Technological Forecasting & Social Change 99 (2015) 106–131

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation

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ARTICLE INFO

Article history:
Received 30 September 2013
Received in revised form 1 February 2015
Accepted 16 June 2015
Available online 11 July 2015

Keywords:
PV
Technological diffusion
Agent-based modeling
Italy

ABSTRACT

We propose an agent-based model to simulate how changes to the Italian support scheme will affect the diffusion of PV systems among single- or two-family homes. The adoption decision is assumed to be influenced by (1) the payback period of the investment, (2) its environmental benefit, (3) the household's income, and (4) communication with other agents. The estimation of the payback period considers investment costs, local irradiation levels, governmental support, earnings from using self-produced electricity vs. buying electricity from the grid, administrative fees, and maintenance costs. The environmental benefit is estimated by a proxy for the CO_2 emissions saved. The household income accounts for the specific economic conditions across different regions and the agent's age group, level of education, and household type. Finally, the influence of communication is measured by the number of links with other households that have already adopted a PV system. In each simulation step, the program dynamically updates the social system and the communication network, while the PV system's investment costs are revised according to a one-factor experience curve. The model's structure is applied for a case study based on the evolution of residential PV systems in Italy over the 2012–2026 period. The model's initial state is calibrated on the basis of the actual diffusion of residential PV in Italy over the 2006–2011 period. Our results show that, following Italy's new feed-in tariff scheme, domestic PV installations are already beyond an initial stage of rapid growth and, though likely to spread further, they will do so at a significantly slower rate of diffusion.

1. Introduction

Following the introduction of a governmental incentive program, the Italian photovoltaics (PV) market has experienced a remarkable growth. Electricity generated by PV systems increased from 35 GWh in 2006 to 10,796 GWh in 2011, an astounding increment (GSE, 2012a; see also Fig. 1 and Table 1). Italy has thus become one of the world's leading PV markets, accounting for about 18% of the global installed PV capacity in 2011 (EPIA, 2012).

Nevertheless, the diffusion of PV across Italy has followed a rather peculiar pattern. The number of installed PV systems is much higher in the north, although the irradiation level is lower there compared to other regions of the country. In addition, most of the installed systems in the north belong to private households and are thus characterized by a small rated power. However, while small-scale PV systems up to 20 kW are overwhelming in number (88% of the total, as of 2011), they account for only 15.5% of Italy's installed PV power (GSE, 2012c; see also Fig. 1). Furthermore, the share of small PV systems with respect to installed capacity has fallen steadily (from 66% in 2006 to 15.5% in 2011) due to the more recent

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http://dx.doi.org/10.1016/j.techfore.2015.06.011
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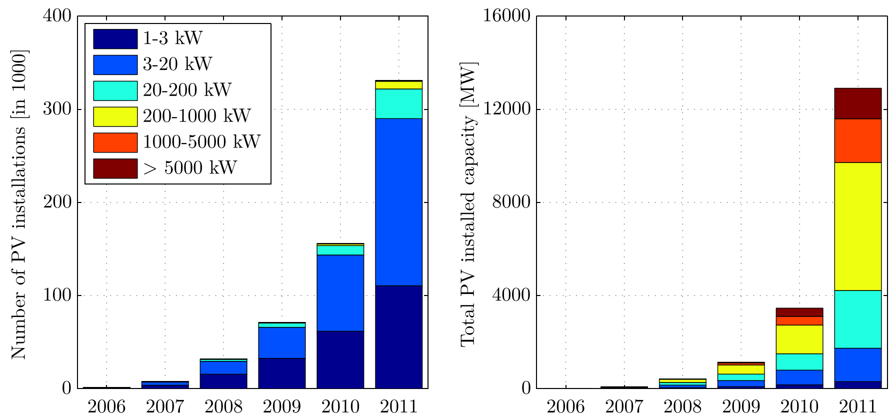

Fig. 1. Evolution of Italy's PV market, 2006–2011.
Source: GSE (2012a, 2012b, 2012c).

installation of large PV farms (mostly located in Central and Southern Italy), a trend that strongly contributed to the PV boom in Italy (GSE, 2012c). As a result, the number, size and electricity generation of PV systems in Italy are rather unevenly spread across the country.

It is thus relevant to investigate whether the residential PV market will grow further, or whether the Italian PV market will be dominated in the future by large PV farms. The objective of this article is to simulate the future diffusion of small residential PV systems under different conditions. Due to the multitude of factors influencing a household's investment decision in favor of an innovative energy technology such as PV, we designed and implemented an agent-based simulation model (ABM). ABMs provide a suitable framework to explicitly model the adoption decision process of the members (agents) of a heterogeneous social system based on their individual preferences, behavioral rules, and interactions/communications within a social network.

To the best of our knowledge, in the recent literature only Zhao et al., (2011) implement an ABM to simulate the diffusion of PV systems. We use their framework as a reference and further extend their model. In particular, following Schwarz and Ernst (2009), we include adaptive socio-economic categories to represent heterogeneous household groups with distinctive attitudes toward adoptions and innovations. The socio-economic groups considered here are based on the Sinus-Milieus® categorization developed by the Sinus-Institut (2011).[1] More specifically, the Sinus-Milieus® paradigm is most relevant for the distribution of the households' income and the determination of group-specific social communication networks. Importantly, in each simulation step, the social system and the communication network are updated dynamically in order to account for demographic changes and new adopters among the population of agents.

Furthermore, we explicitly model the geographical distribution of the agents in order to account for the regional differences that have strongly influenced the PV diffusion in Italy. The investment in a PV system is assumed to depend mainly on (1) the payback period, (2) the environmental benefit of the investment, (3) the household's income, and (4) the influence of communication with other agents. For the estimation of the payback period, the model considers investment costs, local irradiation levels, feed-in tariffs, earnings from using self-generated electricity vs. buying electricity from the grid, as well as various administrative fees and maintenance costs. The environmental benefit of the PV system is estimated via a proxy for the amount of CO_2 saved. The level of the household income is associated with the specific economic conditions of the region where the agent is located, as well as the agent's socio-economic group (age group, level of education, and household type). Finally, the influence of communication is measured by the number of links with other households that have already adopted a PV system. It is assumed that each adopter communicates predominantly, but not uniquely, with other households that belong to the same socio-economic group. Furthermore, the likelihood that different groups interact with each other varies across the categories of agents considered.

The remainder of the paper is structured as follows. Section 2 provides a brief introduction to the current Italian PV support policy. Section 3 gives an overview of the relevant literature concerning the adoption of new technologies, its modeling via agent-based simulation frameworks, and the inclusion of a social system in the modeling architecture. Section 4 presents in detail the structure of the ABM. Section 5 describes the model's calibration, while Section 6 discusses the policy scenarios and the simulation results. Finally, Section 7 delivers the conclusions of the article and highlights strengths and weaknesses of our analysis.

2. The Italian support scheme for PV systems

The current legal framework for the support of PV systems in Italy is called "Conto Energia" (CE). The first CE has been issued in August 2005. Since then, the incentive scheme has been renewed five times with a series of adjustments and changes. An important characteristic of the CE is that support is

[1] The Sinus-Milieus® are a registered trademark product. Whereas the questionnaires used to generate the socio-economic categories are disclosed, the details of the multivariate analyses adopted to assign the questionnaires to the Sinus-Milieus® are not published. This poses a drawback concerning the transparency of the method adopted and the validation of the results. We discuss this aspect in more detail in the Conclusion (Section 7).

Table 1
Evolution of Italy's electricity generation, 2006–2011.
Source: GSE (2012a)

		2006	2007	2008	2009	2010	2011
Total electricity generation	[TWh]	352.7	354.5	353.6	333.3	342.9	346.4
Total PV electricity generation	[GWh]	35	39	193	676	1906	10,796
Share of RES in total electricity generation	[%]	15.9	16.0	16.6	18.8	20.1	23.5
Share of PV in total electricity generation	[%]	0.01	0.01	0.05	0.20	0.56	3.12

granted up to a given amount of total installed PV power, as shown in Table 2 (MSE, 2005, 2007, 2010, 2011, 2012).[2]

Each CE guarantees contracts with fixed conditions for 20 years for grid-connected PV systems with at least 1 kW of peak power. Local electricity providers are required by law to buy the electricity that is generated by PV systems. Furthermore, governmental incentives are tax-free. Beginning with CE 2, the government has also reduced the purchase tax from 20% to 10%.

The CE considers two different support schemes. The first scheme is a net metering plan ("scambio sul posto") designed for small PV systems.[3] The plan is meant to favor the direct use of self-produced electricity. Besides a payment for each produced kWh of electricity, the consumer receives additional rewards for directly consuming the self-generated energy. With the introduction of CE 4, direct consumption is rewarded financially, whereas before 2011 consumers received an energy credit. Importantly, energy that is fed into the grid is bought by the local electricity provider at conditions that are less advantageous than direct self-consumption.

The second support scheme is available to all PV systems, but it is designed for larger plants with no or limited direct electricity self-consumption. The electricity produced is sold to the local energy supplier, for which the CE guarantees an additional feed-in payment.

In general, the incentives granted are higher for small PV systems. The feed-in tariffs (FiT) increase further for PV systems that are based on innovative technologies or systems that are integrated into the building. Additional payments or bonuses can also be received in the following cases[4]: the adopter owns an energy-saving home; the adopter renews his/her roofs because of asbestos; the adopter lives in a small village with up to 5000 inhabitants; the PV system was produced in Europe; the PV system is located on a municipal building, in an old industrial area, or in an old garbage dump.

It is important to mention that in each new version of the CE, the FiT were decreased. Since CE 1 was first issued in 2005, the basic support level has been curtailed from approximately 0.45 €/kWh in 2006 to 0.20 €/kWh in 2012.[5] Besides a reduction in tax revenues due to cuts in the PV purchase tax and the expenses associated with administrative tasks, the Italian government has spent € 9558 million for PV incentives from 2006 to September 2012 (see Table 3). Due to the high costs, Italy introduced a register for new PV systems with the implementation of CE 4. The register is meant to put a cap on the amount of support granted to PV systems for each year, whereby small PV systems (<20 kW) still enjoy register priority. Similarly, the latest version of the support scheme (i.e., CE 5) aims at quickly decreasing the level of the feed-in payments, since grid parity was reached around 2011 and the costs of the support program are high. The FiT in CE 5 are set to decrease further by approximately 10% every 6 months for 2.5 years, starting in September 2012. Afterwards, the FiT will be reduced every 6 months by 15%. Fig. 2 and Table 3 show the different stages of the CE with respect to the installed PV capacity and the incentives paid per year.

3. Literature overview

The modeling and forecasting of technology diffusion have been the focus of theoretical and empirical research since the works of Fourt and Woodlock (1960), Mansfield (1961), Rogers (1962), Chow (1967), and Bass (1969). The adoption and diffusion of innovations is determined by four core elements: the characteristics of the innovation, the structure of the social system where the adoption and diffusion takes place, the communication channels within the social system, and the time–frame of the innovation–decision process (Rogers, 2003). A variety of models focusing on one or more of these elements have been applied to a multitude of research fields and technologies. For an overview, see for instance Mahajan et al. (2000) and Meade and Islam (2006).

In recent years, agent-based simulation models (ABMs) have been widely used to simulate the inherent complexity of the adoption and diffusion process (Dawid, 2006; Kiesling et al., 2012). In particular, ABM frameworks replicate the micro-based behavior of economic actors in order to evaluate and explain meso- and macro-level phenomena. They enable modelers to ascribe specific characteristics to the agents, who independently interact within their environment and among each other according to determined rules (Bonabeau, 2002).

ABMs have also been applied to investigate the adoption of various energy technologies (e.g., Schwoon, 2006; Cantono and Silverberg, 2009; Faber et al., 2010; Zhang and Nuttall, 2011; Zhang et al., 2011; Sorda et al., 2013). However, only Zhao et al. (2011) implement an ABM to simulate the diffusion of PV systems. In their contribution, Zhao et al. (2011) evaluate the impact of different governmental incentives, including the impact of investment tax credits and feed-in tariffs, on the PV diffusion process in two regions in the US. They propose a decision framework where different classes of households purchase a PV system whenever their "desire level" surpasses a certain threshold. The said desire level is a linear function of four factors: advertising, neighborhood, household income, and the PV's payback period.

[2] Note that in our model we do not account for the PV installation caps, as we consider only a sub-group of potential adopters and PV systems.
[3] The first two versions of the CE limited the maximum peak power for this plan to 20 kW. Beginning with CE 3, systems up to 200 kW are also accepted.
[4] The individual bonuses lead to an increase in the FiT that may range from 5% to 30%. Note that the requirements for the award of a bonus have changed over time (MSE, 2005, 2007, 2010, 2011, 2012).
[5] Here we are referring to the basic FiT for small roof-top PV systems.

Table 2
Date of issue, support cap, and reasons for revision of the Conto Energia 1–5.
Source: MSE (2005, 2007, 2010, 2011, 2012).

Conto Energia	Issue	Cap on cumulative PV installed capacity	Reason for update
1	08/2005	100 MW, updated to 500 MW by 2015	Adjustments
2	04/2007	1200 MW, updated to 3000 MW by 2015	Adjustments
3	01/2011	8000 MW by 2020	Cap reached
4	06/2011	23,000 MW by 2016, registration required	Cap almost reached
5	09/2012	Max +3000 MW/a, registration required	Still in place

We build on and extend the framework proposed by Zhao et al. (2011). While our ABM maintains their basic structure, the two models differ significantly in three main aspects. First, our model is adapted to study the Italian PV market. Second, in contrast to Zhao et al. (2011), we attempt to characterize the agents, among other things, according to Rogers' 2003 adopter categories with respect to innovativeness and product characteristics. Third, we calibrate our models differently. We discuss these aspects in more detail in Sections 4 and 5, where the model's structure and calibration are presented.

Importantly, we incorporate differences in attitudes toward adoptions across the agent population as well as across the different elements influencing the adoption decision by using the approach implemented by Schwarz and Ernst (2009). They characterize the heterogeneous social groups and lifestyles of the agent population according to Sinus-Milieus®, and then link these to the adopter categories suggested by Rogers (2003).[6] More details are given in Section 4.2.

Social categories and lifestyles notwithstanding, a variety of elements may be associated with an individual's investment decision in favor of a PV system. As a result, the factors influencing PV adoption and their modeling have been the subject of several publications. These can be grouped into three categories: survey-based analyses (Jager, 2006; Faiers and Neame, 2005; Faiers et al., 2007; Yuan et al., 2011; Zhai and Williams, 2012), PV diffusion and forecasting models other than ABM (Guidolin and Mortarino, 2010; Gallo and De Bonis, 2013), and PV grid parity studies (Ayompe et al., 2010; Yang, 2010; Breyer and Gerlach, 2013).

While one may suspect that the fast-decreasing installation costs of PV systems and the prospect of grid parity PV electricity generation provide strong incentives for the investment in photovoltaic technology by homeowners, it turns out that the adoption decision is also strongly influenced by the perceived attributes of the innovation, such as installation costs, maintenance, complexity, and environmental concerns (Zhai and Williams, 2012). In addition, the adopter characteristics[7] (Faiers and Neame, 2005; Faiers et al., 2007) as well as the communication network play an important role in the actual diffusion process (Jager, 2006).

Therefore, we tried to incorporate in our model these three considerations: the specific attributes of the PV technology, the attitudes and preferences of the adopters according to their respective socio-economic groups, as well as the influence of communication among agents.

[6] Note that Schwarz and Ernst (2009) model the adoption of water-related environmental innovations in Southern Germany. They model the investment decision behavior of their agents based on a utility function rooted on the Theory of Planned Behavior and account for an agent's attitude, perceived behavioral control, and social norm.

[7] In their study of the adoption of residential PV systems in the UK, Faiers and Neame (2005) and Faiers et al. (2007) based their questionnaires on Rogers' (2003) adopter categories with respect to innovativeness and product characteristics.

Table 3
Incentives paid by the Conto Energia, 2006–2012.
Source: GSE (2013b).

Year	2006	2007	2008	2009	2010	2011	2012[a]
Incentives [million €/a]	1	19	91	304	743	3835	4565
Total incentives [million €]	1	20	111	415	1158	4993	9558

[a] Jan.–Sept. 2012.

4. Model description

In our model, we consider small grid-connected PV systems in the 1–20 kW range powered by crystalline silicon solar cells (silicon solar cells had a 93% share of the Italian market in 2011; GSE, 2012b). Furthermore, it is assumed that the PV systems are installed on the roofs of single- or two-family houses.[8] The ABM framework simultaneously accounts for the attributes of the PV systems, the attitude of specific adopter groups, and the communication network thanks to a multi-attribute utility function (Zhao et al., 2011) weighted by adopter preferences according to different socio-economic classes (Schwarz and Ernst, 2009).

The ABM has been programmed in MATLAB and simulates the PV diffusion process on a step-wise yearly basis. Two key components constitute the core structure of the framework: the agent's adoption decision and the representation of Italy's social system. The decision to invest in a PV system depends on static functions fed with data that, in some cases, account for changes in the underlying social structure and communication network. As a result, specific model parameters are updated after each simulation step, as highlighted in Fig. 3. Next, we present in more detail the formulation of the agent's behavioral rules (Section 4.1), the modeling of socio-economic attributes in Italy (Section 4.2), and the agent's communication network (Section 4.3).

4.1. Agent's adoption behavior

An agent represents a household living in a single- or two-family house. The decision to invest in a PV system takes place when the utility of the potential adopter surpasses a certain

[8] Small PV systems could also be installed on the roofs of larger multi-flat building blocks. However, the adoption decision would become much more complicated to replicate, as often several house-owners or groups of families cooperatively decide to make a PV investment.

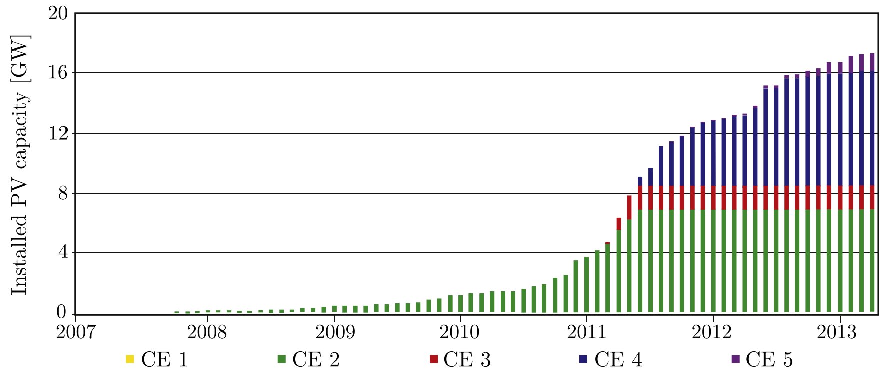

Fig. 2. Stages of the Conto Energia by installed PV installed capacity, 2007–2013.
Source: Own illustration, based on data from GSE (2013a, 2013b).

threshold level. The threshold is determined by comparing the simulation results with the actual diffusion of the PV system during the calibration of the model (see Section 5 for more details). The utility of agent j equals the sum of four weighted partial utilities and is calculated as follows:

$$U(j) = w_{pp}\left(sm_j\right) \cdot u_{pp}(j) + w_{env}\left(sm_j\right) \cdot u_{env}(j) + w_{inc}\left(sm_j\right) \cdot u_{inc}(j) + w_{com}\left(sm_j\right) \cdot u_{com}(j), \tag{1}$$

where

$$\sum_k w_k\left(sm_j\right) = 1 \text{ for } k \in K : \{pp, env, inc, com\} \text{ and } w_k\left(sm_j\right), U(j) \in [0, 1].$$

The partial utilities $u(.)$ account for the payback period of the investment (u_{pp}), the environmental benefit of investing in a PV system (u_{env}), the household's income (u_{inc}), and the influence of communication with other agents (u_{com}). Each partial utility is calculated on the basis of specific influence factors (see Fig. 4) and is normalized[9] in order to lie within the [0,1] interval. The weights $w(.)$ assigned to each partial utility vary according to the agent's Sinus-Milieu® (sm_j) and are determined in the model's calibration. Next, we illustrate how each partial utility is calculated.

4.1.1. Economic utility

The estimation of the economic utility of adoption is based on the expected payback period pp of a specific PV system for agent j. The payback period is then converted into a linear utility function whose value ranges between 0 and 1. The utility function is calculated as follows:

$$u_{pp}(j) = \frac{max(pp) - pp(j)}{max(pp) - min(pp)} = \frac{21 - pp(j)}{20}. \tag{2}$$

In order to ensure that the partial utility arising from the payback period lies within the [0,1] interval, and given that the payback period is calculated over 20 years (i.e., the expected useful life of the PV system), the values corresponding to the minimum ($min(pp)$) and maximum ($max(pp)$) payback periods are 1 and 21 years, respectively.

The payback period is determined by the year in which the net present value (NPV) of the PV system turns from negative to positive. The NPV is defined as the sum of the discounted cash flows ($R(t)$) of the PV system, given the initial investment costs (I_0) and the interest rate (i):

$$\text{NPV} = -I_0 + \sum_{t=1}^{20} \frac{R(t)}{(1+i)^t}. \tag{3}$$

The investment costs are the product of the maximum peak power (P_{MMP}) and the price per installed kW of the PV system (p_{PV}), such that:

$$I_0 = P_{MMP} \cdot p_{PV}(t_0) \tag{4}$$

$$P_{MMP} = G_{STC} \cdot A_{PV} \cdot \eta_{SC} \cdot \eta_{PV}. \tag{5}$$

The peak power of the PV system is computed by the available rooftop area for PV modules (A_{PV}), the efficiency of the solar cells (η_{SC}), the PV system efficiency (η_{PV}), and the irradiation at standard conditions (G_{STC}), which is assumed to equal 1 kW/m^2. The estimation of the system's NPV at a given time period assumes that the price and efficiency of the PV system remain constant. Note, however, that in each simulation step the price per installed kW of the PV system and the cell's efficiency are exogenously updated (see also Section 6.1). In addition, the available roof area for PV modules depends on the type of housing. All other values are kept constant throughout the simulation.

As shown in Eq. (6) below, the cash flow $R(t)$ is composed of five factors. The term $R_{Save}(t,CE)$ includes all earnings that are generated by directly using the produced electricity instead of buying it from or selling it to the grid operator. The terms $R_{Gov}(t,CE)$, $R_{Adm}(t,CE)$, $R_{Main}(t)$, and $R_{Deprec}(t)$ indicate cash flows due to governmental support, administrative fees,

[9] The total utility of an adopter is defined within the [0,1] interval. As a result, all partial utilities need to be normalized. In accordance with Zhao et al. (2011), the utility of the payback period is programmed as a linear function, while all other partial utility functions follow an S-shaped curve, also within the [0,1] interval.

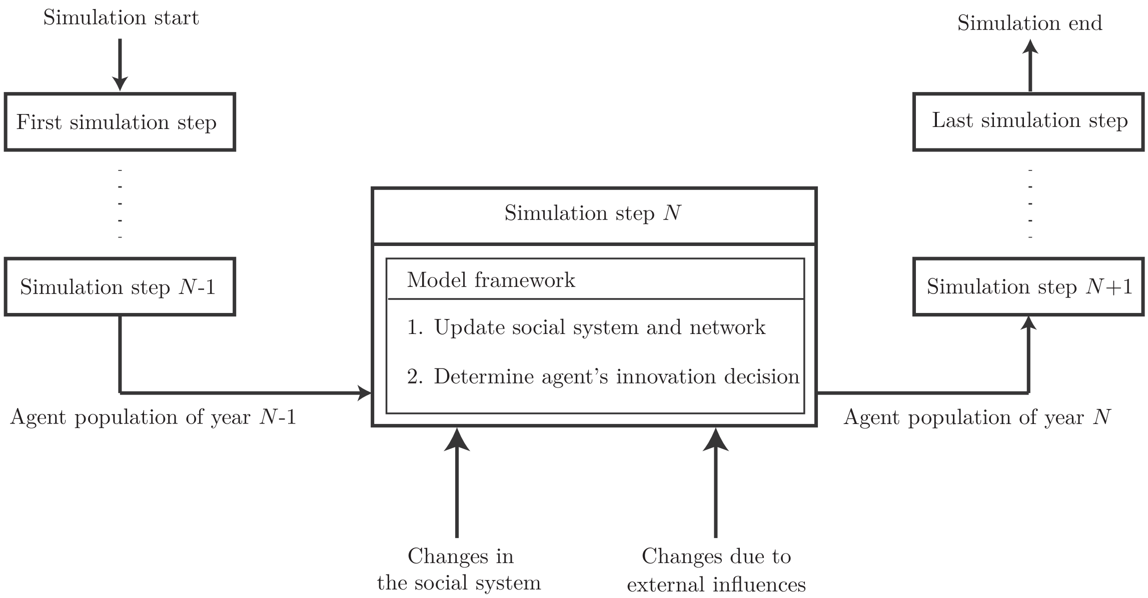

Fig. 3. Schematic diagram of the step-wise simulation process.
Source: Own illustration.

maintenance and upfront costs, and depreciation allowance payments, respectively.

$$R(t) = R_{Save}(t, CE) + R_{Gov}(t, CE) - R_{Adm}(CE) - R_{Main}(t) - R_{Deprec}(t). \tag{6}$$

The explicit estimation of the revenues due to electricity savings[10] ($R_{Save}(t,CE)$) is a function of time t and of the governmental policy in place. As a result, the calculation of $R_{Save}(t,CE)$ varies across the different formulations of the Conto Energia (CE). For the CEs 1–4, the savings are computed by considering the electricity grid as a storage component of the PV system. From the introduction of CE 5 onwards, $R_{Save}(t,CE)$ is calculated as:

$$R_{Save}(t, CE\,5) = E_{PV}(t) \cdot \left[x_{DC} \cdot p_{elec,buy} \cdot \left(1 + \tau_{elec,buy}\right)^{t-1} + (1 - x_{DC}) \cdot p_{elec,sell} \cdot \left(1 + \tau_{elec,sell}\right)^{t-1}\right]. \tag{7}$$

The estimated savings are a function of the produced amount of electricity ($E_{PV}(t)$), the share of direct electricity consumption (x_{DC}), and the price of electricity, which varies depending on whether the consumer is selling it to ($p_{elec,sel}$) or buying it from the grid provider ($p_{elec,buy}$).[11] In addition, electricity prices are assumed to grow geometrically at constant rates ($\tau_{elec,sel}$ and $\tau_{elec,buy}$).[12] The first right-hand side term in Eq. (7) describes the cost savings due to direct consumption of the PV-generated electricity. The second term describes the earnings from selling PV electricity to the local energy provider.[13]

Importantly, the amount of electricity E_{PV} generated by the system is a function of the level of irradiation (E_{Sun}), of the installed nominal maximum peak power (P_{MPP}), and of the predicted PV module abrasion[14] ($\xi_{Abrasion}$). Furthermore, the level of irradiation depends on the region where the house is located, such that:

$$E_{PV}(t) = E_{Sun} \cdot P_{MPP} \cdot (1 - \xi_{Abrasion})^{t-1}. \tag{8}$$

Besides energy savings, an additional positive cash flow is generated by governmental support ($R_{Gov}(t, CE)$), which is based on the FiT given by the CE. The amount of the support is calculated as the sum of three components: a basic payment for the production of electricity ($FiT_{Prod}(CE)$), an incentive for direct PV electricity consumption ($FiT_{DC}(CE)$), and, if applicable, additional bonuses ($FiT_{Bon}(CE)$) that accrue in special circumstances.[15] The cash flows associated with governmental support are then expressed as follows:

$$R_{Gov}(t, CE) = E_{PV}(t) \cdot (FiT_{Prod}(CE) + FiT_{DC}(CE) + FiT_{Bon}(CE)). \tag{9}$$

[10] Electricity may be directly consumed by the owner of the PV system, thus saving part of his/her electricity bill. The owner then sells to the utility provider the surplus PV electricity that is not used for self-consumption.

[11] In general, the amount of money paid by local energy providers is only a fraction of the electricity price they charge consumers for electricity consumption.

[12] Since there is no price increase for $t = 1$, the electricity price grows by the power of $t - 1$.

[13] Note that the second term is independent from and additional to the governmental feed-in tariffs.

[14] Similar to the electricity price (see footnote 12), the abrasion increases over time by the power of $t - 1$.

[15] For instance, a bonus is paid if the roof of the house is renewed due to asbestos, if the PV system is located in a village with less than 5000 inhabitants, or if the PV system consists of components that were produced in Europe. The individual bonuses lead to increments in the FiT that range from 5% to 30%. In the model, bonuses are assumed to increase the basic FiT by about 5% on average.

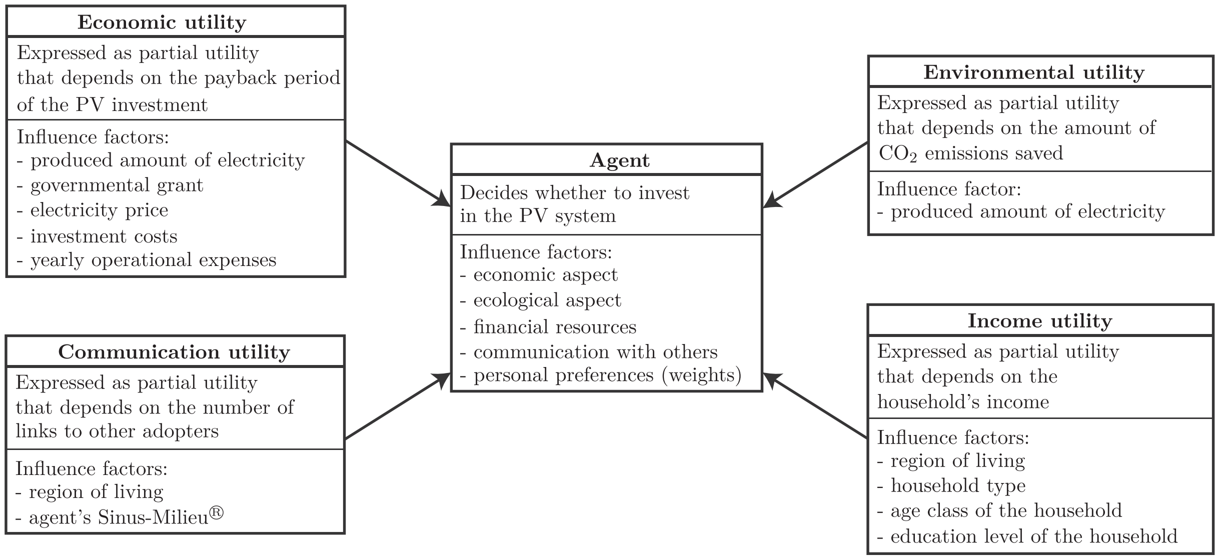

Fig. 4. Factors influencing the agent's adoption-decision process and their representation in the model.
Source: Own illustration.

The adoption of a PV system also entails a series of negative cash flows. Administrative fees ($R_{Adm}(CE)$) have to be paid to the provider of the electricity grid and depend on the specific CE considered, such that:

$$R_{Adm}(CE) = \begin{cases} 30\dfrac{€}{\text{year}} & \text{for CEs } 1-3 \\ 3\dfrac{€}{\text{kW}\cdot\text{year}} & \text{for CEs } 4-5 \end{cases}. \tag{10}$$

Maintenance and upfront costs ($R_{Main}(t)$) must also be considered. Upfront costs (e.g., the consultation of a PV expert/adviser) are paid in the first year of the investment, while maintenance costs occur yearly. Both expenditures are estimated to be a fraction of the initial investment costs:

$$R_{Main}(t) = \begin{cases} \left(\alpha_{upfront} + \alpha_{Main}\right)\cdot I_0 & \text{if } t = 1 \\ \alpha_{Main}\cdot I_0 & \text{otherwise} \end{cases} \tag{11}$$

Finally, the cash flow includes depreciation allowance payments of the PV system ($R_{Deprec}(t)$). The depreciation allowance amounts to a fixed outflow taking place at the end of every year for 20 years, at which point the remaining value of the fixed asset at the end of its useful lifetime is zero.

4.1.2. Environmental utility

The partial utility $u_{env}(j)$ in Eq. (1) is meant to capture an agent's attitude toward the environmental/ecological advantages associated with the adoption of a PV system. Evidence on the importance of environmental concerns in the PV investment decision is given, among others, by Zhai and Williams (2012). The environmental advantages of PV could be measured by the amount of CO_2 emissions saved; however, for reasons of simplicity, the partial utility considers only the expected amount of energy generated by the PV system. In line with Marheineke (2002), we assume that the energy required to produce a PV system is small in comparison to the amount of "green" energy that it generates. The actual output of the PV system depends on its location and technical attributes, and the estimated environmental utility is assumed to follow an S-shaped function.

The use of an S-shaped sigmoid function is taken from Zhao et al. (2011), though, more in general, S-shaped utility functions have a varied range of applications in theoretical and empirical studies (Phillips, 2007; Modis, 2007). Such a formulation implies that agents become less responsive to CO_2 savings as the amount of expected electricity generation increases, and it provides an easy method to normalize the partial utility within the [0,1] interval (see also Footnote 9).

We assumed that the environmental utility is a function of the expected amount of electricity generated over 20 years by the PV system of agent j, which is represented by variable $E_{PV,tot,j}$ in Eq. (12) below. We further assumed that the expected average amount of electricity generated over 20 years by all PV systems at the time of the investment (i.e., variable $\bar{E}_{PV,tot}$) provides a "tipping point". Whenever $E_{PV,tot,j}$ is below the average level, the agent has a positive marginal environmental utility from increasing its electricity generation from a PV system. When $E_{PV,tot,j}$ exceeds the average level, the marginal utility starts to decrease. The environmental partial utility is thus given by:

$$u_{env}(j) = \frac{\exp\left(\dfrac{E_{PV,tot,j} - \bar{E}_{PV,tot}}{1\cdot 10^4}\right)}{1 + \exp\left(\dfrac{E_{PV,tot,j} - \bar{E}_{PV,tot}}{1\cdot 10^4}\right)}. \tag{12}$$

Fig. 5 shows the environmental utility function curve and its operational range. The figure indicates that the environmental utility does not have its minimum at zero. This is due to the fact that PV systems always save energy when operating.

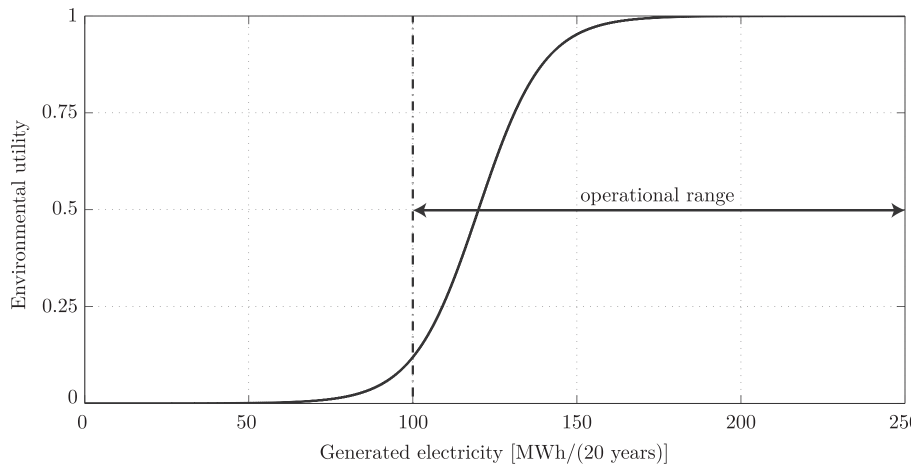

Fig. 5. Utility function of the environmental benefits associated with the adoption of a PV system.
Source: Own illustration.

It is important to mention that the implementation of such a functional form is ad-hoc, and it may be questioned whether it adequately represents the adopters' actual environmental preferences in Italy. However, due to a lack of empirical evidence to test better fitting alternative formulations, we have chosen the simple but effective S-shape parametrization. As suggested by Brenner and Werker (2007) and Werker and Brenner (2004), when no relevant data is available, a model should be left as general as possible (Fagiolo et al., 2007). More on this issue is discussed in the conclusion.

4.1.3. Income utility

The partial utility $u_{inc}(j)$ is based on the household's income, which in turn is determined by the agent's region and his/her socio-demographic attributes. In general, it is assumed that agents with an above-average income are more likely to invest in a PV system. A similar specification is also used by Zhao et al. (2011). This consideration is accounted for in the functional representation of an agent's income utility, whose S-shaped curve depends on agent j's income (N_j) and the average income of all agents in the model ($\overline{N}$), such that:

$$u_{inc}(j) = \frac{\exp\left(\frac{N_j - \overline{N}}{1 \cdot 10^3}\right)}{1 + \exp\left(\frac{N_j - \overline{N}}{1 \cdot 10^3}\right)}. \tag{13}$$

The use of an S-shaped curve is motivated by the same arguments presented in the previous section.[16] However, the very inclusion of this partial utility in the model deserves further consideration. It may be argued that an agent's income level does not directly affect the utility he/she derives from an investment in a PV system. Income, though, may influence other elements, such as environmental preferences, thus ultimately weighing on the PV adoption decision only indirectly.[17] Ideally, this indirect relation would be best captured by *ex-ante* structural equation analyses meant to identify and estimate the causal relationship between the heterogeneous factors influencing the PV investment decision (see, for instance, Byrne, 2010). Unfortunately, there was no data or previous empirical research quantifying these relationships on PV adoption decisions in Italy.

We thus made two simplifying assumptions in our modeling structure. First, the income level is associated, among other things, with the socio-economic background of the agents and their respective lifestyles. This, in turn, influences the weights assigned to the partial utilities across the different types of agents, thereby indirectly influencing the adoption decision (see Sections 4.2 and 5). Second, we decided to assume that income also directly affects investments in PV systems in order to capture the difference between PV adoption patterns in Northern and Southern Italy.[18] As mentioned in the Introduction, despite better irradiation conditions, investments in residential PV in Southern Italy have been lower than those in the North. Given that, for lack of better data, the characteristics ascribed to the different Sinus-Milieus®,[19] lifestyles, and investment attitudes of the agents were not differentiated between the North and the South of the country, we assumed that including the income level into the investment decision would have helped, at least to some extent, to further set apart Northern and Southern Italy, as well as better fit the existing PV distribution for our model's calibration.

4.1.4. Communication utility

Finally, the influence of communication on the adoption decision is represented by the partial utility $u_{com}(j)$. Communication among agents is an important component of the

[16] And, incidentally, it suffers from the same shortcomings.

[17] We thank one of the anonymous reviewers for bringing up this point.

[18] An additional argument is proposed by Zhao et al. (2011), who argue that the direct inclusion of income in the adoption equation via an S-shaped function helps to indicate the ability of a household to invest in a PV system. If income is too low, a household will find it more difficult to purchase the PV system. On the contrary, if the income level is high, the PV investment will not be a significant concern when making the adoption decision.

[19] In accordance with the data available for Italy (For Sale Italia Advertising Agency, 2004), we assumed that the categorization according to Sinus-Milieus® remains the same across all regions. This implies that agents belonging to a given Sinus-Milieus® category equally weigh the different investment decision factors, irrespective of where they are located.

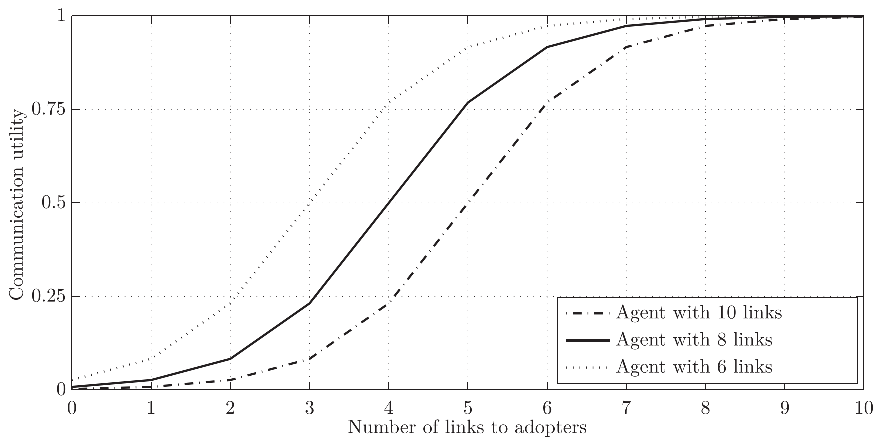

Fig. 6. Response of the communication utility in relation to different communication network configurations.
Source: Own illustration.

diffusion process in general (Rogers, 2003), and of PV systems in particular (Jager, 2006). There are two main types of communication channels: "mass media" and "interpersonal communication" (Rogers, 2003; Lazersfeld et al., 1944).[20] Whereas mass media quickly creates awareness of a product among agents belonging to different social backgrounds, interpersonal communication is considered the most effective communication channel for persuading adopters. The latter occurs via "localite" or direct communication between two or more individuals. This relationship is even stronger if the communication channel links agents belonging to the same socio-economic background (Rogers, 2003).[21]

We elected to incorporate in the model "localite" (or direct) interactions between agents, so as to represent the type of communication that has the most influence on the adoption decision. The influence of communication is expressed as a function of agent j's total number of communication links ($L_{j,tot}$) in relation to the number of links with actual PV adopters ($L_{j,adopter}$). More specifically, in our formulation we assume that as the number of links to PV adopters increases, the agent is subject to an increasingly stronger incentive to invest in a PV system. However, if the number of links to agents who have adopted the PV system is equal to half of the total number of communication links, the partial utility has reached a "tipping point", where the increase in links to adopters shifts from an increasing to a decreasing return on the communication partial utility.[22] Once again, we adopt an S-shaped function to normalize the value of the partial utility and capture the changing returns to communication as the number of adopters increases, as given by the following expression:

$$u_{com}(j) = \frac{\exp\left(\frac{L_{j,adopter} - 0.5 \cdot L_{j,tot}}{0.8}\right)}{1 + \exp\left(\frac{L_{j,adopter} - 0.5 \cdot L_{j,tot}}{0.8}\right)}. \tag{14}$$

It is important to notice that, since there are no or only a few adopters in the social system at the beginning of the diffusion process, communication hardly plays a role initially. The communication utility function, therefore, starts with a value of about zero and increases as the diffusion process unfolds.[23]

Furthermore, the network structure also plays a significant role, as it defines the total number of communication links that an agent has, how/when these links are created, how long they last, and with whom the agents are connected. Detailed information on the network structure and its characteristics are given in Section 4.3. Here it should nonetheless be mentioned that in the model the total number of links (to both adopters and non-adopters) varies according to the Sinus-Milieu® of the agent (see Fig. 6), though communication mostly occurs among agents belonging to the same socio-economic background.[24] The resulting array of functions represented by Eq. (14) nonetheless guarantees that each agent, independently of his/her Sinus-Milieu®, has an equal response to a proportional increase in the number of links to other adopters.[25]

[20] In line with this notion, Zhao et al. (2011) considered communication with neighbors and advertisement as two separate factors directly influencing the PV adoption decision. However, we did not model advertisement, due to a complete lack of data on PV advertisements in Italy at our disposal.

[21] Rogers (2003) also defines interpersonal communication between agents of the same socio-economic background as an "homophile" communication channel, in contrast to "heterophile" communication channels between individuals of different social groups.

[22] Zhao et al. (2011) simply assume that the tipping point is reached when four neighbors are PV adopters.

[23] Note that in Eq. (14) we have divided the numerator of the exponential function by 0.8. Given the parametrization of the equation, this value enables a marginally steeper response of the partial utility function around the "tipping point" than a value of 1. Due to the limited influence of the communication utility in the results of the model, we have not investigated alternative values further.

[24] By doing this, we are consistent with the assumption that communication is most influential between agents within the same socio-economic group.

[25] For instance, consider an agent with six links, three of those links being links to other adopters. The resulting communication utility is 0.5. An agent with ten links, five of which are to adopters, also has a communication utility of 0.5.

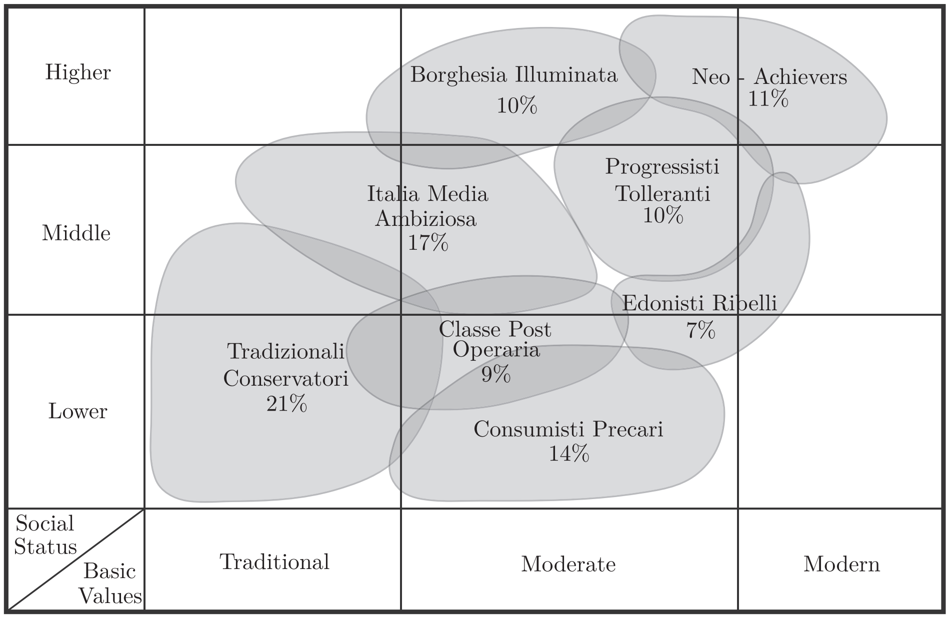

Fig. 7. Share of population by Sinus-Milieus® in Italy, 2003.
Source: Own illustration, based on For Sale Italia Advertising Agency (2004).

4.2. Modeling socio-economic attributes in the PV diffusion process

Investments in a new technology are related not only to economic considerations, but also to specific attitudes toward a technology's attributes (Rogers, 2003). These attitudes are the product, among other things, of an agent's socio-economic background and his/her lifestyle choices.

In the model, the social system is represented by different socio-economic categories. Each category identifies groups of individuals displaying similarities in their socio-economic behavior and consumption patterns. The social system is thereby characterized by sub-groups that have common values and attitudes toward work, family, leisure, money, and consumption. Following Schwarz (2007) and Schwarz and Ernst (2009), we incorporate these socio-economic groups and their attitudes toward innovative technologies in the model by referring to Sinus-Milieus®.

The Sinus-Milieus® include a wide array of social categories that range from the enlightened middle-class ("Borgehsia Illuminata") to consumers–materialists ("Consumisti Precari"). Fig. 7 shows the eight Sinus-Milieus® modeled in our study and displays them as a function of social status and basic values (a more thorough description is given in Appendix A). The model uses freely available Sinus-Milieu® data for Italy from 2003 provided by For Sale Italia Advertising Agency (2004). In addition, the milieus are also associated with the

Table 4
Sinus-Milieus® and adopter categories in Italy.
Source: Own assumptions and illustration, based on For Sale Italia Advertising Agency (2004) and Rogers' (2003) adopter categories.

Sinus-Milieu®	Adopter categories	Reason for assignment
Borghesia Illuminata *Enlightened Middle Class*	Innovators, Early Adopters	Highest income, rational–economic thinking
Neo-Achievers *Neo-Achievers*	Innovators, Early Adopters	Environ. thinking, high income, high knowledge, take risks
Progressisti Tolleranti *Tolerant Progressists*	Early Adopters, Early Majority	Intellectuals, basic ecological and economic thinking
Italia Media Ambiziosa *Average Middle Class*	Early Majority, Late Majority	Consider social norms, influenced by mass media communication
Tradizionali Conservatori *Traditional Conservatives*	Late Majority, Laggards	Do not take risks, adopt only when everyone does
Classe Post Operaria *Working Class*	Early Majority, Late Majority	Consider social norms, strongly influenced by communication
Edonisti Ribelli *Hedonists*	Early Adopters, Early Majority	See the potential of PV systems but do not have money
Consumisti Precari *Consumer-Materialists*	Early Majority, Late Majority	Strongly influenced by peer-to-peer communication

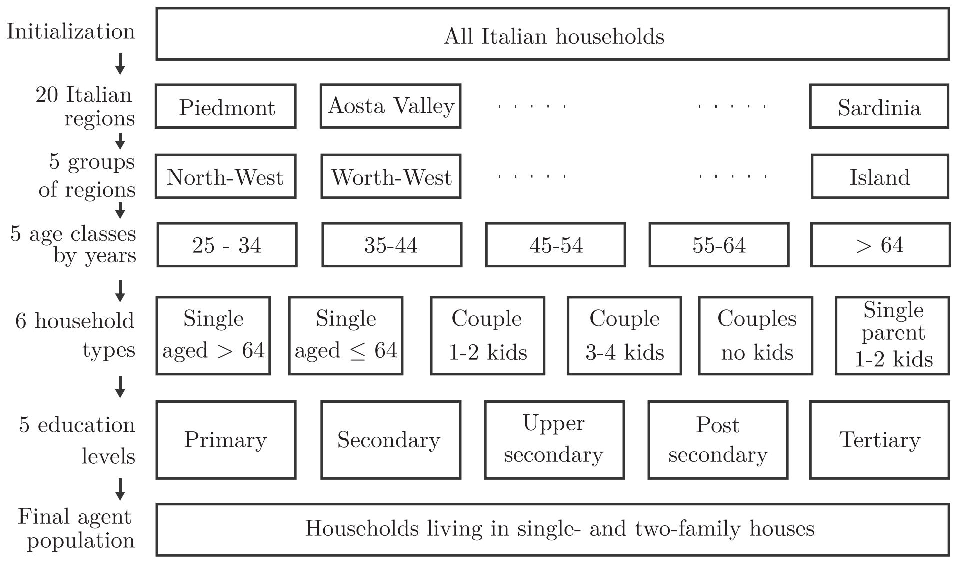

Fig. 8. Initialization and structure of the social system in the model.
Source: Own illustration.

adopter categories defined by Rogers (2003), as illustrated in Table 4.[26]

The Sinus-Milieu® structure of the model is created during an initialization phase that precedes the first simulation period (i.e., *ex-ante* 2006). In the initialization, the agents/households are allocated to the different Italian regions and assigned to various categories. The initialization occurs in the following seven steps, as shown in Fig. 8.

First, we consider the entire Italian population and represent each agent as an individual household.[27] Then, the aggregate agent population is allocated across the different Italian regions. Subsequently, the regions are included into one of five groups, depending on their location (North West, North East, Central, South, Islands).[28] Following this "spatial allocation", the agent population of each individual region is assigned a set of attributes based on the available census statistics (ISTAT, 2012). To begin with, the agents are distributed according to five age classes, which refer to the age group of the main income earner in the household. Consequently, they are appointed to one of six household types.[29] Then, the agents are distinguished according to the highest degree of education achieved by the main income earner. Finally, out of the entire agent population, the model restricts its focus on those agents living in single- or two-family homes.

At this point, the relevant agent population has been created. In the last phase of the initialization process, each household is assigned four additional attributes: its average income, electricity consumption level, type of housing, and its Sinus-Milieu® (see Fig. 9). The allocation of these attributes is discussed in more detail next.

For every region, each one of the 150 agent sub-groups that have been created during the initialization phase is assumed to have a specific income distribution.[30] The distribution of the household income is thus expected to be correlated to the agents' household type, age class, education level, and region. The average household income of each subgroup is determined by available statistical data (ISTAT, 2012), while it is assumed that its distribution can be described by a logarithmic probability function (Statistisches Bundesamt, 2012) whose standard deviation depends on Italy's Gini coefficient, which is about 0.337 (OECD, 2011).[31] Once the income distribution of an agent's sub-group has been determined, the agents within that sub-group are randomly allocated an income level.

The determination of electricity consumption is also performed at the agent's sub-group level. In particular, electricity consumption is expected to be related to the number of members living in the household, which, in turn, is also associated with the household type. The average number of Italian household members, as well as the average energy consumption per household, is based on statistical data (ISTAT, 2012).[32]

[26] The allocation of the adopter categories to the corresponding Sinus-Milieus® is based on the description of the Sinus-Milieus® and assumptions that we made.

[27] In 2006, Italy had a population of about 59.1 million inhabitants, for a total of about 23.9 million households.

[28] This distinction has been made because some of the statistics we use are available only at the aggregate level (i.e., North West and North East).

[29] The six household types are listed in Fig. 8.

[30] In each region, the 150 sub-groups are obtained by considering the 5 age classes, multiplied by the 6 household types, times the 5 education levels. Each single category is formally represented in the model by an object in an array, which makes them easily accessible from a programming point of view. The individual agents that are assigned to each category are saved as vectors, which guarantee high computational speed when calculating, for instance, the NPV.

[31] The Gini coefficient is a measure of income inequality within a country. It ranges from 0 (perfect equality) to 1 (perfect inequality). The Gini coefficient presented here is based on disposable household income, corrected for household size and deflated by the consumer price index (CPI). Italy displays an intermediate level of income inequality in comparison to other developed countries. The OECD average is 0.314 (OECD, 2011), a value between those of Norway (0.256) or Germany (0.295), and those of the USA (0.378) and Mexico (0.476).

[32] Note that, in contrast, the average number of household members in each Sinus-Milieu® rests on own assumptions, as no information of this kind was disclosed in For Sale Italia Advertising Agency (2004). See the Appendix for more information.

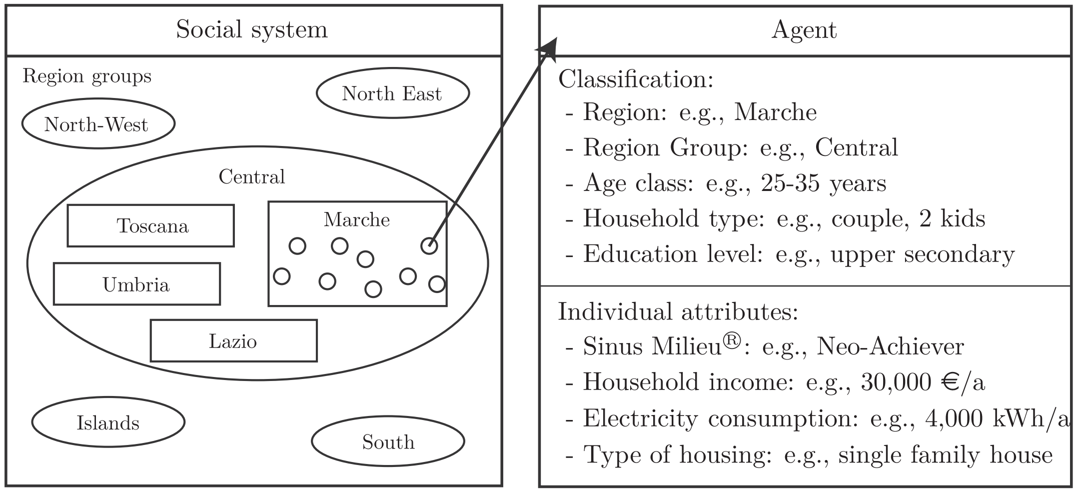

Fig. 9. Attributes of a representative agent in the model's social structure.
Source: Own illustration.

Finally, each agent's housing type is determined in a similar fashion. Importantly, the housing type is linked to the household's income. According to Eurostat (2012), the likelihood that an agent lives in a single-family house is significantly higher if his income exceeds the Italian median by 60%. The probability increases even further for agents living in two-family homes. It is important to differentiate between housing types, as they are associated with different roof areas,[33] which pose a limit to the maximum peak power of the PV system. For instance, since the average household income is higher in Northern Italy, more agents live in single-family houses, resulting in a higher than average PV power per adopter. In Southern Italy there is a higher level of irradiation, but the median income is lower and fewer people live in single-family houses, so that the average PV system is smaller. Importantly, by accounting for two housing types the model has more control over simulation results, thus improving the model's calibration across the different regions.

Finally, each agent is assigned to a Sinus-Milieu® depending on his/her household type, age class, and level of education. Since no detailed information concerning the regional distribution of Sinus-Milieu® was freely available, we created some simplifying rules to perform this allocation. The rules are based on the description of the Sinus-Milieus® characteristics and our own assumptions. The Sinus-Milieus® description and the rule adopted to allocate the agents' to their respective social group are presented in Appendix A.

After its creation in the model's initialization, the social structure is recursively updated at the end of each simulation period. Updating the social structure involves, on the one hand, the model's calibration over the 2006–2010 period and, on the other hand, the implementation of various assumptions about future demographic developments. More specifically, when the population grows,[34] new agents are created and they are assigned the relevant set of attributes according to the aforementioned procedure. Note that in the 2006–2010 period, when new agents are created, they are randomly allocated to one of the Sinus-Milieus® that fit their attributes. In turn, over this time interval, the distribution of the Sinus-Milieus® is allowed to change. Such changes are only minor, though, due to the limited growth of the Italian population and the time frame considered (see Fig. 13). After 2010, the model continues to account for demographic developments. However, even though new agents are created, their allocation to a Sinus-Milieu® is such that the share of each Sinus-Milieu® relative to the total agent population remains constant from 2010 onwards.[35]

One last remark must be made before the next section is introduced. Once the social system is initialized, the model includes about 10 million Italian households as possible adopters.[36] Since each agent has several attributes and needs to perform a series of operations during the innovation–decision process, the model requires a relatively large computer storage capacity and the simulation time can be long. In order to reduce the computational effort, the model includes the option to scale the number of agents,[37] i.e., one agent may represent several households simultaneously, thereby reducing the number of potential adopters and speeding up the simulation process. This process may have implications for the accuracy of the estimations and is discussed in more detail during the model calibration stage described in Section 5.

[33] A household in a single-family house has, on average, a larger roof area available for PV modules than a household living in a two-family house.

[34] In the case of a decrease in the population, the model simply eliminates agents randomly.

[35] While the total number of agents in each milieu may grow, the relative share of each Sinus-Milieu® remains constant. This simplification results from a lack of forecasts concerning the future evolution of Sinus-Milieus® and is justified by the fact that their share remains almost unvaried during the model's calibration over the 2006–2010 period.

[36] In 2006, Italy had a population of about 59.1 million inhabitants and a total of about 23.9 million households, 10 million of which are living in one- or two-family houses.

[37] Each agent has 20 attribute values, and each attribute value requires about 8 bytes of hard-drive memory. If there are 10 million agents, one simulation step requires about 1.5 GB and the whole simulation needs about 30 GB hard-drive storage capacity. As a result, the simulation lasts longer than 12 hours.

Table 5
Probabilities to connect to other agents in own and other Sinus-Milieus® [%].
Source: Own assumptions, based on Schwarz (2007).

Sinus-Milieu®	Borghesia Illuminata	Neo-Achievers	Progressisti Tolleranti	Italia Media Ambiziosa	Tradizionali Conservatori	Classe Post Operaria	Edonisti Ribelli	Consumisti Precari
Borghesia Illuminata	85	10	5	0	0	0	0	0
Neo-Achievers	10	75	10	5	0	0	0	0
Progressisti Tolleranti	5	10	70	10	5	0	0	0
Italia Media Ambiziosa	0	5	10	70	10	5	0	0
Tradizionali Conservatori	0	0	5	10	70	10	5	0
Classe Post Operaria	0	0	0	5	10	70	10	5
Edonisti Ribelli	0	0	0	0	5	10	75	10
Consumisti Precari	0	0	0	0	0	5	10	85

4.3. The communication network

The model's social structure also affects the communication among agents, which in turn influences the adoption decision. As done by Schwarz and Ernst (2009), communication channels between agents are assigned according to the Small-World Network (SWN) algorithm, which was originally created by Watts and Strogatz (1998). SWNs are based on the idea that every individual is connected to anyone else through no more than six degrees of separation (Barabási and Bonabeau, 2003). In addition, SWNs are characterized by a high density of connections with short path-lengths, features also shared with actual social communities. Empirical studies have shown a strong correlation between the number of contacts in a SWN and the agents' gender, age, education, and income (Schwarz, 2007; Zheng et al., 2006).

In the model, the number of communication channels depends on the Sinus-Milieu® of the agent. Furthermore, the SWN algorithm has been adjusted in order to account for the structure of the social system considered. All possible adopters are situated across the 20 regions and have primarily "localite" links to other agents from the same region. In addition, most of the communication channels are modeled to take place between agents belonging to the same socio-economic group (see Table 5).[38] The remaining links are almost uniquely with agents from bordering Sinus-Milieus® (see Fig. 7). Note that the network structure (i.e., the links across specific agents) is created in the initialization of the model and maintained throughout the simulations. However, in order to create an element of uncertainty, there is a small probability in each simulation run that an agent will break up a link and randomly reconnect to another agent (see Table 6).[39]

[38] We have no data to validate the assumptions made about the likelihood to connect with other agents. However, we assigned the probabilities in accordance with the hypothesis that communication is most effective if it occurs between agents in the same social group. In addition, given the relatively limited importance of communication in the aggregate diffusion process (see Section 6), changes to the probabilities would have not made a significant difference to the model's results.

[39] For instance, for any of the 6 links to other agents of a Neo-Achiever, there is a 1% chance that the link will be broken and a new connection will be created with another agent.

5. Model calibration

The model's calibration is similar to what Fagiolo et al. (2007) define as a sort of indirect calibration approach.[40] Several model runs are simulated and the model's results are compared with empirical data. The model parametrization that produces the best results is then chosen.[41]

We calibrate the model with respect to the total number of adopters, the rate of adoption, the installed PV power, and the PV system characteristics over the 2006–2011 period. We target a close resemblance of the simulation results with the actual PV diffusion process at the national level. As adjusting the model in order to fit the PV adoption dynamics of each individual region is particularly difficult, each region is individually calibrated once the model matches the general national PV diffusion trends.[42]

The calibration is performed by adjusting the values of the utility threshold and the weights of the partial utilities across the various socio-economic adopter categories. Changes to the partial utility weights of a specific socio-economic group influence the slope of the adopter curves of that given agent's category, thereby affecting their specific attitude toward the innovation. Changes to the utility threshold, in contrast, shape the whole level/slope of the curves without affecting specific adopter categories.[43]

Fig. 10 shows the results of the calibration for the total number of adopters and the rate of adoption at the national level. The diagrams illustrate the actual PV market data and various simulation runs with different thresholds, while all other parameters are kept constant. The model displays a good fit to the actual number of adopters (Fig. 10, left side). The best results are obtained with a threshold value of 0.539. However, the simulations also turn out to be rather sensitive to variations

[40] Alternatively, Fagiolo et al. (2007) also identify what they define as the "Werner–Brenner" and the "history friendly" approaches. More specifically, the Werner–Brenner approach advocates the use of Bayesian inference to conduct output validation. The history friendly approach constrains parameters in line with empirical evidence in a particular industry.

[41] Due to the large number of possible parameter combinations, there is always a potential scope for multiple solutions. This is one of the main drawbacks of this approach.

[42] Zhao et al. (2011) use a similar method to determine the threshold level. They compare the annual growth rate of PV capacity of their model with global historical data for the annual growth of PV power. However, we think that a model is better calibrated by looking at how the proposed model fits the actual historical diffusion of PV in the area studies, rather than ascribing a threshold that is derived from aggregate world data.

[43] Note that Zhao et al. (2011), for instance, do not perform any calibration on the utility weights, but rather adopt fuzzy set theory to adjust the weights according to a survey conducted by Jager (2006).

Table 6
Number of communication channels and probability to randomly reconnect.
Source: Own assumptions, based on Schwarz (2007).

Sinus-Milieu®	Borghesia Illuminata	Neo-Achievers	Progressisti Tolleranti	Italia Media Ambiziosa	Tradizionali Conservatori	Classe Post Operaria	Edonisti Ribelli	Consumisti Precari
Number of links	7	6	7	8	6	8	9	10
Probability to reconnect [%]	0.5	1.0	1.0	0.75	0.25	0.5	1.0	0.25

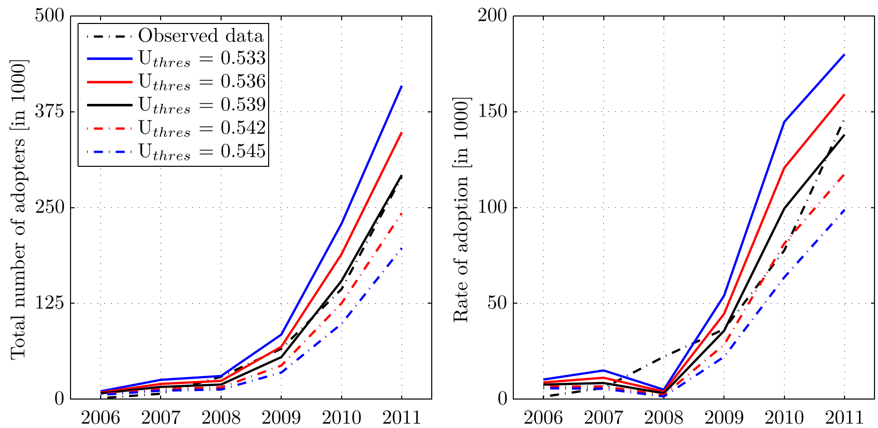

Fig. 10. Outcome of the calibration for different threshold levels, 2006–2011.
Source: Own illustration, based on calibration results.

in the threshold level. A threshold change of ± 0.03 causes a difference in the number of adopters of about $\pm 18\%$, whereas a change of ± 0.06 leads to fluctuations in the $\pm 35\%$ range.

The simulated rate of adoption is less accurate in matching the actual PV statistics (Fig. 10, right side). This is primarily due to the year 2008. In 2008, investment costs were still relatively high and the introduction of the CE 2, which brought a first reduction in support payments, led to a fall in the NPV of the PV system as well as a longer payback period. In the model, PV systems were not as economically appealing as before and this resulted in a lower number of adopters and a lower adoption rate than displayed in the actual market.[44] Nevertheless, the rate of adoption better resembles the actual values in the following years (i.e., 2009–2011), thus still capturing a key trend to be picked up for the successful prediction of the PV market's future development.

Fig. 11 shows the calibration of the total installed PV capacity, the average PV power per adopter, and the average roof surface area of the PV systems. The achieved fit is acceptable for all three parameters. Note that the average roof-surface area of PV systems is assumed to be constant in the model. However, the slightly increasing average installed PV power per adopter is guaranteed thanks to improving PV module efficiency over time.

The partial utility weights implemented in the model are shown in Table 7. They have been determined by trial and error in response to the simulation results during the calibration. Obviously, there may be other value combinations that could help achieve similar or better calibration results. Nevertheless, the chosen values lead to a good fit for most of the Italian regions. Still, it should be explicitly mentioned that the model responds unevenly to changes to different weights. In particular, the weight of the payback period has, due to the linear formulation of its partial utility, a stronger impact on the diffusion process than that of the other weights. Therefore, the weight coefficients should not be directly compared to each other and their value should be interpreted as their relative importance in the adoption decision process.

It should be mentioned that the weights remain constant throughout the simulation period *ex-post* the calibration (i.e., 2012–2026). Obviously, this is a strong assumption. Preferences are dynamic and tend to change over time. Environmental concerns, for instance, are likely to increase among the population.[45] In principle, the model could easily account for dynamic weight preferences as well. However, we decided not to include such changes in the weight variables, as there is no clear mechanism that we could implement in order to describe how these dynamics take place, the degree of the changes, and the interplay between the Sinus-Milieus® and the factors accounted for in the adoption decision. This is a common problem among simulation models, which is discussed more

[44] Note that attempts to overcome this issue by altering the weights of the partial utilities across different adopter categories did not produce significant improvements.

[45] We thank one of the anonymous reviewers for raising this point.

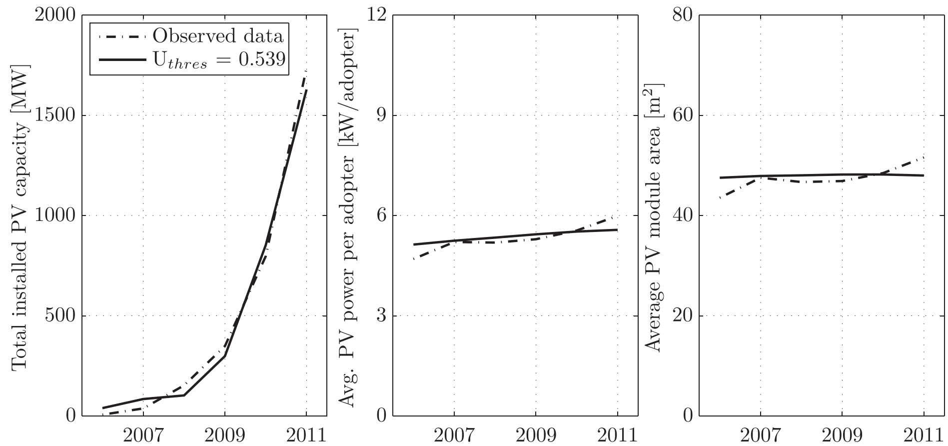

Fig. 11. Calibration of the installed PV capacity, 2006–2011.
Source: Own illustration, based on calibration results.

thoroughly in the Conclusion.[46] An increasing environmental concern is nonetheless indirectly implicit in the model. The communication partial utility can be interpreted as a function of social externalities, whereby the more PV systems are installed among the agent population (a proxy for increasing environmental awareness), the more each household is incentivized to adopt.

In addition, the weights have been assigned so as to replicate the allocation of the Sinus-Milieus® with respect to Rogers' 2003 adopter categories presented in Table 4. Fig. 12 shows the number of new adopters in each Sinus-Milieu® between 2006 and 2011. Initially, the diffusion process is driven mainly by innovators and early adopters (2006–2008). Later, as the rate of adoption increases, also the average middle class is participating in the adoption process (2009–2011). As a result, innovators and early adopters are characterized by higher coefficients for the income and environment weight. Small coefficients for the payback period weight indicate that innovators are willing to take more risk. Later adopters are characterized by higher coefficients for the weight of the payback period, thus stressing their need for financial security.

Fig. 13 shows the distribution of the Sinus-Milieus® over time, regardless of the adoption status. The calibrated distribution of the socio-economic groups fits almost perfectly to the reference values observed in real-world data, which is given as a share of households. The milieus are slightly different across the regions and depend on local socio-demographics. The distribution of the Sinus-Milieus® changes slightly between 2006 and 2011, but no further changes are assumed to take place in the social system (see Section 4.2).

Finally, it is important to have a closer look at the option to scale the number of agents implemented in this model and already mentioned in Section 4.2. The option works well for rather large regions of Italy with many inhabitants, for example Veneto (see Fig. 14 a). For these regions, the agent scale may be increased up to 80 without significant effects on the results of the model. In contrast, the fit of the calibration is more problematic for smaller regions with only few inhabitants, e.g., Molise, when the agent scale is large (see Fig. 14b). The calibration issue arises as the agent scale approaches or even surpasses the number of agents in one or more categories of the regional social system.

During the calibration, and in the further scenarios of the model, an agent scale of 15 is used. This value keeps the simulation duration and the required computational memory small while limiting the calibration error in small regions to a minimum (see Table 8). As a matter of fact, when focusing on the calibration of the model at the national level, the "agent scale-error" in the small regions has a negligible influence, since the number of adopters is comparably small.

6. Scenario analysis and results

After the agent-based diffusion model has been calibrated, it can be used to predict the future Italian PV market under various scenarios. Three simulation scenarios have been tested to consider the sensitivity and validity of the model: a Baseline scenario with the most likely development of the PV market, a scenario with different PV investment costs (Scenario II), and a policy-driven scenario with varying degrees of future governmental PV support (Scenario III). All three scenarios build on the parametrization obtained from the initial calibration.

Table 7
Calibrated weights by Sinus-Milieus®.
Source: Calibration results.

Weights	w_{pp}	w_{env}	w_{inc}	w_{com}
Borghesia Illuminata	0.060	0.350	0.300	0.290
Neo-Achievers	0.070	0.350	0.310	0.270
Progressisti Tolleranti	0.150	0.310	0.265	0.275
Italia Media Ambiziosa	0.150	0.310	0.260	0.280
Tradizionali Conservatori	0.140	0.290	0.260	0.310
Classe Post Operaria	0.140	0.310	0.270	0.280
Edonisti Ribelli	0.135	0.310	0.280	0.275
Consumisti Precari	0.125	0.320	0.280	0.275

[46] A similar argument could be made for any functional form and parametrization representing agents' preferences. A vast amount of alternative changes and formulations can be tested in the sensitivity analyses. We chose to focus on those specifications whose dynamics could be justified by clear mechanisms, i.e., changes to the support policies due to exogenous alterations to the support scheme (Section 6.2) and changes to the investment costs (Section 6.3). The latter are due to increasing maintenance costs, PV degradation and financing costs, while the evolution of PV prices is estimated via an experience curve model based on alternative predictions of the global installed PV capacity.

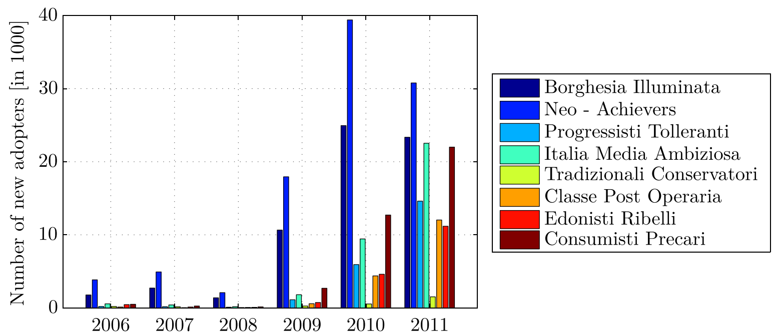

Fig. 12. Number of adopters by Sinus-Milieu®, 2006–2011.
Source: Own illustration, based on calibration results.

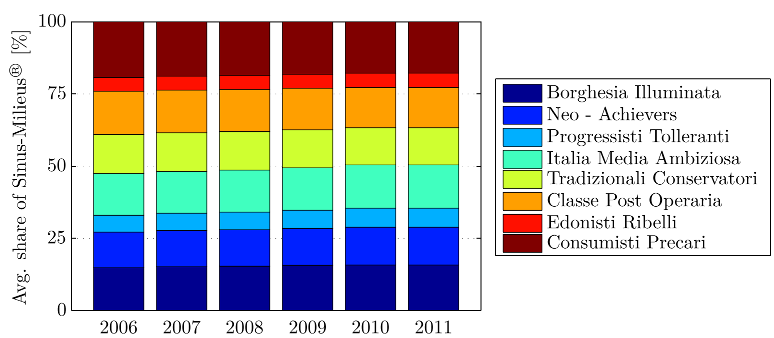

Fig. 13. Distribution of households according to the Sinus-Milieus®, 2006–2011.
Source: Own illustration, based on calibration results.

6.1. Baseline scenario

6.1.1. Description

The Baseline scenario considers the most likely development of the Italian PV market from 2012 to 2026. Governmental support is modeled on the current CE 5. The Italian government has planned to maintain the CE 5 scheme until the end of 2014. Afterwards, the model assumes that incentives will decrease by 15% every six months. Fig. 15 shows the development of the incentive scheme over time.[47]

Besides governmental support, investment costs are probably the second most important factor for the future development of the PV market. They play an important role in the estimation of the "Levelized Cost of Electricity" (LCOE) generation, a measure of the value of electricity self-generation. The LCOE of a PV system depends on its investment costs (I_0), yearly running costs (R_t), financing conditions (i.e., the interest rate i), energy output (E_{PV}), and economic lifetime (n) of the technology (Kost et al., 2012). The LCOE for new PV systems equals the ratio of the total costs of a PV system to the total energy produced over the lifetime of the PV system, measured as:

$$\mathrm{LCOE} = \frac{I_0 + \sum_{t=1}^{n} \frac{R_t}{(1+i)^t}}{\sum_{t=1}^{n} \frac{E_{PV}}{(1+i)^t}}. \tag{15}$$

Usually, the dominant component of the LCOE of a PV system is its investment costs. About half of the investment costs of a PV system are due to the modules' price, the other half is due to the inverter, cables, monitoring systems, and the installation costs (Wirth, 2012).[48] The reduction in PV system prices over time can be ascribed to economies of scale as well as learning effects and improvements in efficiency due to research and development activities (Wirth, 2012; EPIA, 2011). Their cost evolution has often been modeled via experience curves (for a literature overview, see van Sark et al., 2010). Here, we also model the evolution of the PV system price (I_t) at time t by forecasting the price per installed kW power of the system ($p_{PV}(t)$) with a one-factor experience curve; see also Eqs. (3)–(5)). More specifically, it is assumed that $p_{PV}(t)$ is a function of the global cumulative PV power ($ACC(t)$), the experience parameter ($-b$), the price of the system in the base year ($p_{PV}(t_0)$), and the global cumulative installed capacity in the base year ($ACC(t_0)$). The price of the

[47] Fig. 15 shows the average incentive for PV-generated electricity from systems with an installed capacity of up to 20 kW of peak power. Extra payments and payments for direct energy consumption are not included.

[48] Also known as Balance of System (BOS) components.

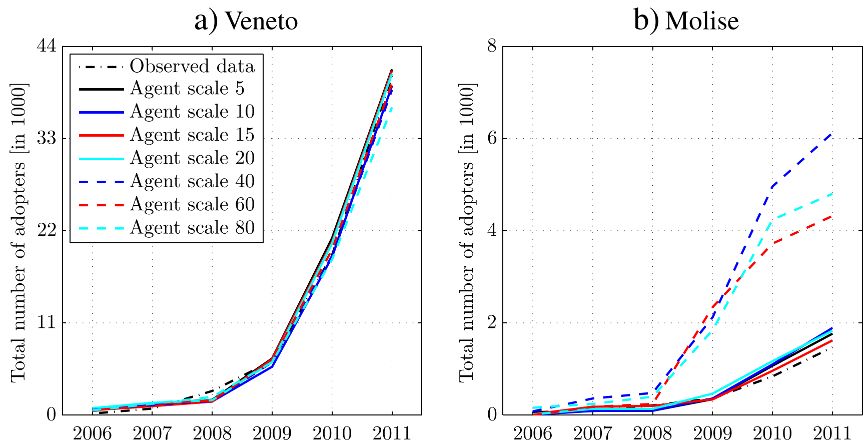

Fig. 14. Influence of the agent scale on the number of adopters in selected regions, 2006–2011.
Source: Own illustration, calibration results.

system per installed kW power at the time t is then given by:

$$p_{PV}(t) = p_{PV}(t_0) \cdot \left(\frac{ACC(t)}{ACC(t_0)}\right)^{-b} \tag{16}$$

$$LR = 1{-}2^{-b}. \tag{17}$$

The model implements a learning rate (LR) of 20% until 2020, followed by a reduced rate of 18% until 2026 (EPIA, 2011). Data for the global cumulative installed PV capacity until 2026 are taken from EPIA (2011). The associated PV system price evolution and the cumulative installed capacity are given in Table 9.

Besides the price per kW, additional assumptions are necessary to estimate changes in the LCOE of a PV system over time. According to Kost et al. (2012), the maintenance cost of a photovoltaic system increases every year by about 2%, with a starting value of circa 1.3% of the initial investment. The intertemporal value of money is discounted at an interest rate of 6% (i in Eqs. (3) and (15)). In addition, the PV investment is financed by borrowing 70% of the required capital at an interest of 5%. The energy output depends on the region where the PV system is located. Degradation of the PV system is also taken into account and amounts to about 0.3% per year (Kost et al., 2012). In addition, the efficiency of the PV panels is assumed to improve with linear increments by 1.5% per year, which leads to an efficiency increase from 13.5% in 2013 to 16.9% in 2026. Similarly, electricity prices are growing linearly by about 2% per year (Kost et al., 2012).

Table 8
Influence of the agent scale on the duration[a] [in s] of the simulation in selected regions, 2006–2011.
Source: Calibration results.

Agent scale	5	10	15	20	40	60	80
Veneto[b]	681	342	230	174	91	64	50
Molise[c]	26	18	16	15	13	12	11

[a] Simulations performed with a utility adoption threshold of 0.539.
[b] Veneto has about 1.9 to 2.0 million households.
[c] Molise has about 300 to 320 thousand households.

6.1.2. Results

The Baseline scenario indicates a stagnation of the diffusion process in all regions. The inflection point of the diffusion process is very distinct and takes place in 2012 (Fig. 16). After the rate of adoption reaches its maximum, the number of new adopters decreases quickly from about 280,000 in 2012 to about 6500 in 2021.

This outcome seems to be consistent with real-world data. According to the latest PV report (GSE, 2013a), the cumulative adoption of PV systems is still growing, but it is slowing down. Between 2007 and 2011, the number of PV installations more than doubled every year. In 2012, for the first time, the total number of new installations was lower than that in the previous year. Installed capacity, while still increasing, has also been growing at a slower pace. Between 2010 and 2011, installed capacity grew by 269%, with a marked increase in the average PV system size from 22 to 38.7 kW. Between 2011 and 2012, installed capacity grew by 29%. Similarly, the average size of newly installed PV systems steadily increased between 2007 and 2011,[49] while in 2012 this indicator dropped to values lower than those of 2010. While our simulation results might overestimate the decrease in PV diffusion, the model still seems to capture the recent slow-down of the investments. This trend may continue for some time, also due to the currently unfavorable economic conditions in Italy.

The simulation results can be also compared with the prediction scenarios proposed by other studies. EPIA (2012), for instance, estimates[50] a total cumulative installed PV capacity in Italy of 23,000 MW by 2016. Our model estimates the cumulative installed capacity of small residential PV systems at about 4400 MW in 2016, which corresponds to a share of about 19.0% of the total in that year. This number is consistent with the actual share of 15.5% in 2011.[51]

[49] Note that there was a jump in the average size of newly installed plants in 2011. This change is probably also due to the activation of several large-scale PV plants.
[50] We refer to their “moderate scenario”. In their “policy-driven” scenario, EPIA (2012) estimates a total installed capacity of 30,800 MW in 2016.
[51] If we used EPIA's (2012) “policy-driven” scenario, the actual share of domestic installed PV capacity drops to 14.3%.

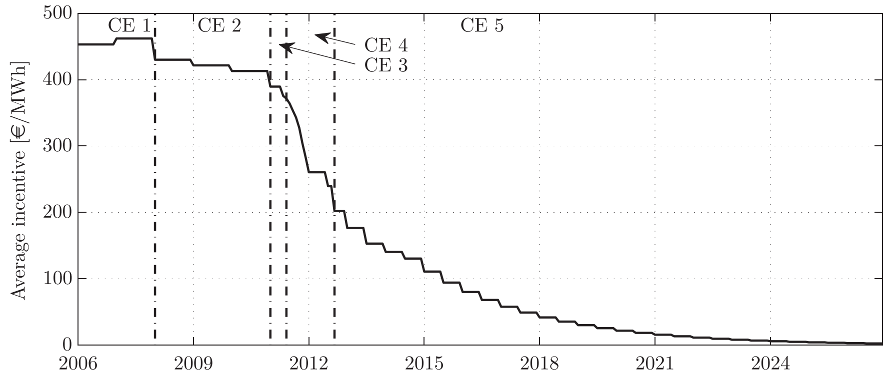

Fig. 15. Incentive scheme in the Baseline scenario, 2006–2026.
Source: Own illustration, based on MSE (2005, 2007, 2010, 2011, 2012) and own assumptions.

A more detailed analysis of the simulated average NPV values of the PV system helps to better explain the results of the model (see Fig. 17, top left box). At the beginning of 2006, PV systems were not profitable. Thanks to the introduction of government support and decreasing investment costs, the average NPV of photovoltaics grew steadily until 2012, when it reached a value of about 15,000.[52] However, starting already in 2011, the incentive scheme has been reduced dramatically. As a consequence, the average NPV will have decreased to 6534 by 2019. Moreover, the CE 5 has changed the calculation method for the clearance balance[53] of direct PV electricity consumption. According to the TIS Innovation Park (2012), the Italian government made this change on purpose, in order to support direct electricity consumption more strongly. As a result of the support scheme changes, the PV system owner needs an electricity storage component for his PV system to receive the benefit payments. The model, however, does not simulate any such components.[54]

Interestingly, the rate of adoption and the NPV of the system increase again from 2021 to 2026. The decline in investment costs eventually makes the PV system economically profitable, despite the small remaining governmental support.[55] The average investment costs, which depend on the given PV system price (Table 9), are the most important component for the estimation of the production costs of the self-generated electricity. As shown in Fig. 17, the model predicts grid parity[56] in 2010. This result corresponds to the actual point in time when residential grid parity was achieved in Italy (Breyer and Gerlach, 2013), thus confirming the good parametrization of the model. After grid parity is reached, the model predicts further reductions in PV electricity production costs, which is in accordance with the assumed decrease in the investment costs and the values forecasted by Breyer and Gerlach (2013).

Understanding the results of the Baseline scenario also requires a closer look at the innovation–decision process of the model. Fig. 18 displays the average share of weighted partial utilities of the calibrated model as a function of time. The diagram includes all agents' utilities, regardless of whether they are adopters or not. As one can see, the influence of the communication network is negligible during the calibration phase and increases only marginally from 2010 to 2013. Afterwards, the influence of communication remains constant. The influence of the households' income and the importance of environmental concerns decrease as PV diffusion expands until 2011. In contrast, the share of weight of the payback period increases between 2006–2012, which can be explained by its linear influence on the partial utility, as well as by the strong increase in the NPV in the first years of the simulation.

Based on these results, it may strike as unexpected that the portion of the weighted economic utility (i.e., the share of the weighted influence of the payback period) is smaller than that of other utilities in absolute value. Indeed, it can be argued that the level of economic utility should be a dominant factor in the decision to adopt a PV system, and that this should also show in relative terms when compared to the other weighted partial utilities. Two remarks must be made on this issue. First, it is hardly possible to validate the relative value of the weighted partial utilities. Second, the relative share of the various utilities arises from the calibration of the model, so that the simulation results match the actual changes in the PV market in Italy over the 2006–2011 period. During this time interval, changes to the main factors influencing the adoption decision were primarily related to the payback period of the PV system, as Fig. 18 indirectly also shows, while the other factors changed significantly less. The relative share of the various weighted partial

Table 9
Cumulative global installed PV power and PV system price developments, 2012–2026.
Source: EPIA (2011) and own calculations.

Year	2012	2013	2014	2015	2020	2026
PV power [GW]	77	88	100	125	345	760
System price[a] [€/kW]	1904	1824	1750	1626	1543	1021

[a] VAT excluded. Prices refer to small-scale (1–20 kW) PV systems.

[52] We always refer to small PV systems up to 20 kW of peak power.
[53] Refers to the savings summand ($R_{save}(t, CE)$) in the PV systems' cash flow (see Eq. (6)).
[54] The inclusion of a storage capacity would significantly alter the NPV valuation of the system. In addition, it would complicate the decision as to when to consume and when to feed in the self-generated electricity.
[55] The average payback period follows a curve that is the inverse of the NPV curve, and thus its shape and evolution over time may be explained in a similar way.
[56] Grid parity takes place when electricity from the grid and self-generated PV electricity (i.e., LCOE) have equal production costs.

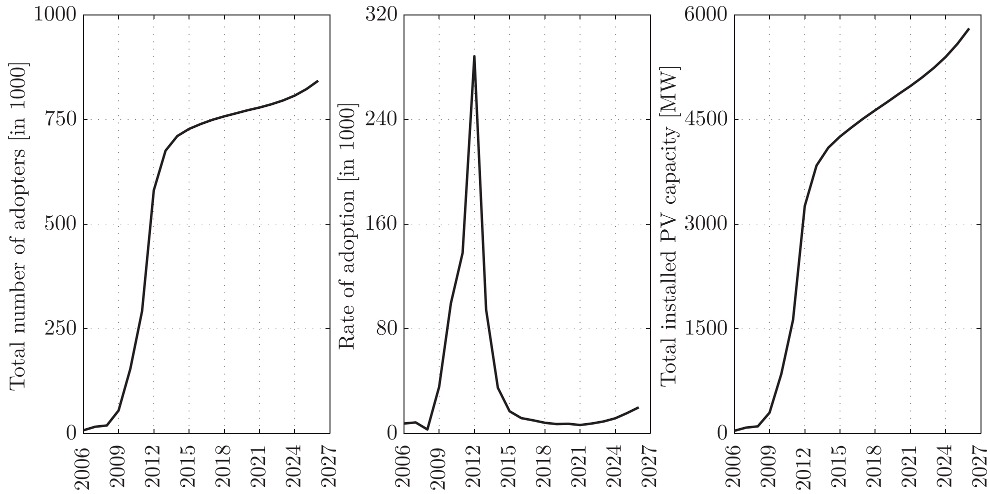

Fig. 16. PV diffusion in the Baseline scenario, 2006–2026.
Source: Own illustration, based on simulation results.

utilities is thus primarily a consequence of the initial calibration and the evolution of the factors underlying the dynamics of the partial utilities (given that the weights remain constant from 2012 onward).

Overall, the model leads to stable and reproducible simulation results, which nevertheless may be questioned. Especially the influence of each partial utility could have been designed in a different way. However, it seems reasonable that communication networks have a rather small influence on the adoption decision, since the share of adopters to the total agent population remains small across the entire simulation period (max. of 6.6% in 2026). Increasing the weight of the communication utility has little to no influence on the outcome of the model. Communication is therefore not likely to be the driving force behind the diffusion process. Since environmental and income effects do not change much over time, they are also not

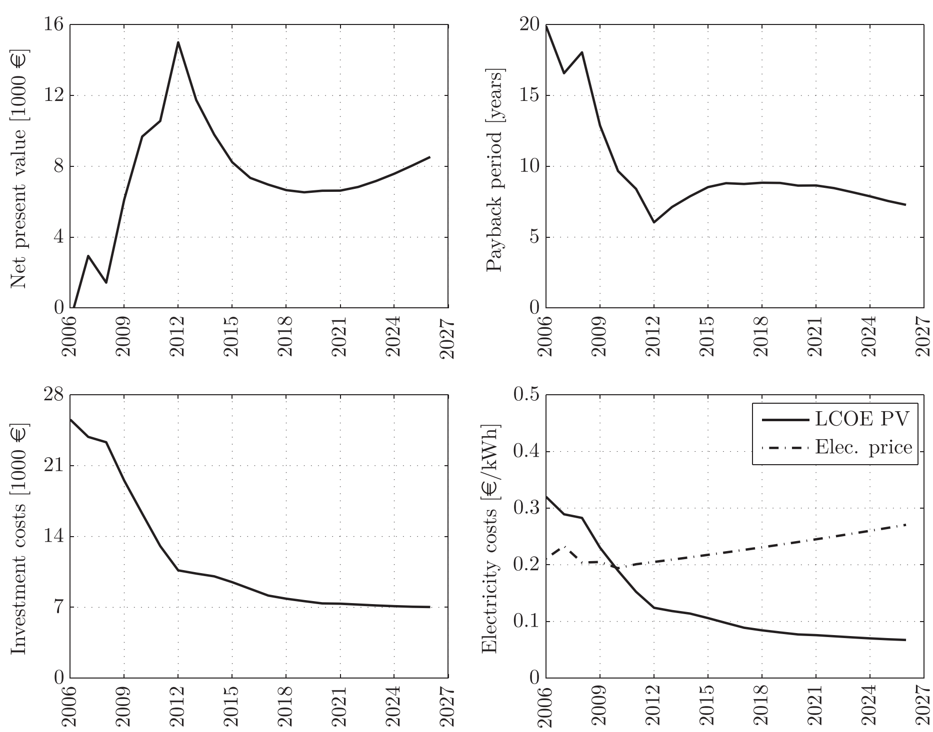

Fig. 17. Average values of key economic indicators in the Baseline scenario, 2006–2026.
Source: Own illustration, based on simulation results.

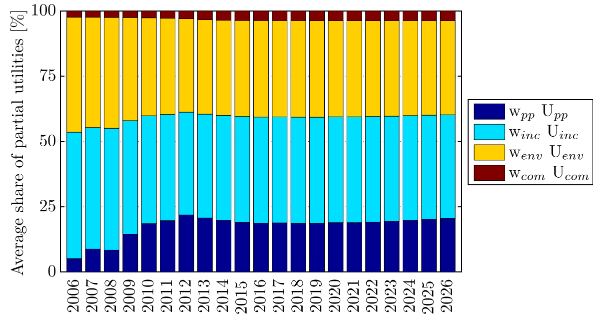

Fig. 18. Influence of the different weighted partial utilities in the Baseline scenario.
Source: Simulation results.

likely to play a leading role for a potential increment in the diffusion process. The only aspect that may lead to and maintain a high rate of adoption is the economic profitability of the PV system. In order to analyze the model's response to different NPV valuations, the following two scenarios further elaborate on governmental PV support and the price of the PV system.

6.2. Scenario II — changes to the support policy

6.2.1. Description

In this scenario, two alternative governmental incentive schemes are implemented. The Baseline scenario is used as a reference for comparisons. Changes to the support scheme take place from 2015 onwards. While the Baseline scenario

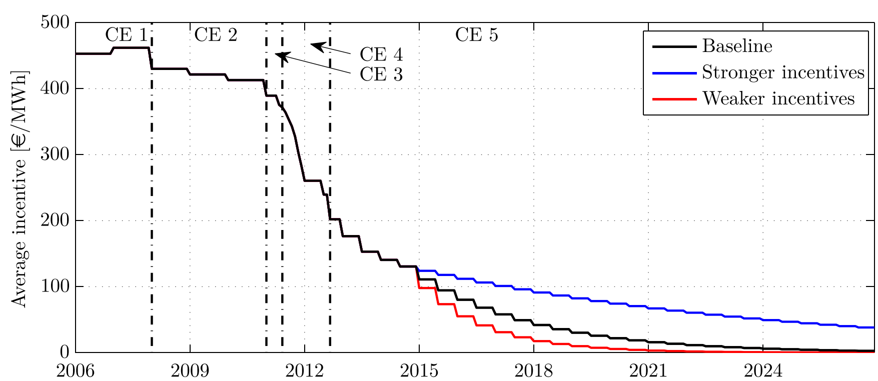

Fig. 19. Alternative incentives for the future PV support scheme in Scenario II, 2006–2026.
Source: Own assumptions and illustration, based on Conto Energia 5.

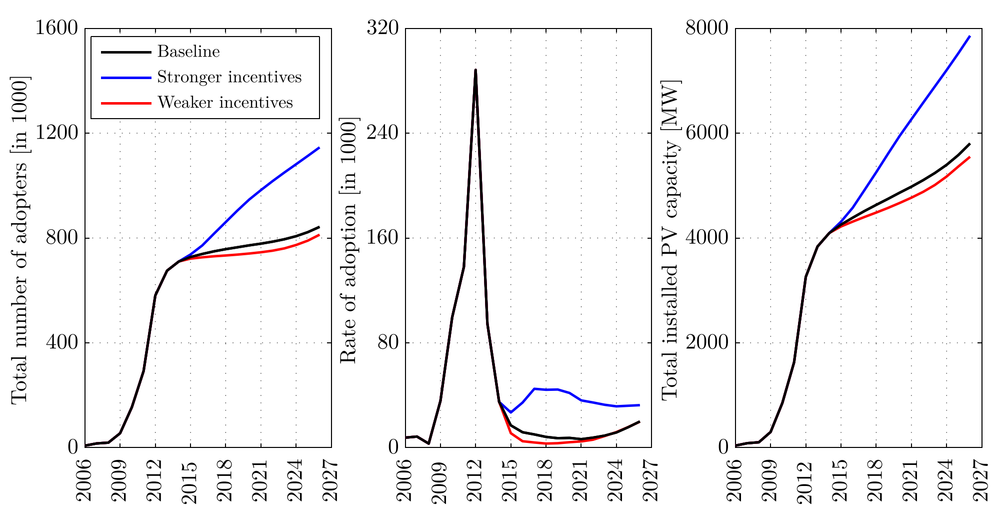

Fig. 20. PV diffusion results in Scenario II, 2006–2026.
Source: Own illustration, based on simulation results.

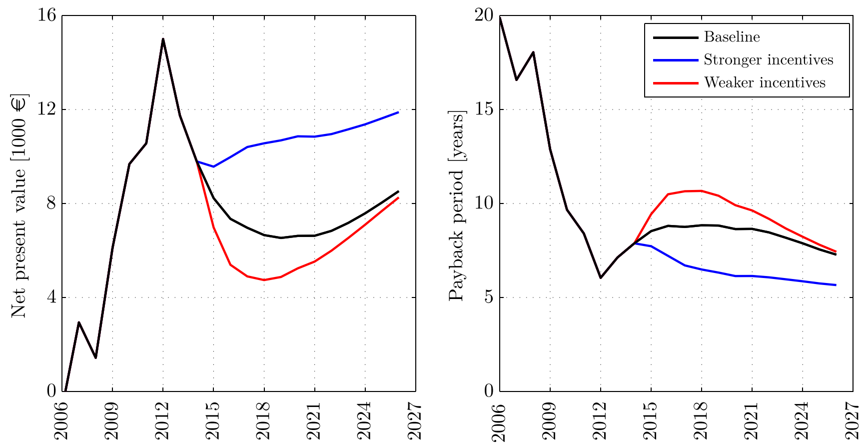

Fig. 21. Average values of key economic indicators in Scenario II, 2006–2026.
Source: Own illustration, based on simulation results.

considers a decrease in incentives of 15% every six months, here in Scenario II the incentives are reduced by 5% and 25%, respectively. The reduction in the incentive payments leads to an end of governmental support before the last simulation year. The alternative with stronger incentives, instead, guarantees governmental support until 2026 and beyond. Fig. 19 displays the alternative support schemes simulated.

6.2.2. Results

The gradual reductions in the incentive scheme by only 5% increase the number of adopters. Cutting back the incentives by 25% does not contribute to significant differences in the results compared to the Baseline scenario (see Fig. 20). Both the Baseline scenario and the "weaker incentive" alternative hardly have new adopters between 2015 and 2026. In contrast, the "stronger incentive" program leads to 36% more adopters by the end of 2026 (1,145,900 households) compared to the reference case. Similarly, the cumulative installed PV power increases to 7900 MW, compared to 4400 MW in the baseline case.[57] Higher incentives secure a shorter payback period of the investment and incentivize, from 2015 onwards, at least 31,000 new adopters per year. Nevertheless, the "PV boom" that characterized the 2009–2012 period could not be replicated.

The two alternative incentive schemes have a strong impact on the NPV and the payback time of the PV system (see Fig. 21). Lower incentives contribute to a drop in the NPV value, which decreases to 5240 in 2018, and then increases again till the end of the simulation period. By 2026, the reduced governmental support scenario shows almost the same NPV as the Baseline scenario. The NPV growth after 2018 is due to decreasing PV investment costs, as it is the case for the baseline simulation. Since in the reference case and in the low incentive alternative the monetary incentives are small and decreasing, the PV price has a stronger influence on the NPV value.[58] On the contrary, the stronger incentive scheme leads to an almost linearly increasing NPV from 2015 till the end of the simulation period. The final NPV in 2026 is about 11,890.

Besides the two alternative incentive schemes presented here, other governmental support programs have been tested to explore the "boundary behavior" of the model. Cutting off the incentives totally in January 2013 leads to a result similar to that obtained with weaker incentives. Maintaining the governmental payments of December 2012 throughout the remaining simulation runs also leads to a similar turning point in the rate of adoption as the one obtained with the "higher incentive" scheme, though the NPV in 2026 is higher. In general, the simulations show that the adoption behavior of the agents can be strongly influenced by the incentive scheme adopted by the government. Small to no incentives lead to a stagnation of the diffusion process. Strong incentive programs, in contrast, rapidly accelerate the diffusion dynamics.

6.3. Scenario III — changes to the investment costs

6.3.1. Description

The third scenario simulates two alternative PV system price developments. Both alternatives are derived from the experience curve model adopted for the PV system price forecast (see Eqs. (16)–(17)). The learning rates are kept constant for different estimates of cumulative global installed PV capacity. For the prediction of the cumulative installed PV capacity, EPIA (2011) provides two additional scenarios based on an optimistic or a pessimistic outlook regarding future PV market development. Table 10 lists these investment cost projections as "low" and "high" PV system price alternatives. Moreover, the table shows the percentage change in relation to the original baseline investment costs.

6.3.2. Results

The results indicate clear differences relative to the Baseline scenario. An incremental reduction in the investment costs of up to 17.6% by 2026 leads to an increase in the total number of adopters by 26.1% to about 1,062,540 households (see Fig. 22). The share of adopters corresponds to about 8.3% of the total agent population. The higher number of adopters also raises the

[57] The individual regions show similar characteristics as the whole nation and are not further analyzed.

[58] As shown in Eq. (3), investment costs in the NPV calculation correspond to a single down payment, while the cash flows (including the support incentives) are discounted over time. As a result, the investment costs have a much stronger direct influence on the final value of the NPV estimation.

Table 10
Forecasted investment costs in Scenario III, 2012–2026.
Source: EPIA (2011).

Year		2012	2013	2014	2015	2020	2026
Low PV price	[€/kW]	1904	1736	1615	1524	967	842
Change relative to baseline	[%]	0	−4.8	−7.7	−6.2	−17.6	−17.6
High PV price	[€/kW]	1904	1833	1784	1749	1543	1342
Change relative to baseline	[%]	0	+0.5	+1.9	+7.6	+31.4	+31.4

total installed PV capacity to 7300 MW. In contrast, the pessimistic scenario regarding investment costs stops the diffusion process. The rate of adoption becomes almost zero and the number of total adopters remains constant from 2013 onwards. Compared to the Baseline scenario, this alternative has 11.7% less adopters in 2026 and a total PV power of only 5100 MW.[59]

The simulation outcome may be explained by looking at the relevant economic parameters that drive the diffusion process of the PV system (Fig. 23). Higher investment costs bring about a decrease in the NPV by 29.3% until 2026. A decrease in the PV price by 17.6%, in contrast, increases the NPV by 16.0% at the end of the simulation. The payback period of the PV system and the cost of self-produced electricity follow similar paths.

By comparing the results of Scenario II and Scenario III, it may be argued that both governmental incentives and the evolution of the PV system price have a significant influence on the adoption process. Based on the simulations' outcome, the scenario with the highest incentive scheme obtained the largest technology adoption. Obviously, a one-to-one comparison of the two scenarios is hindered by the many assumptions made. In particular, the PV system price is assumed to depend on the success of PV adoption at a global scale, not forgetting the imputed economies of scale and learning effects of the experience curve model. In contrast, incentives can be used more flexibly, as they are directly determined by government policy. As a result, though more expensive to taxpayers, they are a better controllable option to accelerate the diffusion of PV technology.

7. Conclusion

While the expansion of large PV sytems may continue, Italy's domestic[60] PV installations have already surpassed an initial phase of rapid growth and, although likely to spread further, they are expected to do so at a significantly slower rate. According to the simulation results, the number of new households adopting photovoltaic technology stagnates under the current support scheme.

In an attempt to adequately account for the complexity of the actual diffusion process of the PV technology, we implement an agent-based model that incorporates four elements influencing the adoption decision: the economic profitability of the investment, environmental considerations, a household's income, and the impact of communication networks. To do so, the model structures the social system into socio-economic classes (Sinus-Milieus®). In total, 150 categories across 20 regions have been implemented by distinguishing between age classes, the level of education, and the household type.

Despite the multiple factors interacting simultaneously, the model simulates reproducible and reasonable results that are in line with observed data over the 2006–2011 period. Overall, the calibration of the model proved to be relatively easy to handle by varying the weights of the innovation-decision process and the utility threshold. The projected diffusion can therefore be evaluated by altering key parameters driving the outcome of the model.

As one might expect, it has been shown that the economic profitability of the investment is the most influential criterion in the adoption decision. As a result, we examined in greater detail the two parameters that most influence it: alternative governmental support schemes and variations in the PV system's investment costs. Compared to the Baseline scenario, a steeper reduction in the support payments would stop the diffusion process at once. On the contrary, a more gentle stepwise decline in the incentive scheme would ensure a greater diffusion of the PV technology. Nevertheless, in the simulation results, the adoption rate that characterized the initial diffusion is never replicated under the latest support policy scheme. A similar outcome is obtained with variations in the expected evolution of the PV investment costs. In general, it may be argued that direct governmental support is more costly to taxpayers, but it is a relatively safe option to ensure a speedier diffusion of photovoltaic technology among private homeowners.

Interestingly, the model managed to accurately predict when grid parity is reached in the Italian market. The model also indicates that self-produced electricity becomes increasingly more advantageous over time. However, Italy witnessed a boom in PV adoption under the influence of strong governmental incentives. Relatively high NPV values were associated with the fast diffusion of the technology. As a result, despite the decline in investment costs and the increasing benefits associated with PV electricity self-generation and direct consumption, the agents do not manage to replicate the profitability levels witnessed during the initial PV boom due to the significant reduction in support granted by the government. Under the assumption that the preferences of investors will not significantly change over time, the lower profitability of PV systems ultimately explains the reduction in new adoption following the introduction of the new support scheme. Environmental concerns and communication also play an important role, but they are not nearly as significant as economic considerations.

Obviously, the model is built on a number of simplifications and assumptions that fundamentally put into question the validity of its predictions. In particular, as already mentioned,

[59] For both alternatives, the individual regions show similar characteristics and are not further analyzed.

[60] In the model, the agent population contains only households living in single- or two-family houses; hence, only the diffusion of small residential PV systems of up to 20 kW power is considered.

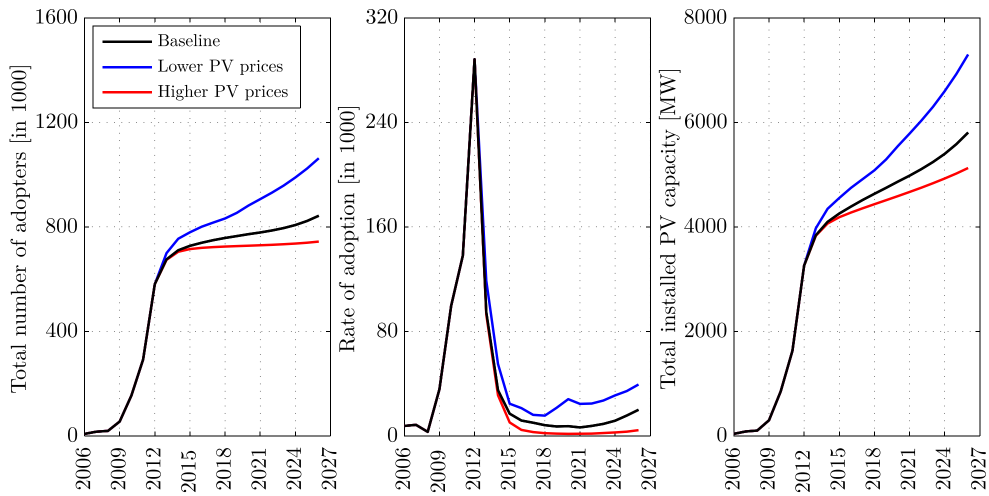

Fig. 22. PV diffusion results in Scenario III, 2006–2026.
Source: Own illustration, based on simulation results.

the model is suspiciously sensible to changes in the utility threshold parameter. Small changes in values contribute to strong changes in the diffusion process. In addition, the categorization according to Sinus-Milieus® is an effective way to represent the multi-faceted aspects of the current social structure. However, its parametrization in the model was rather *ad-hoc* and not substantiated by verifiable empirical research. The empirical validation of the model would greatly benefit from additional research into the causal relationships between the agents' socio-economic background and the factors influencing their PV investment decision. Structural equations could provide, for instance, valuable additional information to the calibration of the model (Byrne, 2010; Fagiolo et al., 2007). While keeping these points in mind, which are shared by many forecasting frameworks, the model's ability to match the actual diffusion of PV systems in Italy at both the national and regional

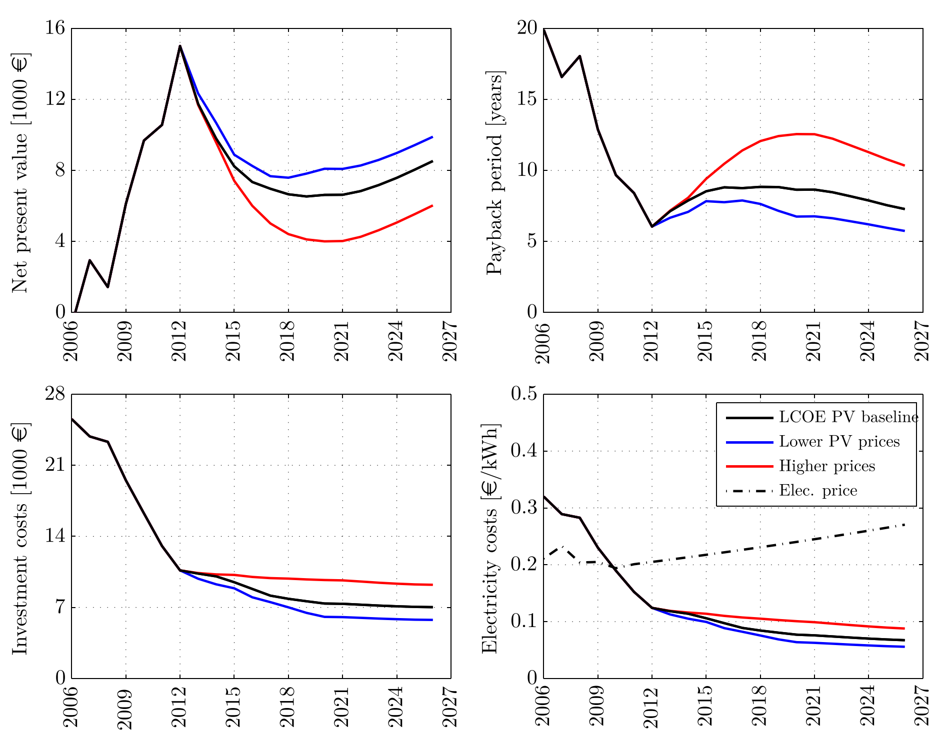

Fig. 23. Average values of key economic indicators in Scenario III, 2006–2026.
Source: Own simulation, based on simulation results.

level are encouraging signs of its potential. Furthermore, the applicability of the proposed framework to other countries and, with small changes, to other renewable energy technologies, calls for future implementations with an improved set of underlying parameters.

Appendix A

The agents in the model are assumed to have different socio-economic backgrounds and lifestyles. These, in turn, are derived from the Sinus-Milieus® characterization that was obtained from a 2002 survey by the For Sale Italia Advertising Agency (2004). The agents are assigned to the individual Sinus-Milieus® on the basis of a set of rules that we created. These matched the attributes of the agents to the description of the Sinus-Milieus®, though in the process we had to make some simplifying assumptions. The next two subsections illustrate how these rules were created. First, we give a description of the Sinus-Milieus®. Second, we explain the rules used to assign the agents to the Sinus-Milieus®.

A.1. The Italian Sinus-Milieus®

Table 11
The Sinus-Milieus® — part I.
Source: For Sale Italia Advertising Agency (2004).

Sinus-Milieu®	Borghesia Illuminata (enlightened middle class)
Characteristics	Highest lifestyle, society's elite, econ. thinking
Type of household	Couples, sometimes with children
Age	Older than 45 years
Education	Highest education
Work	Businessmen, qualified employees and executives
Income	Highest income
Share of population	5.7 million inhabitants (10% of population)
Sinus-Milieu®	**Neo-Achievers (modern performers)**
Characteristics	Performance oriented, seeking individual fulfillment
Type of household	Singles, mostly male
Age	Younger than 35 years
Education	High education
Work	Freelance, specialized employees
Income	Average to high income
Share of population	6.4 million inhabitants (11% of population)
Sinus-Milieu®	**Progressisti Tolleranti (intellectuals)**
Characteristics	Critical intellectuals, socially ambitious
Type of household	Couples, sometimes with children
Age	40–60 years
Education	High and highest education
Work	Freelance, executive employees
Income	Average to high income
Share of population	5.7 million inhabitants (10% of population)
Sinus-Milieu®	**Italia Media Ambiziosa (modern mainstream)**
Characteristics	Modern mainstream, living the social norms
Type of household	Small families and singles
Age	All age classes
Education	Average education
Work	Employees, craftsman
Income	Average income
Share of population	9.7 million inhabitants (17% of population)

Table 12
The Sinus-Milieus® — part II.
Source: For Sale Italia Advertising Agency (2004).

Sinus-Milieu®	Tradizionali Conservatori (traditionalists)
Characteristics	Traditional, conservative, happy with *status quo*
Type of household	Couples and singles
Age	Above 50 years
Education	Low education
Work	Working class
Income	Low income
Share of population	12 million inhabitants (21% of population)
Sinus-Milieu®	**Classe Post Operaria (working class)**
Characteristics	Dislike traditions and financial situation
Type of household	Singles and small families
Age	All ages
Education	Lower and average education
Work	Working class, employees
Income	Average income
Share of population	5 million inhabitants (9% of population)
Sinus-Milieu®	**Edonisti Ribelli (experimentalists)**
Characteristics	Modern and creative, open to new ideas
Type of household	Small families and singles
Age	Younger than 35 years
Education	Higher education
Work	Freelancer, executive employees
Income	Average income
Share of population	4.1 million inhabitants (7% of population)
Sinus-Milieu®	**Consumisti Precari (consumers–materialists)**
Characteristics	Materialists consumers, feel socially in wrong place
Type of household	Mostly singles, sometimes with children
Age	All age classes
Education	Low to average education
Work	Employees, working class
Income	Low to average income
Share of population	8 million inhabitants (14% of population)

Appendix A.2. The rules for assigning the agents to the Sinus-Milieus®

The initialization and calibration of the model's agents into the Sinus-Milieus® is based on the following steps. First, we need to determine the share of households belonging to each milieu. Since the distribution of Sinus-Milieus® provided by For Sale Italia Advertising Agency (2004) is given as a share of the total population, we make some assumptions about the average number of household members in each Sinus-Milieu®. This enables us to obtain a distribution of the milieus as a share of the total households in Italy (see Table 13).

It is now possible to allocate the agents/households across the various Sinus-Milieus®. This allocation process is performed by matching the characteristics provided in Table 14, below, with the actual attributes of the agents already initialized in the model — i.e., the agent's actual household type, age, and education. The attributes required for the matching procedure are derived from the descriptions of the Sinus-Milieus® in Tables 11 and 12, and from our own assumptions.

Table 13
Parameters for the conversion of the share of the Sinus-Milieus®.
Source: own assumptions and For Sale Italia Advertising Agency (2004).

Sinus-Milieu®	Borghesia Illuminata	Neo-Achievers	Progressisti Tolleranti	Italia Media Ambiziosa	Tradizionali Conservatori	Classe Post Operaria	Edonisti Ribelli	Consumisti Precari
Share of population [%]	10	11	10	17	21	9	7	14
Average no. of household members [pers.]	2.5	1.8	4.0	2.7	4.0	2.0	3.1	1.9
Share of households [%]	11.3	16.2	5.5	12.1	15.1	12.4	6.4	21.0

Table 14
Rules for assigning the agents/households to the Sinus-Milieus®.
Source: own assumptions, fitted for the Sinus-Milieus® data for Italy from For Sale Italia Advertising Agency (2004).

Sinus-Milieu®	Borghesia Illuminata	Neo-Achievers	Progressisti Tolleranti	Italia Media Ambiziosa	Tradizionali Conservatori	Classe Post Operaria	Edonisti Ribelli	Consumisti Precari
Household type[a)]	1–5	2–6	2–5	1–6	1–5	1–5	2–5	1–6
Age[b)]	2–5	1–4	2–4	1–4	2–5	1–5	1–3	1–5
Education level[c)]	4–5	2–5	4–5	2–4	1–3	1–3	3–5	1–3

Translation of the attributes

a) Type of household:	(1) Single >60; (2) single ≤60; (3) couple, 1–2 kids; (4) couple, 3–4 kids; (5) couple, no kids; (6) single parent, 1–2 kids
b) Age:	(1) 25–34 years; (2) 35–44 years; (3) 45–54 years; (4) 55–65 years; (5) >65 years
c) Educational level:	(1) Primary; (2) secondary; (3) upper secondary; (4) post-secondary; (5) tertiary

Consider, for instance, the households in a given region that belong to the 45–54 age category, have post-secondary education, and are formed by a couple with 1–2 kids. Each agent from this sub-group of households is going to be allocated an income that is derived from a common distribution (based on mean statistical data), an electricity consumption level (based on the number of household members), housing type, and Sinus-Milieu®. Given the characteristics of the selected sub-group and in line with the rules presented in Table 14, each of these households could belong to one of five different Sinus-Milieus®. The model randomly selects the Sinus-Milieus® to which each agent belonging to said sub-group is ultimately allocated.

Note that, while the allocation of a household to a Sinus-Milieu® is independent of the household's income level, the average income level and type of Sinus-Milieu® to which a household is allocated are both dependent on the aforementioned three factors (household type, education, age). In turn, income and Sinus-Milieus® are indirectly correlated. As a result, in the example given above (i.e., households in the 45–54 age category, with post-secondary education, and consisting of a couple with 1–2 kids), the average income of the agents of this sub-groups is above the Italian average. As one may expect, the members of certain Sinus-Milieus® should have, on average, a higher income than those in other milieus.

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