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# Contents



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## 1 Introduction

Fossil fuels have represented for a long time and still represent the dominant source of energy in the world, but today studies and forecasts on impending oil and natural gas depletion, worsened situation of climate change due to $CO_2$ emissions, 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 with increasing pressure.

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 the 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 in the perspective of meeting energy needs of millions of poor people who currently lack electricity. However, the technology presents also disadvantages especially related to its 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 (2006) 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 to the purchase decision are delayed and more abstract. These are some of the aspects that prevented for a long time a wide adoption of PV systems in several countries.

Notable exceptions are represented by Japan and Germany that were able to stimulate a successful adoption path and create a strong domestic market for photovoltaic cells from the early 1990s, when global warming issues led to consider solar energy as a suitable substitute of fossil fuels for electricity needs. Both countries in early 1990s were minor players in renewable energy industry but within ten 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 PV industry would not have a chance without a strong governmental commitment. This is a crucial point to investigate since PV industry is currently experiencing unprecedented growth in many countries around the world: though grid-connected solar systems still provide less than 1 percent of world's electricity, cumulative installed PV power has dramatically increased in the last year, exceeding 5000 MW. To have an idea of the evolution of this global process, for the first time in 2006, more than half of world's purified polysilicon - the material also used for semiconductor chips - was employed for producing PV systems.

While recent analyses presented at the Solar Power conference held in San José (California) in 2006, expect that PV generated electricity will have costs similar to conventional sources of energy, when production will reach over 10.000 MW, the on-going shortage of polysilicon would ultimately lead to price increases and to a stagnation of the solar cells market, as predicted by 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 a number of new techniques is 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 so-called thin film solar cells, that are based on amorphous silicon and other low-cost materials, appear as a possible, though not yet available, solution for meeting future demand of PV power.

Given that many countries are investing much effort on PV sector, supporting its industrial development and introducing incentive measures to stimulate the internal diffusion of PV systems as electricity generators, we argue that a country-level analysis, able to highlight differences in historical growth patterns among countries and to provide forecasts on future evolution of domestic markets, may be of interest. This may represent a contribution for testing the impact of different policies on growth trends and for offering a temporal outlook to the emergence of a second generation of solar cells.

In this perspective, we choose to ground on well-established innovation diffusion models, namely the Bass Model (Bass, 1969) and the Generalized Bass Model (Bass et al., 1994), whose main purpose is to describe and to forecast the development of an innovation diffusion process on the basis of first adoption data. The concept governing the use of these models in new-product adoption is that of innovation life cycle, assuming that sales of a new product go through stages of launch, growth, maturity and decline (Wind, 1982). This assumption is the rationale for applying the innovation diffusion approach to adoption dynamics of current photovoltaic systems, since we argue that research on PV technologies is developing very rapidly and actual solutions might be soon replaced by newer and more efficient ones. In strategic terms, crucial forecasts concern the point of maximum growth, the peak, and the point of market saturation, when diffusion comes to an end.

Since the purpose of the paper is the provision of forecasts on national diffusion of PV systems, modelling choices play a conclusive role: in particular, while the Bass model is appropriate in some cases, in many others the Generalized Bass model proves to be essential for statistical identification, allowing to recognize the effect on diffusion of external actions, like institutional measures, policies, price strategies, and confirming their importance in PV adoption.

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 these. 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 diffusion processes of several countries. Section 5 is devoted to conclusions.

# 2 Innovation diffusion models

## 2.1 The Bass model

The Bass Model, BM, proposed in Bass (1969), describes the life cycle of an innovation, depicting its characterizing phases of launch, growth and maturity, decline. Its purpose is to forecast the development over time of a new product growth, as result of the purchase decisions of a given set of potential adopters (market potential). 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 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 Equation (1) the variation over time of adoptions, $z'(t)$ , 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 life cycle and its value is assumed constant along the whole diffusion process. A more flexible structure, with a dynamic potential market $m(t)$, is under study; some preliminary results are described in Guseo and Guidolin (2007); for the application examined in this paper, however, only models with a fixed potential market will be considered 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 $z(t)/m$.

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 is a special cumulative distribution:

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

The *proportion of adoptions* $y(t)$ provided by equation (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 equation (3) by the market potential $m$ :

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

Equation (4) depends on 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 in Guseo (2004):

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

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 in Bass et al. (1994), enlarges the basic Bass model by multiplying its structure for 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 initial condition $z(0) = 0$,

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

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 in Bass et al. (1994), 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 and simplified 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, 2005 and Guseo et al., 2007).

A drastic perturbation, whose effect is strong and fast, 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*), $a$ 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). Interestingly, the possibility to define a flexible intervention function has highlighted a large 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, policies, 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 (2007) 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 to 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 IEA are mostly collected from national survey reports and information summaries. In order to avoid loss of information, we used also data from BP (2007) 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).

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 (USA).

We shall recognize that these data series are quite short, which 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 just from 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 on forecasting markets' evolution.

## 3.2 Models used

Consistently with most of the literature on statistical implementation of the Bass model (for a review see for instance Meade and Islam, 2006), in this work we will use a nonlinear least squares, NLS, approach (e.g. Levenberg-Marquardt, see Seber and Wild, 1989)) 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

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

where $z(t)$ 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, $f(\beta, t)$ could be specified according to a BM or a GBM. For example, the BM regressive model is

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

where $z(t)$ are the observed data, namely 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, $\mathrm{Var}(\varepsilon(t)) = \sigma^2$ and different error terms are uncorrelated, $\mathrm{Cov}(\varepsilon(t), \varepsilon(t')) = 0$, $t \neq t'$. 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 (1976) and, among others, Guseo and Dalla Valle (2005). This approach would not be followed here since, of course, we are going to use the short time series we dispose of only to sketch 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 believe that a constant potential is more suitable to the available technology in PV market in a short time period, as that one covered from IEA data described in the previous subsection. Moreover, we notice that the problem of estimates' stability due to a small number of observations would be even more serious in the case of a complex model with a dynamic potential market.

### 3.3 Model adequacy

Since standard $R^2$ measure for this kind of data gives usually very high values whichever "S-shaped" model is fitted, we chose to proceed as follows. 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

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

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 formal test to verify the significance of the $s$ parameters of the GBM that are not included in the BM is therefore given by

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

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.

Measure (12) represents a 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 more adequate model to the dataset.

## 4 Model selection for the 11 countries

### 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 $R^2_{BM} = 0.999797$. This optimal result is however improved by noticing that the first observation, $z_{1992} = z(1)$ equals 19. This

**Table 1:** Japan: parameters' estimates for the model with a parametric origin.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 2777.69 | 114.991 | 2524.6 | 3030.79 |
| $p$ | 0.000122669 | 0.000354787 | -0.000658214 | 0.000903553 |
| $q$ | 0.420644 | 0.0076237 | 0.403864 | 0.437424 |
| $d$ | 5.45908 | 6.97595 | -9.89492 | 20.8131 |

may suggest that the diffusion process did not begin at that time and that a model with a parametric origin (5) could 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. The estimates of parameters in model (5) for the Japan data are presented in Table 1.

Observe that confidence intervals for the potential market, $m$, for $p$ and $q$ are quite narrow even if the number of observations, as underlined in section 3.1, is small. We would make however a big mistake forgetting that confidence intervals for nonlinear models may be really misleading due to significant curvature in the model. For this reason, we will consider their values only as an indication of stability of the corresponding estimate. Notice that $\hat{d} \simeq 5.46$, which suggests that diffusion of photovoltaic systems began in Japan around 1986/1987.

The plot of true and fitted non cumulative installed power is shown in Fig. 1. The first thing to notice is that the pattern of the observed data seems to have a slowdown around year 2001. For this reason, in addition to the parametric origin, both a GBM with an exponential shock (8) and a GBM with a rectangular shock (9) were fitted to the data. None of them led however to a significant gain over the

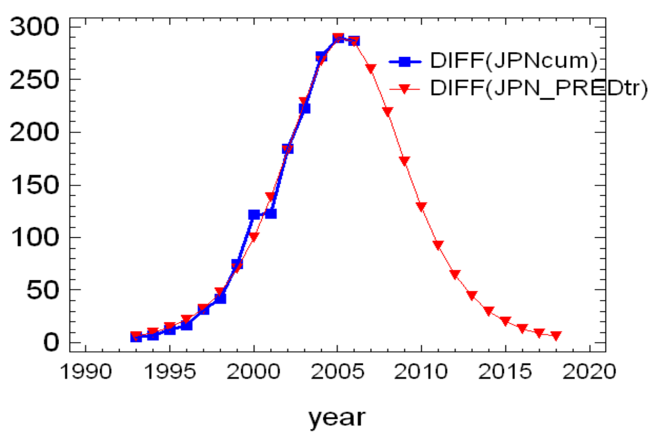


**Figure 1:** Japan: installed power, fitted model and forecasts (non cumulative data).

**Table 2:** Japan: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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 |

simpler model (5), as could be seen from Table 2, where a summary of all models fitted is proposed. The most surprising feature of Fig. 1 is given by future evolution of instantaneous adoptions. A peak is clearly highlighted between 2005 and 2006 and the trend for the next years is a consistent reduction.

Japan's experience is quite unique: from being a PV producer just for small devices like calculators and watches, it became the sector leader in less than ten years. In 1992 the "New Sunshine Program" was launched to promote PV systems, but the most effective initiative for residential PV dissemination was the "70.000 Roofs" program (1994), whose major purpose was to create market awareness and increase production through economies of scale and technology improvements: it ended in 2002 after exceeding all its objectives. Today, the market for residential PV systems in Japan is largely self-supported and driven by market mechanisms. Indeed, public awareness and perception on PV energy has been positively increasing also thanks to effective communication efforts and promotion activities through mass media. The fact that a GBM does not significantly improve the fitting over the simpler BM should not be interpreted as a sign of incentive measures' inefficacy: on the contrary, diffusion does not present a perturbated pattern because strong policies were implemented since the beginning of the life cycle.

## 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 not evidence that the diffusion process may have begun before that date. A simple inspection of the data suggests however 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, indeed, we can see that a GBM with an exponential shock (8) performs much better than the BM. The estimates of parameters in that model are presented in Table 4. Observe that confidence intervals for $p$, $q$ and the three parameters pertaining to the shock are quite narrow. The estimates suggest a positive large shock ($\hat{c} > 0$), arising around 1999 which has not yet run out its effect ($\hat{b} > 0$).

**Table 3:** UK: summary for model's selection.

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

**Table 4:** UK: parameters' estimates for the GBM with an exponential shock.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 28.6024 | 85.9642 | -165.863 | 223.067 |
| $p$ | 0.00347185 | 0.0104254 | -0.0201122 | 0.0270559 |
| $q$ | -0.00288612 | 0.0137298 | -0.0339451 | 0.0281728 |
| $c$ | 3.66026 | 0.968726 | 1.46885 | 5.85168 |
| $b$ | 0.425249 | 0.0807646 | 0.242547 | 0.607952 |
| $a$ | 7.08313 | 0.323608 | 6.35108 | 7.81519 |

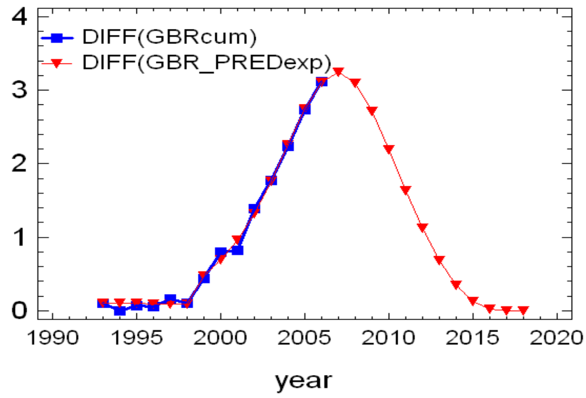


**Figure 2:** UK: installed power, fitted model and forecasts (non cumulative data).

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 for 2007 and the trend for the next years is a consistent reduction.

Although Germany has a much larger installed photovoltaic capacity, its evolution in time follows a profile which is very similar to that we have just seen for United Kingdom. From Table 5 we can see that a GBM with an exponential shock (8) performs much better than the BM. The estimates of parameters in that model are presented in Table 6. Observe that confidence intervals for *all* parameters are really narrow. The estimates suggest a positive shock, arising around 2004 which

**Table 5:** Germany: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (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: parameters' estimates for the GBM with an exponential shock.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 6276.5 | 984.967 | 4048.34 | 8504.65 |
| $p$ | 0.000201869 | 0.0000456941 | 0.0000985012 | 0.000305236 |
| $q$ | 0.415379 | 0.0185829 | 0.373341 | 0.457417 |
| $c$ | 1.7653 | 0.16435 | 1.39351 | 2.13708 |
| $b$ | -0.448399 | 0.136758 | -0.757769 | -0.139029 |
| $a$ | 11.9421 | 0.0861854 | 11.7472 | 12.1371 |

has already fulfilled its effect ($\hat{b} < 0$). The plot of true and fitted non cumulative installed power is shown in Fig. 3. As we noticed both for the Japan data and the UK data, the peak of instantaneous adoptions is forecasted for 2006 and the trend for the next years is a consistent reduction.

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 replaced by 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. We argue that this adjustment is responsible for the acceleration of the diffusion process, exactly occurred in 2004, we have highlighted before. In addition, the "100.000 Roofs" program provided 10-years low interest loans for PV installation, to reduce the high initial costs associated to this technology. This program, ended in 2003, was replaced by the "Solar Power Generation" program, maintaining the provision of soft loans. The promotion of renewables was also supported by creating institutes for collection and publication of data and by organizing training programs to stimulate public awareness.

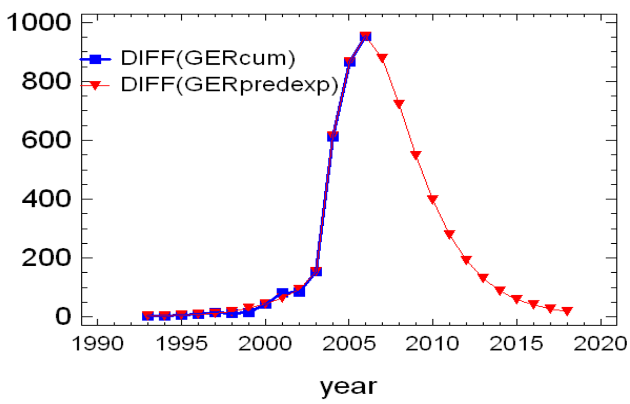


**Figure 3:** Germany: installed power, fitted model and forecasts (non cumulative data).

### 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 concerning Canada are described in Tables 9, 10 and Fig. 5, while Tables 11, 12 and Fig. 6 refer to France).

**Table 7:** Australia: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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: parameters' estimates for the GBM with an exponential shock and a parametric origin.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 1449.69 | 2214.5 | -3656.97 | 6556.35 |
| $p$ | 0.000165352 | 0.000157136 | -0.000197006 | 0.00052771 |
| $q$ | 0.168429 | 0.011983 | 0.140796 | 0.196062 |
| $d$ | 9.77112 | 3.01549 | 2.81737 | 16.7249 |
| $c$ | -0.230408 | 0.907092 | -2.32217 | 1.86136 |
| $b$ | -0.11123 | 0.575294 | -1.43786 | 1.2154 |
| $a$ | 6.97045 | 0.154218 | 6.61483 | 7.32608 |

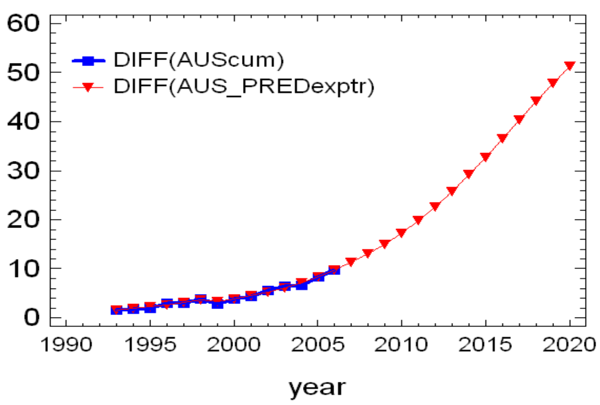


**Figure 4:** Australia: installed power, fitted model and forecasts (non cumulative data).

**Table 9:** Canada: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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: parameters' estimates for the GBM with an exponential shock and a parametric origin.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 310.357 | 1117.26 | -2266.06 | 2886.77 |
| $p$ | 0.0000859332 | 0.000253021 | -0.000497535 | 0.000669401 |
| $q$ | 0.253169 | 0.0309229 | 0.181861 | 0.324478 |
| $d$ | 7.87397 | 9.04687 | -12.9882 | 28.7361 |
| $c$ | -0.604857 | 0.104607 | -0.846081 | -0.363632 |
| $b$ | -0.25316 | 0.165755 | -0.635393 | 0.129074 |
| $a$ | 9.61309 | 0.2123 | 9.12353 | 10.1027 |

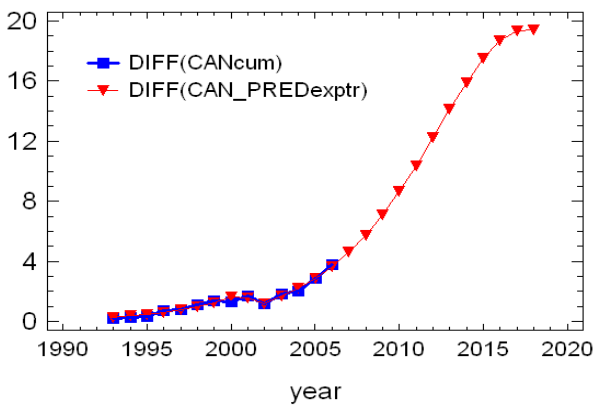


**Figure 5:** Canada: installed power, fitted model and forecasts (non cumulative data).

The data for these countries depict in all cases a diffusion process whose origin is significantly preceding the time of the first observation available. Moreover the evolution was in all cases unsettled by a negative shock arising respectively in year 1998, 2001 and 1997. This may be explained by a temporary slackening of diffusion (after the starting phase when adopters might have been motivated by purely ecologistic grounds), before the launch of incentive policies which were able to capture also adopters motivated mostly by economic reasons.

**Table 11:** France: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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 |

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

| | | | Asymptotic 95.0% Confidence Interval | |
|---|---|---|---|---|
| Parameter | Estimate | Asymptotic Standard Error | Lower | Upper |
| $m$ | 868.768 | 5565.87 | -11966.2 | 13703.7 |
| $p$ | 0.0000473131 | 0.0000984822 | -0.000179788 | 0.000274414 |
| $q$ | 0.292069 | 0.0934977 | 0.0764625 | 0.507676 |
| $d$ | 6.9628 | 19.7786 | -38.6469 | 52.5725 |
| $c$ | -0.28278 | 0.0997944 | -0.512907 | -0.052653 |
| $a$ | 6.00042 | 0.621072 | 4.56822 | 7.43262 |
| $b$ | 13.4982 | 0.205912 | 13.0234 | 13.973 |

Observe that for all the three countries under study, our models forecast a long period of continuous increase in PV capacity, with a peak not preceding 2016. This is mainly the reason why estimates for $m$ should not be fully trusted, since it is known that the BM (and the GBM) gives reliable estimates of the size of potential market only when a mature state in the diffusion process has been reached. We should instead interpret forecasted values as an indication of a "young" market, where steady growth is quite likely to occur.

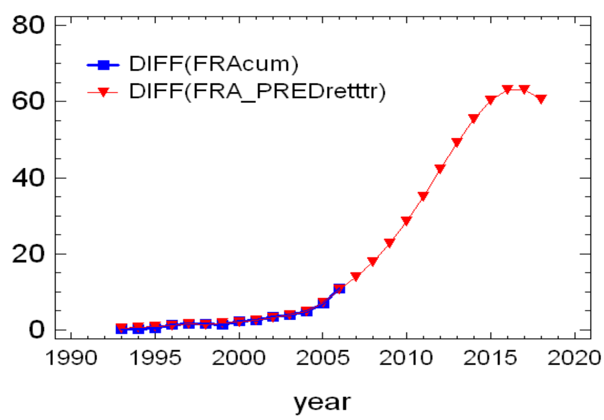


**Figure 6:** France: installed power, fitted model and forecasts (non cumulative data).

### 4.4 Austria and The Netherlands

The two countries analyzed in this subsection have a common very clear pattern in observed data (see Figg. 7 and 8). In both cases the installed PV capacity has already distinctly overtaken its peak. The model selected for both countries (see Tables 13 and 14 for Austria and Tables 15 and 16 for The Netherlands [1] ) 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 in the PV market. The residual market appears rightnow negligible.

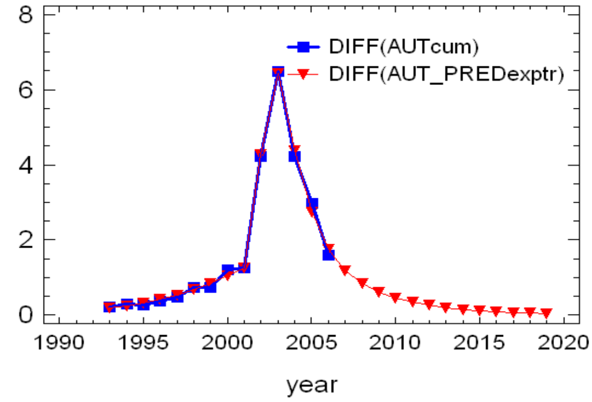


**Figure 7:** Austria: installed power, fitted model and forecasts (non cumulative data).

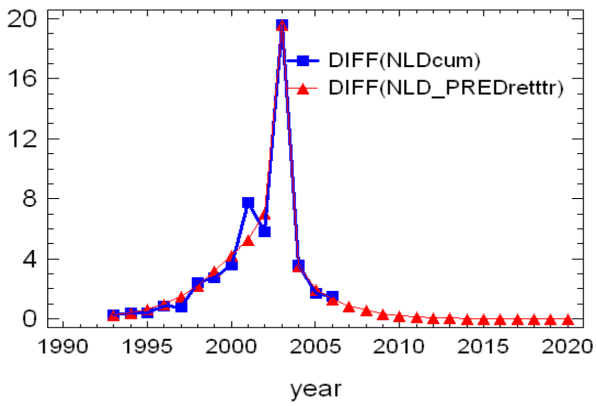


**Figure 8:** The Netherlands: installed power, fitted model and forecasts (non cumulative data).

[1]The model used for The Netherlands was not chosen only according to comparisons among nested models; in this case relevance was given to stability for shock's parameters. In any case, from trends in forecasts' point of view, all competing models were perfectly equivalent.

**Table 13:** Austria: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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: parameters' estimates for the GBM with an exponential shock and a parametric origin.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 30.0769 | 1.0707 | 27.6079 | 32.546 |
| $p$ | 0.0000490733 | 0.000200859 | -0.00041411 | 0.000512256 |
| $q$ | 0.283151 | 0.0183546 | 0.240825 | 0.325477 |
| $d$ | 15.7388 | 15.0982 | -19.0778 | 50.5553 |
| $c$ | 3.54527 | 0.583248 | 2.20029 | 4.89024 |
| $b$ | -0.533971 | 0.118518 | -0.807274 | -0.260669 |
| $a$ | 10.497 | 0.0477802 | 10.3868 | 10.6072 |

**Table 15:** The Netherlands: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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)) | |

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

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 55.1384 | 2.15593 | 50.1668 | 60.11 |
| $p$ | 0.0000912617 | 0.0103138 | -0.0236925 | 0.023875 |
| $q$ | 0.459654 | 0.279202 | -0.184188 | 1.1035 |
| $d$ | 7.19856 | 235.284 | -535.369 | 549.766 |
| $c$ | 2.68429 | 0.571306 | 1.36686 | 4.00173 |
| $a$ | 10.9455 | 0.204942 | 10.4729 | 11.4181 |
| $b$ | 12.0715 | 0.22531 | 11.5519 | 12.5911 |

## 4.5 USA

The United States of America exhibit a much more ambiguous data pattern than that of countries we saw above.

From Table 17 we can see that a GBM with a parametric origin suits well to the data, but no clear indications are given in order to distinguish which type of shock performs better. In Tables 18 and 19 parameters' estimates for both models are shown.

**Table 17:** USA: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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 |

**Table 18:** USA: parameters' estimates for the GBM with a rectangular shock and a parametric origin.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 8666.9 | 15158.9 | -26289.7 | 43623.5 |
| $p$ | 0.0000152879 | 0.000657528 | -0.00150098 | 0.00153155 |
| $q$ | 0.278529 | 0.0329067 | 0.202646 | 0.354413 |
| $d$ | 15.2748 | 151.946 | -335.114 | 365.664 |
| $c$ | -0.478061 | 0.0838715 | -0.671469 | -0.284652 |
| $a$ | 0.873777 | 0.00135609 | 0.870649 | 0.876904 |
| $b$ | 9.72066 | 59.1939 | -126.781 | 146.222 |

**Table 19:** USA: parameters' estimates for the GBM with an exponential shock and a parametric origin.

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 1298.78 | 931.566 | -849.423 | 3446.98 |
| $p$ | 0.0000239927 | 0.00388929 | -0.00894476 | 0.00899274 |
| $q$ | 0.15479 | 0.083422 | -0.0375821 | 0.347162 |
| $d$ | 33.818 | 1002.31 | -2277.51 | 2345.15 |
| $c$ | 0.820944 | 0.301187 | 0.126404 | 1.51548 |
| $b$ | 0.165922 | 0.207429 | -0.312412 | 0.644257 |
| $a$ | 9.52261 | 0.398827 | 8.60291 | 10.4423 |

What we can see is that the profile of available observations could be *very well* modelled (the determination indexes and the squared multiple partial correlation coefficients with respect to the BM are *very* high for both models) either through a GBM with a negative rectangular shock (which essentially describes a slackened diffusion between 1992 and 2002) or through a GBM with a positive exponential shock arising around 2002. 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 true underlying diffusion model is 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 ways of modelling data lead to very different profiles for future observations (see Fig. 9). We believe that, for this country, it would not be safe to trust forecasts until some more data are available.

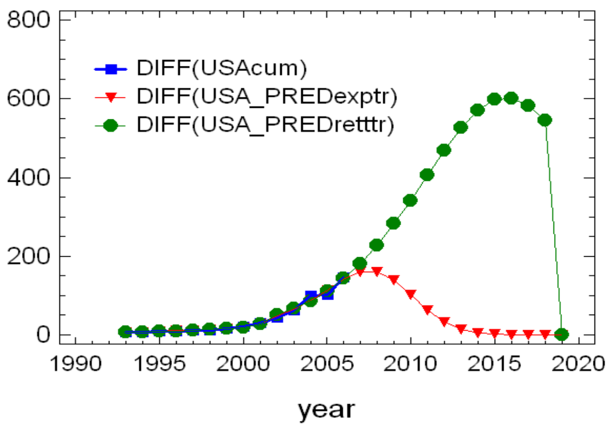


**Figure 9:** USA: installed power, fitted models and forecasts (non cumulative data).

## 4.6 Italy and Spain

Both Italy and Spain show a very “confused” pattern in observed data (see Figg. 10 and 11). Both series are characterized by slowdowns and rapid increases, maybe as consequences of wavering policies underlying shortsighted governs’ choices. This of course heavily affects model fitting. While for Japan a simple BM allowed to describe 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).

Moreover, for the second shock which upset Italy’s data, we face a dilemma similar to that one we described for the USA: we cannot distinguish between a representation with a negative rectangular shock ($c_2 < 0$ in Table 22) depressing evolution from 2002 until 2006, and a representation with a positive exponential

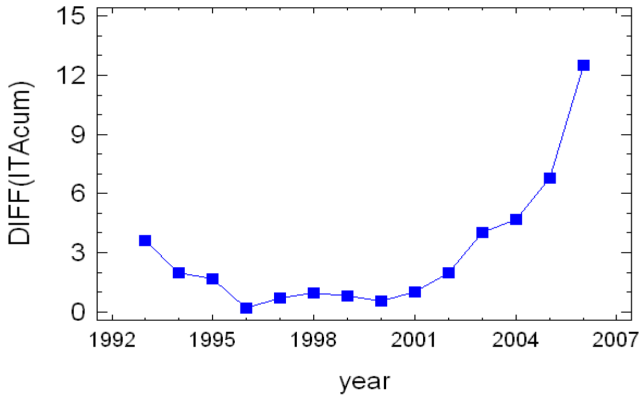


**Figure 10:** Italy: installed power (non cumulative data).

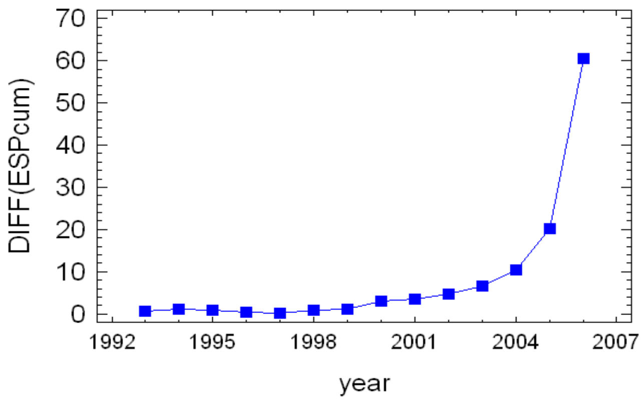


**Figure 11:** Spain: installed power (non cumulative data).

**Table 20:** Italy: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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 |

shock ($c_2 > 0$ in Table 23) arising at the end of the observed series.

Both representations have in 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).

**Table 21:** Spain: summary for model's selection.

| Model | $R^2$ | df | $\widetilde{R}^2$ (vs. BM) | $F$ (vs. BM) | $\widetilde{R}^2$ (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 |

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

| Parameter | Estimate | Asymptotic Standard Error | Asymptotic 95.0% Confidence Interval Lower | Upper |
|---|---|---|---|---|
| $m$ | 1948.41 | 25253.6 | -62968.2 | 66865.0 |
| $p$ | 0.000409193 | 0.00479611 | -0.0119196 | 0.012738 |
| $q$ | 0.275747 | 0.102764 | 0.0115834 | 0.53991 |
| $d$ | 3.98178 | 3.34872 | -4.62641 | 12.59 |
| $c_1$ | -0.85663 | 0.0129575 | -0.889938 | -0.823321 |
| $a_1$ | 2.48646 | 0.146732 | 2.10927 | 2.86365 |
| $b_1$ | 10.2883 | 0.0770978 | 10.0901 | 10.4865 |
| $c_2$ | -0.448726 | 0.224716 | -1.02638 | 0.128928 |
| $a_2$ | 9.96735 | 0.256911 | 9.30694 | 10.6278 |
| $b_2$ | 13.71 | 0.748871 | 11.785 | 15.635 |

**Table 23:** Italy: parameters' 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 |
|---|---|---|---|---|
| $m$ | 1814.68 | 20797.3 | -51646.7 | 55276.0 |
| $p$ | 0.00169414 | 0.019708 | -0.0489671 | 0.0523554 |
| $q$ | 0.0514106 | 0.0345555 | -0.0374174 | 0.140239 |
| $d$ | 1.59343 | 0.292862 | 0.840599 | 2.34626 |
| $c_1$ | -0.80068 | 7.35391 | -19.7046 | 18.1032 |
| $a_1$ | 2.56135 | 0.946623 | 0.127973 | 4.99473 |
| $b_1$ | 10.6626 | 0.95464 | 8.20858 | 13.1166 |
| $c_2$ | 2.15108 | 0.114657 | 1.85634 | 2.44581 |
| $b_2$ | -0.604856 | 0.288974 | -1.34769 | 0.137977 |
| $a_2$ | 13.7751 | 2.08467 | 8.41622 | 19.1339 |

**Table 24:** Spain: parameters' 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 |
|---|---|---|---|---|
| $m$ | 483.521 | 4090.72 | -10032.0 | 10999.1 |
| $p$ | 0.00000656324 | 0.000756132 | -0.00193714 | 0.00195027 |
| $q$ | 0.271079 | 0.0258196 | 0.204708 | 0.337451 |
| $d$ | 20.2642 | 440.272 | -1111.49 | 1152.02 |
| $c_1$ | -0.719857 | 0.0634669 | -0.883005 | -0.55671 |
| $a_1$ | 2.61148 | 0.471535 | 1.39936 | 3.82361 |
| $b_1$ | 7.59353 | 0.240195 | 6.97609 | 8.21097 |
| $c_2$ | 0.0360929 | 0.112497 | -0.25309 | 0.325276 |
| $b_2$ | 1.04996 | 0.445187 | -0.0944342 | 2.19435 |
| $a_2$ | 10.6248 | 3.98519 | 0.3805 | 20.8691 |

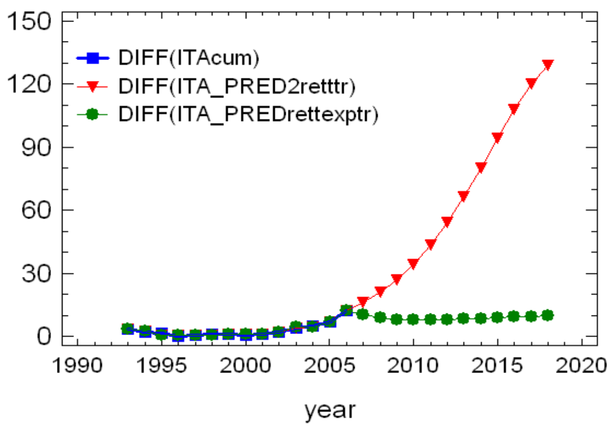


**Figure 12:** Italy: installed power, fitted model and forecasts (non cumulative data).

Caution in interpreting forecasts for these two countries (see Figg. 12 and 13) must be even greater than before for two different reasons: the models used are too rich with respect to the data size and a well-defined take-off for the diffusion process in both countries has not been observed until the last observation available in our dataset. The only safe conclusion to be stated after analyzing these datasets is that PV energy has not played yet a defined role in the strategy of these two countries (on the contrary of most of the countries here studied). This is even more serious, in our opinion, if we think at the potential that this kind of energy source could represent in the Mediterranean area and at almost non existing internal fossil fuels sources.

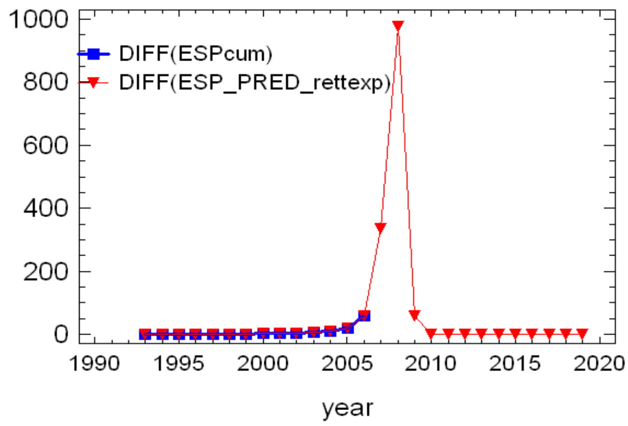


**Figure 13:** Spain: installed power, fitted model and forecasts (non cumulative data).

## 5 Conclusions

In this paper we have applied an innovation diffusion framework to provide some forecasts on the adoption of photovoltaic systems in various countries. As mentioned in sections 3.1 and 3.2, the time series available for model fitting are very short and forecasts should be interpreted only as "likely trends" for future markets' development.

In modelling terms, as a general result, 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 emerged by data analysis for many nations (Italy, Spain, France and USA): 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 possibly exerted by negative externalities.

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[2] 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 rather depending 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.

[2] The current expected life cycle 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.

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 hand, notable cases are represented by Austria and The Netherlands that have clearly overtaken the peak of installed power.

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. However, we argue that these indications on photovoltaic future trends just apply to the technology currently in commerce (which is based on 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 does not specifically support the implementation of PV rather focusing 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 (PVPS, 2007).

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