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Forecasting accuracy of wind power technology diffusion models across countries

Alessandra Dalla Valle, Claudia Furlan*

Department of Statistical Sciences, University of Padua, Padua, Italy

Abstract

Wind power technology is analyzed in terms of diffusion, with incentive effects introduced as exogenous dynamics in the Generalized Bass Model (GBM) framework. Estimates and short-term forecasts of the life-cycles of wind power are provided for the US and Europe, as they have similar geographic areas, as well as for some leading European countries. GBMs have the best performance in model selection, and are ranked first in terms of forecast accuracy over a set of different accuracy measures and forecasting horizons, relative to the Standard Bass, Logistic, and Gompertz models.

Keywords: Diffusion models; Bass; Logistic; Gompertz; Wind power; Forecasting accuracy; Incentives

1. Introduction

An enhanced sensitivity to both environmental problems, such as global warming and air pollution, and energy problems, such as oil depletion, has spread worldwide. The era of fossil fuels is closing and the new prospects are not encouraging. The major oil-exporting countries are near their peak oil production (see Guseo & Dalla Valle, 2005, and Guseo, Dalla Valle, & Guidolin, 2007), and it is well-known that, in spite of the increasingly sophisticated technological approaches to oil mining, the quantity of oil being extracted is lower than either expectations or demand. In light of this, new sources of energy that are both clean and cost-effective are required in the interests of preserving the environment.

In this paper we study the technological diffusion of wind power, which is considered to be an innovation, since it possesses the five attributes that Rogers (1962) uses to define an innovation: relative advantage, compatibility, complexity, trialability and observability. The decision process involved with investing in a wind power system is quite complex. Its adoption implies large markups and a long-term profit horizon, and it takes time to become familiar with the complicated administrative procedure, legislative constraints, architectural and environmental barriers, and technical opinions. Nevertheless, wind power

* Corresponding author. Tel.: +39 049 827 4129; fax: +39 049 827 4170.
E-mail address: furlan@stat.unipd.it (C. Furlan).

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technology provides a distinct advantage in generating clean energy and is completely compatible with the existing electricity grid. Although the technological adaptation required for this form of power system does not allow limited time period or smaller-scale trials, observation of the development of new plants is useful in the decision-making process. For further details on the attributes of innovation for cleaner technology, in particular for a photovoltaic system, see Jager (2005).

Despite a growing level of public interest in environmental protection, very little research has been done on clean technology, as a subcategory of technology, and only minor attention has been paid to quantitative analyses and forecasts. Through their review, Kemp and Volpi (2008) hope to stimulate, in general, wider research in the area of clean technologies. Until now, to the best of our knowledge, only a few attempts have been made to model the process of adopting wind power: Diaz-Rainey (2005), with a diffusion pattern based on logistic and log-logistic models; Söderholm and Klaassen (2007), with a simultaneous innovation-diffusion econometric model, based on a learning curve, applied to some European countries; and Usha Rao and Kishore (2009), with a Bass model for selected states in India. Incentive schemes have been explicitly included in the model by Söderholm and Klaassen (2007), while Usha Rao and Kishore (2009) evaluate the correlation between the diffusion growth and a composite policy index ex post.

In technological diffusion, it is well known that the timing of adoption is affected not only by endogenous mechanisms, but also by exogenous dynamics. However, to date, only a few efforts have been made to unify endogenous and exogenous mechanisms, especially for clean technology (Montalvo & Kemp, 2008), for which the main factor that exogenously affects the rate of adoption is represented by incentive schemes. The Generalized Bass Model (GBM) seems to be particularly suitable for evaluating both endogenous and exogenous mechanisms, as it allows for the inclusion of the innovative and imitative behavior of the adopters of a particular technology, as well as the assessment of the strength of the incentive policies passed by the local governments of a given country.

In this work, we attempt to fill in the gaps with regard to wind power technology by (a) modelling the endogenous dynamics in the framework of the GBM to overtake the models proposed by Diaz-Rainey (2005) and Söderholm and Klaassen (2007); while simultaneously (b) measuring the exogenous mechanisms by including local incentive schemes in the model, extending the model of Usha Rao and Kishore (2009), (c) in a cross-country analysis. Moreover, (d) the proposed GBMs are compared with the common models used in diffusion studies (Bass, Logistic, and Gompertz) through both the BIC and $\bar{R}^2$ adjusted, and in terms of the forecasting accuracy (1 and 3 years ahead) using a set of accuracy measures. Finally, (e) short-term forecasts based on the most reliable models are provided.

The remainder of the paper is structured as follows. Section 2 discusses the GBM in relation to wind power systems, while Section 3 exhibits the data and modeling results of the leading countries with regard to geographic extension. Section 4 provides the forecasting accuracy results of the GBM, relative to the Bass, Logistic, and Gompertz models. Short-term forecasts of GBMs for each region/country follow in Section 5, and our conclusions are given in Section 6.

2. The model

In the field of innovation studies, technological diffusion has a long history, starting in the 1960s with the works of Fourt and Woodlock (1960) and Rogers (1962). In their review, Meade and Islam (2006) highlight the wealth of research on modelling and forecasting the diffusion of innovations and propose several alternative models, including the Bass Model (BM), which was first presented by Bass (1969). The BM (and its generalization) is the only model among the S-shaped curves (e.g., the Logistic and Gompertz models) that includes the innovative and imitative behaviour of adopters introduced by Rogers (1962). Typically, the diffusion of a technology is very slow initially, since adopting it means taking a risk in a situation of uncertainty. Only a few brave adopters are disposed to take these risks, while "*the great majority adopts a wait-and-see approach*" (Kemp & Volpi, 2008). Here, wind power satisfies the assumptions required for the BM to be applied. In particular, the members of the social system adopting this innovation are the individuals who decide to support the companies involved in wind projects, or who install small wind turbines for self-consumption of electricity (single home, farm, ranch, or business). The external communication channels that rule this innovative behavior are represented by the mass-media, newspaper ads, and specialized information meetings, while word of mouth among neighbours/acquaintances represents the interpersonal communication channels. Finally, market saturation is achieved when spatial or environmental constraints do not allow for new installations, or when some new form of innovative technology is introduced to replace the preexisting one.

It is important to take the characterization of the incentive policy into account in the modeling process, since wind power technology is not economically competitive and the incentive policies passed by local governments can either accelerate or delay the adoption of the technology. For recent examples in the literature, see Ben Maalla and Kunsch (2008), who used a Bass model for the replacement of traditional boilers by μ-CHP installations, where several incentive schemes are considered through simulation studies; Diaz-Rainey and Tzavara (2009), who used a Bass-based model for accounting for the willingness to pay for green energy tariffs; and Guidolin and Mortarino (2010), who used a cross-country analysis of photovoltaic systems, where the effects of the local incentive policy were measured in a GBM structure. In the diffusion literature, complex models are not necessarily preferred to simpler ones (Makridakis & Hibon, 2000), but it is important to use a framework that might include external inputs, especially when limited data are available (Islam, Fiebig, & Meade, 2002), as with wind power data. For example, Hardie and Fader (1998) mention the possibility of including covariate effects in a GBM, and Kumar and Krishnan (2002) propose an application of this method in a multinational diffusion setting. On the other hand, Guseo and Dalla Valle (2005) propose an alternative way of including external interventions in a GBM through exponential and rectangular shocks. For wind power, we adopted the latter approach because it allows the modelling of the stationarities and speed variations of adoptions, which are typical of processes that are strongly influenced by changes in incentive policies.

The GBM representation is (Bass, Krishnan, & Jain, 1994):

$$z(t) = m\frac{1-\mathrm{e}^{-(p+q)\int_0^t x(\tau)\mathrm{d}\tau}}{1+\frac{q}{p}\mathrm{e}^{-(p+q)\int_0^t x(\tau)\mathrm{d}\tau}}, \quad 0 \le t < +\infty, \quad (1)$$

where m is the potential market, p and q are the parameters referred to as the quota of innovators and imitators, respectively, and $x(t)$ is an integrable function that oscillates around 1. Through $x(t)$, interventions of a political and economic nature are included in the GBM as exogenous variables. Note that Eq. (1) includes the BM for $x(t) = 1$. For values of $x(t)$ greater than 1 the adoption process is accelerated over time, otherwise it is delayed.

Following Guseo and Dalla Valle (2005), the representation for $x(t)$ of an exponential shock $S_{\mathrm{exp}}(t)$ and a rectangular shock $S_{\mathrm{rect}}(t)$ is

$$\begin{aligned} x(t) &= 1 + S_{\mathrm{exp}}(t) + S_{\mathrm{rect}}(t) \\ &= 1 + c_1\mathrm{e}^{b_1(t-a_1)}I_{[t\ge a_1]} + c_2 I_{[a_2\le t\le b_2]}. \end{aligned} \quad (2)$$

An *exponential* shock $c_1\mathrm{e}^{b_1(t-a_1)}I_{[t\ge a_1]}$ identifies a locally intense impulse that progressively loses its effect. Specifically, a_1 coincides with the beginning of the shock, b_1 expresses how rapidly the shock decays toward 0 and is usually negative, and c_1 indicates the intensity of the beginning of the shock. A *rectangular* shock $c_2 I_{[a_2\le t\le b_2]}$ is another kind of impulse for intervention function $x(t)$ that identifies a perturbation whose effect stays unchanged over a bounded time interval. This impulse begins at time a_2 and ends at time b_2, keeping a given intensity c_2 over the interval (a_2, b_2). Note that setting $S_{\mathrm{rect}}(t) = 0$ in Eq. (2) corresponds to a model with only one exponential shock, while $S_{\mathrm{exp}}(t) = 0$ corresponds to a model with only one rectangular shock.

3. Results of GBMs

The US, although not a subscriber to the Kyoto Protocol, is committed in some way to creating renewable electric energy. However, in terms of wind energy production, the US is usually compared with representative European countries. In this section, we propose a more balanced comparison with Europe, which is similar in geographical extent, and then a comparison among the leading European countries.

Our data consist of the yearly cumulative installed wind turbine capacity, in megawatts (MW), until

2008 (Fig. 1) for Europe, the US, and the leading countries in Europe: Germany, Spain, Denmark, and Italy. The data were sourced from the American Wind Energy Association and the US Department of Energy websites for the US, and from the European Wind Energy Association, BP, Earth Policy Institute Web, and EurObserv'ER websites for the European countries. The data are available from 1981 for the US, from 1990 for Europe as a whole, from 1987 for Germany, from 1991 for Spain, from 1980 for Denmark, and from 1995 for Italy.

For all countries, GBMs were performed using Eq. (2) for $x(t)$; that is, the data were fitted with both types of shocks. Furthermore, nested models with no shocks (BM), with only one rectangular shock and with only one exponential shock were also fitted. For all countries, Table 1 provides estimates and asymptotic standard errors of the best model, selected among the set of nested models with a procedure based on the reduction of the residual deviance (for further details, see Guidolin & Mortarino, 2010, for instance). Table 2 shows the results of a model selection, performed in terms of both the BIC and $\bar{R}^2$ (adjusted for the degrees of freedom) among the GBMs and the most widespread diffusion models. We have taken into consideration the BM model, the Logistic model $z(t) = m/(1 + c\exp(-qt))$, and the Gompertz model $z(t) = m\exp(-c\exp(-qt))$, where $z(t)$ is the cumulative number of adoptions at time t, m is the potential market, and c and q are parameters. Table 3 summarises the main features of the incentive schemes (type and introduction time) and the estimated shocks (onset time and impact) that are dealt with in the following two subsections.

3.1. Europe and the US

For *Europe*, the exponential shock was found to be positive ($c_1 = 1.82$), arising around $(1990 + a_1) \approx 1999$, and its effect was absorbed in time ($b_1 = -0.42$). We cannot identify exactly what caused the exponential shock in 1999, since the time series aggregates data and different incentive policies across several countries. Probably, as we will see in Section 3.2, it corresponds to a significant incentive policy passed by the Spanish government.

For the *US* model, the exponential shock was found to be positive ($c_1 = 5.32$), arising around $(1981 + a_1) \approx 1982$, and its effect was absorbed in time ($b_1 = -0.51$), while the rectangular shock was found to be negative ($c_2 = -0.96$), arising around $(1981+a_2) = 1986$ and ceasing around $(1981+b_2) \approx 1999$. To understand the rationale that led to the identification of the two shocks, we outline the basic points of the American legislation relating to the renewable energy marketplace in the later years. When wind power production was new, the Crude Oil Windfall Profits Tax Act (WPT) of 1980 was effective and additional credits were extended from 1982 to 1985. However, in 1986, the wind power system was excluded from the incentive system scheme, and only in 1992 it was included in the production tax credit (PTC), even if it was penalized relative to solar and geothermal systems. The two identified shocks seem to be the effects of policy choices on incentives; in particular, the exponential shock starts when WPT passed additional credits, from 1982 to the end of 1985, and the rectangular shock lies in the time interval (1986–1999) where there were no specific incentives for wind.

The difference between the two diffusion processes is strikingly obvious, and compared to Europe, the US is still at the beginning of the diffusion process. One aspect which can at least partially explain the gap between the US and Europe is the different incentive policies adopted in the US and in more than 25 countries in Europe. Nowadays, in Europe, there are two main categories of incentive programs: "Feed-in Tariffs", adopted, for example, by Germany, Spain, and Denmark (until 2003); and "Renewable Portfolio Standards (RPS)", adopted, for example, by Italy and Denmark (after 2003). The first incentive system appears to be the most effective; in fact, it allows the interconnection of renewable energy sources with the electricity grid and specifies the price that is paid for every kilowatt-hour produced. For RPS, utilities are required to purchase a percentage of the electricity-generating capacity from renewable resources, and the electricity produced is often traded through the so-called Green Certificates. The incentive policy in the US is quite different. The American PTC is similar to the feed-in-tariffs, but it is smaller and less certain than the subsidies in Europe. Moreover, the PTC applies only for the first 10 years after the initial investment, and does not cover any operating expenses thereafter, although it is well known that 20 years is a common return for clean technologies. For a further comparison

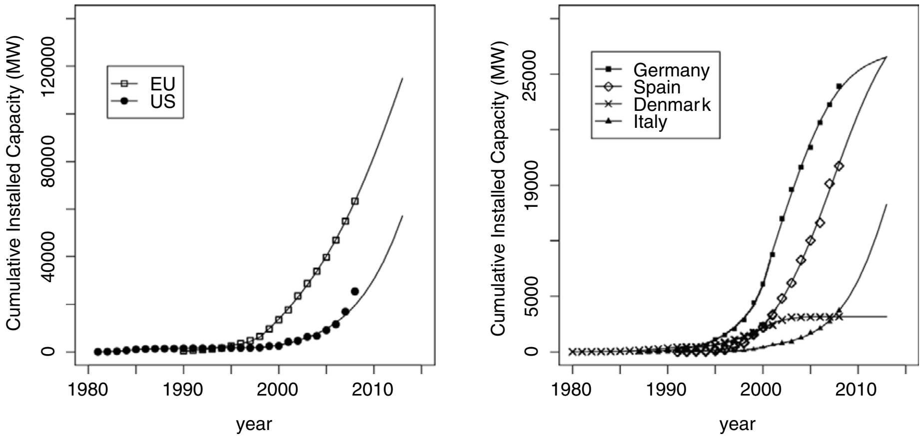

Fig. 1. Cumulative installed capacity of wind power (points) and short-term forecasts (solid lines) up to 2013, for Europe and the US (left panel), and for the leading European countries (right panel). Fitted models correspond to the GBMs of Table 1.

Table 1
Estimates and asymptotic standard errors (in brackets) for GBMs.

Shock	Par.	Europe	US	Germany	Spain	Denmark	Italy
	m	269 692 (223 211)	290 163 (359 491)	27 212 (711)	32 187 (19 395)	3139 (25)	33 183 (103 556)
	p	0.0009 (0.0006)	0.00003 (0.00004)	0.0006 (0.0002)	0.0006 (0.0003)	0.002 (0.001)	0.0006 (0.002)
	q	0.17 (0.04)	0.24 (0.05)	0.35 (0.03)	0.29 (0.18)	0.02 (0.06)	0.38 (0.11)
	$a1$	8.63 (0.31)	1.49 (0.005)	13.73 (0.28)	7.15 (1.74)	14.71 (0.56)	6.98 (1.15)
exp	$b1$	−0.42 (0.17)	−0.51 (0.02)	−1.12 (0.68)	−0.45 (0.77)	0.20 (0.07)	−0.16 (0.29)
	$c1$	1.82 (0.44)	5.32 (0.002)	1.26 (0.52)	1.79 (1.08)	6.61 (12.20)	−0.55 (0.23)
	$a2$		5.00 (0.001)			6.50 (1.49)	
rect	$b2$		17.92 (0.0006)			12.44 (1.10)	
	$c2$		−0.96 (0.01)			5.14 (6.96)	

of the incentive schemes of Europe and the US, see Snyder and Kaiser (2009).

3.2. European countries

For *Germany*, the world's largest user of wind power, an exponential shock has a positive impact on the model ($c_1 = 1.26$), and its effect is absorbed over time. It is placed around $(1987 + a_1) \approx 2001$, corresponding to the Renewable Energy Sources Act, which came into force in 2000 as a replacement for the Electricity Feed Law, encouraging the activation of many new wind power plants. For *Spain*, a positive exponential shock ($c_1 = 1.79$) arises around $(1991 + a_1) = 1998$, and its effect was absorbed over time ($b_1 = -0.45$). The exponential shock corresponds

Table 2
BIC and $\bar{R}^2$ (adjusted) for the GBM, BM, Logistic, and Gompertz models.

Country	BIC				$\bar{R}^2$			
	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp
EU	**234.3**	259.5	263.6	245.4	**0.99968**	0.99845	0.99808	0.99926
US	**81.4**	134.4	135.2	136.5	**0.98658**	0.86166	0.85768	0.85058
Germany	**250.7**	257.2	257.3	268.4	**0.99926**	0.9987	0.99872	0.99789
Spain	211.6	210.6	212.0	**203.0**	0.99763	0.99709	0.99686	**0.99810**
Denmark	**246.5**	288.4	288.2	309.1	**0.99841**	0.98962	0.98969	0.97878
Italy	**119.9**	123.1	125.9	126.1	**0.99767**	0.99625	0.99542	0.99539

Table 3
Incentive schemes: type, introduction time, onset time (or time period for rectangular shocks) and impact of the estimated shocks, across series (Europe excluded).

Country	Type	Introduction time	Onset time	Impact
US	Additional credits of WPT	1982	1982	Positive
	Stop specific incentives	1986–1999	1986–1999	Negative
Germany	Feed-in-law	2000	2001	Positive
Spain	Feed-in-law	1997	1998	Positive
Denmark	New favorable law	1984	1986–1992	Positive
	Feed-in-law	1992	1995	Positive
Italy	Green certificate	2002	2002	Negative

to the introduction of the feed-in-law tariff in 1997, which was particularly beneficial for wind power. For *Denmark*, a positive ($c_2 = 5.14$) rectangular shock arises around $(1980 + 6.5) \approx 1986$, corresponding to new legislation in 1984 which was favorable to the owners of wind turbines, and ends around $(1980 + 12.44) \approx 1992$. The exponential shock was found to be positive and to have a considerable impact ($c_1 = 6.61$), and is positioned around $(1980 + a_1) \approx 1995$. It corresponds approximately to the introduction of the first feed-in-law system incentive scheme of 1992. In 2003, the Green Certificate policy was adopted; this new incentive policy discouraged Danish investors completely, thus stopping the adoption process. For *Italy*, a negative ($c1 = -0.55$) exponential shock is detected at around $(1995 + a1) = 2002$, and its effect was absorbed over time ($b1 = -0.16$). The exponential shock corresponds to the introduction of the Green Certificates in 2002, and, as in Denmark, this type of incentive had a negative impact on the adoption process; however, it was absorbed over time.

Note from Table 2 that both the BIC and $\bar{R}^2$ prefer the GBM to simpler models (except in the case of Spain), despite the BIC's penalty on complexity. The different performance of the model for Spain is probably due to the particular shape of the cumulative adoption curve, which is very suitable for the Gompertz model, in spite of the new incentive policy in 1997.

4. Forecasting accuracy analysis

In this section, we assess the forecasting accuracies of the GBM, BM, Logistic, and Gompertz models through a set of out-of-sample tests that can furnish a rating of the models. In a rolling-origin evaluation (Tashman, 2000), we fixed the origin t of the forecasting period in 2003 and produced forecasts for the next five years until 2008, giving a set of five 1-year-ahead, and three 3-year-ahead forecasts. The forecast accuracy is assessed using multiple different measures (Armstrong & Collopy, 1992; Makridakis et al., 1982). For each forecasting horizon (1 and 3 years ahead) we used the root mean squared error (RMSE), and the mean (MAPE) and median (MdAPE) absolute percentage error (APE). We also present an adjustment of the Relative Absolute Error (RAE), proposed by Armstrong and Collopy (1992), for cumulative functions. They initially defined it as $\mathrm{RAE}_{m,t+h} = |F_{m,t+h} - O_{t+h}|/|F_{rw,t+h} - O_{t+h}|$, where m is the model, t the rolling-origin, h the forecasting horizon, O_{t+h} the observed values at time $t+h$, $F_{m,t+h}$ the predicted values for a forecasting horizon of h for model m, and $F_{rw,t+h}$ the corresponding predicted values for the random walk. The idea of a random walk (that is, a constant function that assumes the value observed at origin t over time) is translated here to a linear function, which grows every year by the increased value observed in $t: F_{rw,t+h} = O_t + h(O_t - O_{t-1})$. The proposed RAE was summarized for each forecasting horizon by the mean (MRAE) and median operator (MdRAE), as well as across different forecasting horizons, by the cumulative sum (CumRAE). Finally, we averaged all of the measures across the six series.

It is understood that, a priori, no one accuracy measure can be considered better than another (Armstrong & Collopy, 1992) for ranking the proposed models. Of all of the accuracy measures introduced above, we decided to present in Table 5 only the indicators which are unit-free and reliable when few sets of series are available, and offer protection against outliers, namely MAPE, MdAPE and MdRAE (for each country, model, and forecasting horizon). However, the other accuracy measures which are used also lead to the same conclusions. The average measures across the countries in Table 5 show that the GBMs have the lowest forecasting errors over accuracy measures, models and forecasting horizons, and that the differences in numeric terms are sizable, especially for MdRAE with a 1-year-ahead forecasting horizon. Among the remaining models, the Gompertz model is the most accurate forecasting model in terms of both MAPE and MdAPE, followed by the Logistic model and BM; however, in terms of MdRAE, the ranking is diametrically opposite. This ranking is not always the same if the analysis moves to the accuracy measure of individual countries. For example, for Spain, the Gompertz model is the most accurate for 3-year-ahead forecasts and the differences with respect to the other models are significant; on the other hand, Germany does not have a benchmark model over either measures or forecasting horizons.

Makridakis and Hibon (2000) highlight the fact that sophisticated or complex models do not necessarily perform better than simpler ones, and that the ranking of models in terms of forecast accuracy depends on the accuracy measures. However, Table 5 provides sufficient evidence that the GBM outperforms the remaining simpler models on average, and also for the majority of the individual countries. The explanation for this probably lies in the fact that the S-shape of the wind power diffusion process is strongly affected by incentive policies, and as a consequence, the GBMs are hardly outperformed by simpler models that do not allow for local stationarities or sudden changes in growth.

5. Short-term forecasts

In Section 4, we found that the GBM is the most reliable method across different scenarios. For this reason, we present here short-term forecasts with respect to the GBMs for each time series: see Fig. 1 for the forecasted growth of wind power capacity until 2013, and Fig. 2 for the corresponding predicted life-cycles. For Europe as a whole, Italy, and the US, the life-cycles are still far from peaking, while for Denmark, Germany, and Spain, the peaks are estimated to have occurred in 2000, 2001, and 2008, respectively. Looking at the slopes of the curves in Fig. 1, it appears that the US is, on the whole, investing more than Europe, even if the gap in MW installed is still huge. The US has a great potential for producing electricity from wind, and this potential should be exploited. Among the European countries, with respect to the cumulative MW installed, Germany and Spain stand out as the leaders. However, Fig. 2 highlights the fact that, while Germany seems to be at the concluding stage of the life-cycle (with the new incentive scheme), Spain is still encouraging the installation of wind power turbines.

For each time series, Table 4 shows the observed rate of increase of MW installed for 2008 (5 years behind), together with the expected MW installed and the corresponding rates of increase for 2009 (1 year ahead) and 2013 (5 years ahead). From a comparison of the predicted 5-year-ahead and the observed 5-year-behind rates of increase, it can be concluded that the wind adoption process will slow down abruptly, especially for the US, Spain, and Germany, for which the decrease is predicted to be more than half. This should be as a consequence of incentive policies that gradually become less attractive over time. Indeed, the intention of governments, in general, is to gradually

Table 4
Observed rate of increase of MW installed for 2008 (5 years behind with respect to 2003) for Europe, the US, Germany, Spain, Denmark, and Italy, together with the corresponding expected MW installed and rates of increase for 2009 (1 year ahead) and 2013 (5 years ahead).

Country	2008 5 years behind (%)	2009 1 year ahead		2013 5 years ahead	
		MW	(%)	MW	(%)
Europe	121	72 310	14	114 962	82
US	300	24 459	[a]	57 144	125
Germany	39	24 564	3	26 516	11
Spain	170	19 246	15	26 601	59
Denmark	2	3 160	0	3 160	0
Italy	313	4 891	31	13 289	256

[a] Not reliable for 2009.

Table 5
1- and 3-year-ahead forecasting accuracies for the GBM, BM, Logistic, and Gompertz models across countries.

1-year-ahead	MAPE				MdAPE				MdRAE			
	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp
EU	**2.8**	4.6	7.0	6.4	**3.0**	5.7	5.9	3.2	**1.73**	5.01	4.16	3.76
US	**13.4**	33.5	19.7	16.9	**14.4**	34.8	21.0	18.6	**1.28**	2.02	1.40	**1.28**
Germany	**4.0**	4.3	4.3	5.9	3.3	3.5	3.5	**3.0**	2.12	2.12	**2.08**	3.89
Spain	7.5	5.3	5.8	**5.0**	6.0	**1.7**	2.2	3.5	1.18	**0.57**	0.74	0.81
Denmark	**2.2**	10.4	10.5	15.3	**1.0**	10.3	10.6	15.3	**3.23**	53.60	55.31	89.90
Italy	**9.6**	9.7	14.4	11.3	**5.1**	7.7	14.3	10.0	1.14	**1.07**	1.32	1.33
Mean	**6.6**	11.3	10.3	10.1	**5.5**	10.6	9.6	8.9	**1.78**	10.73	10.83	16.83
3-year-ahead	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp
EU	10.6	11.8	12.1	**8.7**	14.6	14.6	11.1	**11.0**	1.44	1.44	**1.10**	**1.10**
US	**21.7**	56.3	41.8	39.5	**22.0**	57.1	43.7	42.2	**0.82**	1.67	1.35	1.30
Germany	8.4	8.4	**8.2**	21.8	10.0	10.0	**9.9**	19.1	**1.56**	**1.56**	1.57	9.61
Spain	10.9	19.1	20.0	**1.1**	8.0	18.4	19.5	**1.4**	0.94	2.16	2.26	**0.13**
Denmark	**5.4**	24.5	24.5	38.1	**2.6**	23.3	23.6	41.9	**0.66**	24.41	25.16	49.71
Italy	**26.5**	29.0	41.3	29.0	**15.9**	32.5	40.4	29.5	**1.16**	1.23	1.85	1.57
Mean	**13.9**	24.8	24.6	23.1	**12.2**	26.0	24.7	24.2	**1.10**	5.41	5.55	10.57

reduce the incentives until the technology becomes economically competitive. One-year-ahead forecasts emphasize a sudden stop of adoption in Germany and Denmark, as opposed to the still growing interest of Italian investors. The corresponding rate of increase for the US for 2009 is not provided, since the large number of adoptions that occurred in 2008, which was underestimated by the model, produces an inconsistent forecast.

6. Conclusions

GBMs have been fitted to compare the wind diffusion processes between Europe and the US, and among Germany, Spain, Denmark, and Italy. The effects of local incentive policies were included in these models through exponential and rectangular shock functions. The use of these intervention functions is particularly worthwhile because they highlight the apparent relationship between the economic advantages, derived from incentive tariffs, and the increased number of adoptions, in terms of onset time, strength, and duration. Furthermore, of the most widespread diffusion models, the GBMs have the best performances in terms of the BIC and $\bar{R}^2$ (except for Spain).

The US still has great potential in the field of electrical energy production from wind power,

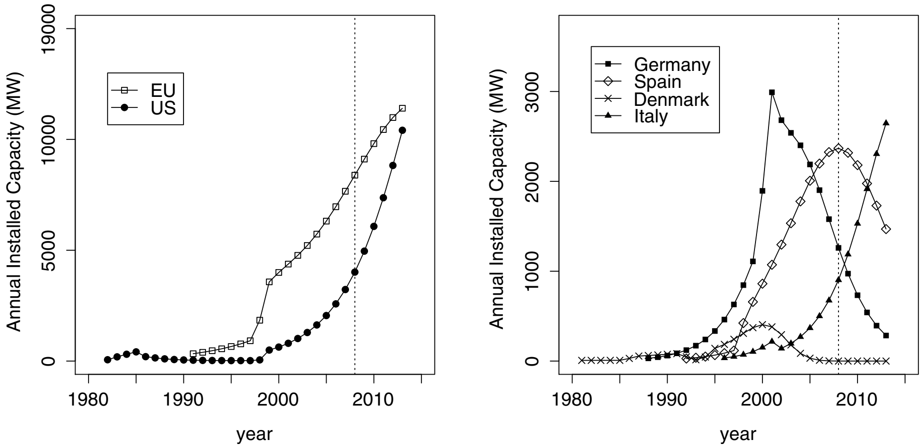

Fig. 2. Predicted life-cycles (points and solid lines), up to 2013, for Europe and the US (left panel), and for the leading European countries (right panel). The vertical line corresponds to 2008.

relative to Europe. The large gap is a result of the minor and less certain incentive schemes. Regarding the European countries analyzed, we can say that, while the life-cycle of the wind adoption process in Germany is approaching its final stage, the process in Spain is still in its middle stage. In Denmark, the change of the incentive scheme from the feed-in-law to the Green Certificate system in 2003 stopped the adoption process abruptly, leading the life-cycle of wind power technology to the very final stage. In Italy, the life-cycle is still at an early stage.

In the analysis of the forecasting accuracy, both on average and for the majority of the individual countries, the GBMs are ranked first in terms of performance for all of the accuracy measures (MAPE, MdAPE, and a revised version of MdRAE) and forecasting horizons (1 and 3 years ahead), outperforming the Bass, Logistic, and Gompertz models. Finally, 1- and 5-year-ahead forecasts with GBMs were provided. It is apparent that adoptions over the next five years will suffer a sharp fall relative to the last five years, especially in the US, Spain, and Germany, for which the decrease is predicted to be more than half.

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