	50 to 60	60 to 70	70 to 80
2020 Energy Use	1.82	1.31	0.46	0.51	0.87
2050 Energy Use	2.24	1.95	2.27	1.91	0.68

[16]For each input, a higher σ means a greater variability of elementary effects. In this case more elementary effects are needed to get an accurate estimate of μ. The efficiency of the Morris method could thus be improved by adjusting the number of elementary effects computed for each input to its σ value. Such a refinement goes beyond the scope of this article.

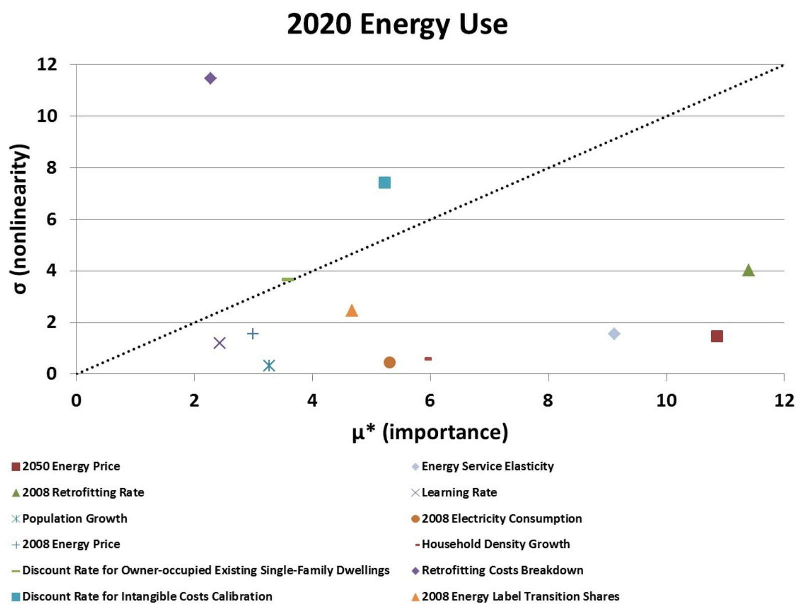


Figure 3: Morris diagram of inputs affecting national energy use for space heating to 2020

4.4. Linearity, monotony and stability of the model

Figures 3 and 4 display the so-called Morris diagrams where for each input, the standard deviation of elementary effects σ are plotted against their mean μ^*. For these diagrams we selected the 12 most important inputs (common to Energy Use in 2020 and 2050) thanks to the previous work of section 4.2.

One can first notice the differing ranges for σ and μ^* between the two graphs, reflecting the increase in global uncertainty over time (discussed in section 4.1).

One strength of the Morris method is to give a sense of the nonlinearity of model inputs[17]. Input nonlinearities can be visualized in the Morris diagrams. Inputs located in the upper left space are deemed to be nonlinear. A high value of σ relative to μ^* indicates possible strong interactions of the associated input with other inputs. Inputs located in the lower right space are deemed to be

[17]We refer here to nonlinearity as a combination of "single input" nonlinearity (regardless of other inputs values, a change of input i has a very different impact on the output depending on where it occurs in the range of variation), and interactions (the same change in input i has a very different impact on the output depending on the value of other parameters). The Morris method cannot distinguish "single input" nonlinearity and interactions. In contrast, the Sobol method is blind over "single input" nonlinearity but can track interactions; either with an aggregate measure of the interactions between one input and all others, or with specific measures of interaction between one input and another (though at a very high computational cost).

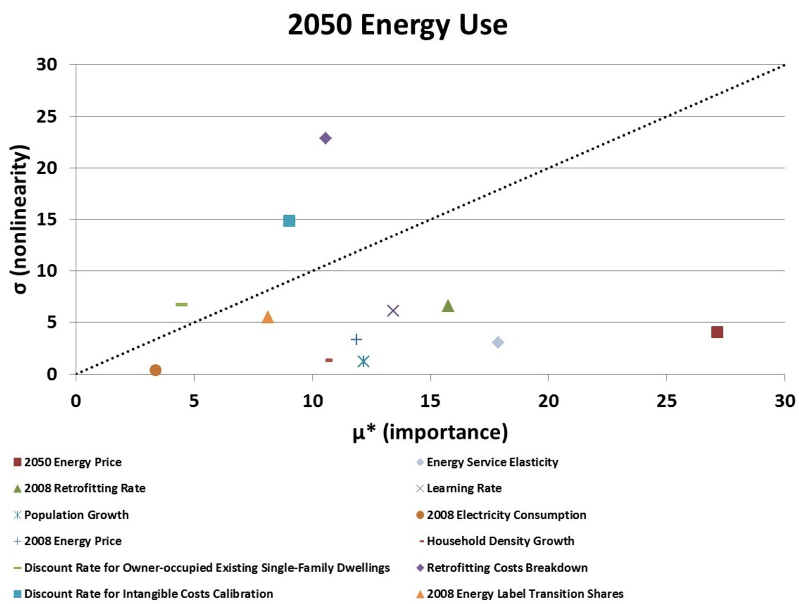


Figure 4: Morris diagram of inputs affecting national energy use for space heating to 2050

Table 4: List of the 12 most influential inputs (common to Energy Use in 2020 and 2050)

Ref	Input
A	2050 Energy Price
B	Energy Service Elasticity
C	2008 Retrofitting Rate
D	Learning Rate
E	Population Growth
F	2008 Electricity Use
G	2008 Energy Price
H	Household Density Growth
I	Discount Rate for Owner-occupied Existing single-family dwellings
J	Retrofitting Costs Breakdown
K	Discount Rate for Intangible Cost Calibration
L	2008 Energy Label Transition Shares

linear.

Three inputs stand out as being nonlinear: the discount rate used to calibrate intangible costs, the one used by owner-occupiers of existing singe-family dwellings, and the retrofitting costs breakdown. These inputs can be seen as different degrees of freedom in the calibration of intangible costs. It is thus coherent that they interact with other inputs. Overall, there are only a few nonlinear inputs, which are not among the very most important inputs, and their degree of nonlinearity is relatively low.

Another strength of the Morris method is to give the monotony of inputs. By monotony we mean whether, on average, an increase in the value of the input induces an increase of the value of the output (in which case we call it "positive monotony"), or conversely a decrease in the value of the output ("negative monotony"). It is also possible for the monotony to be ambiguous, meaning that, depending of the value of input I or other inputs, an increase in the value of inputi induces sometimes an increase and other times a decrease in the value of the output. The monotony can be obtained, for each input, by computing the value of the μ/μ^* ratio. A value of 1 or close (respectively -1 or close) indicates a positive (respectively a negative) monotony. Table 5 displays the monotony of the 13 most influential inputs based on their μ/μ^* ratios in 2020 and 2050.

Table 5: Monotony of the most influential inputs as related to national energy use for space heating

Input	Monotony
2050 Energy Price	negative
Energy Service Elasticity	negative
2008 Retrofitting Rate	negative
Learning Rate	negative
Population Growth	positive
2008 Electricity Use	positive
2008 Energy Price	positive
Household Density Growth	negative
Discount Rate for Owner-occupied Existing single-family dwellings	ambiguous
Retrofitting Costs Breakdown	ambiguous
Discount Rate for Intangible Cost Calibration	ambiguous
2008 Energy Label Transition Shares	negative

Some relations are unambiguous and intuitive. The higher any of the 2050 energy price, the 2008 retrofitting rate, the learning rate or the 2008 energy label transition shares, the larger the number of retrofits and the lower the energy use. On the other hand, the higher any of the 2008 electricity and natural gas demands or the population growth, the higher the energy use. In contrast, the effects of inputs related to retrofitting costs and intangible costs are ambiguous.

A perhaps counterintuitive result is the positive relation between the 2008 energy price and energy use. It can however be explained by the calibration of the retrofitting function to year 2008. All else being equal, a higher energy price at the calibration step implies a higher net present value associated with a retrofit, hence a lower number of retrofits per unit of profitability in the retrofitting function. In subsequent model dynamics, fewer retrofits lead to a higher energy use.

The shares of energy label transitions in 2008 also exhibits a counterintuitive monotony. A higher value of this input reflects a world with more energy efficient retrofits in the initial year than in the reference scenario. Replication of such a world in the calibration process leads to lower intangible costs. If initial intangible costs are lower, their potential for decrease through information spillovers is also lower. In the short- and long-term, this ultimately leads to less energy savings.

One last strength of the Morris method is that the simulation sequence is not impaired by computation crashes. Computation crashes are hard to avoid in sensitivity analysis, as the calibration step involves the resolution of very non-linear systems. The analysis reported here had a failure rate of 2.2%, that is, 124 crashes happened out of 5,760 simulations. This led us to exclude 138 elementary effect calculations[18]. Figure 5 displays the distribution of crashes over the set of inputs. It shows that the excluded elementary effects were not confined to a handful of inputs. No input had more than nine elementary effects excluded out of 80 calculated and most had less than five excluded. Therefore, the low number of crashes experienced in the analysis did not introduce any statistical bias in the results.

4.5. Robustness of the screening

In the previous section, we selected the 12 most important inputs and displayed them in Morris diagrams. To check the robustness of this screening, we perform a variation of the previous Monte Carlo (MC) analysis.

The inputs are divided into two groups: the "top 12 inputs" of Figures 3 and 4 and the "rest of inputs". In addition to the 1,500 initial runs (yielding output Y_{all}), we compute two other rounds of 1,500 runs (yielding outputs Y_{top12} and Y_{rest}).

In Y_{top12}, we re-use the inputs values of the original run for the top 12 inputs and fix the rest of the inputs to their mean value. In Y_{rest}, we fix the values of the top 12 inputs at their mean value and re-use the inputs values of the original run for the rest of the inputs. In other words, Y_{all} and Y_{top12} have the top 12 inputs in common, the other inputs being random in Y_{all} and fixed to their mean value in Y_{top12}. In Figure 6, we plot for 2020 and 2050 Y_{top12} against Y_{all} and Y_{rest} against Y_{all}.

[18] Apart from the first and last simulations of a trajectory, each simulation is used for two elementary effects calculations. One isolated crash then implies the exclusion of two elementary effect calculations. However, if n simulations crash sequentially, only $n + 2$ calculations are excluded. In the analysis reported here, most crashes occurred sequentially.

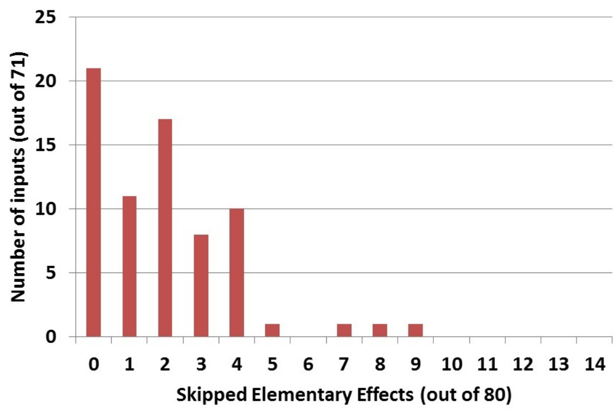
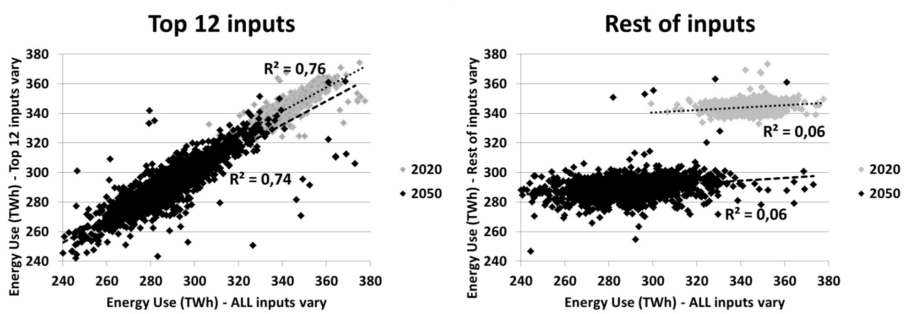


Figure 5: Distribution of excluded elementary effects among inputs



(a) Top 12 inputs

(b) Rest of inputs

Figure 6: Robustness of the screening

One can see that Y_top12 and Y_all are much better correlated than Y_{all} and Y_{rest} (though they have much fewer inputs in common: 12 versus 59). This suggestive evidence is corroborated by the computation of the R-squared.The coefficient for Y_{all} versus Y_{top12} is relatively high (0.76 for 2020 and 0.74 for 2050) but not "perfect": the other inputs matter. Our screening is then robust: most of the uncertainty in the output is indeed due to the uncertainty of the top 12 important inputs.

5. Discussion

5.1. Fitness for purpose of the model

Sensitivity analysis allows modelers to assess the "fitness for purpose" of a model. This can be seen as a heuristic judgement of its quality (Saltelli et al., 2008). The purpose of Res-IRF is to improve behavioral detail in residential sector energy-economy modeling. Several of the model's features are designed to serve this purpose: an endogeneization of the extensive margin of energy efficiency investment, calibrated against the initial retrofitting rate; the utilization of energy carrier, parameterized with an energy service elasticity; the introduction of some barriers to energy efficiency investments.

The fact that the initial retrofitting rate and the energy service elasticity are both found to be among the most influential inputs suggests that disaggregating the different drivers of energy use is a relevant modeling choice. The importance found for these inputs is consistent with the energy price being the most influential input. As it impacts all three margins of energy use, it propagates the variability attached to each. Though theoretically uncontroversial, disaggregating different energy drivers is empirically challenging. In particular, data is needed to make a better estimation of the initial retrofitting rate and the energy service elasticity.

In contrast, the barriers to energy efficiency introduced in the model have been found to have little influence. This is notable for discount rates, which is at odds with the importance they have been reported to have in most other models[19]. As using discount rates to mimic barriers to energy efficiency raises theoretical and empirical concerns first reported by (Jaffe and Stavins, 1994), the finding of low-influence is perhaps not so problematic. Therefore, if we are to improve behavioral detail in the modeling of residential sector energy demand, a basic disaggregation of the different drivers of energy use should be prioritized over focus on a more elaborate incorporation of barriers to energy efficiency.

5.2. Unaddressed uncertainty

The Morris method allows one to fully explore the defined input space, contrary to the OAT method. Though such an analysis may give an impression of completeness, it does not clear all sources of uncertainty. First, the definition of the input space (the varying inputs and their probability distribution) necessarily involves some arbitrary assumptions by the modelers." Second, to keep the analysis manageable, modelers have to focus on a small subset of outputs (otherwise the number of Tables and Figures would be too high). Accordingly, we focused on the output most frequently discussed in policy circles: national energy use for space heating. Admittedly, some outputs not examined here may be affected by inputs that were not found to have much influence in the analysis. Lastly, beyond numbers, the uncertainty embodied in the functional forms and scope of the model can simply not be accounted for in a sensitivity analysis (Oreskes, 1998; Rotmans and van Asselt, 2001).

[19]Note that the discount rate variations examined in this paper are centered around higher values than those typically examined in integrated assessment models, which usually vary in the [0%,5%] range (Goulder and Williams, 2012). This explains partly the lower influence for discount rates found in our analysis.

6. Conclusion

In this paper, we have discussed a sensitivity analysis of Res-IRF, a simulation model of energy use for space heating in French dwellings. Preliminary Monte Carlo simulations revealed that Res-IRF's main output, the energy use for space heating in French households in 2050, varied around the reference scenario by 25% at the 95% confidence level. Subsequent application of the Morris method, which to date has not been widely used by the energy-economy modeling community, revealed that this variability was due for the most part to future energy prices, which are exogenous to the model. Less than 3% of the simulations crashed, which builds confidence in the stability of the model. The model is also quite sensitive to the factors parameterizing the different drivers of energy demand; in contrast, inputs mimicking barriers to energy efficiency are less important. Most inputs have a linear and monotonic influence on the outputs of interest and the polarity of influence is consistent with intuition. Moreover, nearly all exogenous inputs make it among the top most influential inputs, with energy prices ranking first. This means that even though the internal structure of the model accounts for some variability, the model is mainly determined by its exogenous inputs. The fact that exogenous variables dominate output uncertainty indicates that uncertainty in the model is mostly due to the uncertainty in macroeconomic variables, and that uncertainty in the technical and microeconomic characteristics of the building sector matter less.

Even though the exercise did not eliminate all sources of uncertainty, it confirmed for us that the Res-IRF model manages to improve behavioral detail. As such, it provides reliable, intuitive predictions of the effect of energy price on energy demand. Disaggregating the three drivers of energy use also proved to be a relevant modeling choice. Although sensitivity analysis seems like a very obvious thing to do for this kind of energy system modelling, it is rarely done in peer models, probably because it is technically challenging. Lastly, the analysis highlights the need to systematically present several energy price scenarios, to better understand the nature of the barriers to energy efficiency and to collect more data about dwelling retrofits and occupants' behavior.

These conclusions, retrospectively, give more substance to the results in previous work (Giraudet et al., 2011). The takeaway of that work can be summarized as follows: there are technical and behavioral rigidities that affect energy-related decisions which make ambitious carbon dioxide emissions reductions targets in the residential sector difficult to meet in the near future. Other models have reached the same conclusions (Charlier and Risch, 2012; Energy Modeling Forum, 2011). They thus provide an external corroboration of the model which complements the internal corroboration provided by the sensitivity analysis carried out in this work.

Our evaluation suggests some directions for model development. First, many inputs proved to be unimportant in the sensitivity analysis. Res-IRF could be simplified accordingly. For instance, the growth in floor area per capita could be modelled to follow an exogenous trend rather than respond to GDP growth. Second, data is needed to make a better estimation of the empirical parameters identified as being most important. This applies to the retrofitting rate in particular. Third, the analysis revealed that Res-IRF was not very sensitive to variations in representations of the barriers to energy efficiency. However, this point is controversial, both from a theoretical and empirical point of view. Therefore, more research is needed to clarify which barriers should be described in detail in models of energy demand, before concluding on the sensitivity of these models to such barriers.

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AppendixA. Preliminary Assessment of Res-IRF

AppendixA.1. Local sensitivity analysis

Res-IRF's defining paper contained a preliminary evaluation of the model (Giraudet et al., 2012). The numerical values generated in the reference scenario proved consistent with those commonly found in the literature for such variables as the growth rate of the dwelling stock, the rebound effect and the price-elasticity of energy demand. Local sensitivity analysis was conducted on a few parameters suspected to be influential: energy prices, information spillovers, the learning-by-doing rate, discount rates and the heterogeneity parameter (OPEN, 2009; Sorrell et al., 2009; Gillingham et al., 2009). This analysis revealed that the information spillovers and the heterogeneity parameters had a significant impact on the retrofitting rate; the impact of the learning-by-doing rate and the discount rate was low and the impact of energy prices even lower. However, the impact of the energy price on final energy use was high, whereas the impact of all other inputs was low. This illustrates the fact that the energy price has an impact on both energy efficiency investment and capital utilization. In contrast, the impact of other inputs on energy efficient retrofits is partly taken back by the rebound effect.

AppendixA.2. Parallel runs with peer models

Res-IRF was involved in the Energy Modeling Forum's 25th study, focusing on energy efficiency (Energy Modeling Forum, 2011). The study involved a variety of top-down and bottom-up energy-economy models, mostly focusing on the U.S. economy, which were run with standardized assumptions. Compared to other models, sensitivity to energy efficiency policy in Res-IRF[20] proved intermediate. The model, however, exhibited two distinct behaviors. First, the relative impact of a carbon tax on residential energy intensity was almost the largest of all models (Ibid., Figure 10). Again, this is likely driven by the endogenous representation of capital utilization, a feature exclusive to Res-IRF in the study. Second, unlike other models, Res-IRF exhibited some slightly over-additive interactions when a carbon tax was combined with energy efficiency standards (Ibid., Figure 15). A decomposition of this stylized fact at the time of the study revealed that it was driven by the logistic shape of the retrofitting curve. As the model and policies were parameterized, most retrofits were occurring in the convex region of the logistic curve; therefore, an increase in the net present value of retrofitting translated into a more-than-proportional increase in the number of retrofits. Beyond this specific result, the key finding of the study was that regardless of the top-down or bottom-up nature of the models involved, all exhibited rigidities that made the attainment of ambitious carbon dioxide emissions reductions through energy efficiency much harder than those found in pure engineering studies, as exemplified by the widely discussed Mc Kinsey study (McKinsey, 2009).

AppendixA.3. Conclusion

The main takeaway from this preliminary assessment is that Res-IRF results seem plausible, at least compared to past trends and to other models. Still, its

[20]In that study, Res-IRF was linked to IMACLIM-R France. This overarching framework was simply named "IMACLIM" in the study.

main distinctive features, especially information spillovers, capital utilization and retrofitting dynamics proved influential, which motivated the subsequent analysis reported in the present paper.

AppendixB. Model updates

This section updates the description of the model, which was first published in Giraudet et al. (2012).

AppendixB.1. Data refinement

New corrections have been applied to the database of Marchal (2008) to take better account of secondary residence and vacant units, and match the proportion of landlords and tenants with data from INSEE (2008). Based on the OPEN survey (OPEN, 2009), the initial retrofitting rate has been re-estimated at 3%/year instead of 1%/year. Expert elicitation have led to a downward revision of estimates of retrofitting costs (Table 2 in Giraudet et al. (2012)); the cost matrix is now (in €/m^2):

$$C_{INV-0} = \begin{pmatrix} 76 & 136 & 201 & 271 & 351 & 442 \\ 0 & 63 & 130 & 204 & 287 & 382 \\ 0 & 0 & 70 & 146 & 232 & 331 \\ 0 & 0 & 0 & 79 & 169 & 271 \\ 0 & 0 & 0 & 0 & 93 & 199 \\ 0 & 0 & 0 & 0 & 0 & 110 \end{pmatrix}$$

Social housing has been introduced with a 4% discount rate, a value meant to reflect public decision-making. Other discount rates have been adjusted so as to maintain the weighted average discount rate at 20%. The new values are: 8% in owner-occupied single-family dwelling, 15% in owner-occupied multi-family dwellings, 45% in rented single-family dwellings, and 55% in rented multi-family dwellings.

AppendixB.2. Introduction of fuel wood and social housing

Fuel wood has been introduced as a new heating fuel and social housing has been introduced as a new dwelling type. Social housing was directly parameterized from Marchal (2008). In Marchal's database, fuel wood is mixed with all fuels other than natural gas, electricity and fuel oil in a single category. To match this with data from ADEME (2009), it was assumed that 44% of single-family dwellings and 1% of multi-family dwellings in this category were heated with fuel wood.

Fuel wood dwellings are assumed to account for 9% of new dwellings, and social housing 20%. The other categories are adjusted to keep initial proportions (Table 11 in Giraudet et al. (2012)).

Adding a fuel led to an additional row in the matrix of construction costs (Table 8 in Giraudet et al. (2012)). The new row reads as follows: 1200 €/m^2

for constructions meeting the 2005 building code, 1300 €/m^2 for constructions meeting the 2012 building code and 1600 €/m^2 for constructions meeting the 2020 building code.

A column and a row were added to the matrix of fuel switch costs (Table 7 in Giraudet et al. (2012)):

$$\begin{pmatrix} 0 & 70 & 100 & 120 \\ 50 & 0 & 80 & 100 \\ 55 & 50 & 0 & 100 \\ 55 & 50 & 80 & 0 \end{pmatrix}$$

From ADEME (2009), the initial price of fuel wood in 2007 was assumed to be 0.04 €/kWh. The initial floor area in social housing was assumed to be 60 m^2 in existing dwellings and 65 m^2 in new dwellings. A saturation is placed at 75 m^2 and the growth process is the same as in the preexisting model.

AppendixB.3. Energy Service Function

In the previous version of the model (equation (14) Giraudet et al. (2012)), a logistic energy service function was estimated using data from (Cayre et al., 2011). Here, the same data was fitted with an iso-elastic relationship, which is more convenient for subsequent sensitivity analysis: It is easier to vary a constant elasticity than the multiple parameters of a logistic function. The function $F_k(P) = K(\rho_k P)^e$ was estimated, with P the price of energy and ρ_k the inverse efficiency parameter for a dwelling of type k. With ten points (y_i, d_i) where y_i is the utilization rate and d_i the theoretical expenditure, a log-log linear regression yielded $K = 2.72$ and $e = -0.505$.

AppendixC. Indirect inputs used in sensitivity analysis

Some inputs of the model cannot be directly submitted to sensitivity analysis for a variety of reasons. Indirect inputs are built to circumvent this problem.

AppendixC.1. Exogenous inputs

Population, GDP and energy prices follow exogenous trajectories. One common way to assess the influence of input trajectories is to assess sensitivity to a constant annual growth rate. Yet such a factor potentially leads to very high values at the end of the time horizon. We adopt a different approach in our sensitivity analysis.

Each energy price trajectory is parameterized by two random inputs: the short-term price (in 2008) and the long-term price (in 2050). The energy price evolves linearly between these two values over the 2008-2050 period. The energy price value disclosed in table D.6 is for natural gas; the growth pattern is parallel for other fuels.

For the population trajectory, we build a random growth input ξ corresponding to a percentage increase growing over time. The reference values are multiplied by $[1+(1+(Year-2008)/10)\xi]$. We proceed similarly with the GDP trajectory.

AppendixC.2. Initial capital stock

Initial capital stock is, together with the learning rate, the input that parameterizes the learning-by-doing process. It is labeled $K_f(0)$ in equation (7) in Giraudet et al. (2012). It is given in the model as a hypermatrix and varied in the sensitivity analysis by a scalar k as follows: $K_f(0)(1+k)$.

AppendixC.3. Calibration Targets: Shares

All 2008 shares to be replicated by the model (Energy label transitions in existing dwellings, energy labels in new constructions, fuel shares in new constructions, dwelling type shares in new constructions) are given by matrices, the rows of which sum to 1. Sensitivity of the model to such inputs cannot be assessed by simply multiplying the associated matrix by a scalar. Matrix elements must be changed specifically through indirect inputs.

The reference matrix of 2008 energy label transitions against which intangible costs are calibrated is:

$$MS_{ini} = \begin{pmatrix} 25\% & 27\% & 27\% & 21\% & \varepsilon\% & \varepsilon\% \\ & 40\% & 26\% & 31\% & 2\% & \varepsilon\% \\ & & 66\% & 28\% & 6\% & \varepsilon\% \\ & & & 95\% & 5\% & \varepsilon\% \\ & & & & 91\% & 9\% \\ & & & & & 100\% \end{pmatrix}$$

For instance, 26% of the dwellings in energy label F reach label C after retrofit. We build an indirect input α, called 2008 Energy Label Transition Shares, that represents the relative efficiency of 2008 energy label transitions: the higher α, the larger the proportion of transitions toward high energy labels. Input α is symmetric around 0, with negative values reflecting a less energy efficient situation than in the reference situation.

If α is positive, we make the following transformation:

$$a'_{i,i} = a_{i,i}(1-\alpha)$$

and:

$$a'_{i,j} = a_{i,j} + \frac{a_{i,j}}{1-a_{i,i}}\alpha a_{i,i}$$

for $i < j$.

For $\alpha = 0.5$, we thus have:

$$MS_{ini} = \begin{pmatrix} 12\% & 31\% & 31\% & 24\% & \varepsilon\% & \varepsilon\% \\ & 20\% & 35\% & 42\% & 3\% & \varepsilon\% \\ & & 33\% & 55\% & 12\% & \varepsilon\% \\ & & & 47\% & 52\% & \varepsilon\% \\ & & & & 46\% & 55\% \\ & & & & & 100\% \end{pmatrix}$$

If α is negative, we make the following transformation:

$$a'_{i,i} = a_{i,i} + (1 - a_{i,i})|\alpha|$$

and:

$$a'_{i,j} = (1 - |\alpha|)a_{i,j}$$

For $\alpha = -0.5$, we thus have:

$$MS_{ini} = \begin{pmatrix} 62\% & 13\% & 13\% & 10\% & \varepsilon\% & \varepsilon\% \\ & 70\% & 13\% & 16\% & 1\% & \varepsilon\% \\ & & 83\% & 14\% & 3\% & \varepsilon\% \\ & & & 98\% & 2\% & \varepsilon\% \\ & & & & 95\% & 5\% \\ & & & & & 100\% \end{pmatrix}$$

We build a similar input to assess sensitivity of the model to the matrix of initial market shares of new constructions (called 2008 Energy Label Construction Shares).

For fuel shares and dwelling type shares, we adopt a slightly different approach. We assess sensitivity to one element of the matrix and adjust other elements so that the matrix sums to 1. For instance, for fuel shares, we vary the electricity share through indirect input opt_{elec} (named 2008 Fuel Shares):

$$MS_{elec} = (1 + opt_{elec})MS_{elec}$$

We then adjust the shares of other fuels and multiply them by the same scalar λ:

$$MS'_{i \neq elec} = \lambda MS_{i \neq elec}$$

Solving equation $\sum MS_i = 1$, we find:

$$\lambda = 1 - \frac{MS_{elec}}{1 - MS_{elec}} opt_{elec}$$

AppendixC.4. Retrofitting Costs

Retrofitting costs, that is, energy label transition costs are given in the model as a matrix. We assess the sensitivity of the model to the *retrofitting cost magnitude* through a scalar multiplying the matrix. We also assess the sensitivity of the model to the *retrofitting cost breakdown* by multiplying the matrix term by term to the following matrix:

$$\begin{pmatrix} 1 & 1+\frac{\gamma}{5} & 1+\frac{\gamma}{4} & 1+\frac{\gamma}{3} & 1+\frac{\gamma}{2} & 1+\gamma \\ & 1+\frac{\gamma}{5} & 1+\frac{\gamma}{4} & 1+\frac{\gamma}{3} & 1+\frac{\gamma}{2} & 1+\gamma \\ & & 1+\frac{\gamma}{4} & 1+\frac{\gamma}{3} & 1+\frac{\gamma}{2} & 1+\gamma \\ & & & 1+\frac{\gamma}{3} & 1+\frac{\gamma}{2} & 1+\gamma \\ & & & & 1+\frac{\gamma}{2} & 1+\gamma \\ & & & & & 1+\gamma \end{pmatrix}$$

Indirect input γ, if positive, gives relatively more weight to very energy efficient transitions; it gives them relatively less weight if negative.

For construction costs and fuel switch costs, we simply multiply the matrixes by a scalar.

AppendixC.5. 2008 Existing Dwelling Stock Factors

The number of existing dwellings in 2008, given as a hypermatrix in the model, is broken down by energy label (labels G to A), heating fuel (electricity, natural gas, fuel oil and fuel wood) and dwelling type (owner-occupied single- and multi-family dwellings, rented single- and multi-family dwellings and social housing).

The influence of each heating fuel is assessed by a scalar multiplying the number of dwellings in the same fuel category. The influence of dwelling types is assessed in a similar way.

The influence of energy labels is assessed in a more aggregate way, using indirect input κ. The higher κ, the larger the proportion of high energy classes in the housing stock compared to the reference situation. Input κ keeps the number of dwellings labelled C unchanged and changes other labels as follows: label A numbers are multiplied by $1+\kappa/2$, label B numbers by $1+\kappa$, label D numbers by $1-\kappa$, label E numbers by $1-\kappa/2$, label F numbers by $1-\kappa/3$ and label G numbers by $1-\kappa/4$.

AppendixC.6. Energy Service Elasticity

The energy service is given by the following function: $y = Kd^e$, with y the capital utilization rate, d the conventional energy expenditure and e the elasticity of utilization to conventional expenditure. Each time we vary e in the sensitivity analysis, we need to re-estimate K to best fit the data.

We introduce function

$$f(k) = \sum_{i=1}^{10} [ln(y_i) - (k + eln(d_i))]^2$$

which is the sum of squared distances between points from the regression and real data ($k = ln(K)$). As e is fixed, we need to find k_0 which minimizes f.

We have

$$f'(k) = -2\sum_{i=1}^{10}[ln(y_i) - (k + eln(d_i))]$$

and

$$f''(K) = 2 \times 10 > 0$$

Therefore the function is convex and has a minimum in

$$k_0 = \frac{1}{10}\sum_{i=1}^{10}[ln(y_i) - eln(d_i)]$$

AppendixD. Complete list of inputs

Tables D.6-D.12, D.13 and D.14 give the list of inputs involved in the sensitivity analysis.

All inputs follow a truncated normal distribution. One exception is the Heterogeneity Parameter, which follows a discrete uniform distribution. Tables D.6-D.12 display their mean, standard deviation, minimum and maximum values. Indirect inputs are introduced with mark “*”.

Table D.6: List of Inputs: Exogenous inputs

	Input name	Unit	Mean	Std Dev	Min	Max
1	*2008 Energy Price	€/kWh	0.0585	0.003	0.05	0.067
2	*2050 Energy Price	€/kWh	0.08125	0.005	0.067	0.095
3	*Population Growth	none	0	0.004	-0.08	0.08
4	*GDP Growth	none	0	0.02	-0.04	0.04

Table D.7: List of Inputs: Calibration targets

	Input name	Dwelling	Unit	Mean	Std Dev	Min	Max
5	2008 Retrofitting Rate	existing	none	3%	0.5%	1.5%	4.5%
6	2008 Electricity Use	existing	TWh	45	1	43	47
7	2008 Natural Gas Use	existing	TWh	157	1.5	154	161
8	2008 Heating Oil Use	existing	TWh	75	1	73	77
9	*2008 Energy Label Transition Shares	existing	none	0	0.2	-0.5	0.5
10	*2008 Energy Label Construction Shares	new	none	0	0.1	-0.2	0.2
11	*2008 Fuel Shares	new	none	0	0.1	-0.25	0.25
12	*2008 Dwelling Type Shares	new	none	0	0.1	-0.3	0.3

The number of dwellings in 2008 is 24 million with a respective total floor area of 2.2 Gm^2

Table D.8: List of Inputs: Innovation dynamics factors

	Input name	Dwelling	Unit	Mean	Std Dev	Min	Max
13	*Initial Capital Stock	existing	none	0	0.2	-0.5	0.5
14	Learning Rate	all	none	10%	4%	0%	20%
15	Information Rate	all	none	25%	10%	0%	50%
16	Share of variable intangible costs	new	none	95%	15%	50%	99%
17	Share of variable intangible costs	existing	none	80%	20%	50%	99%

Table D.9: List of Inputs: Dwelling Stock Variation Factors (SFD: single-family dwellings, MFD: multi-family dwellings)

	Input name	Dwelling	Unit	Mean	Std Dev	Min
18	Household Density Growth	all	none	-0.007	0.001	-0.009
19	Floor area Elasticity for SFD	all	none	0.2	0.05	0.05
20	Floor area Elasticity for MFD	all	none	0.01	0.01	0
21	Floor area Elasticity for social housing	all	none	0.01	0.01	0
22	Minimum Household Density	all	people/household	2	0.1	1.7
23	Maximum Floor area in SFD	new	m^2	140	10	125
24	Maximum Floor area in MFD	new	m^2	80	5	75
25	Maximum Floor area in social housing	new	m^2	80	5	75
26	Initial Floor area in SFD	new	m^2	120	2	116
27	Initial Floor area in MFD	new	m^2	70	2	67
28	Initial Floor area in social housing	new	m^2	70	2	67
29	Destruction Rate	existing	none	0.35%	0.05%	0.25%
30	Proportion of Non-refurbishable Dwellings	existing	none	5%	1.5%	2%

Table D.10: List of Inputs: Investment cost factors

	Input name	Dwelling	Unit	Mean	Std Dev	Min	Max
31	*Construction Costs	new	none	0	0.1	-0.3	0.3
32	*Retrofitting Costs Magnitude	existing	none	0	0.2	-0.4	0.4
33	*Retrofitting Costs Breakdown	existing	none	0	0.2	-0.4	0.4
34	*Fuel Switch Costs	existing	none	0	0.1	-0.3	0.3

Table D.11: List of Inputs: Theoretical Use of Energy Labels (BC: Building Code)

	Input name	Dwelling	Unit	Mean	Std Dev	Min	Max
35	Label BC2005	new	kWh/m^2/year	120	3	110	130
36	Label BC2012	new	kWh/m^2/year	50	2	45	55
37	Label G	existing	kWh/m^2/year	750	25	710	790
38	Label F	existing	kWh/m^2/year	390	15	365	415
39	Label E	existing	kWh/m^2/year	280	10	260	300
40	Label D	existing	kWh/m^2/year	190	10	175	205
41	Label C	existing	kWh/m^2/year	120	5	110	130
42	Label B	existing	kWh/m^2/year	70	5	65	75
43	Label A	existing	kWh/m^2/year	40	5	35	45

Table D.12: List of Inputs: 2008 Existing Dwelling Stock Factors (SFD: single-family dwellings, MFD: multi-family dwellings)

	Input name	Unit	Mean	Std Dev	Min	Max
44	Floor area of SFD	m^2	112	2	108	116
45	Floor area of MFD	m^2	67	1	65	69
46	Floor area of Social Housing	m^2	67	1	65	69
47	*Energy Label	none	0	0.02	-0.05	0.05
48	*Electricity	none	0	0.02	-0.05	0.05
49	*Natural Gas	none	0	0.02	-0.05	0.05
50	*Fuel Oil	none	0	0.02	-0.05	0.05
51	*Fuel Wood	none	0	0.02	-0.05	0.05
52	*Owner-occupied SFD	none	0	0.02	-0.05	0.05
53	*Owner-occupied MFD	none	0	0.02	-0.05	0.05
54	*Rented SFD	none	0	0.02	-0.05	0.05
55	*Rented MFD	none	0	0.02	-0.05	0.05
56	*Social Housing	none	0	0.02	-0.05	0.05

Table D.13: List of Inputs: Discount Rates (SFD: single-family dwellings, MFD: multi-family dwellings)

	Input name	Dwelling	Unit	Mean	Std Dev	Min	Max
57	Owner-occupied SFD	existing	none	8%	2%	4%	12%
58	Owner-occupied MFD	existing	none	15%	3%	8%	22%
59	Rented SFD	existing	none	45%	5%	30%	60%
60	Rented MFD	existing	none	55%	5%	40%	70%
61	Social Housings	existing	none	4%	2%	1%	8%
62	Owner-occupied Dwellings	new	none	7%	2%	4%	10%
63	MFD	new	none	10%	3%	4%	16%
64	Social Housing	new	none	4%	2%	1%	8%
65	Intangible Costs Calibration	all	none	4%	2%	1%	8%

Table D.14: List of Inputs. Other factors

	Input name	Dwelling	Unit	Mean	Std Dev	Min	Max
66	Envelope Lifetime	all	years	35	4	25	45
67	Heating System Lifetime	all	years	20	3	10	30
68	New Dwellings Lifetime	all	years	25	4	15	40
69	Intangible Costs Lifetime	all	years	30	4	20	40
70	*Energy Service Elasticity	all	none	-0.505	0.04	-0.6	-0.4
71	Heterogeneity Parameter	all	none			5	12