Technological Forecasting & Social Change 77 (2010) 279–296

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Cross-country diffusion of photovoltaic systems: Modelling choices and forecasts for national adoption patterns

Mariangela Guidolin [a], Cinzia Mortarino [b,*]

[a] Department of Business Economics and Management, University of Venezia, Ca' Foscari, Venezia, Italy
[b] Department of Statistical Sciences, University of Padova, Padova, Italy

A R T I C L E I N F O

Article history:
Received 12 January 2009
Received in revised form 29 June 2009
Accepted 20 July 2009

Keywords:
Generalized Bass Model
Innovation diffusion
Nonlinear regression models
Photovoltaic energy

A B S T R A C T

In this paper we propose an innovation diffusion framework based on well-known Bass models to analyze and forecast national adoption patterns of photovoltaic installed capacity. This allows for interesting comparisons among several countries and in many cases highlights the positive effect of incentive policies in stimulating the diffusion of such a technology. In this sense, the Generalized Bass Model proves to be essential for modelling and forecasting. On this basis, we observe important differences in the investments made by countries in the PV sector and we are able to identify whether and when these investments obtained the expected results. In particular, from our analysis it turns out that in some cases incentive measures have been certainly effective in facilitating adoption, while in some others these have not been able to produce real feed-back. Moreover, our cross-country approach is able to forecast different stages in PV evolution: whereas some countries have already entered the mature stage of diffusion, others have just begun. This result may suggest various considerations about the competitive advantage of those countries that invested in alternative energy provisions. In spite of a very diversified scenario in terms of historical patterns of diffusion, we may report, as a general result, the fragile role of innovators for this special market and the dominance of imitative behaviour in adoptions.

1. Introduction

For a long time, fossil fuels have represented and still represent the dominant source of energy in the world, but today studies and forecasts on impending oil and natural gas depletion, a worsening climate change situation due to CO_2 emissions and the need for more security in energy provision are inducing countries to put energy issues on top of their agendas and to look for alternatives to fossil fuels.

Among all the viable solutions, photovoltaic solar energy (PV) is considered one of the most attractive, because it directly converts sunlight into electricity, without production and transportation costs. Moreover, apart from its use in grid-connected systems, PV power systems may be the appropriate solution for off-grid installations, providing electricity to households not connected to the electricity network. This aspect makes the technology even more interesting from the perspective of meeting the energy needs of millions of poor people who currently lack electricity. However, the technology also presents disadvantages, especially those related to initial plant costs. The adoption of a PV system involves a complex decision process, requiring a degree of information that the average consumer is unlikely to have: as observed by Jager [1], in early stages people will have far from complete information and will experience negative short-term outcomes in terms of financial investment and administrative procedures, while positive outcomes associated with the purchase decision are delayed and more abstract. These are some of the aspects that have, for a long time, prevented a wide adoption of PV systems in several countries.

* Corresponding author. Department of Statistical Sciences, via C. Battisti 241, 35121 Padova, Italy. Tel.: +39 049 827 4184; fax: +39 049 827 4170.
E-mail address: mortarino@stat.unipd.it (C. Mortarino).

0040-1625/$ – see front matter © 2009 Elsevier Inc. All rights reserved.
doi:10.1016/j.techfore.2009.07.003

Notable exceptions are represented by Japan and Germany that have been able to stimulate a successful adoption path and create a strong domestic market for photovoltaic cells since the early 1990s, when global warming issues led them to consider solar energy as a suitable substitute of fossil fuels for electricity needs. Both countries in the early 1990s were minor players in the renewable energy industry but within 10 years they became sector leaders, combining public concerns of energy supply security and environmental issues with effective policy measures and laws.

The successful stories of Japan and Germany seem to suggest that the PV industry would not have a chance without a strong governmental commitment. This is a crucial point to investigate since the PV industry is currently experiencing unprecedented growth in many countries around the world: though grid-connected solar systems still provide less than 1% of the world's electricity, cumulative installed PV power has dramatically increased in the last year, exceeding 5000 MW. To illustrate the evolution of this global process, for the first time, in 2006 more than half of world's purified polysilicon — the raw material also used for semiconductor chips — was employed for producing PV systems.

While several analyses presented at the Solar Power conference held in San José (California) in 2006, suggest that PV generated electricity will have costs similar to conventional sources of energy, when production reaches over 10,000 MW the on-going shortage of polysilicon would ultimately lead to price increases and to a stagnation of the solar cell market, as predicted by the Head of Japan's Sharp Solar, Takashi Tomita. Indeed, the limited availability of polysilicon is considered the major constraint for PV industry growth. To overcome this problem many new techniques are being explored in order to increase the efficiency of current technology, while a new generation of solar cells is expected to arise. In particular, technologies with a reduced demand of silicon, like concentrated solar plants, or technologies not relying on silicon, like the so-called thin-film solar cells, that are based on amorphous silicon and other low-cost materials, appear as a possible, though not yet readily available, solution for meeting future demand of PV power.

Though a global analysis of the PV sector would be certainly useful, we find a country-level study more interesting since many countries have recently begun to invest much effort to support the PV industrial sector and, in parallel, have introduced incentive measures to stimulate the domestic demand of PV systems as electricity generators, with different strategies and different results. We believe that a comparison among countries would be useful to describe the global energy scenario, to highlight and explain historical growth patterns and to provide insights on the future evolution of the PV sector. Consequently, our analysis is aimed at explaining the past and trying to offer some perspectives on the future. To this end, we choose to ground our analysis on the historical data of PV installed power and to model these with well-known diffusion models, namely the Bass Model (BM) [2] and the Generalized Bass Model (GBM) [3], in which the evolution of a new product or technology is mainly decided by consumers. In fact, the success of a new technology in a social system (or a market) ultimately depends on consumers accepting it. Indeed, the theoretical foundation of the Bass Model (which identifies consumer adoption as the main driver of diffusion) is one of the major elements for preferring it to other possible *S*-shaped models: fitting the data is not enough if a reasonable interpretation is lacking.

In modelling terms, whereas the Bass Model fits well the observed process in a few cases, in others the GBM proves to be essential for statistical identification, accounting for the effect on diffusion of external actions, like policies and incentives, which suggests that consumer adoption had to be stimulated through external interventions. In other words, if a particular emphasis is posed on end-users as the major driver of diffusion, the institutional element (certainly in the case of PV systems), in the form of incentives and policy measures, seems to have been crucial. The main effect of these institutional interventions has been to facilitate final decisions, offering a credible guarantee towards high levels of investment and personal commitment. While the change induced by these measures has a tangible effect, which is captured with the GBM, we do not consider short-term price dynamics because they do not seem a determining factor for final adoptions.

Support mechanisms that directly stimulated the growth of photovoltaics include feed-in-tariffs, direct capital subsidies and consumer tax deductions. Different countries have employed such tools in different ways to foster internal renewable energy markets. In particular, feed-in-tariffs are the main incentive used for promoting PV adoption. The term feed-in-tariff indicates a monetary reward for producing PV electricity, at a rate per kWh somewhat higher than the retail electricity rate being paid by the customer [4]. Countries not employing some forms of feed-in-tariffs are currently the minority.

The paper is structured as follows. Section 2 presents the basic diffusion models employed in this paper, the Bass Model and the Generalized Bass Model, highlighting some relevant aspects and properties of each. Section 3 is dedicated to discuss some aspects of statistical implementation and the issue of data availability. Section 4 will test the performance of the proposed models for the diffusion process of several countries providing insights on the effectiveness of policy measures and on the country-level evolution of PV systems. Section 5 is devoted to conclusions.

2. Innovation diffusion models

2.1. The Bass Model

The Bass Model, BM, proposed by Bass [2], describes the diffusion of an innovation, depicting its characterizing phases of launch, growth, maturity and decline. Its purpose is to forecast the development over time of a new product's growth, as a result of the purchase decisions of a given set of adopters. These purchase decisions are assumed to be influenced by two sources of information: an external one, like mass media and advertising, and an internal one, namely social interactions and word-of-mouth. These are competing sources of information, whose effect creates two distinct groups of adopters. One group is influenced only by the external source, and we call it innovators; the other is influenced only by the internal one, and these are the imitators.

The formal representation of the BM is a first-order differential equation:

$$z'(t) = p(m - z(t)) + q\frac{z(t)}{m}(m - z(t)). \tag{1}$$

In Eq. (1) the adoption rate, $z'(t)$, is proportional to the residual market, $(m-z(t))$, where m is the *market potential* and $z(t)$ represents the cumulative number of adoptions at time t. Notice that the market potential m depicts the maximum number of achievable adoptions within the diffusion process and its value is assumed constant. More flexible structures with a dynamic market potential, $m(t)$, were examined in the past (see, for instance, Mahajan and Peterson [5]). Recently, some special structures for $m(t)$ have been described by Guseo and Guidolin [6]. For the application examined in this paper, however, we will only consider models with a fixed market potential, m, for reasons that will be clarified in subsection 3.2.

The residual market is modulated by two parameters, p and q. Parameter p represents the effect of the external influence and thus refers to an *innovative* behaviour, while parameter q is the so-called *coefficient of imitation*, whose influence is modulated by the ratio $z(t)/m$. Average values for p and q are 0.03 and 0.38, respectively, as reported by Sultan et al. [7].

If we denote $y(t)=z(t)/m$, we can rewrite the Bass Model as follows:

$$y'(t) = (p + qy(t))(1 - y(t)). \tag{2}$$

The closed-form solution of the Bass Model, under initial condition $y(0)=0$, is a special cumulative distribution:

$$y(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}, \quad t > 0, \quad p, q > 0. \tag{3}$$

The *proportion of adoptions* $y(t)$, provided by Eq. (3), describes the dynamics of the diffusion process in terms of adoption parameters, p and q. The absolute scale representation, i.e. the number of adoptions, $z(t)$, is obtained multiplying Eq. (3) by the market potential m:

$$z(t) = m\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}, \quad t > 0, \; p, q > 0. \tag{4}$$

Eq.(4) depends on the initial condition $z(0)=0$. However, if information and data about the very early stages of a diffusion process are not available, the model may be modified for overcoming this shortage as proposed by Guseo [8]:

$$z(t) = m\frac{1 - e^{-(p+q)(t+d)}}{1 + \frac{q}{p}e^{-(p+q)(t+d)}}, \quad t + d \geq 0, \quad d, p, q > 0, \tag{5}$$

where d is an unknown translation parameter to be estimated such that $z(-d)=0$.

2.2. The Generalized Bass Model

Conceived for taking into account the effect of marketing mix strategies, the Generalized Bass Model, GBM, described by Bass et al. [3], enlarges the basic Bass Model by multiplying its structure by a very general intervention function $x(t)=x(t;\theta)$, $\theta \in \mathbb{R}^k$, assumed to be essentially nonnegative and integrable.

The GBM presents a quite simplified structure

$$z'(t) = \left(p + q\frac{z(t)}{m}\right)(m - z(t))x(t) \tag{6}$$

and its closed-form solution is, under the initial condition $z(0)=0$,

$$z(t) = m\frac{1 - e^{-(p+q)\int_0^t x(\tau)\mathrm{d}\tau}}{1 + \frac{q}{p}e^{-(p+q)\int_0^t x(\tau)\mathrm{d}\tau}}, \quad t > 0, \quad p, q > 0. \tag{7}$$

Notice that the GBM reduces to the Bass Model, when $x(t)=1$, i.e., when there are no external interventions. Interestingly, what was clarified by Bass et al. [3] is that the model internal parameters m, p, and q are not modified by these external actions: function $x(t)$ acts on the natural shape of diffusion, modifying its temporal structure and not the value of its internal parameters; as a consequence, the important effect of $x(t)$ is to anticipate or delay adoptions, but not to increase or decrease them. In other words, this function may represent all those strategies applied to control the timing of a diffusion process, but not its size.

Though $x(t)$ was originally conceived to represent marketing mix variables, its structure is so general that it can take various forms in order to depict external actions other than marketing strategies. For example, it has proven to be suitable for describing interventions that may interact with diffusion, like political, environmental and technological upheavals (see, for instance, Guseo and Dalla Valle [9] and Guseo et al. [10]).

A drastic perturbation, whose effect is strong and time decaying, may be modelled through an exponential function like

$$x(t) = 1 + ce^{b(t-a)}I_{t\geq a}, \tag{8}$$

where parameter c represents the depth and sign of intervention, b describes the persistence of the induced effect and is negative if the memory of this intervention is decaying to the stationary position (*mean reverting*) and a denotes the starting times of intervention, so that $(t-a)$ must be positive.

A more stable perturbation acting on diffusion for a relatively long period, like institutional measures and policies, may be described by a rectangular function giving rise to intervention function

$$x(t) = 1 + cI_{t\geq a}I_{t\leq b}. \tag{9}$$

Parameter c describes here the perturbation intensity and may be either positive or negative, while parameters a and b define the temporal interval in which the shock occurs.

Of course, the actual function $x(t)$ could be designed as a combination of one or many shocks as modelled in (8) and (9). The possibility of defining a flexible intervention function has highlighted a larger perspective on the exploitation of the Generalized Bass Model, which may be applied as an efficient diagnostic for detecting all kinds of external actions affecting a diffusion process. In particular, it proves its strategic importance for country-level modelling, where innovation dynamics are significantly influenced by institutional aspects and policies along with cultural and economic factors, whose effect has to be tested and accounted in forecasting.

3. Statistical modelling

3.1. Data

We build our analysis on the data provided in PVPS [11] by the International Energy Agency, IEA, for the period 1992–2006. These data report the yearly cumulative installed PV power (in MW) for those countries participating in the IEA Photovoltaic Power Systems Programme (IEA PVPS), whose main purpose is to enhance the international collaboration efforts that accelerate the development and deployment of photovoltaic solar energy as a significant and sustainable energy option. The data offered by the IEA are mostly collected from national survey reports and information summaries. In order to avoid loss of information, we also used data from BP [12] which, for the period 1995–2005, report cumulative installed capacity data without roundings (the source of the latter data is again IEA, so both sources are consistent). Observe that these series do not distinguish between in-grid and off-grid power. Separate series exist only for an even shorter period, so we decided to use aggregate data (specific comments about this choice will be given in the analysis of data pertaining to the small group of countries where off-grid capacity gave a relevant contribution).

In particular, we chose to focus on the following 11 countries: Australia (AUS), Austria (AUT), Canada (CAN), France (FRA), Germany (GER), Italy (ITA), Japan (JPN), Spain (ESP), The Netherlands (NLD), United Kingdom (GBR), United States of America (U.S.A.).

The brevity of these data series may introduce difficulties and uncertainties in forecasting: however, the limited availability of information is essentially due to the recent development of PV markets, that have been exhibiting a substantially growing trend only since the early 1990s. Though a limited number of observations may represent an obstacle, we argue that the current growth of the PV sector calls for a specific effort aimed at describing and forecasting market evolution.

3.2. Models used

Consistent with most of the literature on the statistical implementation of the Bass Model (for a review see for instance Meade and Islam [13]), in this work we will use a nonlinear least squares, NLS, approach (e.g. Levenberg–Marquardt, see Seber an Wild [14]) to estimate the model parameters: in doing so we may consider the structure of a nonlinear regression model, resulting from the sum of two components:

$$w(t) = f(\beta, t) + \varepsilon(t), \tag{10}$$

where $w(t)$ is the observed response, $f(\beta, t)$ is the deterministic component, depending on parameter $\beta \in \mathbb{R}^k$ and time t. The second component, $\varepsilon(t)$, is defined as a stochastic process representing the residual term.

In particular, in this context, $f(\beta, t)$ will be specified according to a BM or a GBM. For example, the BM regressive model is

$$w(t) = m\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}} + \varepsilon(t), \tag{11}$$

where $w(t)$ are the observed data, namely the cumulative number of adoptions or sales at time t. The unknown constants m, p and q are the parameters to be estimated.

In general, $\varepsilon(t)$ is a white noise process, so that its mean is zero, $M(\varepsilon(t))$, with constant variance, $\text{Var}(\varepsilon(t)) = \sigma^2$ and different error terms are uncorrelated, $\text{Cov}(\varepsilon(t), \varepsilon(t')) = 0$, $t \neq t'$. Nevertheless, the concrete application of the NLS procedure to several cases has shown that residuals do not always support the hypothesis of a white noise process. A possible answer to this aspect may be given by ARMAX frameworks; see for instance Box and Jenkins [15] and, among others Guseo and Dalla Valle [9]. This approach will not be followed here since we are going to use the short time series we dispose of just to describe the main features of the diffusion process without trying to guess refined forecasts.

As mentioned in subsection 2.1, models with dynamic potential structure $m(t)$ will not be considered here since we think that a constant potential is more suitable to the available technology in the PV market in a short time period, as the one covered from IEA data described in the previous subsection. Moreover, the problem of estimate stability due to a small number of observations would be even more serious in the case of a complex model with a dynamic market potential.

3.3. Model adequacy

Since the standard R^2 measure for this kind of data usually gives very high values whichever S-shaped model is fitted, we chose to proceed as follows (see, for instance, Guseo and Guidolin [6] or Guseo et al. [10]). First the standard BM (11) was fitted to a dataset and the corresponding determination index, R^2_{BM} was calculated. Afterwards, in order to test whether a GBM, with $x(t)$ specified through shocks of the types ((8) and/or (9), provided a significant gain over the BM, the squared multiple partial correlation coefficient

$$\tilde{R}^2 = \frac{R^2_{\mathrm{GBM}} - R^2_{\mathrm{BM}}}{1 - R^2_{\mathrm{BM}}} \tag{12}$$

was calculated (here R^2_{GBM} denotes the determination index of the GBM to be compared to the BM). Measure (12) should be interpreted as the reduction of residual deviance (as a proportion of the residual deviance of the BM) achieved through the fitting of the "larger" GBM (of course, the BM is nested in any GBM). Measure (12) leads, as a consequence, to a stricter criterion to judge the adequacy of a model. A possible test to verify the significance of the s parameters of the GBM that are not included in the BM may be given by

$$F = \frac{\tilde{R}^2(N-k)}{\left(1-\tilde{R}^2\right)s}, \tag{13}$$

where N denotes the number of observations used to fit the model and k is the number of parameters included in the GBM. Under the null hypothesis of equivalence between the BM and the GBM, (13) is distributed as a Snedecor's F with $(s, N-k)$ degrees of freedom, if $\varepsilon(t)$ is normal i.i.d. Nevertheless, measure (12) can be used as an approximate criterion to compare the BM with a GBM. A similar comparison could be used for any pair of nested models in order to choose the most adequate model for the dataset.

4. Model selection for the 11 countries

In this section we present the application of the Bass models to PV diffusion in the 11 selected countries. For each of them we provide parameter estimates and comparisons among different modelling choices, highlighting the relative improvement obtained through more elaborated models (as explained in subsection 3.3). Though each country has its own history and characteristics, we chose to create some clusters according to the structure of observed data and the consequent models employed.

4.1. Japan

We will start our analysis with the Japan data. As mentioned in subsection 3.3, we begin with the BM, whose fitting gives a $R^2_{\mathrm{BM}} = 0.999797$. This optimal result is, however, improved by noticing that the first observation, $z_{1992} = z(1)$ equals 19. This may suggest that the diffusion process began before 1992 so that a model with a parametric origin (5) may fit better. The new model has a $R^2_{(5)} = 0.999864$ and the F statistics to test whether the estimate of parameter d is significantly different from zero equals 5.419. In order to see whether this model may be further improved, since the pattern of the observed data shows a slowdown around year 2001, as evidenced in Fig. 1, in addition to the parametric origin, both a GBM with an exponential shock (8) and a GBM

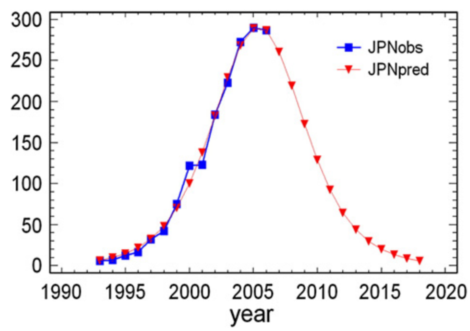

Fig. 1. Japan: installed power, fitted model and forecasts (non-cumulative data).

with a rectangular shock (9) were fitted to the data. None of them led, however, to a significant gain over the simpler model (5), as one may see in Table 1 where a summary of all models fitted is proposed.

The estimates of parameters in model (5) for the Japan data are presented in Table 2. Observe that confidence intervals for the market potential, m, for p and q are quite narrow even if the number of observations, as underlined in Section 1, is small. It is important to remember that confidence intervals for nonlinear models may be really misleading due to significant curvature in the model. For this reason, we will only consider their values as an indication of the stability of the corresponding estimate.

Notice that cumulative installed capacity in 2006, z_{2006}, was 1708 MW which is not so far from m estimate, representing a forecast of cumulative installed capacity at the end of the diffusion process; p and q estimates suggest that the diffusion process was characterized to a very limited extent by the presence of innovators and mainly driven by imitators; finally, $\hat{d} \simeq 5.46$ suggests that the diffusion of photovoltaic systems began in Japan around 1986/1987. This could be easily explained by the Japanese Government's policy: R&D expenditure in PV rose dramatically starting in 1979/1980 [16] in order both to face the oil crisis and to create new competitive industries. Among other energy sources, PV emerged as the most promising one because of previous experience of Japanese industries in PV cells used for small devices like calculators and watches. This focused investment into PV occurring in the early 80s is consistent with our results that place the origin of diffusion a few years after. Later, in 1992, the "New Sunshine Program" was launched to promote PV systems, followed in 1994 by the "70.000 Roofs" program, whose major purpose was to create market awareness and increase production through economies of scale and technology improvements. This program is commonly perceived as the most effective initiative for residential PV dissemination. The fact that a GBM does not significantly improve the fitting over the simpler BM contradicts this belief: PV diffusion in Japan has evolved thanks to the strong policies implemented before the beginning of the life cycle and without the need for further external interventions. Today, the market for residential PV systems in Japan is largely self-supported and driven by market mechanisms. If we try to use our model to predict future evolution of instantaneous adoptions, we see in Fig. 1 that a peak is clearly highlighted between 2005 and 2006, so that PV diffusion in Japan has already entered its declining phase.

4.2. United Kingdom and Germany

The BM for UK data gives a $R^2_{BM} = 0.999252$. Since the first observation, $z_{1992} = z(1)$ equals 0.2, there is no evidence that the diffusion process may have begun before 1992. A simple inspection of data, however, suggests that the process did not evolve in a quiet way, so that we may expect to improve our analysis with a GBM. From Table 3 we can see that a GBM with an exponential

Table 1
Japan: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))
BM	0.999797	12				
(5)	0.999864	11	0.330049	5.419118		
GBM (5) + (9)	0.999916	8	0.586207	2.833333	0.382353	1.650794
GBM (5) + (8)	0.999878	8	0.399015	1.327869	0.102941	0.306010

Table 2
Japan: parameter estimates for the model with a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	2777.690000	114.991000	2524.600000	3030.790000
p	0.000123	0.000355	−0.000658	0.000904
q	0.420644	0.007624	0.403864	0.437424
d	5.459080	6.975950	−9.894920	20.813100

Table 3
UK: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)
BM	0.999252	12		
GBM (8)	0.999861	9	0.814171	13.143885

Table 4
UK: parameter estimates for the GBM with an exponential shock.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	28.602400	85.964200	−165.863000	223.067000
p	0.003472	0.010425	−0.020112	0.027056
q	−0.002886	0.013730	−0.033945	0.028173
c	3.660260	0.968726	1.468850	5.851680
b	0.425249	0.080765	0.242547	0.607952
a	7.083130	0.323608	6.351080	7.815190

shock (8) performs much better than the BM. Parameter estimates are presented in Table 4. Since $z_{2006}=14$, our estimate for m suggests that the diffusion process reached its peak in 2006. Observe that confidence intervals for the shock parameters, a, b and c, are quite narrow. The estimates suggest a positive large shock ($\hat{c}>0$), arising around 1998 which has not yet run its course ($\hat{b}>0$). The positive shock to the diffusion process highlighted by our model is likely to be due to a moment of optimism for the British renewables community when the Labour Party came to power in 1997. The Non-Fossil Fuel Obligation-4 (NFFO-4) was quickly announced in 1997 and provided 1700 MW of new contracts to the renewables industry after a gap of 3 years. After that, at the end of 1998, the NFFO-5 Order was announced with a total of 261 projects contracted and a total capacity of 1177 MW [17]. In the following years similar policies were adopted and this may explain why the positive shock has not yet been exhausted.

The plot of true and fitted non-cumulative installed power is shown in Fig. 2. As we noticed for the Japan data, the peak of instantaneous adoptions is forecasted in 2007 and the trend for the next years is a consistent reduction. In this sense, we observe that measures introduced in UK like the NFFO-4 are generally referred to renewables and not specifically to PV systems. For example, incentive schemes like feed-in tariffs for PV have not been implemented in the UK. The lack of focused policies for PV development appears coherent with the results of our model, where the adoption process seems to have reached a mature stage because the market niche is very limited.

Although Germany has a much larger installed photovoltaic capacity, its evolution in time follows a profile very similar to that of the UK. From Table 5 we can see that a GBM with an exponential shock (8) performs much better than the BM. Parameter estimates are presented in Table 6. Observe that confidence intervals for all parameters are really narrow. As noted for Japan, the process has a strongly imitative nature. The estimates suggest also a positive shock, arising around 2003 which has already run its course ($\hat{b}<0$).

In Germany, between 1990 and 1991 the government passed an energy law, the "Electricity Feed in Law," requiring all public utilities to buy electricity generated from renewables at a minimum guaranteed price, and then replaced the law with the "Renewable Energy Sources Act" (EEG) in 2000. The EEG ruled the favorable payment for electricity production to electricity utilities and was amended in 2004, with an important feed-in tariffs adjustment. In the relevant literature, it is a common opinion (see, e.g., Jager [1])

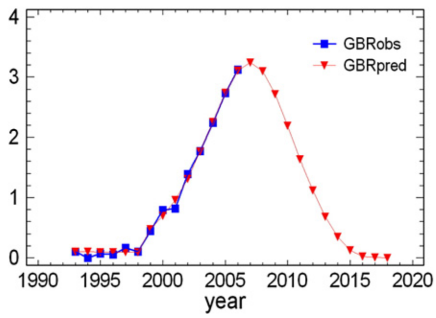

Fig. 2. UK: installed power, fitted model and forecasts (non-cumulative data).

Table 5
Germany: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)
BM	0.997087	12		
(5)	0.997093	11	0.002060	0.022704
GBM (8)	0.999951	9	0.983179	175.346939
GBM (9)	0.999846	9	0.947134	53.746753

Table 6
Germany: parameter estimates for the GBM with an exponential shock.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	6276.500000	984.967000	4048.340000	8504.650000
p	0.000202	0.000046	0.000099	0.000305
q	0.415379	0.018583	0.373341	0.457417
c	1.765300	0.164350	1.393510	2.137080
b	−0.448399	0.136758	−0.757769	−0.139029
a	11.942100	0.086185	11.747200	12.137100

that this adjustment is responsible for a significant acceleration of the diffusion process. However, our model suggests that this acceleration begun earlier, increasing installed power since 2003. The plot of true and fitted non-cumulative installed power is shown in Fig. 3. As we noticed both for the Japan and the UK data, the peak of instantaneous adoptions is forecasted in 2006 and the trend for the subsequent years would be a consistent reduction.

We shall observe that our data do not cover the Merkel government's period and therefore do not allow for an accounting of its “green policies” aimed at the industrial expansion of this sector. This growth, of course, we know by now did have significant consequences on the domestic market, but data will report it only later. We conjecture, however, that this may be a short-period effect on the internal market since the geographical position of this country exerts a limiting effect. For this reason, the peak should not be substantially delayed in time.

4.3. Australia, Canada and France

The three countries under study share many features with respect to the PV diffusion process (results about Australia are outlined in Tables 7, 8 and Fig. 4, results about Canada are described in Tables 9, 10 and Fig. 5, while Tables 11, 12 and Fig. 6 refer to France).

The data for these countries depict a diffusion process whose origin significantly precedes the time of the first available observation. For this reason in the three cases we have applied a model with parametric origin, which improves the fitting in a significant way. Moreover, the evolution was in all cases unsettled by a negative shock arising respectively in years 1998, 2001 and 1997. This may be interpreted as a temporary slackening of diffusion (after the starting phase when adopters might have been motivated by purely ecological grounds), which in some cases precedes the launch of incentive policies able to capture adopters mostly concerned by economic reasons as well.

Observe that for all these countries our models forecast a long period of continuous increase in PV capacity, with a peak not preceding 2016. In this situation, estimates for m should interpreted very carefully, since it is known that the BM and the GBM

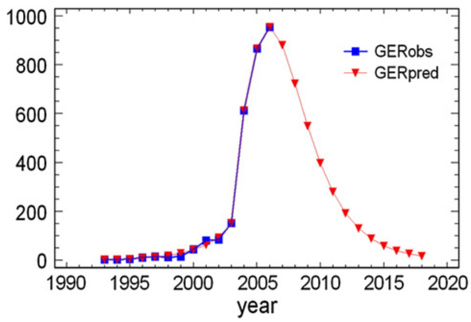

Fig. 3. Germany: installed power, fitted model and forecasts (non-cumulative data).

Table 7
Australia: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))
BM	0.986441	12				
(5)	0.999612	11	0.971384	373.404639		
GBM (5)+(8)	0.999911	8	0.993436	302.696629	0.7706186	8.958801
GBM (5)+(9)	0.999877	8	0.990929	218.471545	0.6829897	5.745257

Table 8
Australia: parameter estimates for the GBM with an exponential shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	1449.690000	2214.500000	−3656.970000	6556.350000
p	0.000165	0.000157	−0.000197	0.000528
q	0.168429	0.011983	0.140796	0.196062
d	9.771120	3.015490	2.817370	16.724900
c	−0.230408	0.907092	−2.322170	1.861360
b	−0.111230	0.575294	−1.437860	1.215400
a	6.970450	0.154218	6.614830	7.326080

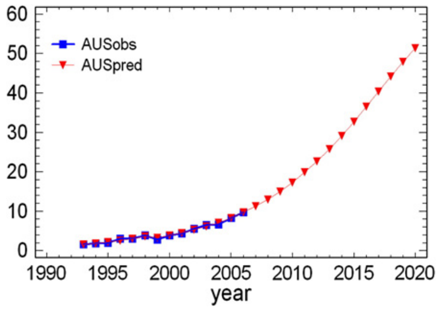

Fig. 4. Australia: installed power, fitted model and forecasts (non-cumulative data).

typically give reliable estimates of the size of market potential when a mature state in the diffusion process has been reached. Instead, we may take forecasted values as an indication of a young market, where steady growth is quite likely to occur. A common result also refers to the value of the proper diffusion parameters; from Tables 8, 10 and 12 we may notice the quite weak contribution of innovators and a more consistent role of imitators.

The markets for PV systems of Canada and Australia present quite similar patterns. Both countries are characterized by the presence of a large share of off-grid installations within the total amount of the installed PV base. By inspecting the diffusion curve of both Australia and Canada we may notice that after an initial growth the adoption process has undergone a temporary slowdown. The presence of slowdowns in diffusion processes has been observed by various authors (see for instance Moore [18] and Goldenberg et al. [19]), arguing that this may be related to the likely existence of a dual market for most innovations, namely early

Table 9
Canada: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))
BM	0.997111	12				
(5)	0.997779	11	0.231222	3.308420		
GBM (9)	0.998781	9	0.578055	4.109926		
GBM (5)+(8))	0.999782	8	0.924541	24.504587	0.901846	24.501529

Table 10
Canada: parameter estimates for the GBM with an exponential shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	310.357000	1117.260000	−2266.060000	2886.770000
p	0.000086	0.000253	−0.000498	0.000669
q	0.253169	0.030923	0.181861	0.324478
d	7.873970	9.046870	−12.988200	28.736100
c	−0.604857	0.104607	−0.846081	−0.363632
b	−0.253160	0.165755	−0.635393	0.129074
a	9.613090	0.212300	9.123530	10.102700

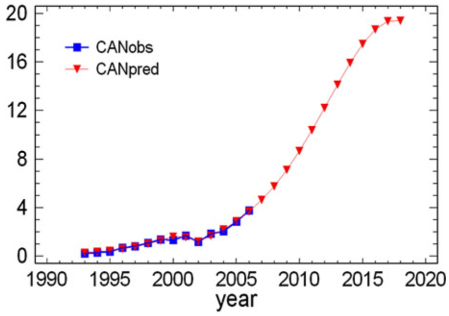

Fig. 5. Canada: installed power, fitted model and forecasts (non-cumulative data).

Table 11
France: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))
BM	0.993928	12				
(5)	0.997300	11	0.555336	13.737778		
GBM (5) + (9)	0.999742	8	0.957510	45.069767	0.904444	25.240310
GBM (5) + (8)	0.999115	8	0.854249	11.722034	0.672222	5.468927

adopters and majority. Though this phenomenon has not yet been explained in a formal way, we suppose that the idea of a dual market could reasonably apply to the PV markets of Australia and Canada, where an early installation base could be motivated by electricity needs of isolated users not connected to the grid, for which PV systems could be the only solution for the provision of electricity. Instead of introducing specialized modelling features, here we used the exponential shock of the GBM to describe this duality. In these cases, using the GBM has served a purpose other than modelling an external perturbation induced by incentive measures and has been useful to identify a behaviour in data seemingly related to internal market structures. Coherently with this view, we report that neither Australia nor Canada have supported PV adoption with strong incentive programs. Having overcome the slowdown phase, both countries are currently facing a steadily growing market, whose development is highly encouraged by an increased awareness of the majority of people about energy and climate change issues.

Table 12
France: parameter estimates for the GBM with a rectangular shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	868.768000	5565.870000	−11966.200000	13703.700000
p	0.000047	0.000098	−0.000180	0.000274
q	0.292069	0.093498	0.076463	0.507676
d	6.962800	19.778600	−38.646900	52.572500
c	−0.282780	0.099794	−0.512907	−0.052653
a	6.000420	0.621072	4.568220	7.432620
b	13.498200	0.205912	13.023400	13.973000

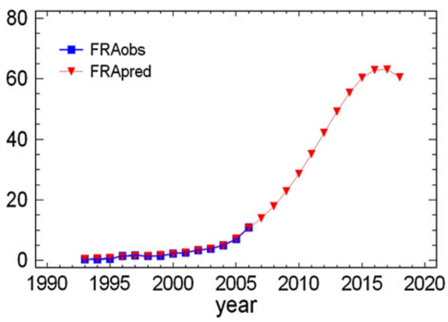

Fig. 6. France: installed power, fitted model and forecasts (non-cumulative data).

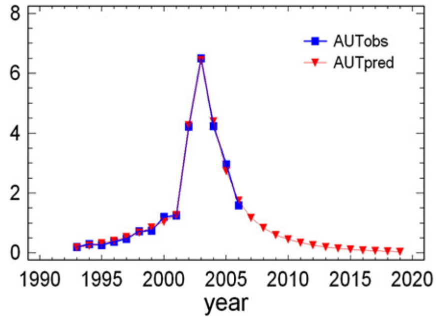

Fig. 7. Austria: installed power, fitted model and forecasts (non-cumulative data).

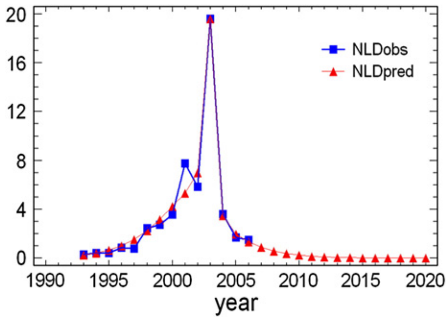

Fig. 8. The Netherlands: installed power, fitted model and forecasts (non-cumulative data).

A different choice was made in the case of France, whose data series has been modelled with a GBM with a rectangular shock: in fact, the fitted model for France identifies a negative perturbation depressing capacity from 1997 until 2004/2005. The end of this slowdown may be linked to the legislation of March 13th 2002, which firstly introduced incentives (observe that the waiting period necessary to get a connection may exceed 2 years). After 2002, the incentive system was periodically enhanced because results were not deemed sufficient, although our model's estimates point conversely to a true improvement. In 2006 the French government raised the income tax credit and the feed-in tariff was also re-evaluated. The actions taken in the last 2 years by the French government cannot be evaluated through our data but seem to support our model's conclusions about a growing trend for the next years.

4.4. Austria and The Netherlands

The two countries analyzed in this subsection share a very clear pattern in observed data (see Figs. 7 and 8). In both cases the installed PV capacity has already overtaken its peak in a distinct way. The models selected for both countries (see Tables 13 and 14 for Austria and Tables 15 and 16 for The Netherlands) highlight a positive large shock arising around 2001/2002 in Austria and between years 2002 and 2003 in The Netherlands. This rapid increase seems to have accelerated adoptions providing a fast saturation of the PV market so that the residual market immediately appears negligible. However, this result is partly attributable to the geographical location of these countries.

Notice that the market potential estimate is in both cases very stable, in accordance with the fact that the peak has been overcome. The model used for The Netherlands has been chosen by not only comparing nested models, but also giving particular relevance to stability of shock parameters, so that we have applied a GBM with a rectangular shock and a parametric origin. In any case, from trends in forecast point of view, all competing models were perfectly equivalent.

Table 13
Austria: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))
BM	0.987557	12				
(5)	0.987921	11	0.029253	0.331484		
GBM (5) + (8)	0.999947	8	0.995741	467.547170	0.995612	605.081761
GBM (9)	0.999388	9	0.950816	57.995098		
GBM (5) + (9)	0.999772	8	0.981676	107.149123	0.981124	138.608187

Table 14
Austria: parameter estimates for the GBM with an exponential shock and a parametric origin.

		Asymptotic	Asymptotic 95.0% Confidence interval	
Parameter	Estimate	Standard error	Lower	Upper
m	30.076900	1.070700	27.607900	32.546000
p	0.000049	0.000201	−0.000414	0.000512
q	0.283151	0.018355	0.240825	0.325477
d	15.738800	15.098200	−19.077800	50.555300
c	3.545270	0.583248	2.200290	4.890240
b	−0.533971	0.118518	−0.807274	−0.260669
a	10.497000	0.047780	10.386800	10.607200

Table 15
The Netherlands: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))		
BM	0.984339	12						
(5)	0.984478	11	0.008876	0.098505				
GBM (8)	0.998578	9	0.909201	30.040084				
GBM (9)	0.998579	9	0.909265	30.063336			(vs. GBM (8))	
GBM (5)+((8)	0.998903	8	0.929953	26.552416	0.929326	35.065330	0.228551	2.370100
GBM (5)+ (9)	0.998947	8	0.932763	27.745489	0.932161	36.641975	0.258973	2.795821
							(vs. GBM (9)	

The Dutch government's decision to end the so-called EPR (Energy Premium Regulation) subvention system on 15th October 2003 resulted in a race for new installations. An additional capacity of approximately 20 MW (vs. less than 6 MW in 2002) still benefited from this system in 2003. The introduction of a new purchase price system for renewable energies called MEP (Milieukwaliteit van de Elektriciteitsproductie) beginning January 1st 2005 proved to be insufficient for a further development of the sector. The 2006 Dutch energy policy aimed at and supported the implementation of proven and almost *competitive* renewable energy technologies to realize the short-term Kyoto and European targets. That approach excluded PV, for which the Dutch policy was focused on price reduction through research and technology development (RTD) leading to internal industry development and implementation in the longer term, not necessarily in the domestic market [11].

Just like the Netherlands, the new installation record registered in Austria in 2003 (6.5 MW) was not enough to satisfy Austria's photovoltaic sector actors. The new purchase price that has been applicable since January 1st 2003 was only valid for the first 15 MWp connected to the power grid. Since this point was reached in only one month's time, no installation able to benefit from this system has been installed since the summer of 2003. In 2006, an amendment to the renewable electricity law (Ökostromgesetz) permitted the introduction of a new feed-in tariff system but its effect cannot be evaluated through our data. In general, we can see that the annual growth rates are very changeable along the whole period, which may be a direct consequence of an unsteady support system in Austria. This situation may be responsible for the weak home market with some internationally well positioned manufacturers nearly exclusively involved in foreign trade, especially in the German market.

4.5. U.S.A

The United States of America exhibit a data pattern much more ambiguous than those already analyzed.

Table 16
The Netherlands: parameter estimates for the GBM with a rectangular shock and a parametric origin.

		Asymptotic	Asymptotic 95.0% Confidence interval	
Parameter	Estimate	Standard error	Lower	Upper
m	55.138400	2.155930	50.166800	60.110000
p	0.000091	0.010314	−0.023693	0.023875
q	0.459654	0.279202	−0.184188	1.103500
d	7.198560	235.284000	−535.369000	549.766000
c	2.684290	0.571306	1.366860	4.001730
a	10.945500	0.204942	10.472900	11.418100
b	12.071500	0.225310	11.551900	12.591100

Table 17
U.S.A.: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs.) (5))
BM	0.978560	12				
(5)	0.989633	11	0.516466	11.749108		
GBM (5) + (8))	0.999702	8	0.986101	141.892617	0.971255	90.10290828
GBM (5) + (9)	0.999675	8	0.984841	129.938462	0.968651	82.39589744

From Table 17 we can see that a GBM with a parametric origin fits this dataset much better than the BM, but no clear indications are given in order to distinguish which type of shock performs better. In Tables 18 and 19 parameter estimates for both models are shown.

We can see that the profile of available observations could be very well modelled either through a GBM with a negative rectangular shock, which essentially describes a slackened diffusion between 1992 and 2001, or through a GBM with a positive exponential shock arising around 2001 (the determination indexes and the squared multiple partial correlation coefficients with respect to the BM are very high for both models). In other words, available data do not allow us to state whether the true underlying diffusion model for PV capacity is the one resulting from data from 2002 to 2006 (for which the rectangular shock represented a slowdown) or the one resulting from data from the beginning until 2002 (for which the exponential shock represented an increase). This is not an unusual dilemma when fitting a GBM to a quite short time series. Of course, the two alternatives lead to very different profiles for future observations (see Fig. 9). We believe that, for this country, it is not safe to trust forecasts until some more data are available.

An analysis of the regulatory environment in the United States is critical to understand the market potential for PV. Despite the Federal tax credit currently available, the United States do not have a coordinated national program to develop PV markets. Net-metering standards dictate the value of PV and allow system owners to sell back electricity to the local utility (economic benefit). Interconnection standards provide uniformity across utility service territories and render the entire process transparent for installers and consumers (infrastructure benefit). A lack of consistent net-metering (economics) and interconnection (infrastructure) standards from state to state creates barriers to growth of the U.S. PV market. Despite these barriers, more than 20 states have renewable portfolio standards, requiring that a certain proportion of a utility's generating capacity or energy sales be derived from renewable resources (among the others, we cite here Arizona, California and New Jersey).

We think that the U.S. pattern shows an unclear trend because it aggregates very different state installations: energy policies are set at state level without a common aim and, moreover, the large geographical extension of this country generates very different solar “efficiencies,” making this energy source not everywhere equally suitable.

Table 18
U.S.A.: parameter estimates for the GBM with a rectangular shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	8666.900000	15,158.900000	−26,289.700000	43,623.500000
p	0.000015	0.000658	−0.001501	0.001532
q	0.278529	0.032907	0.202646	0.354413
d	15.274800	151.946000	−335.114000	365.664000
c	−0.478061	0.083872	−0.671469	−0.284652
a	0.873777	0.001356	0.870649	0.876904
b	9.720660	59.193900	−126.781000	146.222000

Table 19
U.S.A.: parameter estimates for the GBM with an exponential shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	1298.780000	931.566000	−849.423000	3446.980000
p	0.000024	0.003889	−0.008945	0.008993
q	0.154790	0.083422	−0.037582	0.347162
d	33.818000	1002.310000	−2277.510000	2345.150000
c	0.820944	0.301187	0.126404	1.515480
b	0.165922	0.207429	−0.312412	0.644257
a	9.522610	0.398827	8.602910	10.442300

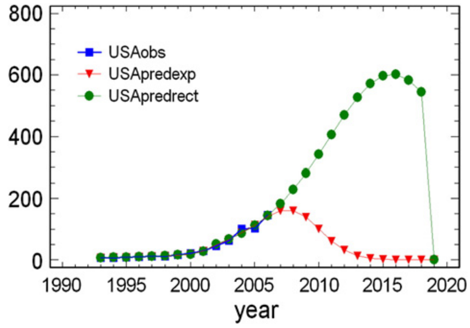

Fig. 9. U.S.A.: installed power, fitted models and forecasts (non-cumulative data).

From the production side, according to PV News, U.S. PV cell production grew 30.9% from 2005 to 2006, reaching 201.6 MW. This growth, according to the Prometheus Institute, was mostly due to the increased production of First Solar (60 MW) while many other U.S. producers were affected by the polysilicon shortage. Essentially, older producers signed advantageous contracts for polysilicon purchase, while up-and-coming manufacturers heavily feel the effects of higher prices. World production of PV cells exceeded 1700 MW in 2005 in spite of tight feedstock supply. A consequence of the rapid growth of PV has been the emergence of a solar-grade silicon supply shortage. This shortage is believed to be temporary, with new supplies and capacity coming on line after 2008. In the meantime, however, this has created an opportunity for thin-film PV and concentrator technologies, which do not use polysilicon feedstock, to accelerate their move from the laboratory into manufacturing and large-scale production. Driven in large part by increases in electricity prices, concerns about climate change, need for energy security, and pro-solar policies, the demand for PV and thus silicon is expected to continue its growth in the United States [20].

4.6. Italy and Spain

Both Italy and Spain show a very confused pattern in observable data (see Figs. 10 and 11). Both series are characterized by slowdowns and rapid increases, maybe as consequences of wavering policies underlying shortsighted governmental choices. Of course, this heavily affects model fitting. While for Japan a simple BM offered an accurate description of the series, both for Italy and for Spain we have an acceptable representation only through a GBM with two subsequent shocks (see Tables 20 and 21).

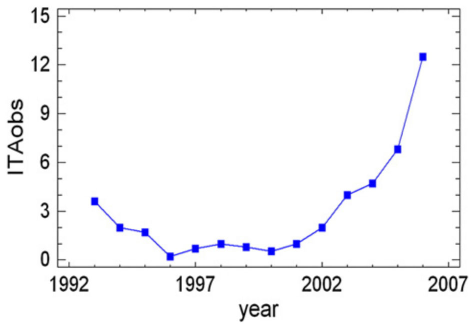

Fig. 10. Italy: installed power (non-cumulative data).

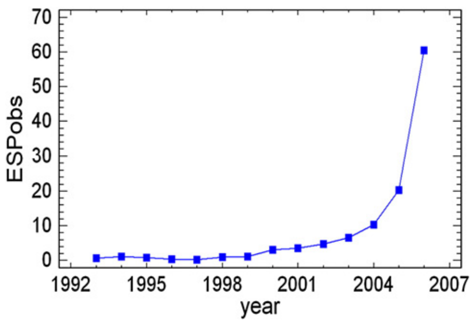

Fig. 11. Spain: installed power (non-cumulative data).

Table 20
Italy: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))		
BM	0.738308	12						
(5)	0.893745	11	0.593969	16.091544				
GBM (5) + ((9)	0.995624	8	0.983278	117.603291	0.958816	62.083486	(vs. GBM (5) + (9))	
GBM (5) + (9) + (9)	0.999641	5	0.998628	519.962197	0.996621	245.812442	0.917962	18.649025
GBM (5) + (9) + (8)	0.999660	5	0.998701	549.058824	0.996800	259.595588	0.922303	19.784314

Table 21
Spain: model selection.

Model	R^2	df	$\tilde{R}^2$ (vs. BM)	F (vs. BM)	$\tilde{R}^2$ (vs. (5))	F (vs. (5))		
BM	0.959763	12						
(5)	0.960136	11	0.009270	0.102925				
GBM (5) + (8)	0.999089	8	0.977359	86.335895	0.977147	114.022686		
GBM (5) + (9)	0.995103	8	0.878296	14.433327	0.877157	19.041318	(vs. GBM (5) + (8))	
GBM (5) + (9) + (8)	0.999972	5	0.999304	1025.739796	0.999298	1185.595238	0.969265	52.559524
							(vs. GBM (5) + (9))	
							0.994282	289.821429

Moreover, for the second shock which upset Italy's data, we face a dilemma similar to the one we described for the U.S.A.: we cannot distinguish between a representation with a negative rectangular shock ($\hat{c}_2<0$ in Table 22) depressing evolution from 2001 until 2005, and a representation with a positive exponential shock ($\hat{c}_2>0$ in Table 23) arising in 2005. Both representations have in

Table 22
Italy: parameter estimates for the GBM with two rectangular shocks and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	1948.410000	25,253.600000	−62,968.200000	66,865.000000
p	0.000409	0.004796	−0.011920	0.012738
q	0.275747	0.102764	0.011583	0.539910
d	3.981780	3.348720	−4.626410	12.590000
c_1	−0.856630	0.012958	−0.889938	−0.823321
a_1	2.486460	0.146732	2.109270	2.863650
b_1	10.288300	0.077098	10.090100	10.486500
c_2	−0.448726	0.224716	−1.026380	0.128928
a_2	9.967350	0.256911	9.306940	10.627800
b_2	13.710000	0.748871	11.785000	15.635000

Table 23
Italy: parameter estimates for the GBM with a rectangular shock, an exponential shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	1814.680000	20,797.300000	−51,646.700000	55,276.000000
p	0.001694	0.019708	−0.048967	0.052355
q	0.051411	0.034556	−0.037417	0.140239
d	1.593430	0.292862	0.840599	2.346260
c_1	−0.800680	7.353910	−19.704600	18.103200
a_1	2.561350	0.946623	0.127973	4.994730
b_1	10.662600	0.954640	8.208580	13.116600
c_2	2.151080	0.114657	1.856340	2.445810
b_2	−0.604856	0.288974	−1.347690	0.137977
a_2	13.775100	2.084670	8.416220	19.133900

Table 24
Spain: parameter estimates for the GBM with a rectangular shock, an exponential shock and a parametric origin.

Parameter	Estimate	Asymptotic Standard error	Asymptotic 95.0% Confidence interval Lower	Upper
m	483.521000	4090.720000	−10,032.000000	10,999.100000
p	0.000007	0.000756	−0.001937	0.001950
q	0.271079	0.025820	0.204708	0.337451
d	20.264200	440.272000	−1111.490000	1152.020000
c_1	−0.719857	0.063467	−0.883005	−0.556710
a_1	2.611480	0.471535	1.399360	3.823610
b_1	7.593530	0.240195	6.976090	8.210970
c_2	0.036093	0.112497	−0.253090	0.325276
b_2	1.049960	0.445187	−0.094434	2.194350
a_2	10.624800	3.985190	0.380500	20.869100

common the part of the model pertaining to the first negative rectangular shock, which is also a feature of the model selected for Spain; see Table 24.

A well-defined take-off for the diffusion process in both countries has not been observed until the final observation available in our dataset. For Spain this is essentially a consequence of the improvement in photovoltaic-origin electricity purchase conditions resulting from Royal Decree 436/2004 of March 2004. It is worth noting that the feed-in tariff for Spanish PV electricity has the particularity of not being a fixed price; instead, it is calculated as a function of a percentage of the mean price of electricity during the year in progress.

Italy's first real PV policy was the “Tetti Fotovoltaici” (*Solar Roofs*) program adopted in March 2001 to provide significant financial assistance for investment (the first negative rectangular shock ends in 2001/2002 in both possible models). Decree 387/03, whose purpose was to enforce the European directive of 2001 on production of renewable electricity, came into force on 31st January 2004 and this may explain the estimate of b_2 in Table 22 or the estimate of a_2 in Table 23 pointing to 2005 as a “change-point.” After that Italy's Government promoted a new purchase price system adopted by decree on the 15th July 2005 (with a new decree on the 26th July that raised the ceiling of total capacity admitted to new tariffs) and a new, less bureaucratic system, was put in place by the Decree of the 19th February 2007.

The interpretation of forecasts for these two countries has to be even more careful than for other countries for two different reasons (see Figs. 12 and 13): the models used are too rich with respect to the data size and big upheavals have changed the most

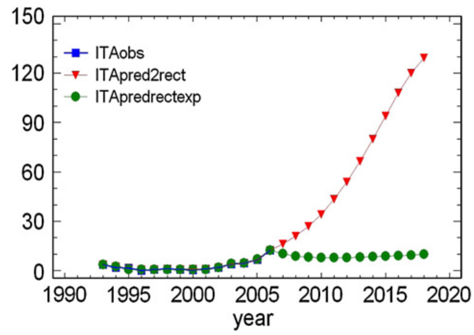

Fig. 12. Italy: installed power, fitted model and forecasts (non-cumulative data).

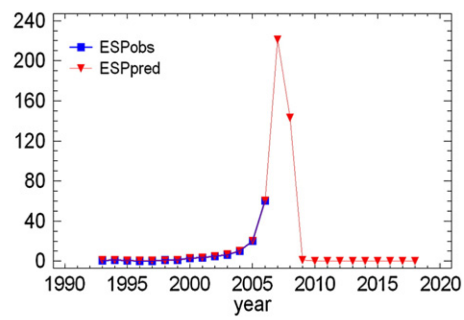

Fig. 13. Spain: installed power, fitted model and forecasts (non-cumulative data).

recent profile of these series. The only safe conclusion we may infer after analyzing these datasets is that PV energy has not yet played a defined role in the strategy of these two countries. This is even more serious, in our opinion, when considering the potential of this kind of energy source in the Mediterranean area, which almost completely lacks fossil fuels sources.

5. Conclusions

In this paper we have applied an innovation diffusion framework to provide some insights on adoption processes of photovoltaic systems in various countries. As mentioned in Sections 1 and 2, the time series available for model fitting are very short and forecasts should be interpreted only as “likely trends” for future markets' development.

As a general result, in modelling terms, we have found that the Generalized Bass Model is essential to account for the presence of exogenous interventions and therefore to confirm the role played by incentive measures in stimulating diffusion. Moreover, the GBM has proven to be suitable for modelling a specific pattern that emerged through a data analysis for many nations (Italy, Spain, France and U.S.A.): a better fitting has been achieved introducing a rectangular negative shock acting on the initial phase of diffusion. This could be interpreted as a chilling effect exerted by negative externalities. Although the action of network externalities in diffusion is a well-known phenomenon not yet formalized, which would probably require a more specific modelling effort, we appreciate the great flexibility of the GBM, which may be used to describe this systematic depression in a satisfactory way, especially with short data series.

The difficulty experienced by the photovoltaic sector in many countries is confirmed by the very low values of parameter p estimates in all the cases considered, which indicates the fragile role of innovators in this particular market. Indeed, technologies for durable products whose returns are delayed in time[1] imply a high risk propensity, thus reducing the number of potential “pioneering” consumers. In addition, the adoption of an *energy* technology involves decisions with a high degree of complexity: the choice does not rely just on final consumers, but rather depends on feasibility constrains typical of essentially grid distributed goods. In this sense, institutional commitment appears a necessary factor for photovoltaic energy to be a successful alternative to fossil fuels. Incidentally, we observe that our analysis focused only on the evolution of domestic PV markets, without taking into account competitive dynamics with other renewable energy sources.

As we have seen in this paper, each country presents important specificities with respect to photovoltaic diffusion: while nations like Japan, Germany and UK have already reached a mature stage of the process, others, like Australia, Canada and France still face a steadily growing market.

Extreme cases are represented, on the one hand, by Italy and Spain, that have begun to invest in this sector very recently, on the other, by Austria and The Netherlands, that have clearly overtaken the peak of installed power.

It is interesting to point out that, when our work was finished, IEA published new data reporting installed capacity for 2007, see PVPS [4]. Our models' forecasts substantially agree with the new data for almost all countries. In particular, there is a *perfect* match for Japan, Australia, Canada, The Netherlands and the U.S.A. A partial exception is represented by Germany for which the new observation entails a shift of the peak of about 2 years, but we have to remark that the IEA, besides adding the final observation, also modified the size of the 2004–2006 data. A special case is that of Austria for which the 2007 observation indicates an unexpected spurt of adoptions: our model could not certainly predict such a change occurring when the peak has been clearly overtaken. Not surprisingly, the most critical situations are represented by Italy and Spain: for these countries the IEA reports a dramatic growth in installations for 2007, whose size goes beyond our predictions. Moreover, we have to say that we do not expect that our predictions might account for future substantial changes in countries' policies.

In a critical phase for energy like the current one, such forecasts on the evolution of one of the most promising renewable alternatives to fossil fuels that prospect a decline in various countries may appear at least a surprising result. One may notice that the most rapid diffusion of photovoltaic systems has occurred in not particularly “sunny” regions. This fact, together with a high degree of ecological commitment, may partially explain a limited and fastly saturated market niche in some of these countries (UK, Austria and The Netherlands). Another reason for a short cycle may be the search for self-sufficiency in energy provision and the decision to exploit it to generate new industrial opportunities. This was achieved through strong government policies. Notable examples are Japan and Germany. Moreover, these general indications on photovoltaic future trends may only apply to the technology currently in commerce (which is based on massive use of purified polysilicon, whose cost is increasing due to exploding demand and constant supply) and not to emerging technologies for solar energy. In this perspective, we find interesting the sign given by the Dutch government that, as underlined in subsection 4.4, does not specifically support the implementation of PV but rather focuses on research and development, in order to reduce the costs, over time, of PV electricity for which a central role is planned only in the longer term, after 2010 [11].

As new technologies are emerging, an open question is whether waiting for a new generation of PV systems could reduce the disadvantage of the laggards: these will probably benefit from decreased plant costs. Conversely, those countries that heavily invested in the current technology will hardly be able to migrate to a new one without forsaking previous investment returns.

[1] The current expected lifecycle for an installed PV plant is around 25 years and, even with feed-in tariffs, initial investments require at least 10–15 years to be fully covered.

Acknowledgements

The authors wish to thank Renato Guseo for helpful comments on previous drafts. This research was supported by Fondazione CARIPARO, Project “Innovation Diffusion Processes: Differential Models, Agent-Based Frameworks and Forecasting Methods.” Progetti di Eccellenza 2007–2008.

References

[1] W. Jager, Stimulating the diffusion of photovoltaic systems: a behavioural perspective, Energy Policy 34 (2006) 1935–1943.
[2] F.M. Bass, A new product growth model for consumer durables, Manage. Sci. 15 (1969) 215–227.
[3] F.M. Bass, T.V. Krishnan, D.C. Jain, Why the Bass model fits without decision variables, Mark. Sci. 13 (1994) 203–223.
[4] PVPS, Trends in photovoltaic applications — survey report of selected IEA countries between 1992 and 2007, 2008, Report IEA-PVPS T1-17, 2008, (www.iea-pvps.org/products/download/rep1_17.pdf).
[5] V. Mahajan, R. Peterson, Innovation diffusion in a dynamic potential adopter population, Manage. Sci. 24 (1978) 1589–1597.
[6] R. Guseo, M. Guidolin, Modelling a dynamic market potential: a class of automata networks for diffusion of innovations, Technol. Forecast. Soc. Change 76 (6) (2009) 806–820 http://dx.doi.org/10.1016/j.techfore.2008.10.005.
[7] F. Sultan, J.H. Farley, D.R. Lehmann, A meta-analysis of applications of diffusion models, J. Mark. Res. 27 (1) (1990) 70–77.
[8] R. Guseo, Strategic interventions and competitive aspects in innovation life cycle, Technical Report, vol. 11, Department of Statistical Sciences, University of Padova, 2004, (http://www.stat.unipd.it/ricerca/fulltext?wp=308).
[9] R. Guseo, A. Dalla Valle, Oil and gas depletion: diffusion models and forecasting under strategic intervention, Stat. Methods Appl. 14 (2005) 375–387.
[10] R. Guseo, A. Dalla Valle, M. Guidolin, World oil depletion models: price effects compared with strategic or technological interventions, Technol. Forecast. Soc. Change 74 (2007) 452–469.
[11] PVPS, Trends in photovoltaic applications — survey report of selected IEA countries between 1992 and 2006, 2007, Report IEA-PVPS T1-16, 2007, (www.iea-pvps.org/products/download/rep1_16.pdf).
[12] BP, Statistical Review of World Energy 2007, 2007 (http://www.bp.com/).
[13] N. Meade, T. Islam, Modelling and forecasting the diffusion of innovation — a 25-year review, Int. J. Forecast. 22 (2006) 519–545.
[14] G. Seber, C. Wild, Nonlinear Regression, Wiley, New York, 1989.
[15] G.E.P. Box, G.M. Jenkins, Time Series Analysis: Forecasting and Control, Prentice Hall, New Jersey, 1976.
[16] C. Watanabe, K. Wakabayashi, T. Miyazawa, Industrial dynamism and the creation of a “virtuous cycle” between R&D, market growth and price reduction. The case of photovoltaic power generation (PV) development in Japan, Technovation 20 (6) (2000) 299–312.
[17] C. Mitchell, P. Connor, Renewable energy policy in the UK 1990–2003, Energy Policy 32 (2004) 1935–1947.
[18] G.A. Moore, Crossing the Chasm: Marketing and Selling Technology Products to Mainstream Customers, Harper Collins, New York, 1991.
[19] J. Goldenberg, B. Libai, E. Muller, Riding the saddle: how cross-market communications can create a major slump in sales, J. Mark. 66 (2) (2002) 1–16.
[20] Solar Energy Industry Association, Our Solar Power Future: The U.S. Photovoltaics Industry Roadmap, 2003 (www.seia.org).

Mariangela Guidolin is a post-doc research assistant at the University of Venezia — Ca' Foscari, Department of Business Economics and Management. She earned her Ph.D. in Economics and Management at the Department of Economics, University of Padova, Italy. Born in 1978, she was educated at the University of Padova. Her current research interests include innovation diffusion models, emerging energy technologies, new drugs' life cycle.

Cinzia Mortarino is an Associate Professor, since 2006, at the Department of Statistical Sciences at the University of Padova, Italy. Born in 1969, she received her Ph.D. degree in Applied Statistics to Economic and Social Sciences from the University of Padova and worked as an Assistant Professor also in the Faculty of Economics at the University of Modena and Reggio Emilia, Italy. Her research interests include design of experiments, statistical quality control, innovation diffusion models, statistical methodology and applications.