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Simulating the Diffusion of Residential Rooftop Photovoltaic, Battery Storage Systems and Electric Cars in Italy. An Exploratory Study Combining a Discrete Choice and Agent-Based Modelling Approach

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Abstract: Rooftop solar photovoltaic (PV) systems could significantly contribute to renewable energy production and reduce domestic energy costs. In Italy, as in other countries, the current incentives generate a modest annual increase after the generous fiscal incentives that kick-started the PV market in the 2008–2013 period. Several factors are, however, at play that can speed up the installation process, such as the improvements in PV technology at declining prices, the increased availability of battery-storage (BS) systems, the growing use of electric appliances, the uptake of electric cars, and the increased environmental awareness. We integrate two research methodologies, discrete choice modeling and agent-based modeling, to understand how these factors will influence households' decisions regarding PV and BS installations and how agents interact in their socioeconomic environment. We predict that in Italy, given the preference structure of homeowners, the continuing decline in costs, and the social interaction, 40–45% of homeowners will have PV or PV and BS installed by 2030, thanks to the existing investment tax credit policy.

Keywords: rooftop solar photovoltaic; battery-storage systems; electric cars; discrete choice modeling; agent-based modeling

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1. Introduction

According to a recent estimate [1], in Italy, solar photovoltaic (PV) systems installed in buildings could reach a total nominal power of 46 GW with a yield of 50.4 TWh/year (The total production of 50.4 TWh/year is subdivided as follows: buildings in residential areas with continuous fabric (4.0 TWh/year); buildings in residential areas with discontinuous and sparse fabric (18.5); buildings in industrial, commercial, infrastructural and other artificial areas (5.6); buildings in a predominantly rural area (17.8); buildings in a predominantly natural area (2.2); façades (2.2)). This energy would satisfy 15.8% of the Italian electricity consumption, which equaled 318.6 TWh in 2019. Compared with the current installed capacity of 4 GW, deriving from the 800,000 rooftop installations (ranging from 1 to 20 kWp), there is still a large unused potential. Our estimate is that solar PV generators are installed in about 8% of the buildings, much less than in Australia, where about 24% of suitable private dwellings are equipped with rooftop solar modules [2]. In fact, in Italy, as in other European countries, after the generous fiscal incentives which kick-started the market in the 2008–2012 period, the current incentives generated a modest annual increase (more details in the next section). Several factors are, however, at play that can speed up the installation process. First, the continuous improvements in PV technology and efficiency and the declining PV prices make PV installations even more appealing. As [3] pointed out, rooftop PV systems not only enable households to consume energy from the grid but also allow these households to generate it, thus becoming prosumers. Second, the increased use of electric appliances (e.g., heat pumps, electric ovens, etc.) and especially the uptake of electric cars increase the household consumption of electricity, strengthening the economic rationale for self-generating electric power. Refs. [4,5] reported that people who already have an electric vehicle (EV), or are interested in buying one, are increasingly looking for green electricity solutions for charging their EV at home. At the same time, [4] underlined that several companies (e.g., Tesla in the U.S. and Sonnen in Germany) have recognized the increase in customer demand for combined offers of EVs and renewable energy and have started offering bundles made up of an EV and solar-power charging equipment. Third, the growing availability of battery-storage (BS) systems at reasonable prices could allow households to store the electricity produced during the day for more convenience for family needs in hours when the grid prices are higher. Such a trend has also generated a commercial offer for a bundling acquisition of PV + BS or even PV + BS + EV (e.g., EnelX in Italy (EnelX s.r.l., belongs to the Enel S.p.a. group and promotes renewable energy solutions including solar PV panels bundled with BS (https://www.enelxstore.com/it/it/prodotti/energia-solare, accessed on 28 May 2021) and wall box charging solutions coupled with EV leasing (https://www.enelxstore.com/it/it/prodotti/mobilita-elettrica/noleggio-auto-e-moto/juice-motion, accessed on 28 May 2021)), [6]). Fourth, climate change has increased environmental awareness, so that growing number of people are searching for means to reduce their carbon footprint [7]. Fifth, social interaction, information from PV or BS owners derived from acquaintances and social media, peer pressure, and advertisement and commercial promotion from producers and installers could also contribute to the spread of PV and BS adoption.

Because of the above-described goals and technological developments, it is important to understand and predict market development and energy system evolution. The crucial actors for rooftop solar PV and BS system installations are households. Understanding how households make decisions and interact in their socioeconomic environment is key to predicting which role they could play in the transition toward renewable energy. In turn, understanding and modeling PV and BS adoption would provide us with the framework to estimate how policies could effectively speed up the energy transition. Given the complexity and heterogeneity of households' behavior in making energy-related decisions, along the lines suggested by [8], we integrate two research methodologies: discrete choice modeling (DCM) and agent-based modeling (ABM). The former is used to identify the main determinants of individual choices, while the latter enables the researcher to predict how individual decisions of interacting agents translate into overall system developments. The results presented in this paper might support decision-makers (consumers, manufacturers, business developers, and policymakers) and illustrate the impact of alternative incentivizing structures.

The main peculiarities of our study are the following.

- The agents' decision process is based on utility maximizing behavior derived from the micro-economic theory and the random utility paradigm postulated by [9].
- The agents' utility functions are empirically grounded [10] since their parameters are estimated using an ad hoc collected dataset on revealed and stated preference data. The model allowed us to account for individuals' heterogeneity and identify potential covariates such as socio-demographics (e.g., income, age, and education) and social and informational factors. To our best knowledge, this is the second paper, after [8], to combine ABM and DCM in energy innovation studies.
- Differently from [8], who studied PV adoption only, our study incorporates three "green" innovations, PV, BS, and EVs, taking into account their synergic interaction.
- It evaluates the impact of fiscal incentives on PV and BS uptake.

The paper is structured as follows. Section 2 illustrates government regulation and the evolution of PV and BS adoption in Italy. Section 3 reviews the related literature on ABM and DCM. Section 4 describes the survey and the sample characteristics. Section 5 presents the discrete choice model and the econometric results. Section 6 illustrates the design of the ABM simulation model and how it has been parametrized, validated, and calibrated. Section 7 presents the simulation results, describing a base case scenario and the role of fiscal incentives, social interaction, and stochasticity. Section 8 concludes and draws some policy implications. Part of the documentation is included in the Supplementary Material.

2. Government Regulation and the Evolution of the PV and BS Adoption in Italy

There is a widespread consensus that in most countries, residential PV uptake is due to government support (see Supplementary Material). From 2005, Italy incentivized solar PV, including residential PV systems, under the name "Conto Energia" (Energy Account). Conto Energia consisted of payment for electricity production from photovoltaic systems permanently connected to the electricity grid. Instead of subsidizing the up-front cost (as was previously the case), it remunerated energy production. The incentive, proportional to the energy produced, lasted for 20 years and varied by size or type of PV plant, up to pre-set maximum levels of energy generated or total incentive. From 2005 to 2013, there were five different incentive versions of the Conto Energia, each updating or redefining the previous one. Initially, incentives were quite generous 0.445 €/kWh (1 kW < Power $\leq$ 20 kW), 0.46 €/kWh (20 kW < Power $\leq$ 50 kW), and 0.49 €/kWh (50 kW < Power $\leq$ 1 MW), but they were progressively reduced with the motivation that PV costs were declining and that the grid parity was close to taking place. The total cost of the Conto Energia program is estimated to be 7.6 billion euros. It was covered by a mandatory levy included in the electricity bills of final energy consumers. The 5th Conto Energia ended on 6 July 2013. It was replaced by an investment tax credit (ITC) to reduce up-front investment costs. Currently, the ITC allows households to deduct 50 percent of the cost of installing an energy system (PV and BS) from the stated taxes over 10 years. Under the new regulation, households can sell excess self-produced energy. The remuneration of the energy produced at the residential level is termed "scambio sul posto" ("exchange on the spot"). It consists of a reduction of the energy bill (The exact formula to calculate the monthly energy bill reduction is Cs = min (Oe; Cei) + CUsf $\times$ Es. Cs is the "exchange on the spot" contribution. Oe (in €) is the cost of energy drawn from the grid, varying by time of the day and location. Cei (in €) is the value of the energy fed to the grid, varying by time of the day and location. CUsf (in €) is a fixed amount usually charged in the energy bill, accounting for administrative costs, grid connection, and maintenance. Es (in kWh) is the total energy exchanged, equal to min (kWh fed to the grid; kWh drawn from the grid)) or a direct payment when the total energy produced is higher than that consumed. The reduction depends on the relative amount of energy consumption and production, their timing, and the geographical location. The energy produced is valued between 0.070–0.105 €/kWh [11], about 50–60% of the energy price charged to the final consumer, consequently favoring self-consumption. In May 2020, the Italian government released the Decreto Rilancio n° 34/2020 (Revival Decree) to counteract the economic crisis caused by COVID-19. The Decree introduced an ITC equal to 110% on investments generating energy savings. These also include PV and BS installations as a part of a major intervention that significantly improves the economic efficiency of the building. Eligible beneficiaries are individuals, condominiums, cooperatives, social housing projects, and ONLUS associations. Furthermore, the housing regulation mandates that all new buildings and the ones that undergo major restoration work should satisfy a percentage of their energy needs for heating/cooling and hot water with renewable sources (e.g., solar, wind, biomass, waste, a percentage of the electricity from the grid) (Art. 11 of Legislative Decree 28/2011 mandates the following percentages of renewable sources: for private and public buildings located outside the historical centers private buildings 50% and 55%, respectively; for those located in historical centers 25% and 27.5%).

The impact of the Conto Energia is clearly visible in Figure 1, both in terms of the number of PV installations and in terms of installed capacity. PV installations in the classes 1 to 3 kW and 3 to 20 kW increased enormously during the years of the Conto Energia, more than doubling each year in the period 2008–2010. In the period 2011–2013, the annual growth rate was, on average, 36% in number and 35% in capacity. After 2014, the average annual growth rate stabilized at 6–7% in number and in capacity.

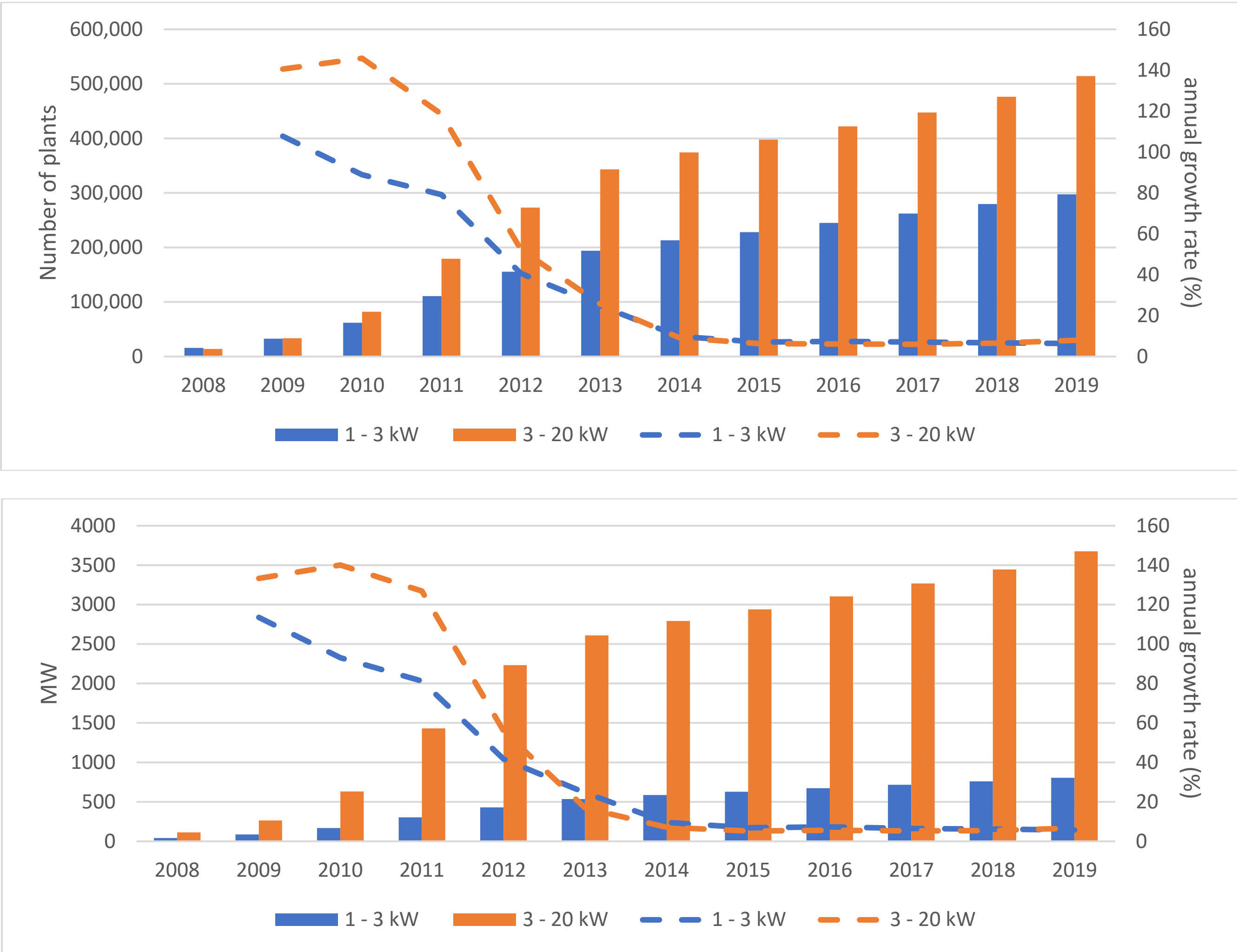

Figure 1. Number of PV systems and amount of PV capacity in Italy in the two smaller classes of power.

3. Related Literature

In this section, we review the literature on the use of agent-based modeling and DCM to study PV and BS adoption.

3.1. Agent-Based Models

Agent-based models (ABMs) can capture the actions and interactions among autonomous agents to understand a system's behavior, how it changes over time, and what governs its outcomes. Instead of using a representative agent as a reference agent, ABMs allow considering the complex heterogeneity among agents with their own characteristics and behaviors [12]. In the next paragraphs, we review the literature related to energy systems in general and PV and BS adoption more specifically. ABMs present a large variety of issues and features that cannot be accounted for in this Section (for a detailed review, see [10]). Our review mainly focuses on these topics: (a) how the agents' decision process is modeled; and (b) how the parameters used to operationalize the decision process are estimated.

One of the first papers where ABM has been used for studying the diffusion of PV systems is [13]. Agents make decisions comparing the "desire level", resulting from a weighted linear combination of four factors (payback period, household income, word-of-mouth effect, and advertisement effect), with a threshold. The key challenge for the researchers is to identify the weights and threshold values that account for the heterogeneity in human cognition, personality, or profile. The authors assume that each weight follows a triangular distribution centered on the average score, which in turn is derived from fuzzy set theory using data published in previous studies. As for the threshold, they tested different threshold values and compared the estimated annual growth rate of PV capacity with historical data.

Ref. [14] analyzed the impact of different policies on solar systems adoption by households in Emilia-Romagna, Italy. Households consider installing PV based on a number of attributes derived from a survey, but unfortunately, no details are provided on how the attributes are evaluated. Ref. [15] simulated how changes to the Italian support scheme might affect the diffusion of PV systems among single- or two-family homes. In line with [13], they assumed that the adoption decision is influenced by the payback period of the investment, its environmental benefit, the household's income, and communication with other agents. PV adoption takes place when the utility surpasses a certain threshold level. The weights assigned are based on the agent's Sinus-Milieu® model and are determined in the model's calibration. The threshold is chosen by comparing the simulation results with the actual diffusion of the PV system. Ref. [16] adopted the partial utility approach proposed by [15]. They used a systematic calibration method based on minimizing the mean-squared error between predicted and actual adoption instead of the less sophisticated visual qualitative trial-and-error method used by [15]. Ref. [17] modeled the probability of adopting PV as a function of only the perceived payback period and a logistic curve that reflects consumer choice behaviors. The analysis is carried out at an aggregate level, without surveying for individual preference heterogeneity. Ref. [18] used lasso least angle regression to identify which features impact purchase decisions the most. They found that the significant variables are the payback period, the maximum budget stated by the respondent, the greenness, and the social effect. Ref. [19] extended the study [18] by comparing Germany and, Ontario, Canada. Ref. [20] took a different approach: the agents in the ABM are buildings placed in a geographically accurate information system. Ref. [21] stressed the importance of social interaction and exposure to social media without detailing how these variables affect decisions. Ref. [22] merged methodologies belonging to ABM and automated parameter tuning. The former relies on self-reported behavior, derived from surveys and enables the identification of drivers and barriers. The latter uses historical data on observed behavior to tune these drivers/barriers in a model and make more reliable predictions. They acknowledged that the process of extracting drivers and barriers from self-reported behaviors and embedding them in an agent-based model is not straightforward. They used data derived from an online questionnaire concentrating on the general attitudes towards photovoltaic and semi-structured interviews with apartment block caretakers and photovoltaic installation companies. However, the authors admitted that even "when drivers and barriers have been identified, it is not clear how these parameters are weighted and which is their relative importance in understanding the decision making strategy of different house owners." To solve this issue, they developed an empirical tuning technique using observed data on the historical PV installation rate. Finally, [23] presented an integrated framework to capture the interplay between financial and the often overlooked attitudinal aspects. They combined an integer programming model and an agent-based model to factor in the role of human behavior.

3.2. Discrete Choice Modelling

Discrete choice models (DCMs) have been widely applied since the 1970s in numerous research fields (e.g., transportation, marketing, environmental evaluation, and economics). The main assumption is that decision-makers have preferences and choose among discrete alternatives the one that maximizes their utility [9]. DCMs are estimated via revealed and stated choice data. Only a limited number of studies concerning residential energy equipment applied DCMs. Ref. [24] used stated choice data to measure households' preferences for battery attributes and functionality in Queensland, Australia. Ref. [25] performed a choice experiment in six Mediterranean countries to study the public acceptance of PV and to build integrated photovoltaic technologies, considering both the private and the public dimensions. Ref. [26] used stated preferences in the context of building retrofits. Ref. [27] investigated individuals' choice behavior regarding home renewable energy equipment in the city of Weiz, Austria. Refs. [2,28] investigated intentions and barriers to adopting rooftop solar panels in the city of Darwin, Australia. None of these studies has integrated DCM into an ABM study. To the best of our knowledge, the only study that proposed to integrate DCM and ABM is [8]. They discussed the benefits of the methodology to study PV adoption in the Netherlands, providing only a brief and sketchy presentation of its implementation in the case study.

4. Survey and Sample Characteristics

Our survey, conducted between December 2020 and March 2021, aimed to collect the data needed to parametrize the ABM model with a special focus on how homeowners make decisions and how they collect and spread information. A special focus was on actual and stated choices under hypothetical scenarios. An example of a scenario presented to respondents is illustrated in Figure 2.

	PV	PV+BS	NO CHOICE
PV Price/kW (Inverter included)	€1600	€1700	None of the two. I prefer to rely on the grid
PV Warranty	15 years	25 years	
BS Price/kWh		€1000	
BS Warranty		10 years	
BS Brand		Other than Tesla Powerwall	
Tax relief on the total expenditure (over 10 years)	75%	110%	
Your choice	☐	☐	☐

Figure 2. Example of a stated-choice scenario.

We asked respondents to imagine owning a single-family detached or semi-detached house without a photovoltaic or an energy storage system and to choose between the three alternatives presented in the scenarios: (A) purchase of a PV; (B) purchase of both the PV and the BS; (C) continue to rely only on the grid. A critical aspect of the success of a stated preference study is the use of relevant and realistic attributes and levels. We based our selection on an extensive literature review, web research, conversations with EV, PV, and BS retailers, and experts in the field. With respect to the studies based on semi-structured interviews using the rating and ranking technique (e.g., [29]) or the Likert-scale method (e.g., [30]), the main advantage of choice experiment studies is that forcing respondents to compare and choose among alternatives, it allows researchers to estimate the trade-offs among the attributes. An important disadvantage is that only a limited number of attributes could be compared at the same time not to overburden the respondents [31]. For a review of how this dilemma has been solved in previous studies, check the Supplementary Material. In our case, after carrying out a pre-test with 50 respondents, we opted for characterizing our choice alternatives with the following attributes: PV price, inclusive of the inverter (€/kW), PV guarantee (in years), BS price (€/kWh), BS guarantee (in years), BS brand (Tesla Powerwall or other brands) and percentage of ITC on the total investment costs.

The attribute levels are reported in the Supplementary Material. The rationale for our choice of attributes is that we wanted to provide respondents with the information needed to evaluate the economic advantage of their choice (purchase price and ITC) since many studies documented the primary importance of this dimension ([29,32]). As reported in Section 2, the ITC, in particular, represents the main policy instrument used in Italy to spur PV and BS adoption. The length of the guarantee was introduced since it is commonly provided in commercial ads and websites and was deemed important by the promoters and potential customers we interviewed during the pre-test phase. Finally, we wanted to test the importance of the brand, but only in the case of the Tesla Powerwall, given its popularity and its crucial role in starting the BS market. Note that we did not provide explicit information on the payback period. We left it to the respondents to make their own evaluation since the payback period depends on several site-specific (solar radiation, roof size, etc.) and household specific conditions (appliances, EV ownership, habits, etc.). Furthermore, we did not mention the current Italian feed-in-tariff (FiT), which is updated annually by the energy authorities and represents a less predictable revenue component, similar to the electricity price charged by the energy providers. Using the Ngene Software, we developed a D-efficient design of the choice tasks [33] with the a-priori coefficients based on pre-test interviews.

We also collected data on the self-assessed and objective knowledge of the PV and BS systems to test whether and how it influences adoption decisions. For the same purpose, we asked respondents about the knowledge and purchase intention of an EV. Next, we questioned respondents about their source of information (peers, web, and promoters) regarding energy-related issues and about the number and intensity of their social interactions. Finally, we asked about their socioeconomic characteristics (gender, age, education, and income), type of dwelling, and current ownership of PV, BS, or EV.

For obvious reasons, administering a hypothetical choice experiment on PV and BS adoption is much more difficult than in the case of conventional shopping goods such as a food product (oil, coffee, wine), an electronic device (cell phone, tablet), or even a car ([34,35]) or another vehicle ([36,37]). The decision on whether to install rooftop solar PV systems or a BS system requires a high degree of technical and financial knowledge. Hence, people rely on experts' advice or adopters' experience, especially from relatives, friends, and neighbors. Such a difficulty is clearly reflected in the number and type of interviews that we have been able to collect. We administered interviews via web platforms (e.g., Teams, Skype) because of pandemic restrictions. The questionnaire was set up with online software (Google Forms), and the respondents could answer anonymously. In order to introduce the topic and to explain the terminology, however, most interviews were introduced by an interviewer. Notwithstanding such an effort, several people felt that they were unable to make an informed choice and refuse to provide answers to the questionnaire. As a result, we were able to collect only 155 valid interviews. Our sample is consequently not representative of the Italian population.

The issue of weak sample representativeness is common in choice experiment studies. The above-quoted surveys on PV adoption report similar difficulties (see Supplementary Material for details). A detailed illustration of our sample and of the information collected during the interviews is contained in the Supplementary Material. In summary, most respondents were men (77%), under 30 years of age (88%), and more than 60% living in the Friuli Venezia Giulia, where the University of Trieste is located. Overall, about 80% of the respondents were students, and 17% were employed. The main reason is that we opted for interviewing engineering students mainly due to their familiarity with energy issues. Half of the respondents live in apartments, and half in single-family houses. About 30% of the respondents own a PV (a large percentage compared to the overall diffusion in the population, estimated to be about 8%), but only 3% have a BS, and 5% own an EV. The statistics about PV and BS knowledge, source of information, and source of interaction are reported in Section 6.2.

Notwithstanding the limited representativeness of the sample, we believe that our sample has some merits. It can indicate how homeowners make their decisions regarding PV and BS adoption and how they react to cost decreases and incentivizing policies for two reasons. The first is that households tend to rely on experts who have a technical background similar to the one owned by most of our respondents (engineering students). Hence, the opinions expressed by our sample are likely to be influential over larger sections of the population. The second is that the biased composition of the sample is offset when parametrizing the ABM model. In fact, having identified the preference structure of the different socio-demographic segments of the sample, the overall model results are obtained by weighting each segment according to its representativeness in the Italian population. Overall, however, the results of our study should be interpreted as exploratory, as mentioned in the subtitle.

5. Discrete Choice Model and Econometric Results

Revealed preference (RP) and stated preference (SP) data have been widely used to understand user preferences and choices. RP surveys collect actual choices from the respondents and can help identify market shares and the main determinants of people's choices. They are, however, limited to existing alternatives. SP surveys, instead, expose respondents to hypothetical scenarios and record their choices under different circumstances. They can be useful for testing consumer responses to new alternatives that have not yet been implemented. However, the responses may be misleading or less reliable if the scenarios and alternatives are not carefully designed. SP data can avoid multicollinearity issues and extend the attributes' range, but they suffer from hypothetical bias. The advantages of RP and SP data can be thus enhanced and the limitations reduced by combining the two sources of data. Joint estimation of RP and SP datasets is technically possible by 'scaling' the utility function, as described in [38].

We analyzed consumers' preferences using the multinomial logit (MNL) model. Firstly, we estimated an MNL separately for each data type k (RP or SP). The individual n is assumed to consider the full set of J proposed alternatives in each choice situation $t \in T$ and to choose the alternative with the highest utility [9]. The utility U_{njt} s/he receives from choosing alternative $j \in J$ in the choice task t is defined as:

$$U_{njt}^{k} = ASC_{j}^{k} + \beta'^{k}_{j} X_{njt} + \gamma'^{k}_{j} Z_{n} + \varepsilon_{njt}^{k} = V_{njt}^{k} + \varepsilon_{njt}^{k} \quad (1)$$

where ASC is the alternative-specific constant, X is the vector of the attributes presented in the stated choice experiments, Z is a vector of socioeconomic characteristics, β and γ are the respective vectors of fixed but unknown coefficients. The random part of the utility is unknown to the analyst (ε_{nj}) is independent and identically distributed (IID) extreme value type 1. Defining V_{nj} the systematic part of the utility function (the sum of the known explanatory variables) for each data type k (RP or SP), the probability of an individual n choosing alternative j can be calculated as:

$$P_{nj}^{k} = \frac{e^{V_{nj}^{k}}}{\sum_{j} e^{V_{nj}^{k}}}$$

After testing the two databases separately, we merged and jointly used them to analyze the underlying variance heterogeneity since the variance of the error term may differ according to the dataset type (We defined the scale parameter as $\lambda_k = \frac{\pi^2}{6\sigma_k^2}$, where σ_k^2 denotes the variance of the error term of each dataset and λ_k has an extreme value type I distribution over the alternatives j of each dataset. The RP scale is normalized to one for identification, and the SP scale is estimated. We specified the scale parameter for the SP database as $\lambda_{nt} = [(1 - \delta_{nt,RP}) \cdot \lambda] + \delta_{nt,RP}$, where $\delta_{nt,RP}$ is a dummy variable that takes the value 1 if the tth choice situation of individual n refers to an RP choice and zero otherwise). We analyzed the sample by differentiating between those who already had solar panels and those who did not. Since the observed differences could be the result of scale factor differences (i.e., variance differences) in addition to those attributable to actual parameters, we applied the procedure proposed by [39] to test whether the scales of the two datasets are equal and, if not, whether parameters differ after accounting for differences in scale.

We tested several specifications and reported in Table 1 the results of 4 different joint RP-SP MNL models, estimated using the Apollo package in R [40]. Model (1) is based on the choices of the respondents living in an apartment, Model (2) on those of respondents living in a single house, while Model (3) is based on the entire sample. Although the sign and the statistical significance of the main variables are similar, their magnitude is different. We tested whether or not the null hypothesis that the preference structure of two subsamples is similar can be rejected. It resulted that it can be rejected with a high degree of confidence, implying that the two samples have a different preference structures. Note that such a result has been obtained even if we presented the choice scenarios asking respondents to imagine living in a single house, irrespective of the type of dwelling they actually live in. Consequently, we dropped the data referring to the respondents living in apartments and further investigated the preference structure of the homeowners. Across all model specifications, attributes' coefficients are statistically significant and have the expected sign. The purchase price negatively affects the utility of purchasing a PV, separately or jointly, with a BS. A longer warranty period encourages the choice of PV or BS. The Tesla Powerwall brand enjoys higher utility relative to other brands. A higher ITC encourages PV and BS adoption, indicating that governmental policies foster PV and BS adoption.

Table 1. Joint RP-SP MNL estimates.

	(1) Apartment Owners	**(2) Homeowners**	**(3) Apartment + Homeowners**	**(4) Homeowners**
	Estimate (Std. Err.)	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**
ASC_{PV} (relative to grid)	−1.293 (3.087)	−1.863 (1.268)	−1.815 (1.183)	−5.557 *** (1.503)
ASC_{PV+BS} (relative to grid)	5.805 (5.153)	−1.141 (2.006)	−0.236 (1.909)	−3.247 ** (1.626)
Purchase price (€)	−12.937 *** (2.757)	−4.421 *** (0.917)	−6.126 *** (0.885)	−3.339 *** (0.907)
Warranty PV (years)	0.602 *** (0.145)	0.26 *** (0.059)	0.327 *** (0.053)	0.175 *** (0.046)
Warranty BS (years)	0.798 *** (0.252)	0.423 *** (0.116)	0.554 *** (0.109)	0.268 *** (0.08)
BS Brand	2.193 ** (1.071)	0.839 ** (0.414)	0.78 ** (0.391)	0.614 ** (0.307)
Investment Tax Credit	0.257 *** (0.056)	0.109 *** (0.023)	0.138 *** (0.02)	0.075 *** (0.019)
Age				1.326 ** (0.54)
Education				1.206 ** (0.487)
Income				0.249 (0.166)
PV knowledge				0.236 *** (0.081)
EV ownership				2.546 *** (0.69)
SP-to-RP scale [(a)]	0.128 *** (0.029)	0.34 *** (0.077)	0.246 *** (0.037)	0.554 *** (0.148)
Apartment vs. Homeowners scale			1.015 (0.074)	
PV vs. non-PV owners scale				0.939 (0.117)
Model diagnostics				
N. of individuals	76	79	155	79
N. of observations	988	1027	2015	1027
LL(0)	−1085.429	−1128.275	−2213.704	−1128.275
LL(final, whole model)	−804.8048	−830.0592	−1654.801	−812.6706
LL(RP)	−19.23311	−63.69376	−98.47501	−68.87179

Table 1. *Cont.*

	(1) Apartment Owners	(2) Homeowners	(3) Apartment + Homeowners	(4) Homeowners
	Estimate (Std. Err.)	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**	**Estimate (Std. Err.)**
LL(SP)	−785.5717	−766.3654	−1556.326	−743.7989
Adj. Rho-square (0)	0.2512	0.2572	0.2484	0.2673
AIC	1625.61	1676.12	3327.6	1653.34
BIC	1664.78	1715.59	3378.08	1722.42

Legend: age (coded 1: younger than 30 years old; 0: over 30); household annual income (coded 1: Up to €30,000; 2: €30,000–€70,000; 3: €70,000–€100,000; 4: over €100,000); education level (coded 1: with a University degree or a Ph.D.; 0: otherwise); PV self-declared level of knowledge (coded 1: low to 10: high); EV ownership (coded 1 for EV owners; 0 otherwise). [(a)] The t-statistic corresponding to the RP-SP scale factor is computed with respect to a value of 1; a value of 1 indicates no scale difference in the RP and SP choice contexts. ***, **, * indicate significance at 1%, 5% and 10% respectively.

In Model (4), we tested the impact of the socio-demographic characteristics, interacting them with the ASCs of the PV and PV + BS alternatives. In line with other studies (e.g., [41]) but differently from [42], we find that age influences the utility associated with both PV and PV + BS: younger respondents (under 30 years old) are more likely to adopt a PV or PV + BS, relative to the older respondents. Confirming the previous literature (e.g., [43]), we find that education is a significant driver for PV adoption. Consistently, respondents who self-declare to have high knowledge of PV systems have a higher propensity towards PV adoption. On the contrary, we estimated that household income is not a statistically significant determinant, in line with [43,44]. Finally, our data confirmed that EV owners have a higher propensity to buy a PV combined with a BS.

As explained above, these results capture the combined information derived from actual and stated choices. A test on the scale parameter against the null hypothesis of taste invariance indicates that the null hypothesis can be rejected with a high degree of confidence. Such a result signals that there is a significant difference between the actual choices and the stated ones under hypothetical scenarios.

6. ABM Simulation Model

6.1. Agent-Based Model Design

The ABM model design is relatively simple. Homeowners who live in detached houses are modeled as agents. In line with [45], a second agent active in the model is the PV and BS promoters, including both manufacturers and installers. Their role is to contact homeowners and explain the technical and financial characteristics of their products. As discussed above, one of the most relevant aspects of an ABM is what decision agents make and what criteria they use to make such decisions. In our model, homeowners choose between (a) drawing electricity from the grid, (b) installing a PV, and (c) installing both PV and BS (Figure 3).

Consistent with the DCM approach, we assume that the criteria used to make decisions is utility maximization based on their preference structure. With reference to the categorization proposed by [10], our model is an economic model empirically grounded in a statistical DCM. An alternative to the utility-maximizing agent could have been to model agents' decisions based on the current and future total cost of ownership. For instance, [17] assumed that homeowners adopt rooftop PV systems depending on the perceived payback period for their investments, given rooftop PV costs and utility electricity prices. The advantage of the utility-based approach is that it encompasses both monetary and non-monetary variables and allows differentiating decision makers based on their socioeconomic (e.g., age, income, education) and psychological attitudes.

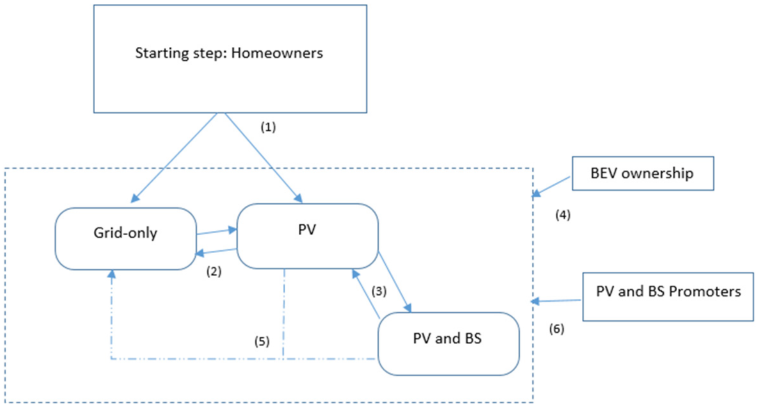

Figure 3. Homeowners' choice.

Based on the econometric results, the homeowners' utility functions are the following:

$$U_{grid} = ASC_{grid}$$

$$U_{PV} = ASC_{PV} + \beta_1 Price_{PV} + \beta_2^{PV} Warranty_{PV} + \beta_4 ITC_{PV} + \gamma_1 Age + \gamma_2 Income + \gamma_3 Education + \gamma_4 PVknowledge$$

$$U_{PV+BS} = ASC_{PV} + \beta_1 (Price_{PV} + Price_{BS}) + \beta_2^{PV} Warranty_{PV} + \beta_3^{BS} Warranty_{BS} + \beta_4 ITC_{PV+BS} + \beta_5^{BS} Brand_{BS} + \gamma_1 Age + \gamma_2 Income + \gamma_3 Education + \gamma_4 EVowner$$

We were also able to differentiate between the utility function of the current PV owners and non-PV owners, estimating similarities and differences in the scale parameter and coefficients (see Supplementary Material).

The model assumes that homeowners assess and reassess their decisions based on their preferences, socioeconomic status, information level, and prevailing (changing) prices. We assume that:

- the choice depicted as (1) in Figure 3 is made by comparing U_{grid} and U_{PV}, parametrized with the Non-PV homeowner's coefficients;
- the choice depicted as (2) is made by comparing U_{grid} and U_{PV}, parametrized with the PV homeowners coefficients;
- the choice depicted as (3) is made by comparing U_{PV}, parametrized with the PV homeowners coefficients, and U_{PV+BS}.

As reported in the literature, EV ownership and increasing electricity demand lead car drivers to reassess their choices on installing PV and BS [4]. Such an occurrence is depicted as (4) in Figure 3.

Finally, the model recognizes that adopters and promoters influence technology adoption via web or face-to-face advertising. In our model, such interactions are operationalized via two channels. The first one consists of a word-of-mouth channel, depicted as (5) in Figure 3: PV and PV+BS owners "send a message" in the Java code suggesting grid-only homeowners adopt the PV or PV+BS technology. The impact of social interaction depends on the number of social contacts and on their persuasiveness. The second channel (6) consists of promoters periodically contacting and advising homeowners on the technical and financial properties of PV and PV+BS, evaluated and eventually accepted to a certain degree by homeowners.

6.2. Parametrization, Validation, Calibration

We implemented the model for the year 2016–2030 using AnyLogic 7.0.3, a widely used Java-based software for ABMs.

An important step is to parametrize the model making use of the best available data sources regarding past and future trends. In the econometric analysis, we found that age, education, self-assessed PV knowledge, and BEV ownership play a statistically significant role in shaping installation decisions. Hence, we searched for information on how such variables are distributed in the Italian population. With regard to social interaction, we derived the assumptions from our sample. Most of the respondents (79%) obtained information on PV and PV+BS via the promoters' channel, either visiting websites (67%) or direct contact with a promoter (12%). The word-of-mouth channel (the interaction with PV and PV+BS adopters) accounts for the remaining 21% of the social interaction. The frequency of social interaction is twice a year for 50% of the sample, once a month for 26% of the sample, and once a week for 8% of the sample, while 17% of the sample declares no interaction on the topic. The average number of people per month with whom the respondents talk about energy issues is 3.4, with a distribution reported in the Supplementary Material. The assumptions about the evolution of the PV and BS costs are of crucial importance. Our best assumptions are based on several formal and informal sources, as illustrated in the Supplementary Material. PV prices have rapidly declined after 2010. We assume that they will continue to decline but at a much less rapid pace. On the contrary, we assume still relevant reductions for BS costs due to rapid technological progress and still unexhausted economies of scale. Given the large uncertainty connected with the future evolution of PV and, especially, BS costs, we will test the impact of our assumption on PV and BS uptake in the sensitivity analysis section.

The validation has been performed as follows. Conceptual validity and micro-face and macro-face validation are guaranteed by the fact that individuals make decisions based on preferences, information, and attitudes, in line with the random utility model. Empirical input validation is provided by the RP-SP dataset and by the recent empirical evidence on technology trends. Cross-model validation is achieved by comparing the ABM results with those obtained in the DCM framework.

The calibration phase guarantees history-friendly results. As suggested by [22], it would be useful to validate the model by splitting the historical data into two temporally separated parts, using the earlier data for calibration and the later data to validate the model's predictive accuracy. We could not perform such a task due to insufficient data on BS uptake in Italy. In our case, it has been possible to calibrate the model only from 2016 onwards because, although rooftop PV was a well-established product, the Tesla Powerwall was announced in 2015, and the Powerwall 2 was unveiled in October 2016 (see Supplementary Material for details).

Figure 4 compares our model's estimates of PV installations and the actual ones, available either as the number of installations belonging to the 1–3 kWp group or that belonging to the 1–20 kWp group. The former represents the most likely estimate of the number of rooftop PV installations, while the latter includes some installations larger than those usually installed on building roofs. Since our model's estimates fall between the two groups, they can be considered a satisfactory approximation of the real-world installations in the period 2016–2019 (more details in the Supplementary Material).

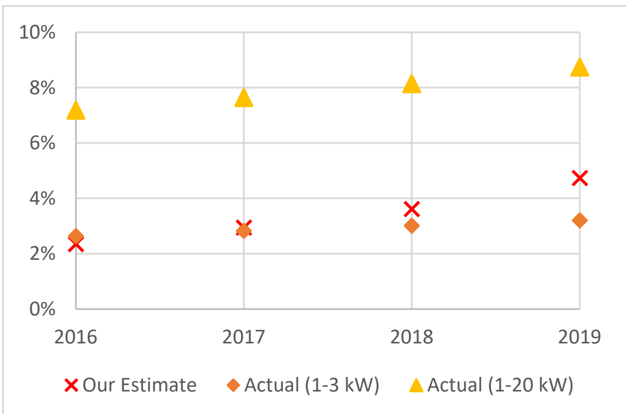

Figure 4. Estimated vs. actual PV installation.

7. Simulation Results

We start by simulating the pace of adoption of PV and BS in the base case scenario, characterized by the current ITC equal to 50%, the existence of social interaction, the assumptions on the evolution of PV and BS prices, and BV penetration. Then we vary the percentage of ITC to 0%, 25%, and 75%. Next, we compare the base case with and without social interaction. Finally, we perform a sensitivity analysis on our assumptions regarding the evolution of PV and BS prices, allowing for stochasticity in the model.

7.1. Base Case Scenario

Under the base case scenario, our model predicts that a large percentage of homeowners will continue relying on the grid only for their electricity supply during the coming decade, notwithstanding the incentives (Figure 5). However, PV installations will grow at an annual average rate of 23.7%, thanks to the declining PV and BS costs, the increase in EV ownership levels, and the word-of-mouth effect. By May 2028, 50% of houses equipped with PV are estimated to add BS. By 2030, the model predicts that 56% of homeowners will rely on the grid, and 44% will have PV (either with BS or without BS (PV only)), 75% of which with BS.

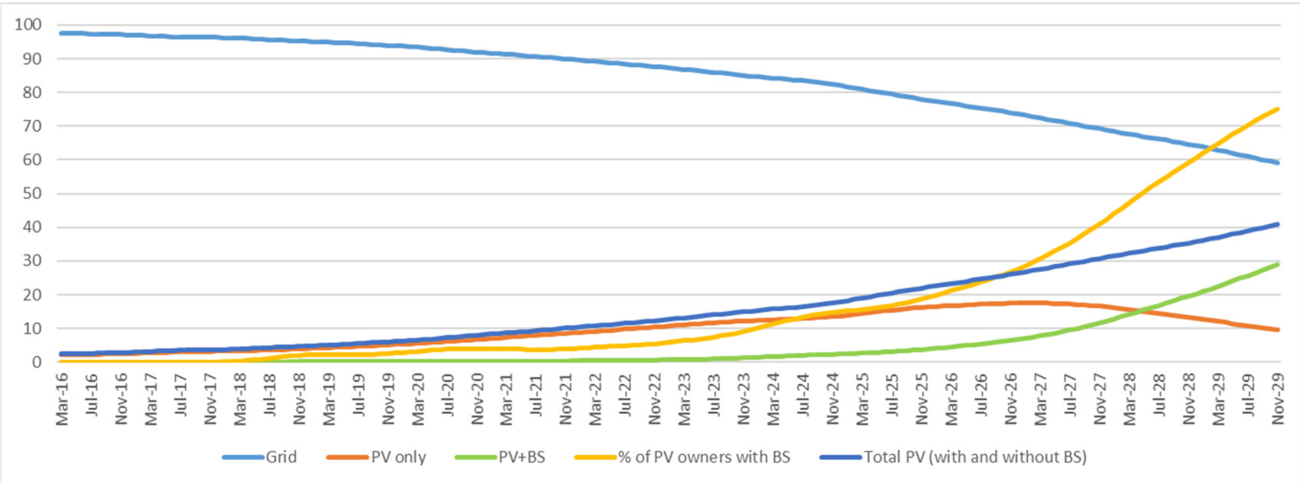

Figure 5. Simulation results in the base case scenario with the current 50% fiscal incentives.

7.2. Varying Fiscal Incentives

We simulate what would have been the PV and BS uptake under three hypothetical scenarios: S1—without fiscal incentives (no ITC); S2—with ITC equal to 25%; S3—with ITC equal to 75% (Figure 6).

In the absence of fiscal incentives (no ITC), there would have been very few PV installations almost up to the end of the third decade (max 4.9%), notwithstanding the cost decreases. With ITC equal to 25%, PV installations would have gained adoption in the third decade, but they would have reached a 9% acceptance only in 2030, which is almost equivalent to the current rooftop solar PV uptake. The implication is that the current generous 50% ITC has been crucial in convincing homeowners to install PV. If the fiscal incentive had been 75% starting from 2016, our model predicts that the PV uptake would have been much faster, reaching 40% in 2021 and 94% in 2030. This indicates that homeowners are quite sensitive to the economic aspects and that the fiscal incentives are the driving force for PV uptake in Italy.

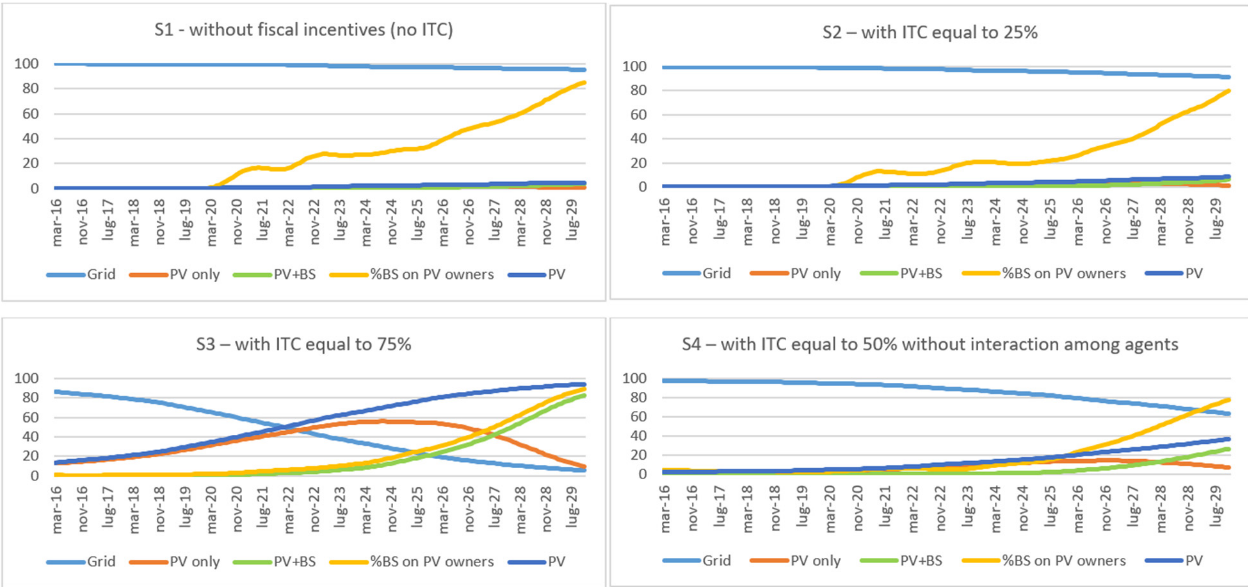

Figure 6. Simulation results.

7.3. The Importance of Social Interaction

An interesting exercise that can be performed with ABMs is to estimate the impact of social interaction on PV and PV+BS uptake. In the base case scenario, we have muted the communication among agents (neither the promoters nor the adopters send messages to the potential adopters) so that homeowners make decisions based only on their preferences and the cost evolution of PV and BS. The results are illustrated in Figure 6. Compared to the base case scenario, the final PV uptake in 2030 would be 4.5% lower, 2.3% due to fewer PV-only installations, and 2.2% due to lower uptake of PV + BS.

7.4. Sensitivity Analysis

Our model's major source of uncertainty is the future evolution of PV and BS prices. Consequently, we performed a sensitivity analysis to test how the distribution between grid-only, PV, and PV + BS would change if our assumed PV and BS trends are 10% and 5% lower or 5% and 10% higher than the one we have assumed (Figure 7). We accounted for these changes by multiplying our assumed value by a price adjustment factor equal to 0.9, 0.95, 1.05, and 1.11, respectively.

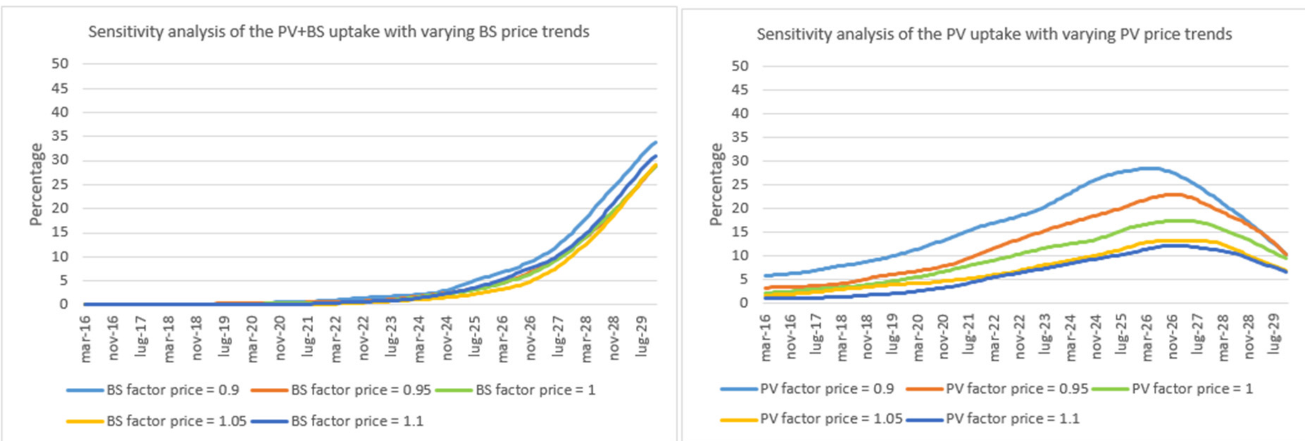

Figure 7. *Cont.*

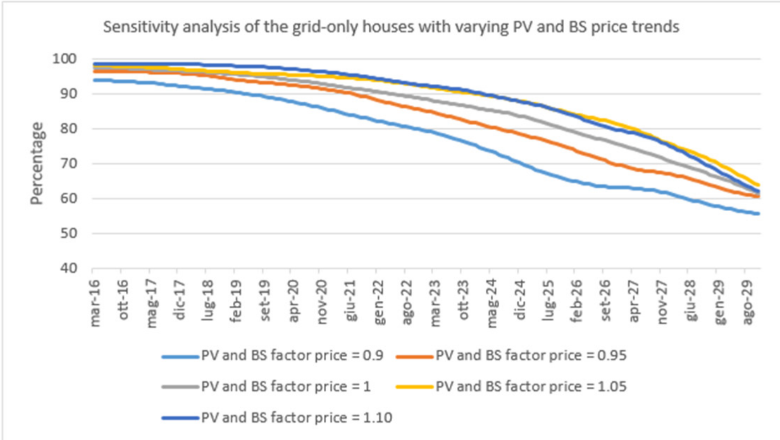

Figure 7. Sensitivity analysis.

The various adjustment factors lead to quite different trends, with differences ranging from 5 to 10% for BS, 10 to 15% for PV adoption, and 15 to 20% for grid-only houses. Interestingly, the main differences are in the central years of the decade, but the end result is much less spread out. Our model predicts that PV + BS adoption will occur in 29–34% of the households, 7–10% of the households will have PV only and 56–62% will draw their electricity from the grid only.

Finally, we tested the impact of simultaneous variation of PV and BS prices. We report in Figure 8 only the variations in the 2030 percentages. The ABM predicts that PV installations might vary from 3.3 to 9.1, with an average of 5.5%. PV + BS installations vary from 21.4 to 58.6, with an average of 37.9%. Grid-only households range from 34.5% to 72.3%.

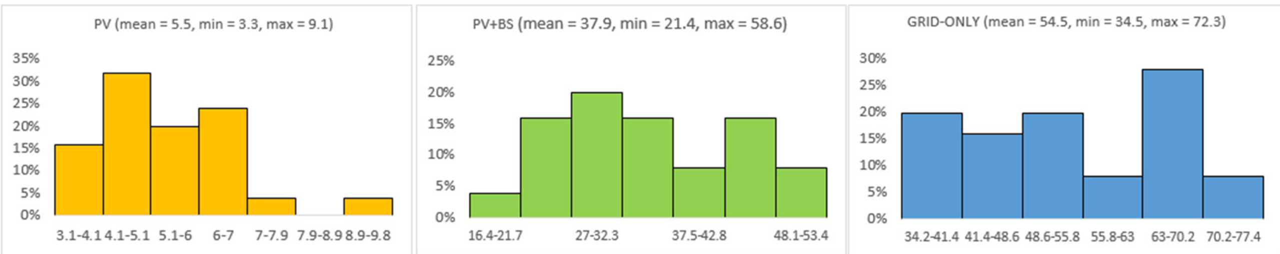

Figure 8. The impact of simultaneous variation of PV and BS prices on 2030 percentages.

7.5. Stochasticity

The results so far reported are estimated using a fixed seed; that is, the model random number generator is initialized with the same value for each model run, thus making the model runs reproducible. Alternatively, the AnyLogic software allows us to account for stochasticity by using a random seed value for the pseudorandom number generator. The model we developed contains some inherent stochasticity associated with three components of the model: (a) the random choice framework of the utility function, (b) the random association of the socioeconomic characteristics in the population, and (c) the random contact rate between the agents when sending the message to buy PV and BS. Running the model with a random seed and 10 replications, in the base case scenario, with the current fiscal incentives equal to 50% of the installation costs, leads to the results illustrated in Figure 9.

While accounting for stochasticity, the 2030 value for PV installations is estimated to vary between 4.3 and 6.5%, with a mean value of 5.2%. PV + BS installations are estimated to vary between 34.3 and 38.1%, with a mean value of 35.8%. The houses relying only on the grid are estimated to range from 54.5% to 58.5%, with a mean value equal to 56.9%. The distributions within the estimated intervals are reported in Figure 9.

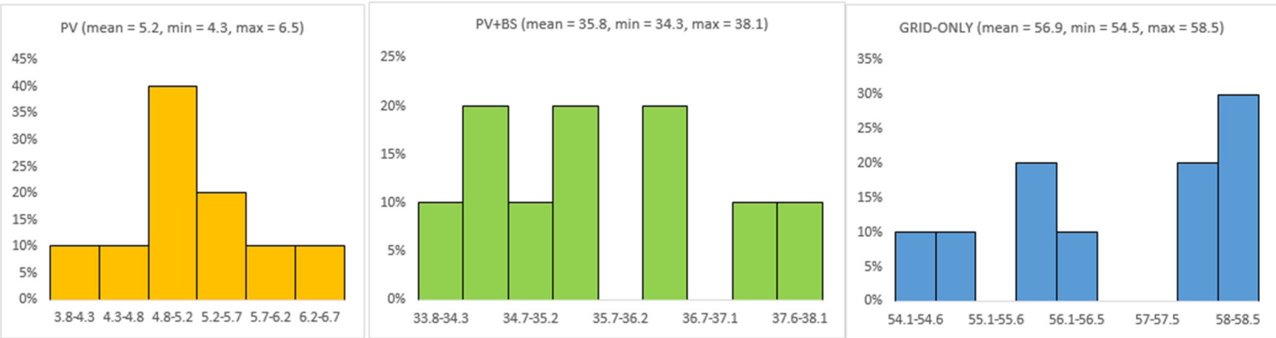

Figure 9. Results of the stochastic model in the base case scenario.

Overall, although there is a large level of uncertainty connected with our model predictions due to the various sources we have identified (i.e., PV and BS price trends, social interaction, and stochastic factors), the results presented suggest two conclusions. First, the prospects for PV and BS uptake in Italy within the coming decade are quite good, provided the current ITC policy is financially sustainable for the State budget. Second, ITC is an important determinant of PV and BS adoption and largely determines the overall uptake. An interesting analysis to carry out based on our predictions for future research would be to evaluate the current ITC policy's social efficiency and its optimal level.

8. Conclusions and Policy Implications

In this paper, we integrated two research methodologies, DCM and ABM, to simulate PV and BS uptake in Italy. We estimate that, given the preference structure of homeowners, the continuing decline in costs, and the social interaction, PV and BS uptake is likely to increase progressively to up to 40–45% in 2030 with the existing ITC policy. Increasing the ITC to 75% would further accelerate the pace of uptake but with a relevant financial burden for the State budget, mostly likely politically unacceptable since its cost would result in higher energy prices for the consumers. The recently enacted 110% ITC (termed Superbonus) might not make a large difference because it applied only in case of major energy efficiency improvements. On the other hand, we have estimated that a reduction of the ITC would slow down considerably the uptake. Consequently, assuring financial policy stability is likely the best choice for the Italian regulator.

Important policy improvements are, however, possible in many regards. Firstly, PV and BS installations should make progress not only among homeowners but also for other types of dwellings (condos). The establishment of energy communities is one of the tools that the Italian legislator is trying to facilitate from a legal, administrative, and financial perspective. It is estimated that tenants occupy about 2 million buildings in Italy. Incentivizing rooftop solar PV installments in these buildings could hence greatly help increase the share of renewable energy. Our survey has provided empirical evidence that the people living in shared dwellings share a similar interest in PV and BS adoption if the financial propositions are favorable. Moreover, since PV marginal costs decrease with size [46], it is quite likely that energy communities could be an interesting proposition.

Secondly, a number of non-financial measures can facilitate PV and BS uptake. Although our survey has not considered environmental motivation, several papers have shown that environmental awareness is one of the drivers for becoming a prosumer [47]. Enhancing climate change awareness could then contribute to PV and BS diffusion. Another well-documented barrier is the uncertainty and mistrust that these new energy systems work without too many complications and inconveniences [47]. Spreading trustworthy information, providing technical support, clarifying the financial aspects, and supporting credit opportunities are crucial. As argued by [29] on these aspects, there is a role both for the business and public sectors (municipal energy advisers or the Italian Energy Agency ARERA). Another important non-financial barrier is the complex administrative system. In

Italy, promoters are responsible for carrying out all the necessary paperwork. However, this adds complexity and costs to the process. A relevant issue is also the installation of PV panels in the historical centers and the need to balance conflicting goals: preserve aesthetics and cultural heritage and promote energy innovation and efficiency.

Thirdly, it is quite likely that the uptake of EVs will enhance the interest in self-energy production. The increase in household energy consumption decreases the PV payback period ([2,11]) and makes EVs definitely more sustainable than conventional ICE cars. Recent data show that in Germany, 24% of EV drivers self-produce their electricity (DIHK, 2020). As EV uptake in Italy makes progress, so will PV and BS demand.

Obviously, our model has several limitations. A first shortcoming is an admittedly small size and weak representativeness of our sample. As discussed above, there is a trade-off between survey complexity and the number of interviews that we could collect with available research funds at our disposal. Nonetheless, we believe that our sample has some merits and could provide the basis for understanding future trends in PV and BS adoption. Because of this limitation, the results of this paper should be interpreted as exploratory, while a full-scale randomized survey at the national level is planned for future research. Moreover, it should be recognized that the decision to install a PV and a BS is very complex. Several factors play a role, including technical, economic, attitudinal, informational, and aesthetical ones. No study can claim that all these factors have been fully considered, and our study is no exception. Although we tried to ground our model on empirical data and model how agents make decisions, we took into account only a limited number of determinants. As explained above, our model is based on actual and stated choices, and it is left to the respondents to value whether, in the different scenarios, the investment is financially sound or not. Hence, in contrast with previous studies ([11,28,48]), we made no explicit use of financial metrics such as FiT, interest on a loan, payback period, or net present value as attributes of the scenarios. The advantage of our approach is that it mimics real-world choices characterized by uncertainty about the future financial performance of the investment and that it incorporates non-monetary factors in a theoretically coherent manner. The disadvantage is that we do not model how these financial metrics play out in the adoption decision. However, based on previous studies concerning Italy ([11,49]), it appears that the economic and environmental perspectives of adopting solar energy are, in most instances, quite promising, in particular when coupled with driving an EV ([6,50]). Moreover, our model does not account for roof characteristics, geographical location, and solar radiation, nor does it consider household composition and energy consumption. The need to keep the interview as brief as possible to prevent respondents' fatigue induced us to not investigate these aspects, which might play a relevant role in homeowner decisions. Our model does not consider the energy options available for multi-household buildings because they are still in the initial phase in the Italian context. As discussed by [4], energy communities permit all electricity customers, whether homeowners with a roof or tenants without a roof, to participate financially in an energy agreement, sharing its costs and benefits. A further limitation of our study is that we did not explore how the decision process to install PV and BS takes place within the household [51] and who are the main decision-makers. The difficulty, however, is not simply exploring the family dynamics but incorporating them coherently in the ABM.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en16010557/s1. Figure S1: Evolution of residential PV price in Italy; Figure S2: Percentage of BEVs in the Italian car fleet in the period 2016-2030; Figure S3: Evolution of residential BS price in Italy; Table S1: Descriptive statistics of the sample; Table S2: Attributes' levels; Table S3: Assumptions on socio-economic characteristics of the Italian population; Table S4: Assumptions on social interaction; Table S5: Utility coefficients of PV and non-PV homeowners. References [52–65] are cited in the supplementary material.

Author Contributions: Conceptualization: R.D., M.S., A.M.P.; methodology: R.D., M.S., A.M.P.; software: R.D., M.S.; validation: R.D., M.S.; formal analysis: R.D., M.S., A.M.P., N.B.; investigation: R.D., M.S., A.M.P., N.B.; data curation: R.D., M.S., A.M.P., N.B.; writing—original draft preparation: R.D., M.S.; writing—review and editing: R.D., M.S., A.M.P., N.B. All authors have read and agreed to the published version of the manuscript.

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