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Smart-Grids and Climate Change. Consumer adoption of smart energy behaviour: a system dynamics approach to evaluate the mitigation potential.

By Elena Claire Ricci, Università degli Studi di Milano, Centro Euro-Mediterraneo sui Cambiamenti Climatici and Fondazione Eni Enrico Mattei

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Keywords: Smart-Grids, Demand Response, Demand Management, System Dynamics, Consumer Choices, Climate Policy

JEL Classification: C61, Q42, Q54

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1 Introduction

Nowadays, national power networks are faced with various challenges: i) increasing demand and reliance on electricity implies the necessity to improve their efficiency, security and quality of service; ii) climate change issues bring about the need to manage an increased amount of renewable energy sources; iii) current trends in society suggest to aim at a greater interactivity with consumers, that are becoming used to be more active.

Though, even with these new pressures arising, current electric power systems have remained qualitatively very similar to how they were in the last century; although capacity and efficiency have been increased, the qualitative architecture of the network has not changed significantly, especially from the consumer side.

Recently, there is a lot of interest regarding Smart-Grids, i.e., the idea of introducing I&CT features into the power network, so that it will be able to transmit and manage not only electricity but also information. Indeed, in the US, 4.5 billion$ of the economic stimulus package of the Obama administration were allocated to smart grid related projects (O'Grady, 2009). In the EU, smart grids have been part of the strategic research agenda since, at least, 2007 (SmartGrids, 2007) and "The Commission has acknowledged that, by enabling substantial gains in energy efficiency, ICT-based innovations may provide one of the potentially most cost-effective means to help Member States achieve the 2020 targets" (European Commission, 2009).

The analysis of the mitigation potentials of smart-grids is quite complex because it includes various technologies and possibilities under one term and also because its effects will depend on the level of consumer participation. This, in fact, is not a mitigation option that cannot only be centrally planned and implemented, but in order to unravel its whole potential it needs to be combined with end-user engagement.

For these reasons it is important to take into consideration not only costs and technical aspects, but also consumer behaviour/responses, in line with the new *Knowledge-Society* trends that are emerging in various disciplines. Smart-grids - differently from Super-grids or other more traditional technologies - open towards a *Knowledge Economy* context where the enhancement of consumer empowerment and knowledge is particularly taken into account.

The broad aim of this work is to highlight and evaluate the potential that a qualitative transformation of the power grid may have. More specifically, in this paper, we analyse how a greater and active involvement of the end-users may contribute to the reduction of the electric sector carbon footprint. The interest in this topic is confirmed by the EU Commission that welcomes a paradigm shift in the structure of the electric distribution grid so that it will become: "user and customer centric, service oriented and […] able to support the migration towards a low-carbon economy and society" (European Commission, 2009).
Indeed, in order to take advantage of the full potential of the electric grid modernization it is necessary to aim at a qualitative evolution of the network able to grasp and deal with the social and cultural trends that are emerging in current society. An example of these trends is that of Smart-Cities, that is a new emerging concept of cities where new models of active involvement of citizens are being experimented within the integrated management of many sectors (such as mobility, electricity generation, logistics, security, etc.). Modern technology developments allow a greater interaction with clients and current global environmental problems need the active participation of citizens in order to be tackled effectively (Chakravarty *et al.*, 2009). These circumstances, together with current trends in other sectors that aim at empowering citizens, are the main motivational drivers of our analysis. Smart-Grids, in particular, and the innovation of the power network could represent the opportunity for the power system to align itself with the new services of the new knowledge-based society.
We are therefore interested in analysing the potentials embedded in consumer engagement in the context of the power system. This includes end-user production, but also demand management, i.e. the effects, for example, of information diffusion and of the management of differentiated pricing policies. The idea is to outline an analysis that includes the different technological options and possible consumer behaviour/responses enabled by the implementation of smart-grid technologies and services.
This paper aims at identifying possible consumer adoption dynamics of smart-grid enabled behaviour and to evaluate the resulting impacts in terms of demand reduction, system cost reduction, opportunities for mitigation. To do so, we (*i*) identify the most important phenomena and motivations that influence the uptake of the actions enabled by smart grid technologies; (*ii*) highlight the complex feedback relations among them; (*iii*) build a system dynamics model to simulate these interactions and identify possible consumer adoption dynamics; (*iv*) analyse the temporal evolution of the stock of consumers that exploits the smart grid opportunities; and (*v*) translate these behaviours in impacts.
In this paper, the phenomena are analysed both qualitatively and quantitatively with the aim of, eventually, producing results that can be used to include smart grids within the technological mitigation options of integrated assessment models (IAMs). These models have up to now excluded Smart-Grids because the calibration for this technology is not straightforward as there are many aspects to take into account, some of which are at a scale that is not representable in such models. Though, we consider important to include, even if in an approximated manner, this option into the IAM framework, as these models are often used to inform and influence policy decisions. In this direction, our aim is to develop consumer adoption dynamics that can allow to consider, even if in an approximated way and with a certain degree of uncertainty, this important option in economic-climate models. This is a first prototype and its relevance is mainly methodological. It builds on the currently available data, that are scarce as implementations of consumer empowerment are at their primitive stages. Nevertheless, the model is a flexible platform that can be easily modified and calibrated once more specific data becomes available. Note that this data should be of quite easy access for policy makers.
The paper looks at a part of the literature that is quite scarce; i.e., the economic evaluation of consumer engagement potentials for mitigation objectives and the economic evaluation of the new emerging role of the consumer/"prosumer" as an active agent within the power system. Instead, most of the literature on Smart-Grids takes more of a technological and engineering perspective.
The rest of the paper is structured as follows, Section 2 briefly discusses the new options introduced by Smart-Grids; Section 3 describes the methodology adopted and the model; Section 4 reports the model specifications for the application to the case of Italy, the simulation results and the impact assessment. Sections 5 and 6 discus and summarize the results. The Appendix reports a sensitivity analysis of the results with respect to the model parameters.

2 Smart-Grids and consumers

’Smart-Grid’ is an umbrella term that includes many different technological options that enable the transformation of the power grid into a sensitive network.

In particular, for our analysis, we are interested in studying the effects of the introduction of smart metering systems. The technological options enabled by smart meters, at the household level, are:

- the bi-directional flow of electricity;
- the two-way flow of real-time information.

These technological features allow:

- end-points to introduce electricity into the system;
- utilities to gain more information on real-time loads and load patterns;
- consumers to have access to better information on their consumption;
- to implement time-related tariffs.

The latter four consequences of smart meter implementation, generate the following economic implications, respectively:

- the empowerment of the consumer, that can become a prosumer;
- an increased control on the power system, which in turn has societal benefits, such as a more efficient management, a decrease in the number of power outages and the reduction of extra capacity needed to sustain the system;
- avoid some of the informational problems at the base of the “energy paradox”;
- the establishment of the correct price signals that allow product differentiation of electricity consumption, that is non-homogeneous over time and season, in terms of production costs and impacts.

Indeed, up to now the consumer has always had a passive role in the system with very little choice. Because the demand for electricity, and energy in general, is not a demand *per se*, but a demand for the services that electricity can provide (lighting, refrigeration, food preparation, washing, entertainment, heating, cooling, etc.), end users had - or still have - no access to data concerning the costs of the energy services used. In addition, payment is often distant from consumption and aggregated, making it even more difficult for the consumer to associate a price to the service. A good description of the consumer’s electricity-consumption decisional-environment is given by Kempton & Montgomery (1982) and Kempton & Layne (1994):

> *“…consider groceries in a hypothetical store totally without price markings, billed via a monthly statement…How could grocery shoppers economise under such a billing regime?” (Kempton & Layne, 1994).*

In such a store, the shopper would have to estimate item price by weight or packaging, by experimenting with different purchasing patterns or by using consumer bulletins based on average purchases (Kempton & Montgomery, 1982).

Indeed, Darby (2006) shows the importance of feedback in making energy use more visible and quantifiable and, consequently, for triggering energy-use behavioural changes. Feedback is a ’self-teaching tool’ and it also improves the effectiveness of other information or advise on energy-use (Darby, 2006).

The invisibility of energy resources makes consumers blind not only to their level of consumption, but also to the level of consumption of others and the “appropriate” consumption level, that may serve as reference (Ehrhardt-Martinez *et al.*, 2010). Thus, it also hinders the effect that social norms may have on consumption patterns (Ehrhardt-Martinez *et al.*, 2010).

Therefore, this new amount and timing of information could have significant effects; even in the worst case scenario - with no behavioural changes that favour the environment or society - smart metering will at least make the consumer (potentially) more conscious of its choices.

The increased monitoring potentials of Smart-Grids both at the system and consumer level will enable to identify and remove ’previously hidden sources of waste’ (Ehrhardt-Martinez *et al.*, 2010). Indeed, flat tariffs and low information on the impacts of power consumption make consumers use energy ’at random’ (Block *et al.*, 2008). Therefore, the conveying of price signals and ethical awareness will also enable to reach consumption patterns that are closer to those optimal for society.

3 Methodology

3.1 Modelling approach

The complexity of the decisional processes related to the end-user when deciding his energy management strategies, now enriched with new additional options, poses some methodological issues in the selection of the modelling platform to use for the analysis. For other electricity generation or transmission technologies that are more centralised it is appropriate to set up an optimization model based on the assumption of perfect rationality of the agents, as investments involve policy-makers and industries, that can be approximated as rational agents. The decisional process of citizens, with regards to daily consumption decisions, is a complex process, as human rationality is different from that of profit-maximising agents, and it is characterised by utility functions that include many more dimensions over and above economic gains (e.g., ethical principles, social acceptability, imitation, information retrieval costs and effort, etc.). Moreover, the concept of perfect information is far away from reality due to information availability, time-constraints and cognitive limitations (Simon, 1955). Indeed, nonlinear models of social system behaviour are arising in the literature (Vogstad, 2004; Sterman, 2000).

We have decided to study the dynamics of consumer adoption of ’smart energy behaviour’[1] building a model based on System Dynamics as we believe this is an appropriate method to analyse from a systemic point of view the behaviour of complex systems. System Dynamics is a modelling framework first introduced by Jay Forrester in the mid-fifties and published with the book ’Industrial Dynamics’ (Forrester, 1961) that is now applied to various scientific domains (Forrester, 1991).

These kinds of models are developed to study systems characterized by interdependences, mutual interactions, informational feedbacks, and circular causality, mainly for the purpose of policy analysis and design (System Dynamics Society). The concept at the core of this approach is that of feedbacks[2] - mainly informational -, loops and endogenous change to study how the system structure and its rules determine its behaviour. Indeed, exogenous disturbances are the triggers of system behaviour, but the main causes are contained within the structure of the system itself (System Dynamics Society).

The first step is that of building a conceptual model based on causal-loop diagrams, that is very close to the Systems Thinking discipline, that builds qualitative models in which the relation and the complex interconnections between the parts of the system are made explicit (Meadows, 2008).

The second step is to build a simulation model translating mathematically these relations; this is usually done by means of coupled non-linear first-order differential (or difference) equations.

Given the large number of variables involved and the complexity of their interdependencies, there is the need of a further step, that is the building a computer-based numerical platform to evaluate quantitatively and graphically the resulting dynamics (System Dynamics Society, Mella 2007).

The main aim is that of having a simulation tool able to test different policies and evaluate how things change over time[3] and how to influence the dynamic paths. The stability of the equilibrium of the system has been studied theoretically/analytically. Moreover, because the phenomena under evaluation are at their primitive stages and because of the consequent absence of good data, we have built a model with stochastic parameters.

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[1] The concept of ’smart energy behaviour’ in the specific context of our modelling framework will be defined more specifically in Section 3.2

[2] «A feedback structure is a setting where existing conditions lead to decisions that cause changes in the surrounding conditions that influence later decisions. That is the setting in which all our actions take place» (Forrester, 1991).

[3] Please note that time by itself is not seen as a cause (System Dynamics Society); although the behaviour of the system changes over time it is not modelled as a function of time itself, but it is dependent on conditions within the system that change over time.

The basic structure of our model builds on Bass (1969) and on the models used in epidemiology. We take inspiration from the Susceptible-Infectious (SI) Models used in epidemiology to describe the evolution of epidemics (Murray, 2002). In these models, the population is divided into two classes: those "susceptible" to the disease and those that are "infectious". The interactions between these types of individuals determine the spread of the infectious disease and the pattern of its diffusion. In our model, the "disease" is what we have called 'smart energy behaviour'.

The Bass diffusion model, developed by Frank Bass in the late 1960s (Bass, 1969), is a system dynamics model that studies the diffusion of products focusing on the interactions between individuals divided into two categories: "users" and "potential users". In addition to the logistic innovation diffusion model, Bass takes into account also external information sources - such as advertising - that are able to generate "early adopters" (Sterman, 2000).

Except for the case of home electricity generation, the adoption of smart energy behaviour differs from the classical innovation diffusion process by three main characteristics:

1. the cost for the adoption is not monetary, but in personal effort terms;
2. the adopted behaviour does not make life easier, but if anything, more difficult;
3. the gain is not an increase in comfort, but is an economic or social reward.

Differently from biological epidemics, in the case of smart energy behaviour:

- the "infection/contagion" is voluntary both for the infected and for the infectant;
- the diffusion pattern is not strictly related to territorial closeness, as communication can travel long distances; although, social mechanisms still maintain a linkage with territorial distribution, think for example at the imitation effect that seeing solar panels installed on neighbouring houses may have on households.

In the specific context of Smart-Grids and consumers, we are aware of two agent based simulation models of technology adoption by Hamilton *et al.* (2009) and Zhang & Nuttall (2007). In the first paper, the authors build a spatial model to analyse the diffusion of the switch from grid supply to autonomous production of electricity through solar power or micro combined heat and power within a virtual city. The main driving force for change is the perceived relative attractiveness between old and new technologies (Hamilton *et al.*, 2009), but there is also a "fashion" effect. In the second paper, the authors apply another spacial agent-based model to study the interactions between residential customers and electricity suppliers when the former decide whether to acquire a smart meter or not and from which supplier. The authors model two interaction effects: price information - from the suppliers - and word of mouth - among the residential customers. Although both of these papers are of high interest and well developed, our aim is to try to focus more deeply on the motivations underlying the change and to analyse a greater variety of consumer behaviour enabled by the implementation of Smart-Grids, with the similar aim (Nuttall *et al.*, 2009) to study the dynamics of the system before it reaches the equilibrium and to highlight to policy-makers the importance of the modelling choices when dealing with the evaluation of complex systems.

3.2 Model Description

Our model has been designed specifically to study the behaviour of small end-users of the electric power sector, that in our opinion is under-studied in the economic literature, but corresponds to the novelty of the effects induced by the introduction of smart-grids in the electricity system. Indeed, we focus on the residential sector and the unit of our analysis is the household at the level at which contracts are decided, bills are paid and electric meters are installed.

Having considered households as the main unit of our analysis, we have grounded the model of the variety of consumer behaviour on six (basic) options that can emerge once smart meters and tariff policies are in place. Indeed, our model comprises:

- shift of consumption to less expensive (less polluting - congesting) hours,

- reduction of consumption while maintaining similar comfort levels,
- behaviour and home automation,
- energy efficiency improvements,
- enrolment in demand response programs,
- electricity autonomous generation;

more in general, we will refer to these activities as ’smart energy behaviours’. The main characteristics of these actions in terms of benefits, costs and effort are described in Table 1.

	Upfront Costs	Economic Savings	Eco-friendly ’label’	Effort
Shift	no	immediate	yes, private	yes
Reduction	no	immediate	yes, private	yes
Automation	small to large	yes	yes, private	no
Energy Efficiency	medium Δ costs	yes	yes	no
Demand Response	no	yes	yes, private	initial[4]
Production	large	in the future	private+public	initial

Table 1: Costs and benefits of consumer behavioural options

This table is an example of the multi-level facets of the possible actions analysed in this paper. Indeed, each consumer may be drawn by some of them and not by others, depending on its preferences.
More specifically, the variety of consumer behaviour has been modelled through ten different ’styles of behaviour’ that each consumer may adopt. These are depicted in the squared boxes of Figure 1 and are characterized by different levels of the six previously described activities. The styles/boxes are organized under three general categories/branches of the model.

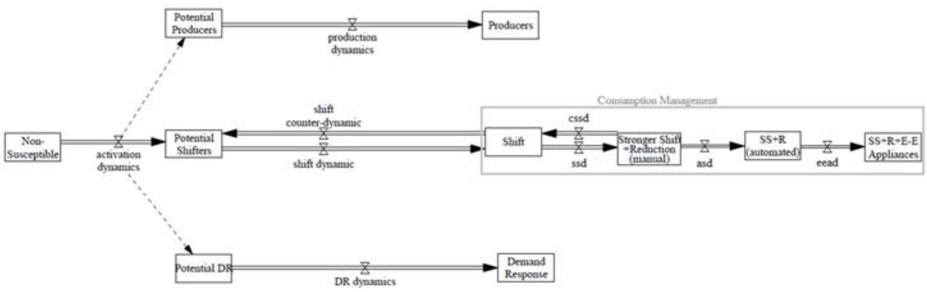

Figure 1: Stock and Flow diagram

Indeed, in our model the empowerment of the end users and the increased variety of possible behaviours has been analysed with the function:

Smart Behaviour = *f*(Production, Consumption Management, Contract Management).

Production. The introduction of two-way smart meters, enables the end-user to become not only a sink-node, but also a source-node in the grid. This will stimulate a change towards a new power grid architecture that moves away from the previous paradigm of centralised large-scale generation. The feature of production is certainly a very important novelty in the behaviour of the consumer, not available in the old architecture of the power grid. This means that every household that has capital and “space” availability - here intended as a rooftop or some land that can be equipped with solar panels - may become a producer of electricity. Policies to incentive end-user grid-injection are already in place in various countries.

Consumption Management. The introduction and diffusion of smart-meters and the related price-policies allows an empowered consumption management by the end-users. The consumer is now able to better associate a price to the energy services that he consumes, and is therefore able to better optimise his consumption patterns. In addition, electric-power-system operators are able to give more accurate price signals that induce a finer electricity-good differentiation. Indeed, electricity consumption in different hours or different days of the

[4] Initial effort here refers to the effort in finding and choosing the program, system or provider.

year is associated with different production costs and environmental and societal impacts. In this model, we test the simplest price policy: that is the application of a differentiated tariff to the consumer, but other more complex and advanced options are available. The consumer response to these new information and tariffs is varied. The first easier option is to shift some of its consumption, and secondly to reduce its consumption, most likely, maintaining the comfort level by means of various options discussed in Section 2 and 3.3.

Contract Management. The implementation of advanced metering systems allows new and more advanced user-provider relationships. With the liberalization of the electricity market, the consumer is able to select its electricity provider and choose among different consumption plans. The increased information and price signals on the costs associated to the energy services used, strengthen consumer capability of optimizing consumption patterns. The additional technological opportunities introduced by smart meters allow the proposal/enrolment in innovative schemes, such as, for example, rewarded curtailment contacts (Demand Response), real-time pricing or other tariff structures.

All these three new lines of action increase the variety of services that can be provided by electricity-providers and open to the possibility of new players/businesses entering the market. Indeed, the evolution of the power grid towards a ’smart network’ might induce a greater level of competition on the electricity market, that has proved in recent years - at least in Europe - difficult to flourish (European Commission, 2011a). Indeed, Hartway *et al.* (1999) considers these options related to smart-metering and time-differentiated tariffs to be:

> «value-added products [for utilities] to profitably retain and attract load [in a deregulated market] ».

The aim of this work is to study the dynamics of consumer adoption of these ten different stylized behaviours to be able to grasp the effects of the more general smart-energy-behaviour dynamics induced by smart-grids. The evolution of consumer behaviour is influenced by several motivations and context variables. Figure 2 shows which variables are included in our model and how they are interconnected. A more in detail explanation of the single variables will be included in the next Section.

Different structures of the model could be possible; after several trials we have chosen this one as we consider these ten styles to well represent the situation, keeping in mind the parsimony principle in building a model and the need to capture into the model the complexity of the phenomena.

3.3 Model Specification

The ten behavioural styles (or “boxes”) represent the stock variables of the model and the double arrows represent the flows of households that move from one style to another.

As it is possible to see in Figure 1, the model starts with the ’Non-susceptible’ box, that contains, at a certain time *t*, all the households that, at time *t*, are not able to adopt ’smart energy behaviours’ - as defined in our framework - because they do not have an activated smart meter or they are not aware of the changes occurred to their electricity meter and billing system that enable them to consider a change of habits. This corresponds to the stadium zero of the model, similar to the situation where the power grid is not “smart”.

The installation and activation of a smart metering system together with the introduction of ’smart energy behaviour’ incentive-policies and the knowledge of this, triggers the availability of a variety of options for the end-user. This is due to: *i*) the increased awareness of own consumption and related costs; *ii*) the saving opportunities; *iii*) the new selling option. Together with these two triggering effects, we assume the existence of information campaigns and Demand-Side-Management (DSM) policies aimed at increasing consumer awareness of the economic opportunities and of the environmental protection possibilities, as well as at triggering a willingness to be “greener”.

As specified in the previous Section (Section 3.2), we have chosen to model these “styles” on three different and interconnected levels - production, consumption management and contract management - that are represented in three different branches of Figure 1.

More in detail, the central branch is a sequence of activities:

- Shift;
- Stronger Shift + Reduction, done manually;

- Stronger Shift + Reduction, automatized;
- automatized Stronger Shift + Reduction + Energy Efficient Appliances;

that involve the management of household consumption and that we have assumed can be ordered.

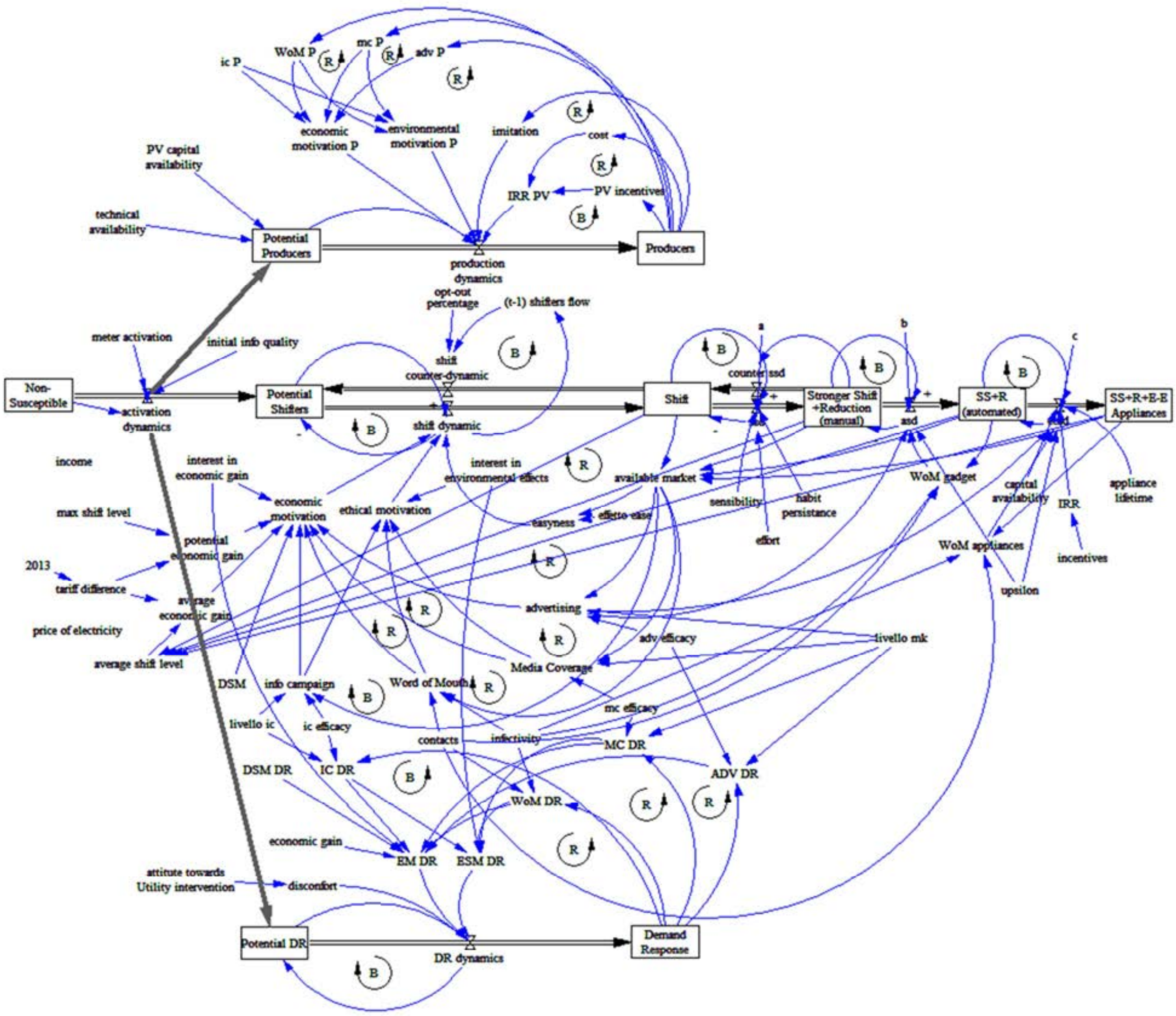

Figure 2: Stock and Flow diagram

As depicted in Figure 2, the households belonging to the ’Non-susceptible’ box can change box and become susceptible of a behavioural change once their electric meter is smart and activated, and they become aware of the change. The latter two activities determine the ’activation dynamic’ flow, depicted in Figures 1 and 2 between box ’Non Susceptible’ and box ’Potential Shifters’.

Once certain households become susceptible to the “smart energy behaviour epidemic”, they move into the ’Potential Shifters’ box. Here are all the households that would be able to undertake a behavioural change but do not do so. Over time and under specific “influences” considered in the model (See Figure 2), some households decide to change their behaviour and they may adopt a first easy type of action, that is the shift of some electricity consumption from more expensive (polluting and congesting) hours to some cheaper (less polluting and congesting) hours. Doing so, they move from the ’Potential Shifters’ box to the ’Shift’ box. We have also modelled the possibility for households to change their mind once they have tried the “new” behaviour if they perceive that the effort is not worth the benefit, see the left-pointing double arrow that exits the ’Shift’ box entering the ’Potential Shifters’ box[5].

[5] We have assumed that the people that return to the previous box are able to move back into the more proactive box in the future. This is a simplifying assumption, that captures the fact that a change in outside conditions may induce households that opted-out in the past to restart the “smart” behaviour

The people in this box are assumed to undertake only a minor level of shifting; once they get more accustomed to it and/or they gain a stronger motivation for doing so, they may move to the 'manual Stronger Shift+Reduction' box, that collects households that undertake a stronger level of shift in energy consumption and they also reduce some of their electricity usage, mainly wasteful, maintaining their comfort level essentially unchanged. We have also modelled the counter-flux for households that decide to return to a lower effort condition. The consumption shift and reduction actions - of the latter box - are assumed to be done manually; some households may also decide to buy (or might be given) some device and/or service that may help the acquisition of price/cost information or automatize some electricity shifting/saving activities improving the shifting/saving efficacy of the household. Doing so, they move from the 'manual Stronger Shift+ Reduction' box to the 'automated Stronger Shift + Reduction' box.

Finally, the household may decide to purchase energy-efficient appliances reducing even the non-directly controllable part of their power load.

Households that are susceptible to smart energy behaviour, i.e. those that exit the 'Non-susceptible' box can also decide whether to enrol in demand response programs and - for those that have capital and "space" availability - to start producing electricity themselves. These actions are not mutually exclusive, but instead, in our model each household has to decide "its position" with respect to the three different types of actions.

Figure 2 depicts the motivations that - in our model - may induce households to move between the ten styles. In particular, starting from the central branch, we have assumed that the main motivations that may induce the choice to start to actively manage the household consumption patterns are two: the possibility of encountering an economic saving on the electricity bill (namely "economic motivation") and of protecting the environment ("ethic motivation"); we have included the social motivation for the de-congestion of the power grid in the environmental-social motivation, labelled "ethic motivation". Imitation for reasons not related to economic savings or environmental and social issues - like fad and fashion - has not been included for this set of actions, as they are "invisible" to people outside of the household, but it could be included if empirical data were to show its relevance. Indeed, certain DSM policies could trigger a competition among households on who is "greener", if they allow environmental friendly behaviour to be visible and quantified (Nye & Burgess, 2009; Allcott, 2011).

The strength of the economic motivation depends essentially on: (*i*) the level of interest in an economic saving, that is in turn related to income, (*ii*) the level of potential and average saving induced by the pricing policy and the price of electricity, and (*iii*) the effectiveness of different channels of information in delivering motivation for a behavioural change. The latter, together with the level of interest in environmental issues, determines the strength of the ethical motivation.

The information channels that we have included in our study are:

- *Information Campaigns.* We include here all public awareness campaigns on electricity consumption and their effects on the electricity system costs and/or environmental impacts. The messages conveyed (together or individually) are focused on the fact that that it is possible to save money, the environment and induce societal benefits.

- *Demand Side Management.* We include here all the options that the utility has to inform the customer on its consumption patterns and the available options to change them in order to incur an economic saving and/or a positive effect on the environment and society.

- *Media Coverage.* We assume that once the behavioural changes start to spread (available/market size), the Media is going to report and comment on this phenomenon, allowing for a greater number of people to become aware of the options and consider the possibility to change, likewise, their consumption behaviour.

- *Advertising.* We have assumed that once the market size - of people that are interested in changing their consumption patterns - becomes interesting, more companies/businesses will enter the market offering products and services that can increase the saving potentials, and that these will start to advertise their products/services allowing a greater number of people to become aware of the saving possibilities that a change in consumption is able to induce.

- *Word of Mouth*. We have also included the "word of mouth" channel that is a very powerful persuasion mechanism. The idea is that the households that have tried the new type of behaviour and are satisfied with it, will spread the word about the benefits of this change. The people that are in contact with the latter households receive this additional and personal information that may "infect" them, generating a positive feedback.

All of the above effects are made more effective/enhanced as the *easiness* to undertake the various actions increases. This easiness is in turn affected by the availability of additional products and services that arise once the market size of potential customers gets large enough. In our setting, the first two[6] information channels are modelled as exogenous as they depend on policy decisions, the last three channels instead arise within the model.

Once the household has decided to undertake, at least, the first behavioural change, it can decide to do even more. On average, as habit persistence decreases and sensibility increases more people will move to the more effort involving boxes. Moreover, the purchase or free receival of gadgets - that can help *i*) the visualization of consumption patterns and costs, *ii*) improve the (remote) controllability of appliances, or *iii*) allow the use of services that provide tailored information and recommendation - can improve the effectiveness of the household decision to shift and reduce electricity consumption. As these nodes get more relevant, they are also more able to attract new households due to a reinforcing loop.

For what concerns the demand response branch, we here consider the enrolment in contracts whereby the utility is allowed to intervene on the household consumption, with no or little notice, for a certain number of critical times during the year. The service curtailments and the availability provided are rewarded in monetary terms. We have assumed that the motivations of taking part to these programs are similar to those for deciding to shift and reduce consumption, though an increased discomfort may arise in correspondence of the curtailment; this, in addition to the fact that certain households would not approve of the utility directly being able to control their meter, has led us to model this flow at a lower level than the previously described ones. There again, some households may instead prefer to be curtailed for a few hours a year and gain the same amount of money with no effort at all.

The self-production branch has been modelled considering the availability of capital and the opportunity of installing micro-generation modules. Important impacts are also related to public policies and the availability and characteristics of private services. The main motivational forces are related to economic savings and environmental/social motivation (as for the previous two branches) but also include an imitation effect, as, for example, solar panels or micro-wind turbines are (most of the times) clearly visible by non-household members.

Potentially, consumers should be divided into classes that try to model the differences in consumer sensitivity to different stimuli. These classes could be based on ideological categories (related, for example, to the weight given to environmental or social issues when taking consumption decisions), interest in technology, age and propensity to change, income, education, or other variables that emerge from the literature; and should be characterised by different reaction function calibration. Though, due to the lack of data, in the first example application of the model described in Section 3.4, we only account for welfare differences, so as to not include additional assumptions that would be difficult to estimate and justify.

3.4 Model equations

Section 3.3 has described qualitatively the stocks, the flows, the "motivational" variables and all the interconnections of our model (Figure 2). In order to be able to build a simulation tool we have translated there relations into equations.

The main structure of the model is a system of ten non-linear first-order differential equations with stochastic parameters, that depict the integrated evolution of the different "styles" of consumer behaviour. These are:

[6] Although the Information Campaigns start as exogenous stimuli, they stop once a certain level of "infected" population is reached.

$$\begin{cases} \frac{d(NS_t)}{dt} = -\, ad(NS_t, t) & (1) \\ \frac{d(PS_t)}{dt} = ad(NS_t, t) - sd(PS_t, S_t, SSRm_t, SSRa_t, EA_t, t) + & (2) \\ \qquad + csd(PS_t, S_t, SSRm_t, SSRa_t, EA_t, t) & \\ \frac{d(S_t)}{dt} = sd(PS_t, S_t, SSRm_t, SSRa_t, EA_t, t) + cssd(S_t, t) + & (3) \\ \qquad - csd(PS_t, S_t, SSRm_t, SSRa_t, EA_t, t) - ssd(S_t, t) & \\ \frac{d(SRRm_t)}{dt} = ssd(S_t, t) - cssd(S_t, t) - asd(SSRm_t, t) & (4) \\ \frac{d(SRRa_t)}{dt} = asd(SSRm_t, t) - eead(SSRa_t, t) & (5) \\ \frac{d(EA_t)}{dt} = eead(SSRa_t, t) & (6) \\ \frac{d(PP_t)}{dt} = ad(NS_t) - pd(NS_t, PP_t, t) & (7) \\ \frac{d(P_t)}{dt} = pd(NS_t, PP_t, t) & (8) \\ \frac{d(PDR_t)}{dt} = ad(NS_t) - drd(PDR_t, DR_t) & (9) \\ \frac{d(DR_t)}{dt} = drd(PDR_t, DR_t) & (10) \end{cases}$$

In the previous system of equations, the state variables are indicated as:

- NS_t is the number of households that, at time *t*, are unable to adopt a 'smart energy behaviour';
- PS_t is the number of households that, at time *t*, are potentially able to adopt the shift consumption behaviour;
- S_t is the number of households that, at time *t*, actually adopt the shift consumption behaviour;
- $SSRm_t$ is the number of households that, at time *t*, actually adopt the manual stronger shift and reduction of consumption behaviour;
- $SSRa_t$ is the number of households that, at time *t*, actually adopt the automated stronger shift and reduction of consumption behaviour;
- $SSRa_t$ is the number of households that, at time *t*, actually adopt the energy efficient appliances and automated stronger shift and reduction of consumption behaviour;
- PP_t is the number of households that, at time *t*, are potentially able to adopt the electricity production behaviour;
- P_t is the number of households that, at time *t*, actually adopt the electricity production behaviour;
- PDR_t is the number of households that, at time *t*, are potentially able to adopt the demand response behaviour;
- DR_t is the number of households that, at time *t*, actually adopt the demand response behaviour.

We refer to the total population as $TP_t = TP_o$ that is constant. The flows between stocks are indicated as:

- *ad* - activation dynamics - Flow of new people that have the possibility to change their behaviour (knowledge+technology);
- *sd* - shift dynamics - Flow of new people that decide to change their behaviour by shifting part of their electricity consumption to the lower rate/lower impact segment;
- *csd* - counter shift dynamics - Flow of new people that decide to stop shifting;
- *ssd* - (manual) stronger shift dynamics - Flow of new people that decide to increase their behaviour by manually shifting a larger part of their electricity consumption and reducing wasteful consumption;
- *cssd* - counter (manual) stronger shift dynamics - Flow of new people that decide to stop the manual stronger shift and consumption reduction behaviour;

- *asd* - automated stronger shift dynamics - Flow of new people that decide to increase the effectiveness of their consumption shift/reduction behaviour by using some products or services to automate some actions;
- *eead* - energy efficient appliances dynamics - Flow of new people that decide to buy energy efficient appliances in addition to the previous actions.
- *pd* - production dynamics - Flow of new people that decide to change their behaviour by starting to produce electricity;
- *drd* - demand response dynamics - Flow of new people that decide to change their behaviour by enrolling in demand response programs.

4 Case Study

We here apply the general model described in the previous Sections to the particular case of Italy. Italy is an interesting laboratory because there has been the largest deployment of smart-meters that covers the entire population. Although the electric network has not completely been innovated to become a smart-grid, the deployment of smart-meters is the most relevant step in the empowerment of the end-user.

4.1 Detailed Model Specification

For this particular implementation, the fluxes have been detailed with auxiliary variables on the basis of some specific context-dependent driving forces and of the available data in the literature and in national databases. This particular implementation is meant to be just a first attempt to study the evolution of a very interesting and important phenomenon. We do not claim this model to be exhaustive nor conclusive, but rather a compromise between the interest in a quantitative analysis and the data availability at this very primitive stage. To account for the uncertainty in the estimation of the parameters, in the case study we apply a Monte-Carlo (MC) approach and perform 2500 simulations with the values of the parameters extracted from probability distributions whose mean is equal to the values in the literature.

In order to account for the differences that economic welfare may have on certain parameters, we have stratified the population according to their level of satisfaction of the economic condition of the household. This stratification is particularly useful when estimating the parameters related to the interest in environmental protection and in the economic saving potentials of behavioural changes. Values have been elaborated from the micro-data of ISTAT (2011).

The *ad* flux of Equations (1) and (2) has been detailed as follows:

$$ad(NS_t,t)=ma(t)\cdot NS_t\cdot qi\ ,$$

$$ma(t)=\min(0.33\cdot t,1)\ ,$$

with *ma* - meter activation - being the percentage of smart meters that are activated by time t, and *qi* - initial-information quality - being the percentage of people that take notice of the information provided, i.e., that know they have new options, equal to 0.78. These parameters have been estimated from the activation rate of 2010 (AEEG, 2011b) and on the basis of the percentage of consumers that state to be satisfied of the comprehensibility of the display on the smart meter, taken as a lower bound for the households aware of the change and able to access the additional information (ISTAT, 2011).

The numeric value of the *sd* flow represents the number of households that move to the ’shift’ stock in an infinitesimal unit of time. The households that change box/behaviour are those that are sensitive to at least one of the motivational drivers (economic and/or ethic). This is, formally, the union of the households that are sensitive to economic and/or environmental and social issues. To calculate this quantity it would be necessary to know the joint-distribution of these two motivational drivers among the households. Unfortunately, this value is not available in the literature. Values for the single effects are instead available, but for these to be of use - and avoid double-counting - it is necessary to also know the size of the intersection, i.e., the number of households that are sensitive to both stimuli. The size of the intersection can be calculated from the single values only if one of the following three assumptions holds:

- *disjunction* (i.e., households are sensitive to one or the other stimulus, but never to both). In this case, the measure of the union is the sum of the two individual values;
- *inclusion* (i.e., being sensitive to one stimulus (the smallest) implies being sensitive also to the other). In this case, the the measure of the union is the maximum between the two single values;
- *independence* (i.e., the proportion of households that are sensitive to the economic motivation is identical among the households that are interested or not interested in the environmental motivation, and viceversa). In this case, the measure of the union is the sum of the two values minus their product).

The first two assumptions are quite extreme and certainly not realistic, the third is an intermediate case and therefore might be closer to the real situation. For this reason, we introduce in our model the third assumption, and in order partially overcome this approximation, we have: (*i*) stratified the population for economic welfare and assumed independence just within the stratum, and (*ii*) performed a multivariate sensitivity analysis of these (and other) values.

The *sd* flux depends on all the active consumption management stocks, therefore, to simplify notation we indicate as CM_t the set of the variables S_t, $SSRm_t$, $SSRa_t$, and EA_t. Indeed, the *sd* flux of Equations (2) and (3) has been detailed as follows:

$$sd(PS_t,CM_t,t)=\left[em(CM_t,t)+esm(CM_t,t)-em(CM_t,t)\cdot esm(CM_t,t)\right]\cdot(1+ea(CM_t))\cdot PS_t \ ,$$

where *em* - economic motivation - is the percentage flow of people that decide to shift because of economic reasons (without the effect of ease) and *esm* - environmental social motivation - is the percentage flow of people that decide to shift because of environmental/social reasons (without the effect of ease).

The auxiliary variable *ea* - ease - represents a reinforcing effect that “ease in shifting” has on the decision to shift and is defined as:

$$ea(CM_t)=\frac{1}{3}\cdot mk(CM_t) \ ,$$

where *mk* - available market - represents the percentage of people that have already changed behaviour by starting to actively manage their electricity consumption $((S_t+SSRm_t+SSRa_t+EA_t)/TP_o)$ and that therefore constitute potential customers for firms interested in producing related goods and services.

The economic and ethical (environmental/social) motivation percentage flows are constituted by the percentage of households, that in the unit of time, change their behaviour due to some information, channelled through one of informational vectors of model. Again, to avoid double counting households that are sensitive to more than one informational channel, we have assumed the - less extreme - hypothesis of independence. The percentage flows *em* and *esm* are, consequently, defined as:

$$em(CM_t,t)=1-(1-ic_e)(1-dsm_e)(1-mc_e)(1-adv_e)(1-wom_e) \ ,$$

$$esm(CM_t,t)=1-(1-ic_{es})(1-mc_{es})(1-wom_{es}) \ ,$$

where ic_e (information campaigns effect), dsm_e (demand side management effect), mc_e (media coverage effect), adv_e (advertising effect), and wom_e (word of mouth effect), are the percentage of people that change behaviour (shift) because of info-campaigns / demand-side-management / media-coverage / advertising / word-of-mouth on the economic benefits of the new behavioural options induced by smart-metering. Similarly, ic_{es}, mc_{es}, and wom_{es} are defined for the environmental and social benefits. More specifically, they are defined as:

$$ic_e(CM_t,t)=\begin{cases}\eta_{ic}\cdot ies\cdot\sqrt{\dfrac{pg(t)}{pg_o}} & for\ mk_t(CM_t)<0.5\\ 0 & for\ mk_t(CM_t)\geq 0.5\end{cases} \ ,$$

$$ic_{es}(CM_t) = \begin{cases} \eta_{ic} \cdot iee & for\ mk_t(CM_t)<0.5 \\ 0 & for\ mk_t(CM_t) \geq 0.5 \end{cases} ,$$

$$dsm_e(t) = \eta_{dsm} \cdot ies \cdot \sqrt{\frac{pg(t)}{pg_o}} ,$$

$$mc_e(CM_t,t) = \eta_{mc}(CM_t) \cdot ies \cdot \sqrt{\frac{pg(t)}{pg_o}} ,$$

$$mc_{es}(CM_t,t) = \eta_{mc}(CM_t) \cdot iee ,$$

$$adv_e(CM_t,t) = \eta_{adv}(CM_t) \cdot ies \cdot \sqrt{\frac{pg(t)}{pg_o}} ,$$

$$wom_e(CM_t,t) = \eta_{wom}(CM_t) \cdot ies \cdot \sqrt{\frac{ag(CM_t,t)}{ag_o}} ,$$

$$wom_{es}(CM_t) = \eta_{wom}(CM_t) \cdot iee .$$

The quantities η_j - effectiveness of the *j*th information channel - represent the effectiveness of the informational channels on households that are interested in their content. Instead, the variables *ies* - interest in economic savings - and *iee* - interest in the environmental effects - represent the percentage of households (for each segment of the population) that are interested in economic savings and the percentage of households that are interested in the environmental effects of their actions (and act consequently), respectively. We have estimated these values analysing the micro data of ISTAT (2011), calculating the joint distribution of these interests and the welfare condition. More specifically, as a proxy for the share of households interested in the environment we have calculated the distribution of people that declare that environmental problems are among the three worst problems of the country. As a proxy for the share of households interested in economic savings, we have considered the percentage of consumers that have changed their electricity provider or decided not to change for lack of information on the savings or for lack of actual savings, conditioned to knowing of the possibility to do so.

For the economic motivation, we have also added a reinforcing/reducing effect related to the potential economic gain - *pg* - (or average economic gain - *ag* - in the case of personal communication) associated with the behavioural change, that is related to the price difference in the tariff for the various time segments (*td* - tariff difference). The values of $pg_{\circ}$ and $ag_{\circ}$ are those of the reference situation. More specifically, these quantities are defined as:

$$pg(t) = msl \cdot td(t) ,$$

$$ag(CM_t,t) = asl(CM_t) \cdot td(t) ,$$

with:

$$td(t) = \begin{cases} 0.1 & for\ t<2013 \\ 0.3 & for\ t \geq 2013 \end{cases} ,$$

$$msl = 0.5 ,$$

$$asl(CM_t) = \frac{(\Theta_S \cdot S_t + \Theta_{SSRm} \cdot SSRm_t + \Theta_{SSRa} \cdot SSRa_t + \Theta_{EA} \cdot EA_t)}{S_t + SSRm_t + SSRa_t + EA_t} .$$

We define the *msl* - maximum shift level - as the maximum percentage of electricity consumption that can be managed by the residential consumer from Molderink *et al.* (2009) and Block *et al.* (2008). The quantity *asl* - average shift level - is, instead, the average of the percentage savings that are incurred (and reported) by the households that are actively managing their electricity consumption, where Θ_k is the percentage saving for the *k*th behavioural style.

As described in Section 3.3, the information-campaign effect and the demand-side-management effect are exogenous stimuli that trigger the first-adopters; the central values of the relative parameters η_{ic} and η_{dsm}, used in our simulations, are: 0.05 and 0.074. These values are taken from Snyder & Hamilton (2002), Haug (2004), Snyder (2007) and adapted from eMeter (2010). Note that we estimate these parameters from the literature by assuming that the percentages referring to people can be transferable to the household unit/level.
Moreover, we assume that while demand side management policies can continuously be improved, information campaigns cease once a certain level of population has adopted the targeted behaviour. The central value of this level is assumed to be 50%. The efficiency parameters of the remaining three effects, that are endogenous in the model and arise only once (and proportionally) there are already some adopters of the behaviour, are modelled as follows:

$$\eta_{mc}(CM_t) = \begin{cases} \frac{0.05}{0.3}\cdot mk(MC_t) & \text{for } mk(CM_t)<0.3 \\ 0.05 & \text{for } mk(CM_t)\geq 0.3 \end{cases} ,$$

$$\eta_{adv}(CM_t) = \begin{cases} \frac{0.016}{0.3}\cdot mk(MC_t) & \text{for } mk(CM_t)<0.3 \\ 0.016 & \text{for } mk(CM_t)\geq 0.3 \end{cases} ,$$

$$\eta_{wom}(CM_t) = c\cdot i\cdot mk(MC_t) ,$$

where *c* is number of contacts that a household has in the unit of time - i.e., number of households to which a "smart-energy behaving household" talks about its benefits - and *i* is their relative infectivity, i.e., the percentage of people that are affected by the contact and decide to act consequently. The values for these two parameters (c=19 and i=0.02) and the numerical values in the above equations for η_{mc} and η_{adv} are adapted from the literature (Sultan *et al.*, 1990; Yoo *et al.*, 2010; Haug, 2004). In particular, for the media-coverage case the values are taken from the literature on a wide interest topic like health. Assuming that health is of interest to the whole population, we use this literature value as a proxy for the effectiveness of media coverage on interested population. Recall that the percentages of households interested in economic savings and/or in the environmental effects - namely, *iee* and *ies*, are calculated from ISTAT (2011).
The counter-flow *csd* is defined as the number of people that decide to stop shifting after having tried this behaviour for one year, more specifically:

$$csd_t(CM_{t-1},t-1)=op\cdot sd_{t-1}(CM_{t-1},t-1) ,$$

with *op* being the opt-out percentage, equal to 0.005 (REF).
Once the household has entered the active consumption management macro-box, by starting with the soft shifting behaviour, it can increase its effort and effectiveness in achieving economic savings and benefits for the environment and society by moving along the other sub-boxes. The fluxes are defined as follows:

$$ssd_t(S_t,SSRm_t)=\gamma_{ssd}\cdot S_t ,$$

$$cssd_t(S_{t-1},SSRm_{t-1})=op\cdot ssd_{t-1}(S_{t-1},SSRm_{t-1}) ,$$

$$asd_t(SSRm_t,SSRa_t)=\left(\gamma_{asd}+c\cdot i\cdot \frac{SSRa_t}{TP_o}\right)\cdot(1+\uparrow\cdot\eta_{adv}(CM_t))\cdot SSRm_t ,$$

$$eead_t(SSRa_t,EA_t)=\left(\gamma_{eead}+c\cdot i\cdot \frac{EA_t}{TP_o}\right)\cdot(1+\uparrow\cdot\eta_{adv}(CM_t))\cdot SSRa_t .$$

We are not able, at present, to estimate the γs from the literature as the phenomenon is at its primitive stages, therefore we choose the following central values 0.2, 0.1 and 0.05, but we choose a probability distribution with a high variance. Note also that here we model advertising as having a strengthening effect on adoption as found in Haug (2004). Indeed, we multiply η_{adv} by a term ↑ ($\uparrow=\frac{0.09}{0.016}$) so that this product's saturation level is 0.09.

As described in Section 3.3, the demand response dynamic - *drd* - is modelled as having similar motivational channels as the active consumption management case, though the reduced comfort in the curtailment periods has lead us to reduce its diffusion speed, compared to that of the soft shifting behaviour. Indeed,

$$drd(PDR_t,DR_t)=\left[em_{dr}(DR_t)+esm_{dr}(DR_t)-em_{dr}(DR_t)\cdot esm_{dr}(DR_t)\right]\cdot dsc\cdot PDR_t \ ,$$

$$em_{dr}(DR_t)=1-(1-ic_{e,dr})(1-dsm_{e,dr})(1-mc_{e,dr})(1-adv_{e,dr})(1-wom_{e,dr}) \ ,$$

$$esm_{dr}(DR_t)=1-(1-ic_{es,dr})(1-mc_{es,dr})(1-wom_{es,dr}) \ ,$$

$$ic_{e,dr}(DR_t) \ = \begin{cases} \eta_{ic}\cdot ies\cdot\sqrt{\dfrac{eg(t)}{eg_o}} & for\ DR_t<0.5 \\ 0 & for\ DR_t\geq 0.5 \end{cases} \ ,$$

$$ic_{es,dr} \ = \begin{cases} \eta_{ic}\cdot iee & for\ DR_t<0.5 \\ 0 & for\ DR_t\geq 0.5 \end{cases} \ ,$$

$$dsm_{e,dr}(t) \ = \ \eta_{dsm}\cdot ies\cdot\sqrt{\frac{eg(t)}{eg_o}} \ ,$$

$$mc_{e,dr}(DR_t) \ = \ \eta_{mc,dr}(DR_t)\cdot ies\cdot\sqrt{\frac{eg(t)}{eg_o}} \ ,$$

$$mc_{es,dr}(DR_t)) \ =$$

$$adv_{e,dr}(DR_t) \ = \ \eta_{adv,dr}(DR_t)\cdot ies\cdot\sqrt{\frac{eg(t)}{eg_o}} \ ,$$

$$wom_{e,dr}(DR_t) \ = \ \eta_{wom,dr}(DR_t)\cdot ies\cdot\sqrt{\frac{eg(t)}{eg_o}} \ ,$$

$$wom_{es,dr}(DR_t) \ = \ \eta_{wom,dr}(DR_t)\cdot iee \ ,$$

$$\eta_{mc,dr}(DR_t) \ = \begin{cases} \dfrac{0.05}{0.3}\cdot\dfrac{DR_t}{TP_o} & for\ DR_t<0.3 \\ 0.05 & for\ DR_t\geq 0.3 \end{cases} \ ,$$

$$\eta_{adv,dr}(DR_t) \ = \begin{cases} \dfrac{0.016}{0.3}\cdot\dfrac{DR_t}{TP_o} & for\ DR_t<0.3 \\ 0.016 & for\ DR_t\geq 0.3 \end{cases} \ ,$$

$$\eta_{wom,dr}(DR_t) \ = \ c\cdot i\cdot\frac{DR_t}{TP_o} \ ,$$

where *dsc* - discomfort - is the parameter that reduces the diffusion rate. No literature quantitative has been found on this topic, therefore we have chosen a hypothetical conservative central value of 1/3 and included such parameter in the stochastic analysis.

For the production dynamic branch we have decided to change approach (at least in this first modelling attempt) and model it so that it replicates estimates of distributed generation diffusion from the literature, due to the fact that some specific data and estimates are available. Model improvements and refinements would be certainly possible but at the moment there are two main obstacles, namely the very early primary stages of the process and the commercial interest in the data necessary that has not allowed us to retrieve some important data for the model calibration. This will be possible once initial data will be gathered and made available.

For what concerns the electricity production branch of the model, although the problem can be theoretically approached in a similar way than for the other branches, in this case, the phenomenon is not at such early stages and, therefore, it is possible to extrapolate some trends from the data. We choose to do so as, currently, data on the time dynamics is more available in the literature compared to data for estimating the parameters that define the different cognitive decisions of the consumers when considering if and when to become prosumers. For the other two branches of the model we have considered the modelling approach more appropriate as the data to extrapolate the time dynamics of adoption have not yet been collected or disclosed. The only results available are those of pilot studies that we use for estimating the impacts of consumer adoption, but that in most case concern samples of people that voluntarily decide to take part to the experiment.

Concerning the MC approach, the values of 21 parameters for the 2500 simulation have been randomly extracted from probability distributions with mean equal to the value found in the literature. Figure 3 depicts the sample densities for chosen parameters. Most parameters have been associated with beta-distributions with standard deviation equal to 0.01, except for c - number of contacts – for which we chose a Poisson probability distribution with mean and variance equal to 19.

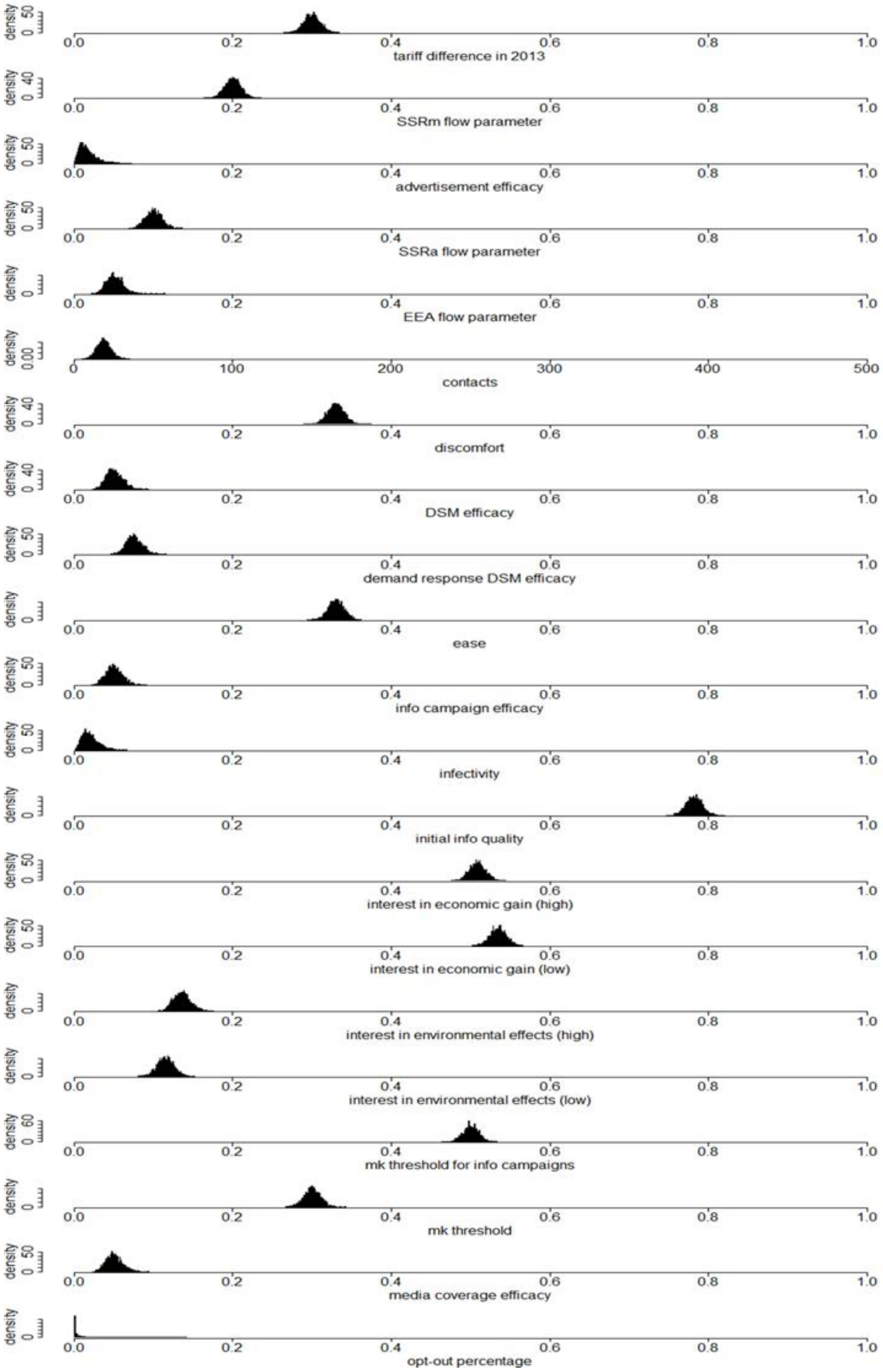

Figure 3: Parameter sample densities

4.2 Theoretical analysis of the equilibrium

Our system of equations is too complex to be able to solve it to find an analytical solution. Nevertheless, it is possible to prove theoretically the existence, and uniqueness, of the equilibrium and to study its stability.
This is useful to prove the coherence between the numerical simulations that will be described in the following Section (Section 4.3) and the theoretical properties of the system.
To find the equilibrium and to study its stability characteristics, we have had to simplify the model slightly, by:

- removing the time dependency of the variables - in order to have an autonomous system of equations, even if our model has proved to be at least asymptotically autonomous, as time-varying parameters converge to constants.
- simplifying the step functions, in order for the values to be differentiable;

For this kind of analysis, we have collapsed all the variables into time-varying, time-invariant, and stock-variable dependent terms. We have solved the system so that the above derivatives are contemporaneously set to zero and found the following equilibrium solutions:

$$\begin{cases} NS_t = 0 \\ PS_t = 0 \\ S_t = 0 \\ SSRm_t = 0 \\ SSRa_t = 0 \\ EA_t = \overline{EA_t} \\ PDR_t = 0 \\ DR_t = \overline{DR_t} \\ PP_t = 0 \\ P_t = \overline{P_t} \end{cases}$$

Moreover, it can be proved that the following conservation laws hold:

$$\frac{dNS_t}{dt}+\frac{dPS_t}{dt}+\frac{dS_t}{dt}+\frac{dSSRm_t}{dt}+\frac{dSSRa_t}{dt}+\frac{dEA_t}{dt}=0 \qquad \forall t$$

$$\Rightarrow \frac{d(NS_t+PS_t+S_t+SSRm_t+SSRa_t+EA_t)}{dt}=0 \qquad \forall t$$

$$\Rightarrow NS_t+PS_t+S_t+SSRm_t+SSRa_t+EA_t=cost \qquad \forall t$$

$$\frac{dNS_t}{dt}+\frac{dPDR_t}{dt}+\frac{dDR_t}{dt}=0 \qquad \forall t$$

$$\Rightarrow \frac{d(NS_t+PDR_t+DR_t)}{dt}=0 \qquad \forall t$$

$$\Rightarrow NS_t+PDR_t+DR_t=cost \qquad \forall t$$

$$\frac{dNS_t}{dt}+\frac{dPP_t}{dt}+\frac{dP_t}{dt}=0 \qquad \forall t$$

$$\Rightarrow \frac{d(NS_t+PP_t+S_t+P_t)}{dt}=0 \qquad \forall t$$

$$\Rightarrow NS_t+PP_t+P_t=cost \qquad \forall t$$

Given the above conservation laws and the initial conditions (below), it straightforward to identify the equilibrium points:

$$\begin{cases} NS(0) = 13.4 * 10^6 \\ PS(0) = 6.7 * 10^6 \\ S(0) = 0 \\ SSRm(0) = 0 \\ SSRa(0) = 0 & \Rightarrow \overline{EA} = NS(0) + PS(0) = 20.1 * 10^6 \\ EA(0) = 0 & \Rightarrow \overline{DR} = NS(0) + PDR(0) = 20.1 * 10^6 \\ PDR(0) = 6.7 * 10^6 & \Rightarrow \overline{P} = NS(0) + PP(0) = 20.1 * 10^6 \\ DR(0) = 0 \\ PP(0) = 6.7 * 10^6 \\ P(0) = 0 \end{cases}$$

The system admits ∞^3 equilibrium points that are univocally determined by the initial conditions.
To investigate the stability of the equilibrium points, we have linearized the system and computed the eigenvalues of the Jacobian Matrix; these turn out to be all negative except for three that are equal to zero, confirming the stability of all equilibrium solutions.
In the current version of the model all classes, except for the last ones, are expected to get empty as *t* increases. If future empirical evidence will contradict this asymptotic behaviour, frictions could be added to the model, i.e., replacing, where appropriate, $Stock_i(t)$ with $Stock_i(t) - \varphi_i$ in the right-hand-side terms of the differential equations of system 11. Though, these would only mean that a certain amount of the stock of households would remain in the various boxes, generating an equilibrium of the type:

$$\begin{cases} \overline{NS} = \phi_{NS} \\ \overline{PS} = \phi_{PS} \\ \overline{S} = \phi_S \\ \overline{SSRm} = \phi_{SSRm} \\ \overline{SSRa} = \phi_{SSRa} \\ \overline{EA} = NS(0) + PS(0) - \sum_i \phi_i \\ \overline{PDR} = \phi_{PDR} \\ \overline{DR} = NS(0) + PDR(0) - \sum_i \phi_i \\ \overline{PP} = \phi_{PP} \\ \overline{P} = NS(0) + PP(0) - \sum_i \phi_i \,. \end{cases}$$

Note that some of the above φ_i could be zero.

4.3 Simulation results

To perform the calculations for identifying the adoption dynamics we have implemented the theoretical model in the Vensim PLE Plus computer-based platform. This software applies the Runge-Kutta method, of order four and with time step 2^{-7} years, for solving numerically the system of differential equations.
Due to the uncertainty embedded in most of the parameters included in the model, we adopt a Monte-Carlo (MC) approach and configure the system of equations with stochastic parameters. We perform 2500 simulations, for each of which the values of the parameters are obtained by joint independent random sampling from the probability distributions described in Section 4.1. We obtain 2500 solutions associated with 2500 possible realizations of the vector of the parameter values. These results have been analysed using the statistical environment R (R Development Core Team, 2010).
Figure 4 shows the trajectories of each of 2500 simulations, highlighting the dynamics of the stocks along time from year 2010 to 2100. The colour is used to distinguish among different dynamics and is the same across all Figures. The 2500 MC replications are ordered and coloured according to the value of aggregated shift at year 2030. Figure 5 represents the pairwise quantiles of the above simulations for the six behavioural boxes/stocks of the consumption management branch of the model, to highlight their dispersion.

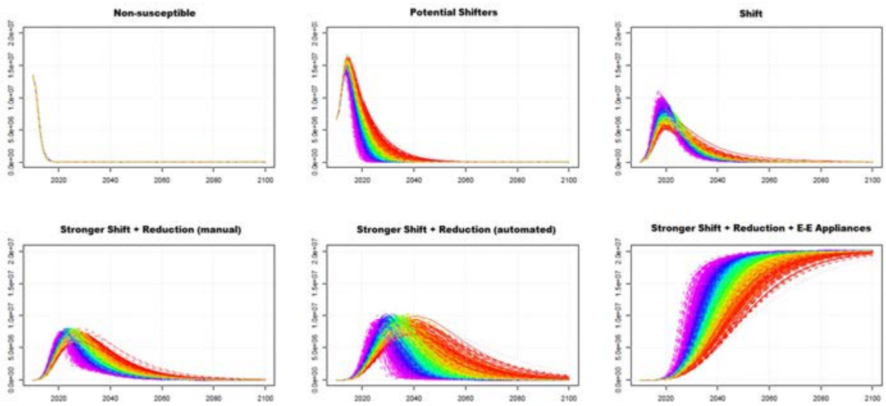

Figure 4: Consumption Management stock quintile dynamics

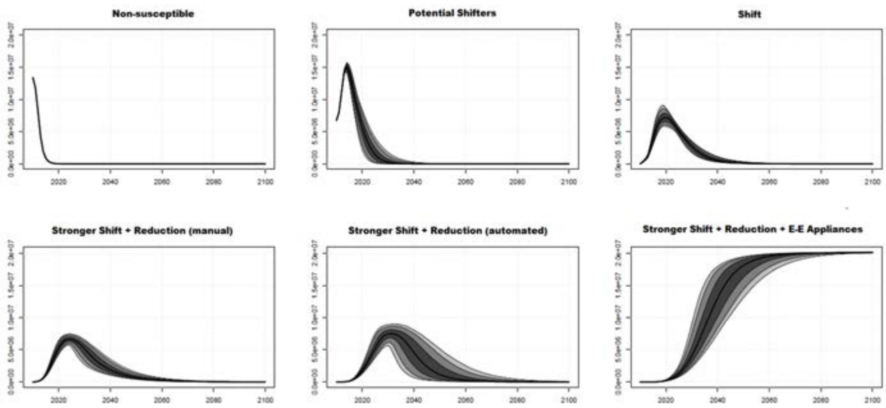

Figure 5: Consumption Management stock quintile dynamics

These Figures show the growth and the decline of the different stocks of the Consumption Management branch of the model. At first site, at least two major features are evident: i) an increasing effect of the uncertainty of the parameters moving from stock 1 to stock 6; ii) an increasing delay of the peaking period, moving from plot 2 to plot 4. Indeed, the dynamic of the first stock, corresponding to the ’Non-susceptible’ population, is almost unaffected by uncertainty; the related flow is mainly affected by the speed of the activation of the smart-meters by the utility, which is known. In all simulations, this stock results almost completely empty by 2023.

The second stock - that of the Potential Shifters - always presents a peak around 2014 of about 15 million households, with quite a low variability. Looking at the different MC replications, a higher peak seems to generally mean a slower declining dynamic. This high-peak slow-decline pattern is associated with a delayed and lower peak of the Shift stock (plot 3, Figure 5). In this stock, early peaks can reach values up to ten million people, while delayed peaks can go down to five million households. Notice also that all MC replications tend to peak around 2020.

The early/late dynamic of the different MC replications - identified by the colour of the curves - is preserved (and probably imputable to the height of the peak reached in plot 2) along all the successive stocks. Despite this, differently from plot 2 and 3, the height of the peaks observed in plot 4 and 5 seems to be independent of the delay of the trajectories. The peak reaches a value between 6-8 million households around 2022-2030 in plot 4, and between 7-12 million around 2030-2040 in plot 5. In the latter box there is a very high level of uncertainty concerning the emptying time, that ranges from 2040 to more than 2100, causing for example, that in 2040 the stock ranges between zero and one million households, making prediction very hard. A similar level of uncertainty is transmitted and amplified in the last box.

Figures 6 and 7 show such dynamics for the first 15 years when predictions are more credible both because of the effect of the parameter uncertainty and because closer to the situation for which parameters where estimated.

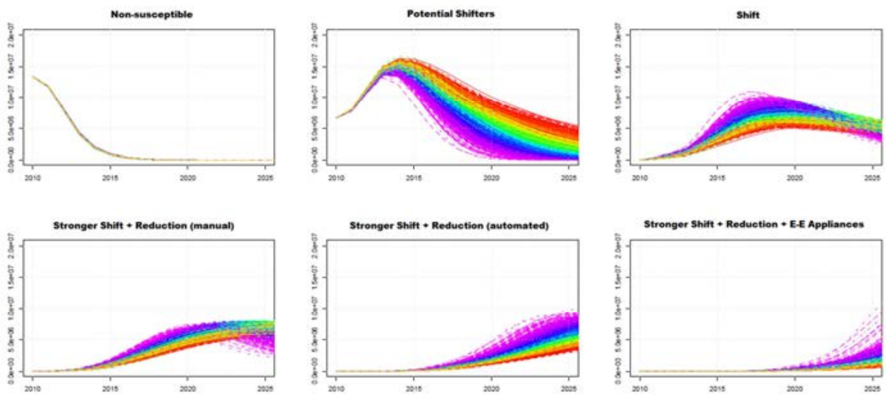

Figure 6: Consumption Management stock dynamics up to 2025

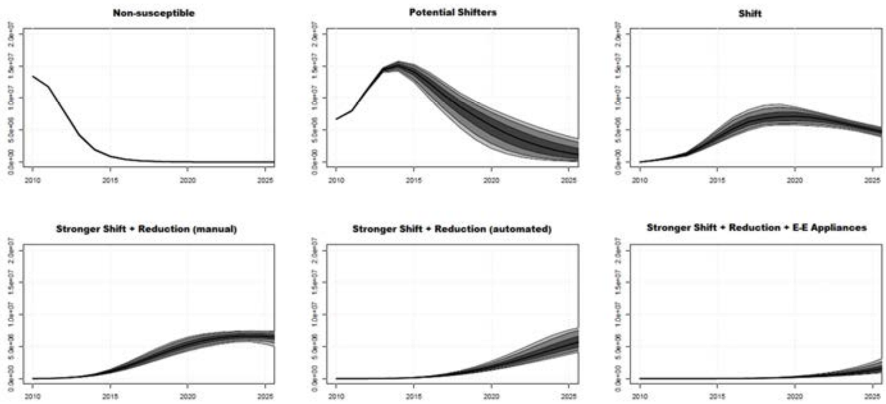

Figure 7: Consumption Management stock quintile dynamics up to 2025

From these graphs we can notice some short-term internal dynamics within the Consumption Management super-box, i.e., that the ’automated Stronger Shift+ Reduction’ and ’automatized Stronger Shift + Reduction + Energy Efficient Appliances’ stocks do not fill significantly before 2015 and 2020, respectively.

The flows between the last four boxes - included in the Consumption Management super-box - have been modelled in a very simplistic way for lack of specific literature, therefore, the most sound results are those depicted in Figure 8 and 9, where the last four classes are aggregated. These Figures confirm that the uncertainty of the parameters largely affects the dynamics of the last three stocks, while their aggregation is less affected.

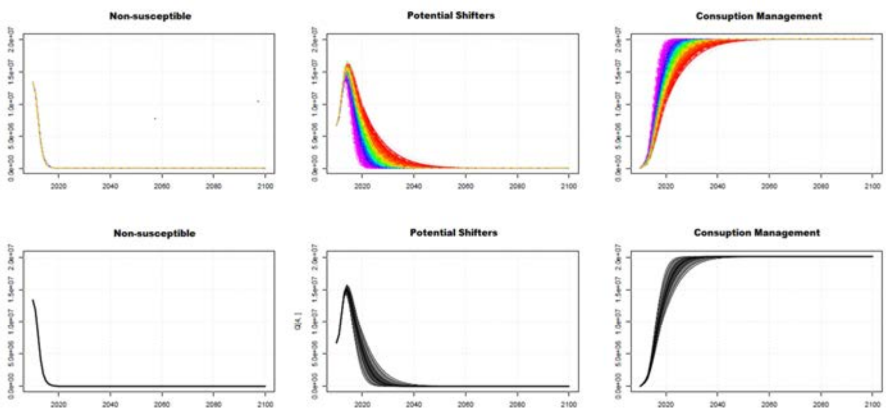

Figure 8: Aggregate Consumption Management stock and quintile dynamics

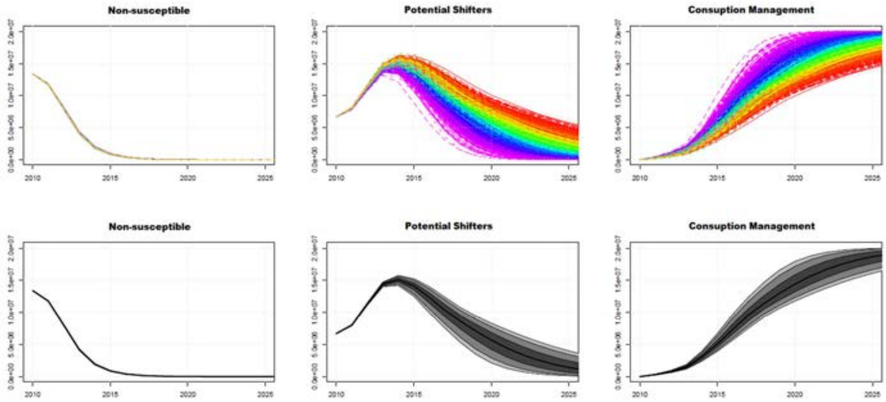

Figure 9: Aggregate Consumption Management stock and quintile dynamics up to 2025

Figure 10 depicts the stock dynamics and the relative pairwise quantiles for the enrolment in demand response programs. Compared to the dynamics of consumption management (Figure 8), the dynamic of adoption is slower, as expected due to the discomfort parameter. Moreover, the resulting dynamics are also characterised by more uncertainty.

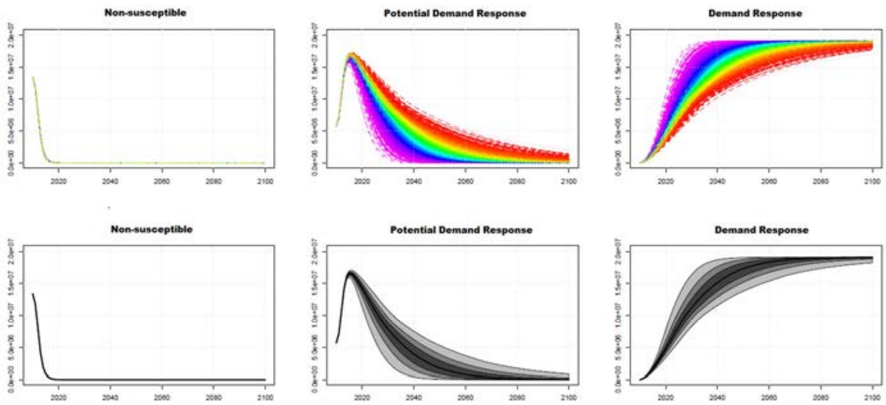

Figure 10: Demand Response stock and quintile dynamics - coloured by DR value at t=20

4.4 Adoption impact assessment

After having solved the system of equations and identified the adoption dynamics, we are interest in evaluating the impacts of such adoption patterns on the power system. To do so, we need to attach a specific effect on electricity consumption for each of the ten behavioral stages analysed.

In recent years, various pilot studies have been performed, to estimate the effects of behavioural changes that follow the installation of smart meters and/or the application of differentiated tariffs (Ehrhardt-Martinez *et al.*, 2010; Olmos *et al.*, 2010). Moreover, the literature on informational feedbacks is quite large even if results are not always consistent (Darby, 2006; Neenan & Robinson, 2009). The values that we use in this assessment are taken from the PowerCents DC pilot experiment (eMeter, 2010) and adapted from (European Commission, 2011b); indeed, we use as reference the following values:

- Shift box: 9% consumption shift and 0% consumption reduction;
- manual Stronger Shift+ Reduction box: 23% consumption shift and 5% consumption reduction;
- automated Stronger Shift+ Reduction box: 36.8% consumption shift and 10% consumption reduction;
- automatized Stronger Shift + Reduction + Energy Efficient Appliances: 40% consumption shift and 20% consumption reduction;

Figure 11 depicts the overall shift in energy consumption, i.e, the percentage of total residential electricity consumption that is shifted, due to the evolution of the stocks described in the previous Section. On the left panel the 2500 trajectories are reported, while on the right-hand-side panel the pairwise quantiles are outlined. Notice how consumption shifting starts from 2010 and its level grows fast, at nearly one percentage point per year between 2015 and 2030. Compared to the evolution of the stocks, that was characterised by a significant uncertainty, the variability of the dynamic of the aggregate shifting effect is strongly reduced, due to some kind of balancing effect among the last four stocks. This is good news since these are the values that will be used for the impact assessment of smart grids.

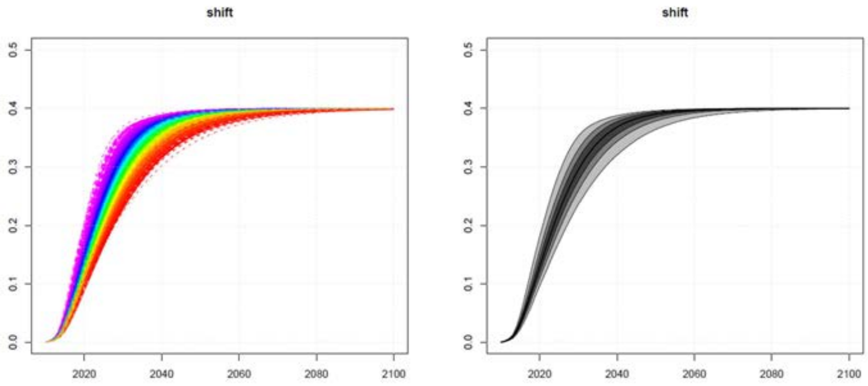

Figure 11: Total percentage shift

Electricity consumption reduction (Figure 12) presents similar trends, but starts later and reaches lower values with a lower slope. This is due to the increased effort and/or comfort loss entailed in consumption reduction with respect to consumption shift. The Appendix reports the results of a sensitivity analysis of such patterns with respect to the main parameters of the model.

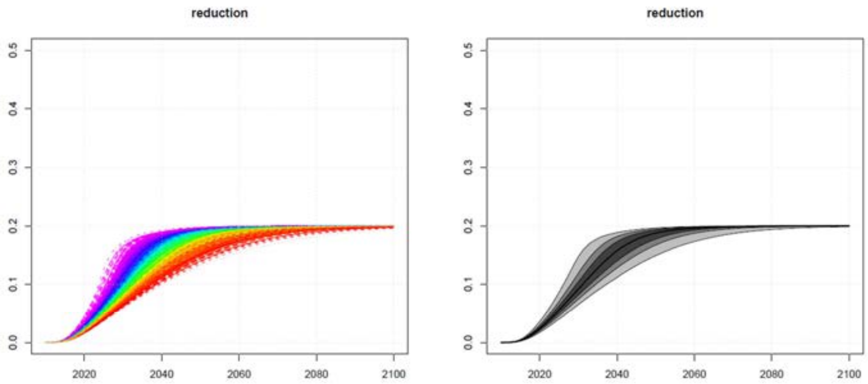

Figure 12: Total percentage reduction

The value of shifting consumption is related to the patterns of electricity demand, which are not constant during the day or the year, but are instead characterised by peaks. Electricity generation and transmission systems are sized according to the maximum peak load (plus a margin to account for forecasting errors or emergencies), as demand needs to be satisfied at all times. This means that part of the capacity installed is used only for a very limited amount of hours during the year. Therefore, a shift in consumption that smooths load curves may give the possibility to delay capacity expansion and to better use the available capacity, lowering overall plant and capital cost requirements. Indeed, even if customers are not subject to real-time pricing, the utilities that provide them the service, need to buy electricity at whole-market prices, that generally depend on the marginal cost of the most expensive generator that is injecting energy into the grid. This means that when demand peaks, even the most inefficient generators are able to enter the market, thus increasing electricity prices. If demand is instead shifted to lower-demand periods, efficient generators are favoured as they are able to increase their market share. This will reduce the volatility of electricity prices (reducing both high and low peak prices) and, possibly, enable to exploit efficient production opportunities during low-demand times, for generation that is not programmable, such as that with wind and solar energy.

We have tried to quantify the potential benefits and costs of the adoption trends identified with our model and described in the previous Section. As a reference value we take the (point-wise) median of the 2500 simulations, whose impacts in terms of percentage consumption shift and reduction - with respect to total residential electricity demand - are reported in Table 2.

	2015	2020	2025	2030
Shift	3.28%	12.99%	22.44%	29.56%
Reduction	0.36%	2.45%	5.63%	9.22%

Table 2: Percentage of total residential electricity consumption that can be shifted and avoided

Given that the Italian electricity consumption from the residential sector is around 69,353 GWh/year (AEEG, 2011a), we find that the amount of load that can be shifted is the one reported in Table 3. The same Table reports the corresponding level of generating capacity that can be avoided (or deferred in time), given the 11 hours of peak that are defined in the current tariff structure, and given a power plant capacity factor of 85%. Note that we are interested in evaluating the possible substitutability with respect to fossil fuel or nuclear power plants. As a reference, consider that 76% of Italy's thermoelectric power plants are under 800 GW, and that a reference nuclear power plant is in the order of 1 GW.

In addition to the generation capacity savings, consumption management enables to avoid, or defer in time, also transmission capacity expansions; though these benefits are not accounted for in this analysis.

	2015	2020	2025	2030
Peak load reduction (GWh/y)	2273	9009	15561	20498
Peak capacity reduction (GW)	0.93	3.70	6.38	8.41

Table 3: Peak load reduction potentials by shifts in consumption

A2A (2010) reports the amount of CO_2 emissions and the system costs that could be avoided if all Italian households were to shift ten percent of their consumption in the cheaper-tariff time-segment. We use these values to calculate the CO_2 emissions and various cost savings induced by the shifting behaviour adoption dynamic that emerges from our model (Table 4), assuming that the marginal effects are constant as the number of household shifting or reducing their consumption increases or decreases. As a reference, note that the Italian objective of emission reduction for the period 2008-2012 was of cutting 13.67 $MtCO_2$/y. Of these, 9.5 $MtCO_2$/y were assigned to the electricity sector (Ministero dell'Ambiente, 2007).

	2015	2020	2025	2030
CO_2 emission reduction (Mton CO_2/y)	0.15	0.58	1.01	1.33
CO_2 emission costs reduction (M€/y)	2.95	11.69	20.19	26.60
Fuel costs (M€/y)	26.22	103.92	179.50	236.44
Plant costs (M€/y)	39.34	155.88	269.24	354.67

Table 4: Avoided CO_2 emissions and costs by shifts in consumption

These benefits should be added to the 500 million € that Enel is saving each year because of remote operations on smart meters. The related benefits include remote-meter reading, reading-error reduction, real-time information on low-voltage loads, remote activation/deactivation of service, customer messaging, outage and tampering detection.

A more efficient use of the system infrastructure induces savings for the operators of the system and will enable, in time, also bill savings for all customers. The households that actually change consumption pattern and shift their demand to the low-peak segment will also benefit from direct immediate economic savings. These savings, evaluated on the basis of the average annual consumption of an Italian household and on the current tariff structure, are 2.73 €, 6.99 €, 11.18 € and 12.15 € for a shift of 9%, 23%, 36.8%, 40%, respectively. Aggreagate savings over time are reported in Table 5. For now, savings are low, as the price difference between the two segments for the consumer is very low, around 10%, but it will increase from 2013 when the tariff structure will be updated to follow more closely whole-market prices (A2A, 2010).

	2015	2020	2025	2030
Aggregate savings (M€/y)	20.0	79.4	137.1	180.6

Table 5: Aggregate households bill savings by shift in consumption with the 2010-2012 tariff scheme

Additional economic and environmental benefits are induced by electricity consumption reduction. Recall that our analysis evaluates reductions with virtually no loss of comfort for the household members, indeed we refer to savings of wasteful power like vampire loads and/or automated reduction of consumption. Table 6 reports the load demand reduction that may be achieved by means of a more conscious use of electricity in everyday behaviour, and the relative size of generating capacity. Note that here we spread the consumption reduction over all the 24 hours of the day. Also the impact on CO_2 emissions is evaluated on average emissions and not on peak load emissions. The Table also reports an estimate of the generating cost savings calculated on the basis of the average cost in 2011 (GME, 2011).

	2015	2020	2025	2030
Peak load reduction (GWh/y)	250	1700	3906	6391
Peak capacity reduction (GW)	0.03	0.23	0.52	0.86
CO_2 emissions reduction (Mton CO_2/y)	0.14	0.98	2.25	3.68
CO_2 emission cost reduction (M€/y)	2.88	19.58	44.99	73.62
Generation cost reduction (M€/y)	19.65	133.64	307.05	502.40

Table 6: Peak load reduction potentials by reduction in consumption, maintaining constant comfort levels

Bill savings, for households that decide to reduce their electricity consumption, in percentage terms correspond to the percentage of consumption savings; while aggregate savings in absolute terms are reported in Table 7. We report range-values between a minimum and a maximum, as savings depend also on the total consumption of the household, i.e., tariffs are differentiated not only for time-of-use, but also for the level of aggregate household consumption.

	2015	2020	2025	2030
Min aggregate savings (M€/y)	27.6	187.2	430.1	703.8
Max aggregate savings (M€/y)	67.2	456.2	1,048.3	1,715.4

Table 7: Aggregate households bill savings by reduction in consumption with the 2010-2012 tariff scheme

At the household level, bill savings range between: 19-46 €/hh/y for a 5% reduction, 38-93 €/hh/y for a 10% reduction, and 76-185 €/hh/y for a 20% reduction. As a reference, recall that vampire-loads in the EU are estimated to correspond to 10% of total residential consumption (ACEEE, 2008).

Notice that consumption reduction has a much stronger economic saving potential for the consumer with respect to the shifting saving potential. Consumption shift away from peak time segments is efficient in allowing economic, environmental and capacity savings for the system, while economic savings for the customer - with the current tariff scheme - are very low, even if they are prospected to grow after 2013.

Savings due to consumer engagement are high, especially if we consider that they have no (or very little) generating costs, indeed the costs are mostly in terms of effort by the consumer. Here emerges the importance of engaging with the consumer, to make him more empowered and conscious of the multi-level impacts of its consumption decisions.

Figure 1 shows the cumulative savings over time compared to the costs of installing the smart meters. We do not include savings by the consumer as these are revenue losses[7] for the electricity providers and, therefore, they are neutral for the whole system. Instead, we depict the latter cumulative savings with respect to total cost for installing smart meters in Figure 14, as these costs in Italy are ultimately paid by consumers on the bill.

Note that these values do not take into account the possible bill savings that can arise from lower generating costs due to the comparative advantage of distributed generation in certain vulnerable areas of the network. These graphs show that the investment costs for installing the smart metering infrastructure are balanced by the

[7] In the current rewarding system.

related benefits that accrue in the following years, the investment is repaid in a short amount of time (4-10 years depending on what cost savings are considered). Note that these evaluation are only indicative as they extend current values in the future, and they take into account only a sub-set of benefits induced by smart meters. For example, outage reduction strongly reduces system costs, though we do not currently have this data for Italy; in the US, outages shrink by 24.5% the revenues of the electric power sector (ISGI, 2010). Recall also that these results are based on the dynamics of a first application of our model based on the data available up to now.

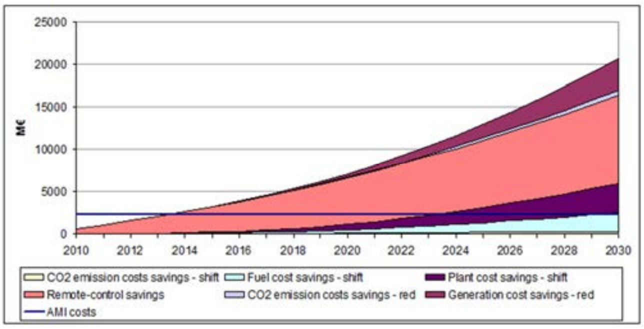

Figure 13: Advanced-Metering-Infrastructure costs and power system cost-savings

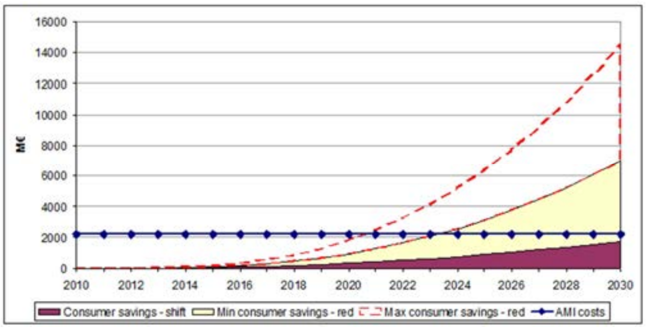

Figure 14: Advanced-Metering-Infrastructure costs and aggregate consumer bill savings

The contribution of consumers by shifting or reducing consumption may help increase the energy efficiency of the system, that is one of the objectives of the 20 20 20 EU strategy. Indeed, if we consider its classical definition, energy efficiency is improved because shifting and/or reducing peak load favours the most efficient power producers. Moreover, if we consider the end product, i.e., the energy services demanded by customers, consumption shift and/or reduction - keeping comfort levels constant - are able to provide the same amount of services with lower consumption of electricity (and consequently: lower consumption of primary sources, lower emissions and lower costs).

For what concerns demand response, customers enrol in these rewarded load-curtailment programs, that become active at critical times, by reducing the electricity services available. The consumer benefit is a monetary reward in exchange of the possibility of a loss in comfort for a limited number of times during the year. On the other side, the system is able to react to critical peaks in demand without service interruptions, and both society and utilities are able to face lower peak prices. Demand response contracts are useful for dealing with temporary emergencies, but could be also used as a more regular management option for avoiding expensive additional capacity expansion needed just for a very limited amount of hours per year. Current demand response programs in the US (that include also commercial and industrial activities under pre-planned prioritazation schemes) count 5 million customers and are potentially able to reduce peak load by 41 GW, that correspond to a six percent peak-load-reduction (FERC, 2008). Our results are only indicative, because in Italy no demand response program for residential customers has been proposed, but from the literature we can verify that adoption trends similar to the ones we find could have very important effects on the power system (GE, 2010; FERC, 2008). For example, in the US, a 3% reduction in peak demand for the 100 more expensive hours of the year would generate 145-300 million $ per year of savings (Brattle, 2007). Moreover, the annual costs for power interruptions in the US is estimated in 80 billion $ per year relative to a total annual sector revenue of 326 billion $ (ISGI, 2010). The previous figures do not take into account the “social” cost of service interruptions:

in the US, the willingness to pay to avoid black-outs is evaluated to be around 5$ to avoid one hour of outage (Watch, 2010).

The minimum target of the 2010-2012 AEEG tariff structure in Italy is to distribute consumption in the following way: 1/3 in higher price/cost/impact segment and 2/3 in the other. Therefore, given the demand response adoption rates identified in the previous Sections, the maximum demand response potential linked to residential customers in Italy is reported in Table 8.

	2015	2020	2025	2030
Enrolled Households (Millions)	1,644	4,788	8,298	11,215
Potential load reduction (GW)	0.78	2.26	3.91	5.29

Table 8: Residential customer demand response potentials

The other main source of emission reduction for the electric sector induced by consumers is related to self-generation with micro electricity generators based on renewable sources of energy. With respect to the other options for consumers some adoption data are already available. The extrapolation of a trend to use for future years is quite complicated as the ones available are the initial installation rates of a new emerging phenomenon, and also because they are strongly related to the high PV incentives that have been available for residential consumers in Italy. Future trends will indeed depend on the evolution of such incentive policies, in addition to that of module prices and consumers energy and environmental awareness.

In any case, if we look at the data in 2011, we can get an idea of the magnitude of the possible impacts. Indeed, from the literature we find that PV generation in Italy is able to reduce emissions by 6.3 Million ton CO_2/year (GIFI, 2011). Of the total installed capacity, 14.6% is by residential households (GSE, 2011), therefore the impact is of 919,800 ton CO_2/year.

Generation with PV has reduced fuel import by 2Mtep/y; of this, 14.6% is due to residential customers. In addition, there are beneficial effects also on the local economy (75% of the costs of installation are in favour of local producers), employment and also state tax revenue (GIFI, 2011).

In Italy, incentives cost 1.5% of the total electricity bill, which is about 1/5 of what consumers finance with the A3 component of the bill, that includes financing also for other types of generation, R&D, and benefits for other sectors.

Moreover, a study by APER shows that as of 2013 bill cost saving should be visible for the Italian consumers, due to the lower cost of distributed PV generation in the most vulnerable areas of the power network. Assosolare (2011) calculates the benefits to be around 1.9 €/MWh of average reduction of the national unit price of electricity (PUN).

5 Discussion

Our results show that consumers can be successfully involved and that they do respond to appropriate stimuli. The speed of the diffusion of the different smart energy behaviours is strongly influenced by the actions of policy makers and electric power providers. Indeed, policies can be targeted to both consumers - for example with awareness campaigns - and utilities - for example by imposing best practices or price schemes, like it has happened in Italy with the differentiated tariff by the electric energy and gas authority (AEEG). Moreover, the role of electricity providers in promoting the diffusion of such behaviours is also crucial, as they can decide to implement the minimum activities imposed by regulation or to design proactive initiatives to take advantage of the new opportunities of interaction with the end-user. An example of these two kinds of approaches can be seen in the Italian market, where certain providers are designing and using the new options, and encouraging consumers to take on an active role in the electric system, offering (*i*) information and tips on how to reduce wasteful consumption, (*ii*) services to install solar panels in residential dwellings, and (*iii*) taking part in various research projects on innovative functionalities of smart grids and demand response programs. On the contrary, other providers advertise the opportunity to enrol in flat tariff schemes, favouring consumer passivity, although this constitutes a “voluntary passivity”.

Literature shows how the use of smart metering and price signals, and the diffusion of distributed generation brings about benefits to all parts: consumers, utilities and society.

In this direction, there is a value to be attached to electric self-sufficiency. This self-sufficiency is not intended in a pauperistic way, but follows the idea of taking advantage of local opportunities to reduce environmental impacts and increase economic opportunities within communities, in connection with the global system, that has the role of integrating 'local energy ecosystems'. These new options affect a market that is in equilibrium, therefore, in order to modify it (by integrating more renewable and distributed real and virtual generation sources supported by Smart-Grids) there is the need of an outside "push" (low carbon policies, low risk energy strategies, etc.). Indeed, there is a strong risk of contrast between small smart and active prosumers and large utilities that aim at maximising their revenue. Policy need to be developed so that these two realities can synergically interact, for example changing the reward system for utilities in a way that revenue is not only influenced by the quantity of customer consumption, but also the quality of consumption (energy efficiency, self-generation, shift and reduction of consumption with respect to previous years, interaction with customers and services provided for load management, etc.).

There are, indeed, in current literature, many proposals to completely automatize also the load management, i.e., the demand side of the phenomenon, putting therefore the consumer out of the game. We also consider automation to be a positive aspect to reduce effort and increase efficacy, though the automation included in our model is one available to the consumer, and therefore a voluntary, programmable and reversible automation on specific actions, at specific times with specific criteria. The more diffused engineering approach is most likely easier to administer, but it loses the chance to take advantage of the social and cultural implications that the technological advancements of the power grid may have. We instead consider the opportunity of a qualitative change in the end-user's role to be very important.

6 Conclusions

The aim of the paper is to analyse the system effects of Smart-Grids in the light of climate change mitigation policies, with particular attention to the new opportunities and behavioural changes available to end-users, that can now become active and "Smart" electricity users/"Prosumers".

We simulate the adoption of Smart-Grid enabled behaviour by consumers within a System Dynamics model, that considers ten possible behavioural stages. The stylized behavioural stages modelled include various combinations of the following actions: (*i*) no change in consumption patterns, (*ii*) shift in electricity consumption, (*iii*) reduction in electricity consumption, maintaining similar comfort levels, (*iv*) home automation and energy efficiency improvements, (*v*) enrolment in demand-response programs, and (*vi*) electricity generation. The flow of households from one stage to the others is influenced by many factors; the motivational drivers that are modelled are (*i*) economic savings and (*ii*) environmental and societal benefits; while the main informational channels included are: (*i*) information campaigns, (*ii*) demand-side-management policies, (*iii*) word of mouth, (*iv*) media coverage, and (*v*) advertising. Our System Dynamics model builds on Bass (1969) and the Susceptible-Infectious (SI) models applied in epidemiology and is used to simulate the diffusion process of what we define as "Smart energy behaviours".

More in detail, we firstly propose a conceptual model that can be used as a prototype to estimate models for local evaluations, and secondly simulate a first application to the case of Italy, where the largest deployment of Smart-meters has taken place, up to now. Data availability is still quite scarce as the phenomena involved are at their very early stages, but the model can be easily updated once more specific data are available; in any case, the emerging trends and qualitative adoption dynamics appear to be quite stable to small variations in the parameter values (For details, see the Appendix).

Our simulations show the quantitative importance of the effects of consumer behavioural changes. Indeed, we find that, on average, consumer involvement may induce an aggregated shift in total residential electricity consumption of 13.0% by 2020 and of 29.6% by 2030; and reduction in residential electricity consumption (just by reducing wasteful consumption) of 2.5% by 2020 and 9.2% by 2030. These consumption changes may have strong impacts on the system operating costs (in the order of 380 M€/y by 2020, 1203 M€/y by 2030), on the CO_2 emissions (in the order of 1.56 MtonCO_2/y by 2020, 5.01 MtonCO_2/y by 2030), and on customer savings (ranging between 266-535 M€/y by 2020 and 884-1896 M€/y by 2030, in aggregate terms). These results show that the smart energy behavior epidemic does spread, i.e., the consumer can be successfully involved in the

better management of the power system, using appropriate signals (Information, Communication and Knowledge). Indeed, consumer engagement can generate important effects in the short and medium term.
The most important factors in promoting consumer adoption are the parameters that define the strength of the word-of-mouth effect and the efficacies of the other informational channels. This may help policy makers design effective policies to accelerate the adoption process.
The previous result confirms the importance of modelling the phenomena using a tool that is able to capture the many interdependencies and the epidemic-kind dynamics.
Finally, our results confirm the relevance of consumer involvement and the importance of developing marketing strategies able to engage with the different types of consumers, to take advantage of the different “prosumer” preferences and in order to increase the system management improvements and the climate change mitigation opportunities.

7 Future developments

Future developments of this work will deepen the analysis of the styles of electricity consumption by end-users (“Smart” and “Non-Smart” users) and of the new contracts that are arising, in order to better analyse the evolution of the roles of the various players on the energy system and their impacts.
It will also extend the analysis with respect to the impacts and potentials of distributed micro-generation, and analyse the contribution of public buildings, and of commercial and non-energy related industrial activities.
When specific data will be available, the model will be calibrated with such data to improve the calculations of the diffusion phenomena and of the impacts, costs and benefits of different policies.
It will also explore the potentials of citizen aggregation to go beyond the individual physical limit of space/“roof” availability

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Appendix - Sensitivity Analysis

An additional interesting analysis is to investigate, at a first order approximation level, the ultimate effect of each single model parameter on the dynamic of the system and, in particular, on the impacts that can be generated on residential consumption (i.e., Aggregate Shift, Aggregate Reduction, Demand Response adoption).

This sensitivity analysis is carried out by means of OLS regression. Figures 1, 1, 1, report the scatter plots of Aggregate Shift, Aggregate Reduction, and Demand Response adoption in 2020[8] versus the corresponding values of the model parameters, for the 2500 simulations. Point colours are the same as those used for the simulation curves of the Figures of Section 4.3 and 4.4. Moreover, in each scatter plot the corresponding univariate-regression line is depicted with the corresponding R^2 index. From these plots it is already possible to identify some strong positive dependencies (e.g., Infectivity, Contacts, other informational channels efficacy, etc.) and some negative ones (e.g., opt-out percentage).

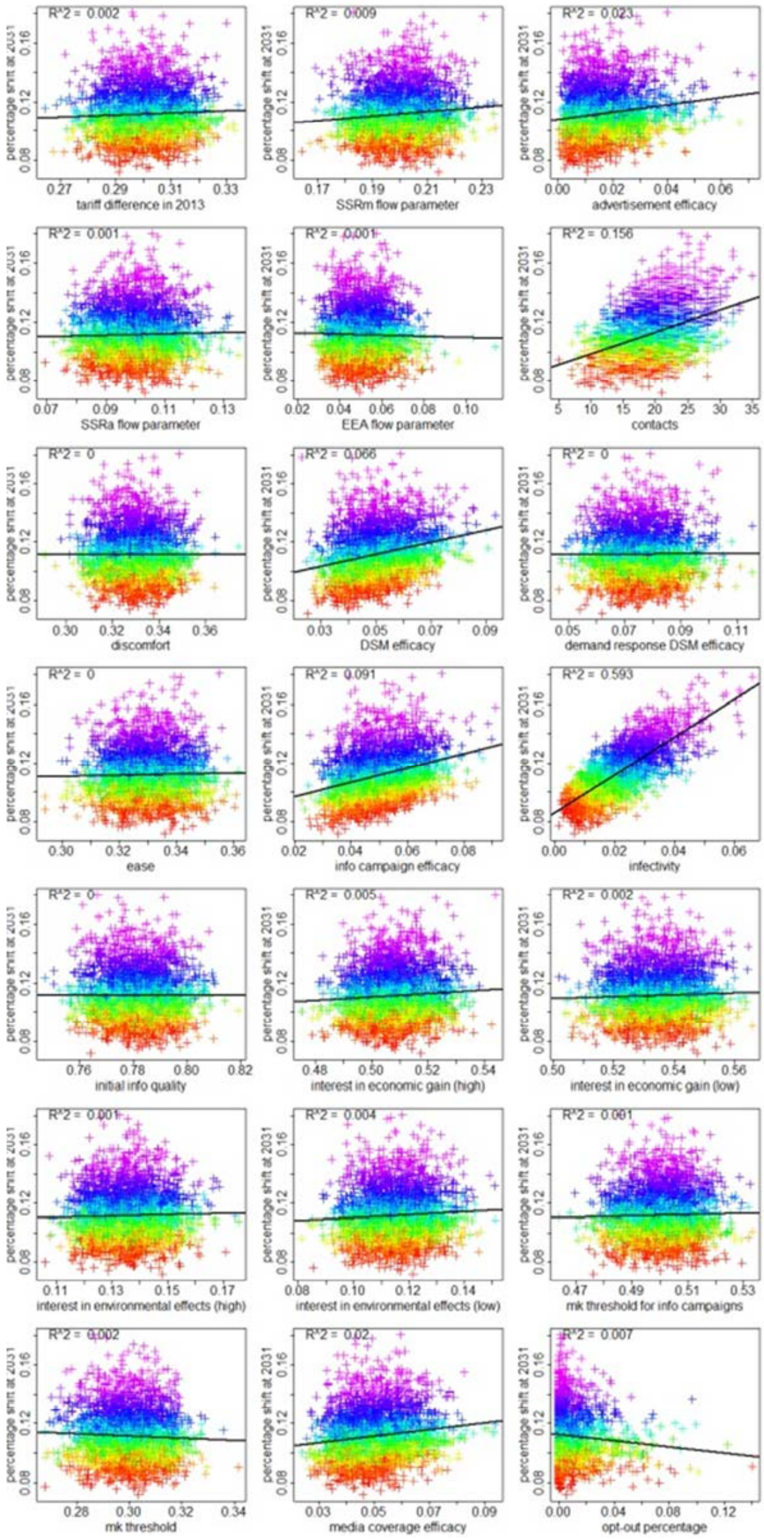

Figure 15: Scatter plot of Aggregate Consumption Shift vs. model parameters - univariate regression

[8] This year has been chosen as a reference year for the sensitivity analysis as it is one of the years in which the differences among the 2500 simulations is stronger

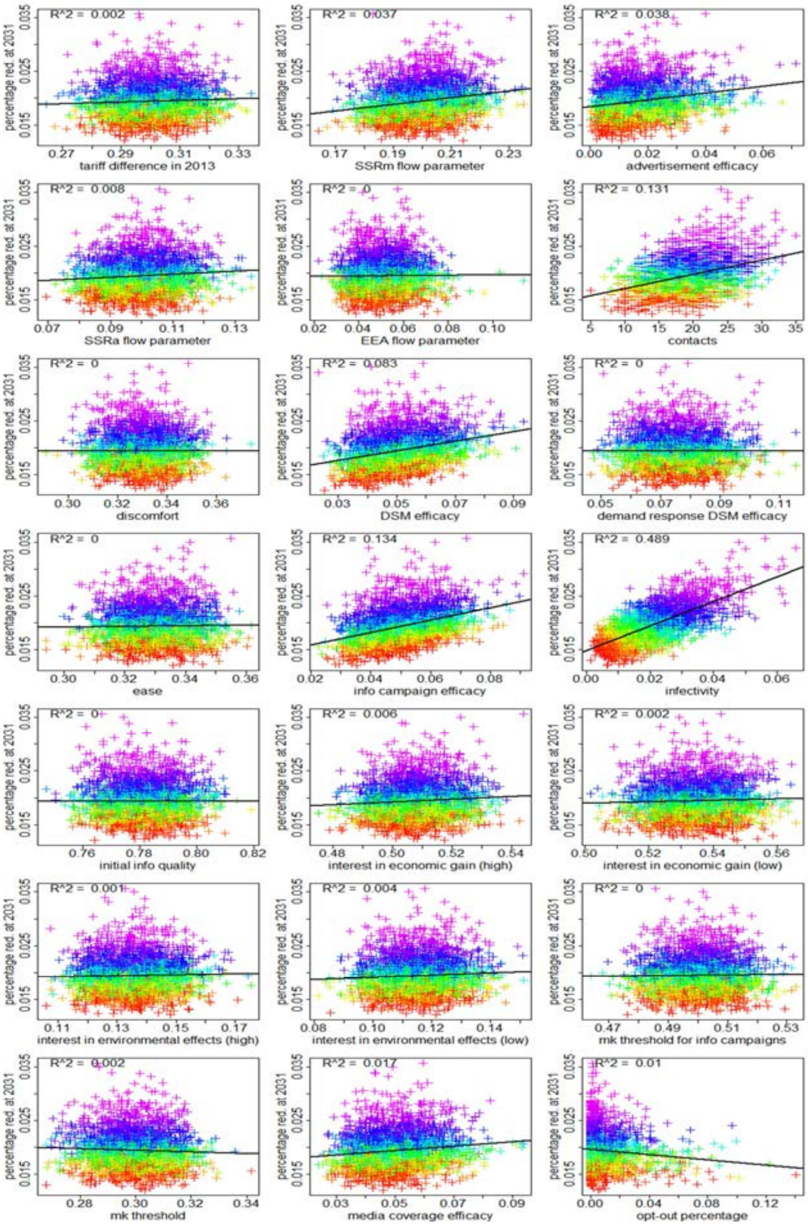

Figure 16: Scatter plot of Aggregate Consumption Reduction vs. model parameters - univariate regression

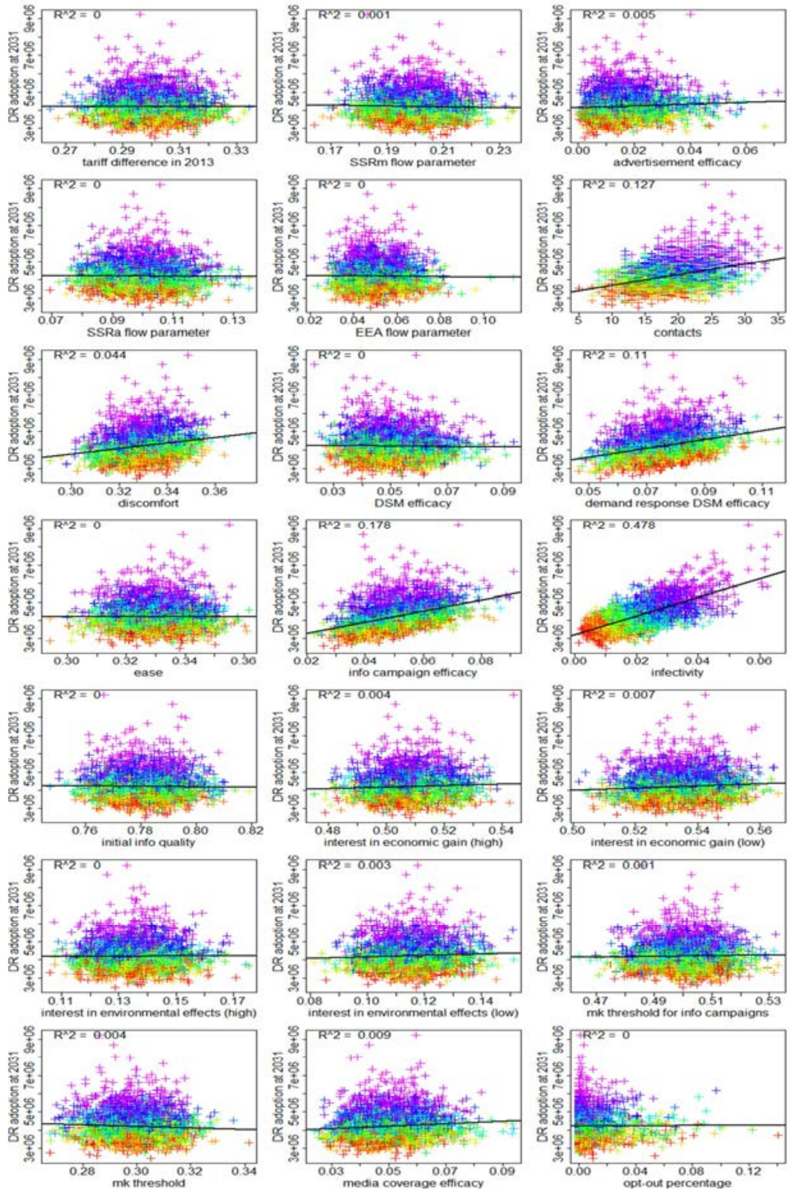

Figure 17: Scatter plot of Demand Response adoption vs. model parameters - univariate regression

A more precise analysis of these dependencies can be carried out by looking at Tables 9, 10, 11, where for each model parameter some indexes of the corresponding uni-variate regression are reported: estimate of the β coefficient, its standard deviation, t-statistic, significance of the t-test. In these tables, the model parameters are ordered accordingly to their significance. The corresponding ranking can be considered as a marginal sensitivity ranking.

Model Parameter	β est.	β est. std. dev.	t-statistic	significance
infectivity	1.29E+00	2.14E-02	6.01E+01	***
contacts	1.47E-03	6.85E-05	2.15E+01	***
information-campaigns efficacy	4.88E-01	3.10E-02	1.58E+01	***
demand-side-management efficacy	4.12E-01	3.11E-02	1.32E+01	***
advertisement efficacy	2.50E-01	3.26E-02	7.66E+00	***
media-coverage efficacy	2.24E-01	3.15E-02	7.12E+00	***
SSRm flow parameter	1.53E-01	3.27E-02	4.69E+00	***
opt-out percentage	-1.02E-01	2.47E-02	-4.12E+00	***
interest in economic gain	1.15E-01	3.30E-02	3.49E+00	***
interest in environmental effects 0	1.04E-01	3.24E-02	3.20E+00	**
tariff-difference in 2013	7.63E-02	3.19E-02	2.39E+00	*
available market threshold value	-7.49E-02	3.22E-02	-2.33E+00	*
interest in economic gain 0	6.96E-02	3.28E-02	2.13E+00	*
SSRa flow parameter	4.37E-02	3.37E-02	1.29E+00	
available market threshold value for information campaigns	4.29E-02	3.35E-02	1.28E+00	
interest in environmental effects	3.85E-02	3.23E-02	1.19E+00	
EEA flow parameter	-3.73E-02	3.29E-02	-1.13E+00	
ease parameter	3.70E-02	3.33E-02	1.11E+00	
demand-side-management efficacy for demand response	1.33E-02	3.31E-02	4.02E-01	
discomfort parameter	-1.07E-02	3.23E-02	-3.32E-01	
initial-information quality	-2.56E-03	3.29E-02	-7.77E-02	

Table 9: Summary indexes of Aggregate Consumption Shift vs. model parameters - univariate regression

Model Parameter	β est.	β est. std. dev.	t-statistic	significance
infectivity	2.27E-01	4.65E-03	4.87E+01	***
information-campaigns efficacy	1.15E-01	5.87E-03	1.96E+01	***
contacts	2.62E-04	1.35E-05	1.94E+01	***
demand-side-management efficacy	9.00E-02	5.99E-03	1.50E+01	***
advertisement efficacy	6.28E-02	6.28E-03	1.00E+01	***
SSRm flow parameter	6.17E-02	6.26E-03	9.85E+00	***
media-coverage efficacy	4.00E-02	6.14E-03	6.52E+00	***
opt-out percentage	-2.40E-02	4.79E-03	-5.02E+00	***
SSRa flow parameter	2.85E-02	6.53E-03	4.37E+00	***
interest in economic gain	2.45E-02	6.41E-03	3.82E+00	***
interest in environmental effects 0	2.07E-02	6.29E-03	3.28E+00	**
available market threshold value	-1.52E-02	6.24E-03	-2.43E+00	*
interest in economic gain 0	1.51E-02	6.36E-03	2.37E+00	*
tariff-difference in 2013	1.41E-02	6.20E-03	2.28E+00	*
interest in environmental effects	8.07E-03	6.28E-03	1.29E+00	
ease parameter	6.71E-03	6.46E-03	1.04E+00	
available market threshold value for information campaigns	6.35E-03	6.50E-03	9.77E-01	
EEA flow parameter	4.08E-03	6.39E-03	6.39E-01	
demand-side-management efficacy for demand response	2.52E-03	6.44E-03	3.91E-01	
discomfort parameter	-2.44E-03	6.28E-03	-3.89E-01	
initial-information quality	1.18E-03	6.39E-03	1.84E-01	

Table 10: Summary indexes of Aggregate Consumption Reduction vs. model parameters - univariate regression

Model Parameter	β est.	β est. std. dev.	t-statistic	significance
infectivity	5.10E+07	1.07E+06	4.77E+01	***
information-campaigns efficacy	3.03E+07	1.30E+06	2.33E+01	***
contacts	5.88E+04	3.08E+03	1.91E+01	***
demand-side-management efficacy for demand response	2.42E+07	1.38E+06	1.75E+01	***
discomfort parameter	1.50E+07	1.40E+06	1.08E+01	***
media-coverage efficacy	6.66E+06	1.40E+06	4.75E+00	***
interest in economic gain 0	6.09E+06	1.44E+06	4.22E+00	***
advertisement efficacy	5.22E+06	1.45E+06	3.59E+00	***
interest in economic gain	4.42E+06	1.46E+06	3.03E+00	**
available market threshold value	-4.29E+06	1.42E+06	-3.02E+00	**
interest in environmental effects 0	4.11E+06	1.43E+06	2.87E+00	**
SSRm flow parameter	-2.08E+06	1.45E+06	-1.43E+00	
available market threshold value for information campaigns	1.87E+06	1.48E+06	1.27E+00	
demand-side-management efficacy	-1.14E+06	1.42E+06	-7.99E-01	
initial-information quality	-1.14E+06	1.45E+06	-7.84E-01	
EEA flow parameter	-9.52E+05	1.45E+06	-6.55E-01	
interest in environmental effects	8.22E+05	1.43E+06	5.75E-01	
ease parameter	7.77E+05	1.47E+06	5.28E-01	
SSRa flow parameter	-7.87E+05	1.49E+06	-5.28E-01	
opt-out percentage	5.59E+05	1.10E+06	5.10E-01	
tariff-difference in 2013	-3.85E+05	1.41E+06	-2.73E-01	

Table 11: Summary indexes of Demand Response adoption vs. model parameters - univariate regression

More interestingly for extracting policy implications is a ranking based on a *ceteris paribus* sensitivity analysis, since in real-life applications policy-makers may be interested in knowing the effect of varying the level of one parameter keeping the other unchanged. This kind of sensitivity has been carried out by means of a multivariate linear regression. This regression model allows to overcome the masking effect due to the high number of regressors. Figures 18, 19, 20, report the scatter plots of the residuals of the regression of Aggregate Shift, Aggregate Reduction, and Demand Response adoption with respect to all model parameters, except for the one under examination, vs. the value of the same parameter.

In Tables 12, 13, 14 the results of the regression are reported. Also in these tables, the model parameters are ordered accordingly to their significance. As expected, due to the unmasking effect, more variables turn out to be significant. For this type of linear regression model, it is known that the regression coefficients represent the average effects on the response associated with a unit increment of the regressor, if the other regressors remain unaffected. Therefore, for example, we can expect a percentage point increment in the word of mouth infectivity to generate an increment in the aggregate consumption shift at 2020 of 1.28 percentage points, if the other model parameters remain unaffected, and so on.

Our results show that for the Shifting behaviour, infectivity is by large the most effective parameter, followed by contacts, information-campaign efficacy and demand-side-management efficacy. The parameters relative to the Demand Response and *eea* are uninfluent, coherently with the model configuration.

For consumption reduction, we have very similar results. Note that here *eea* is significant as there is a considerable difference between the redution level of the SSRa box compared to that of the EEA box.

For the demand response adoption, infection confirms its primary role; information-campaign efficacy, specific demand-side-management efficacy, contacts and the discomfort level due to load curtailments are also important. Also here, the parameters that result not significant are those that do not interact with this branch of the model.

In synthesis, even if in all cases all the parameters relevant to the model branch result influent, we can see hoe the most important parameters are those that govern the word of mouth effect and the other informational channels, suggesting that these should be the ones targeted by policies.

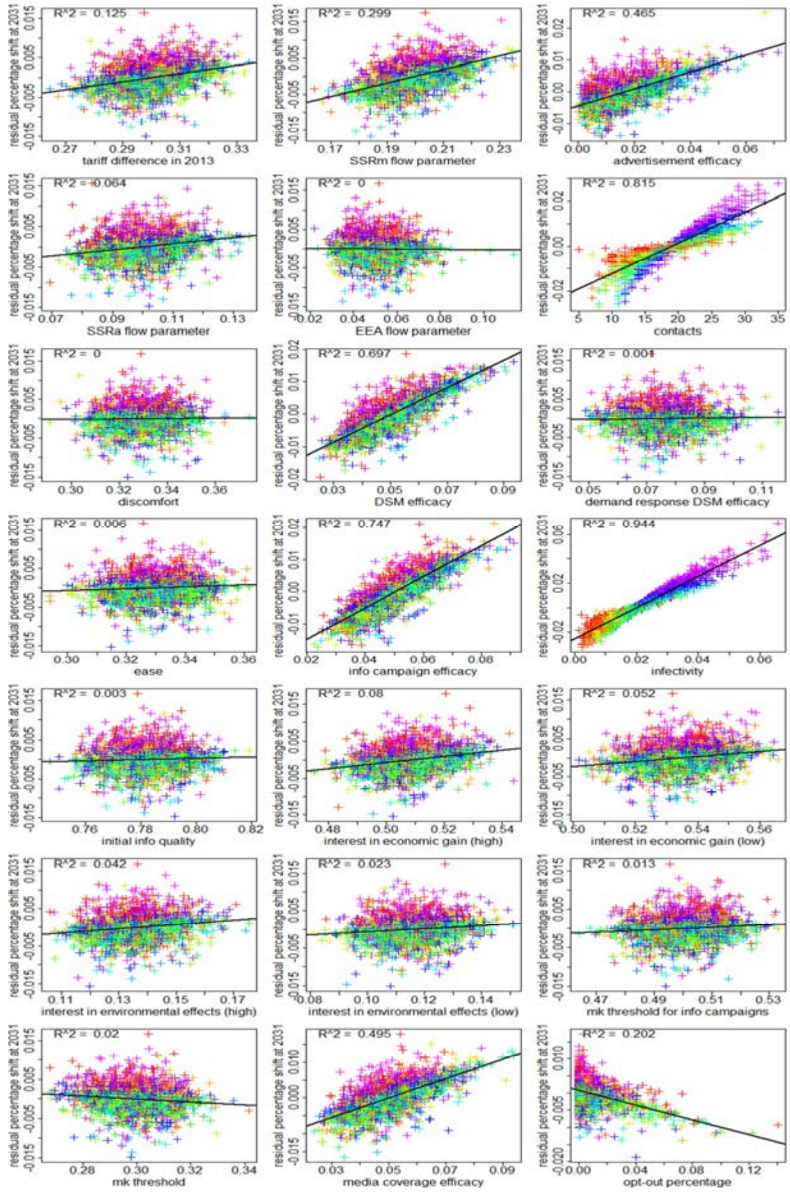

Figure 18: Scatter plot of Aggregate Consumption Shift vs. model parameters - multivariate regression

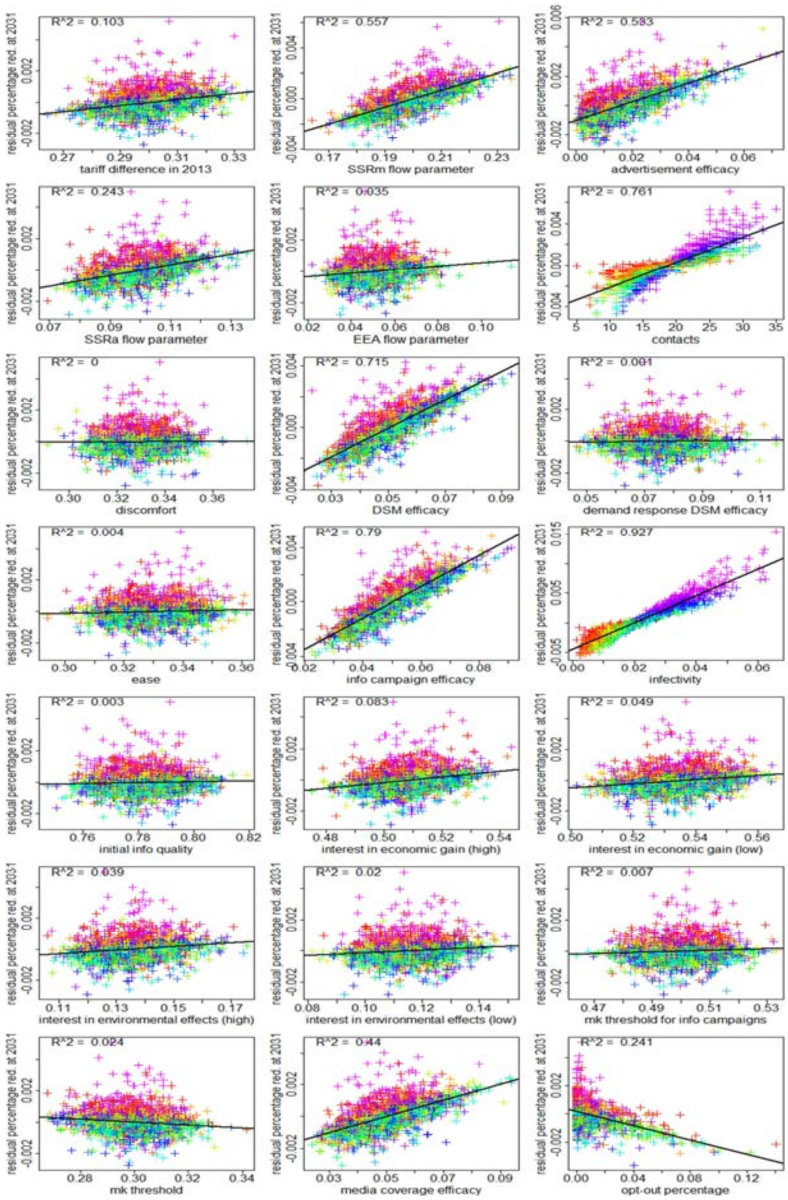

Figure 19: Scatter plot of Aggregate Consumption Reduction vs. model parameters - multivariate regression

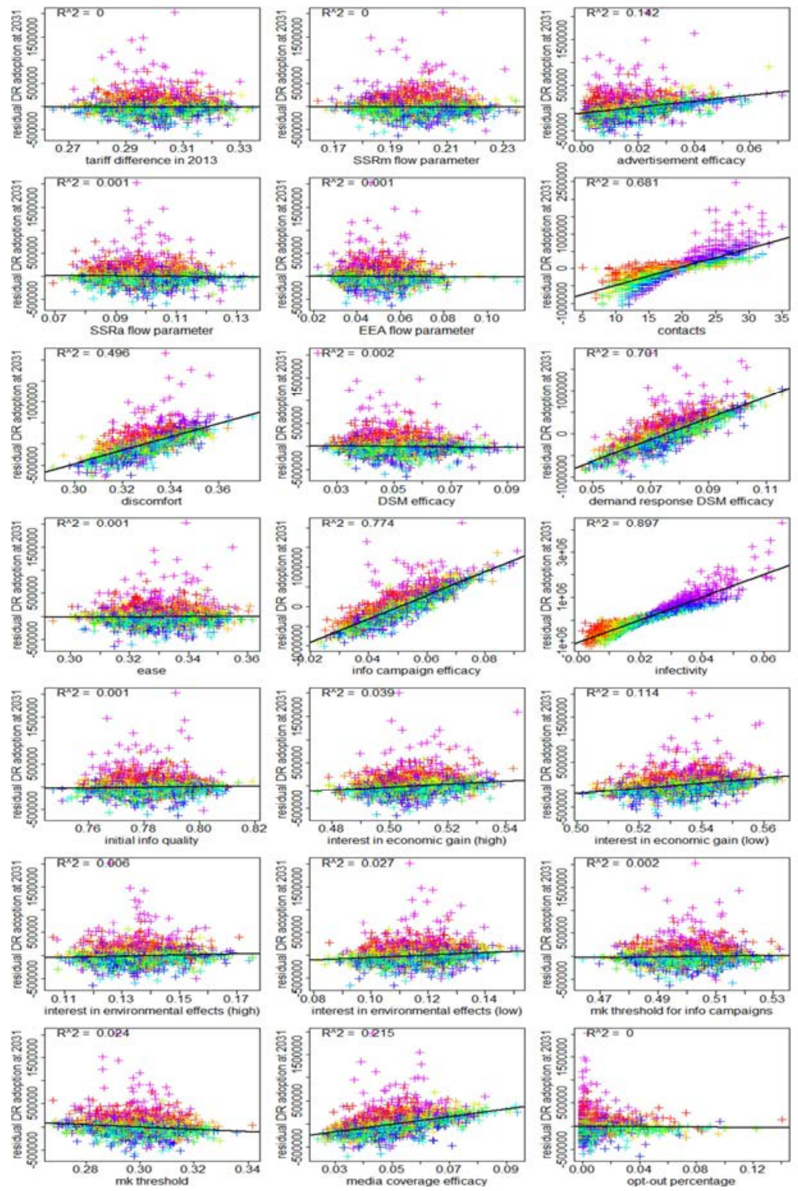

Figure 20: Scatter plot of Demand Response adoption vs. model parameters - multivariate regression

Model Parameter	β est.	β est. std. dev.	t-statistic	significance
infectivity	1.28E+00	5.97E-03	2.14E+02	***
contacts	1.36E-03	1.33E-05	1.02E+02	***
information-campaigns efficacy	4.85E-01	5.79E-03	8.38E+01	***
demand-side-management efficacy	4.26E-01	5.75E-03	7.42E+01	***
media-coverage efficacy	2.72E-01	5.68E-03	4.80E+01	***
advertisement efficacy	2.68E-01	5.88E-03	4.56E+01	***
SSRm flow parameter	1.88E-01	5.87E-03	3.20E+01	***
opt-out percentage	-1.07E-01	4.42E-03	-2.42E+01	***
tariff-difference in 2013	1.02E-01	5.71E-03	1.79E+01	***
interest in economic gain	8.34E-02	5.89E-03	1.42E+01	***
SSRa flow parameter	7.44E-02	6.03E-03	1.24E+01	***
interest in economic gain 0	6.85E-02	5.85E-03	1.17E+01	***
interest in environmental effects	5.80E-02	5.76E-03	1.01E+01	***
interest in environmental effects 0	4.33E-02	5.79E-03	7.48E+00	***
available market threshold value	-3.91E-02	5.73E-03	-6.82E+00	***
available market threshold value for information campaigns	3.32E-02	5.97E-03	5.57E+00	***
ease parameter	2.28E-02	5.94E-03	3.84E+00	***
initial-information quality	1.48E-02	5.87E-03	2.51E+00	*
demand-side-management efficacy for demand response	7.79E-03	5.90E-03	1.32E+00	
EEA flow parameter	-4.33E-03	5.86E-03	-7.39E-01	
discomfort parameter	4.18E-03	5.76E-03	7.26E-01	

Table 12: Summary indexes of Aggregate Consumption Shift vs. model parameters - multivariate regression

Model Parameter	β est.	β est. std. dev.	t-statistic	significance
infectivity	2.27E-01	1.25E-03	1.81E+02	***
information-campaigns efficacy	1.15E-01	1.22E-03	9.47E+01	***
contacts	2.42E-04	2.79E-06	8.68E+01	***
demand-side-management efficacy	9.35E-02	1.21E-03	7.75E+01	***
SSRm flow parameter	6.76E-02	1.23E-03	5.49E+01	***
advertisement efficacy	6.45E-02	1.24E-03	5.22E+01	***
media-coverage efficacy	5.10E-02	1.19E-03	4.28E+01	***
SSRa flow parameter	3.44E-02	1.27E-03	2.72E+01	***
opt-out percentage	-2.52E-02	9.28E-04	-2.71E+01	***
tariff-difference in 2013	1.91E-02	1.20E-03	1.60E+01	***
interest in economic gain	1.80E-02	1.24E-03	1.45E+01	***
interest in economic gain 0	1.39E-02	1.23E-03	1.13E+01	***
interest in environmental effects	1.17E-02	1.21E-03	9.68E+00	***
EEA flow parameter	1.12E-02	1.23E-03	9.10E+00	***
available market threshold value	-9.04E-03	1.20E-03	-7.51E+00	***
interest in environmental effects 0	8.39E-03	1.22E-03	6.90E+00	***
available market threshold value for information campaigns	5.13E-03	1.25E-03	4.09E+00	***
ease parameter	3.95E-03	1.25E-03	3.17E+00	**
initial-information quality	3.16E-03	1.23E-03	2.56E+00	*
demand-side-management efficacy for demand response	1.79E-03	1.24E-03	1.45E+00	
discomfort parameter	7.68E-04	1.21E-03	6.35E-01	

Table 13: Summary indexes of Aggregate Consumption Reduction vs. model parameters - multivariate regression

Model Parameter	β est.	β est. std. dev.	t-statistic	significance
infectivity	5.01E+07	3.36E+05	1.49E+02	***
information-campaigns efficacy	2.97E+07	3.26E+05	9.12E+01	***
demand-side-management efficacy for demand response	2.49E+07	3.32E+05	7.50E+01	***
contacts	5.35E+04	7.47E+02	7.16E+01	***
discomfort parameter	1.58E+07	3.25E+05	4.85E+01	***
media-coverage efficacy	8.15E+06	3.20E+05	2.55E+01	***
advertisement efficacy	6.68E+06	3.31E+05	2.02E+01	***
interest in economic gain 0	5.88E+06	3.29E+05	1.78E+01	***
interest in economic gain	3.23E+06	3.32E+05	9.73E+00	***
interest in environmental effects 0	2.69E+06	3.26E+05	8.25E+00	***
available market threshold value	-2.47E+06	3.23E+05	-7.65E+00	***
interest in environmental effects	1.27E+06	3.24E+05	3.90E+00	***
available market threshold value for information campaigns	6.65E+05	3.36E+05	1.98E+00	*
demand-side-management efficacy	-6.27E+05	3.24E+05	-1.94E+00	.
SSRa flow parameter	-6.07E+05	3.39E+05	-1.79E+00	.
initial-information quality	5.53E+05	3.30E+05	1.67E+00	.
EEA flow parameter	-4.03E+05	3.30E+05	-1.22E+00	
ease parameter	3.71E+05	3.34E+05	1.11E+00	
opt-out percentage	-2.39E+05	2.49E+05	-9.60E-01	
tariff-difference in 2013	-2.05E+05	3.21E+05	-6.38E-01	
SSRm flow parameter	-1.13E+05	3.30E+05	-3.42E-01	

Table 14: Summary indexes of Demand Response adoption vs. model parameters - multivariate regression

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