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Short-term forecasts of the spread of wind power technology across countries

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Keywords: Comparative studies, Diffusion models, Electricity, Intervention analysis, Technology forecasting, Time series.

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1 Introduction

An enhanced sensibility with respect to environmental problems, such as alarming global warming and air pollution, and to energy problems, such as oil depletion, is spreading all over the world. The era of fossil fuels is declining and the new perspectives are not encouraging. The peak of oil in all the major oil-exporting countries (see, for instance, Guseo & Dalla Valle (2005) and Guseo et al. (2007)) is quite near, and it is well-known that, in spite of the increasingly sophisticated technological approaches to oil mining, the quantity of oil extracted is lower with respect to expectations and demand. Moreover, air pollution, greenhouse gases, and environmental damage caused by the use of fossil fuels for the production of energy and for other targets (for instance, the production of plastic matter) are becoming a serious threat to our health and environment. Energy production, by means of fossil fuels, induces negative externalities because it imposes social costs in increased health expenses, in reduced agricultural productivity, and in the worldwide global warming when carbon dioxide or other air pollutants are produced by burning. We can also include military costs to ensure access to oil, reclamation of polluted sites, and destruction of wild habitats.

In this scenario, new sources of energy that are both clean and cost-effective have to be promoted to maintain the same standard of living and to preserve the environment. Wind energy, in particular, is a kind of clean, inexhaustible, readily available energy with the advantage that this type of energy aids in the reduction of greenhouse gas emissions because wind energy does not produce any type of air pollution. Moreover, wind power has negligible fuel costs and low maintenance costs, which are low marginal cost and a high proportion of capital cost. The greater obstacle to the development of wind power technology is surely the availability of the wind. It stands to reason that windy places are more suitable than others to be exploited for this renewable energy technology. It was estimated that wind power available in the atmosphere is much greater than current world energy consumption. So, at least theoretically, wind power would be sufficient for our necessities even if, beyond the positioning of sites, other facets are being debated such as the transmission lines, the cost of site acquisition, the environmental impact of wind power structure, and the storage of energy produced in excess and not immediately used. With respect to the latter aspect, we point out that technological progress in this field has been very fast: we refer to wind turbine power, which has doubled in comparison to six years ago, and to storage capacity, which, though a crucial obstacle to the development of wind power, is becoming more and more efficient.

The increasing interest in wind power technology has encouraged the study of the dynamics of its adoption over years. Potential adopters are individuals who decide to support companies involved in wind projects, or to install small wind turbines for self-consumption of electricity (single home, farm, ranch, or business). Moreover, since this technology can be considered an innovation, because it is a new system of producing electricity, the wind power spread can be modelled inside a framework of diffusion of innovations. Meade & Islam (2006) highlight in their review 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 framework is appropriate here since it allows to distinguish explicitly between innovators and imitators. This characterization is important because wind power technology is not economically competitive; it is affected by the difficulties highlighted above, and since it requires a large amount of start-up capital, long-term returns are implied. Furthermore, the incentive policies passed by countries' local governments play an important role because they anticipate or delay the time of adoption of the technology. The Generalized Bass Model (GBM), introduced by Bass *et al.* (1994), seems to be suitable. Indeed, one of the peculiarities of this model is that it is possible to include, with respect to the standard version of the model, marketing-mix variables useful for separating external inputs from life-cycle behavior. In contrast to the current use of marketing-mix variables, such as price and advertisement, we use here incentive policies, modelled through shock functions as in Guseo & Dalla Valle (2005) and Guseo et al. (2007). This modelling allows to assess the strength of adopted policies and, in some ways, the effects of governments' decisions.

The aim of this paper is, then, to model the life-cycle of this renewable energy resource, depicting the dynamics that have characterized its growth and detecting possible interventions to improve its utilization. We analyzed the wind power adoption process, firstly, in the United States and in Europe and, secondly, in the leading European countries (Germany, Spain, Denmark, and Italy). In particular, we believe that the usual comparisons made between the United States and each of the European countries are misleading because these comparisons do not take into account the enormous difference in geographic size, that, in this context, appears to be quite relevant. For each country, incentive policies were detected in time and evaluated with respect to the intensity, highlighting the effects of different local laws. A forecasting accuracy analysis was carried out for each time series, comparing the Generalized Bass model with the Bass, Logistic, and Gompertz models in an out-of-sample test study with a rolling origin. Several accuracy measures – i.e., MAPE, MdAPE, and a revised version of MdRAE – were evaluated for short-term forecasting horizons (1 and 3 years ahead). Finally, taking into account the forecasting accuracy results, short-term forecasts were provided to predict the diffusion dynamics in the next few years.

In particular, Section 2 presents an overview of the data and Section 3 the main properties of the Generalized Bass model. Results are presented for Europe and the US in Section 4, and for the leading European countries in Section 5. Section 6 provides the forecasting accuracy results of the GBM, when compared with the Bass, the Logistic, and the Gompertz models. Short-term forecasts of GBMs for each region/country follow in Section 7 and conclusions in Section 8.

2 Overview of data

The data consist of yearly cumulative installed wind turbine capacity in megawatts until 2008 (Figure 1) for Europe, the US, and for the leading countries in Europe: Germany, Spain, Denmark, and Italy.

American data are available from 1981 ($n = 28$) and were available until 1998 from the AWEA Web site, and from 1999 from the U.S. Department of Energy Web site. Data for Europe ($n = 19$) were found from 1990 to 1996 and for 2008 on the EWEA Web site, and from 1997 to 2007 on the BP Web site. Whereas, for the European countries, except Italy, data were extracted from the Earth Policy Institute Web site until 2007 and from the EWEA Web site for 2008: the German time series starts in 1987 ($n = 22$), the Spanish in 1991 ($n = 18$), and the Danish in 1980 ($n = 29$). The Italian data ($n = 14$) begin in 1995 and were collected on the EWEA Web site, except from 2000 to 2007, for which the source is the EurObserv'ER.

The most striking features of Figure 1 (left panel) for the United States are a good starting in the adoption process in the first part of the time series, followed by stationary behavior in the middle, and a great propensity to installing wind power toward the latter years. In terms of equal geographic size, from 1995 Europe has invested in wind power more than the United States, and for 2008, the difference is approximately of 40 000 MW. Figure 1 (right panel) shows the diffusion process of wind power capacity for the analyzed European countries. A shared pattern consists of a significant acceleration of adoption after the technology startup; in particular, this acceleration has been stronger and had major impact for Germany and Spain, while the acceleration has been frozen for Denmark since 2000. Motivations and explanations for the accelerations and recessions in the behavior of the time series will be assessed in Sections 4 and 5.

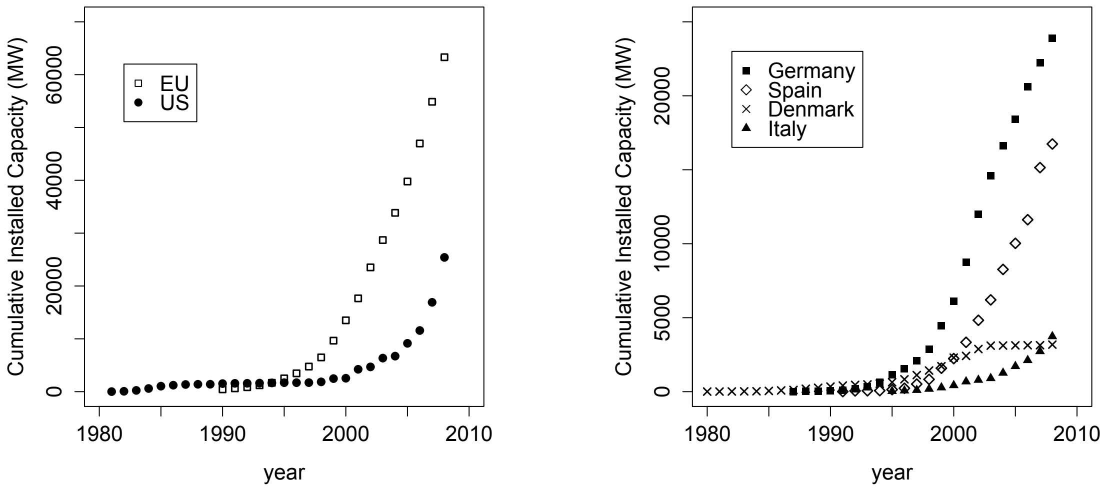


Figure 1: Cumulative installed capacity (megawatts) of wind power for Europe and the US (left panel), and for the leading European countries (right panel).

3 The Model

Innovations and their perception in a social system play a fundamental role in diffusion models. The timing and the interpersonal communications channels among individuals, who have different propensities toward adoption, characterize the growth function shape of an adoption process (Bass *et al.* , 2000).

Apropos, Bass (1969) introduces the Standard Bass model that differentiates between early adopters, who are influenced by external channels of communications (e.g., advertising, mass media), and later adopters, who are influenced by interpersonal communications (e.g., word-of-mouth). The Bass model has been widely used, for its properties and parameters' meaning, to model diffusion processes, since it was introduced in several research fields; see, for example, Mahajan et al. (1990), Takada & Jain (1991), Islam & Fiebig (2001), Talukdar et al. (2002), Sundqvist *et al.* (2005) and Hsiao et al. (2009). Bass *et al.* (1994) propose the Generalized Bass Model that outperforms the standard version because the Generalized Bass

Model allows the inclusion of marketing-mix variables, which are under the control of managers; this could be useful for aiding managers in planning strategic policies (Mahajan et al. , 2000). For wind power, managers are represented by countries' governments and the marketing-mix variables by the incentive policies (law updates included).

In forecasting 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 with limited data (Islam et al. , 2002). Hardie & Fader (1998), for example, mention the possibility of including covariate effects in a GBM, and Kumar & Krishnan (2002) propose an application of this method in a multinational diffusion setting. On the other hand, Guseo & Dalla Valle (2005) propose an alternative way of including external interventions in a GBM through, for example, exponential and rectangular functions. For wind power, we adopted the latter approach because it allows us to model stationarities and speed adoption variations, which are typical of processes strongly influenced by changes in incentive policies.

The Generalized Bass model can be included in a non-linear regressive framework:

$$w(t) = f(\underline{\beta}, t) + \epsilon(t) = z(t) + \epsilon(t), \tag{1}$$

where $w(t)$ represents the cumulative adoption data, $f(\underline{\beta}, t)$ is the deterministic component specified through cumulative functions $z(t)$ of adoption over time, $\underline{\beta}$ is the vector of parameters, and $\epsilon(t)$ is assumed to be a white noise process. To estimate the parameters of the model, we use a non-linear least squares estimation method following the algorithm of Levenberg-Marquardt (Seber & Wild , 1989).

The representation of the Generalized Bass model, introduced by Bass *et al.* (1994), is a first-order differential equation:

$$z'(t) = m\left(p + q\frac{z(t)}{m}\right)\left(1 - \frac{z(t)}{m}\right)x(t), \tag{2}$$

where m is the potential market, p and q are the parameters referred to the quota of innovators and imitators, respectively, and $x(t)$ is an integrable function that oscillates around 1. The latter allows the inclusion of exogenous variables that identify interventions of a political and economic nature, which are assumed to have effects on the diffusion process. The general closed form solution of Equation (2), under $z(0) = 0$, is

$$z(t) = m\frac{1 - e^{-(p+q)\int_0^t x(\tau)d\tau}}{1 + \frac{q}{p}e^{-(p+q)\int_0^t x(\tau)d\tau}} \qquad 0 \le t < +\infty. \tag{3}$$

Note that Equation (2) includes the Standard Bass model for $x(t) = 1$, while for $x(t)$ greater than 1, the adoption process is accelerated over time, and on the contrary, for $x(t)$ smaller than 1, the adoption process is delayed. It is important to underline that the intervention function $x(t)$ modifies only adoption time and neither the potential market nor the innovators and imitators parameters p and q. The intervention function $x(t)$ incorporates exogenous covariates, including, for example, political measures, economic local provisions, and so on.

Guseo & Dalla Valle (2005) proposed a specification of $x(t)$ that was useful for depicting and modelling strategic interventions that significantly modify the diffusion of energy products, e.g., oil and gas. A simple representation of $x(t)$ may be based on one *exponential* shock that identifies a locally intense impulse that progressively loses its effect. The mathematical form of the exponential shock is

$$x(t) = 1 + c_1 e^{b_1(t-a_1)} I_{[t \geq a_1]}, \tag{4}$$

where $I_{[h_1<t<h_2]}$ is a indicator function assuming value equal to 1 if the shock occurs in the interval $[h_1, h_2]$ and value equal to 0 otherwise, 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. The *rectangular* shock is another kind of impulse for intervention function $x(t)$ that identifies a perturbation whose effect stays unchanged over a bounded time interval:

$$x(t) = 1 + c_1 I_{[a_1 \leq t \leq b_1]} \tag{5}$$

where $[a_1, b_1]$ is the close interval in which a shock may occur, while c_1 identifies the intensity of the effect of the exogenous intervention and can assume both positive and negative values. This impulse begins at time, say, a_1 with a given intensity, keeps holding over the interval of length $(b_1 - a_1)$, and then suddenly disappears. A further kind of representation for $x(t)$ pertains to mixtures of different shocks, referring to particular situations in which a series of political interventions, signed at different times, have different effects on diffusion models. The mathematical representation of, for example, two successive shocks (exponential and rectangular) is the following:

$$x(t) = 1 + c_1 e^{b_1(t-a_1)} I_{[t \geq a_1]} + c_2 I_{[a_2 \leq t \leq b_2]}, \tag{6}$$

where the involved parameters are the same as the preceding examples. It is important to underline that Equation (6) is purely demonstrative and that any combination of impulses both in number and in typology is theoretically possible.

For diffusion processes, it is also possible to determine the asymptotic cumulative component of innovators, which it is not affected by $x(t)$, as a function of p and q (Guseo & Dalla Valle , 2005):

$$AQ(p, q) = \frac{p}{q} \ln\left(1 + \frac{q}{p}\right). \tag{7}$$

Ordinary diffusion processes are characterized by an innovator quota that is usually between 8% and 36%.

4 A comparison of Europe and the US

The Kyoto Protocol, entered into force on 16 February 2005, sets targets for the reduction of the greenhouse gas emissions. The production of electric energy through wind systems is one of the ways to respect Kyoto limits. For this reason, the countries that signed the Protocol started to promote incentives policies for the adoption of these new technologies. The US, although not a subscriber to the Protocol, is also committed in some way to creating renewable electric energy.

In this section, we propose a comparison of Europe and the US since, as discussed in Section 1, the potentiality of the US should be compared with a region of similar size and characteristics as Europe. Taking into account the visual impression of Figure 1, pointed out in Section 2, we perform for Europe a Generalized Bass Model (1) with Equation (3) for $f(\underline{\beta}, t)$ and Equation (4) for $x(t)$ (i.e., one exponential shock) while, for the US, model (1) with equation (3) for $f(\underline{\beta}, t)$ and Equation (6) for $x(t)$ (i.e., one exponential and one rectangular shock). Estimates, asymptotic standard errors, R^2, and asymptotic cumulative component of innovators $AQ(p, q)$ are provided in the first half of Table 1. Both models have very good fit ($R^2 = 0.9997$ for Europe and $R^2 = 0.9965$ for the US). Standard errors are sometimes rather high, but it is well known that, especially for short time series, in non-linear modelling, they can give only indicative information about estimate accuracy. We think the models are reliable, but they must be used for short-term forecasts (i.e., 5 years maximum) since diffusion processes need more past history to provide long-term forecasts. Moreover, in both regions, the asymptotic quota of innovators is particularly low with respect to the standards of ordinary diffusion processes, especially for the US. When incentives are released, the word-of-mouth effect powerfully dominates the behavior of investors, making this process characterized by a very low rate p of innovators and a high rate q of imitators.

For *Europe*, the exponential shock has been detected to be positive ($c_1 = 1.82$), arising around $(1990 + a_1) \approx 1999$, and its effect was absorbed in time ($b_1 = -0.42$). For Europe, 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 5, it agrees with a significant incentive policy passed by the Spanish government.

For the *US* model, the exponential shock has been detected 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 has been detected to be negative ($c_2 = -0.96$), arising around $(1981 + a_2) = 1986$ and ceasing around $(1981 + b_2) \approx 1999$. To understand the reasons that led to the identification of the two shocks, we outline the basic points of the American legislation of the renewable energy marketplace of the latter years. When wind power production was new, the Crude Oil Windfall Profits Tax Act (WPT) of 1980 was effective. It increased the energy tax credit of the Energy Tax Act of 1978 (ETA), and furthermore, these additional credits were extended from December 1982 to December 1985 for some renewable energy technologies, such as the wind power system. Investors probably believed in this clean way of producing electric energy, and this led to a rapid increase in production in those years. Unfortunately, in 1986, although the business energy tax credit was extended for some renewable energy systems, such as solar and geothermal, the wind power system was not included. In 1992, the Energy Policy Act established a production tax credit (PTC) that penalized the wind power system, with respect to solar and geothermal systems. Therefore, since 1986 the wind power system has not been economically supported by any significant energy tax, and the adoption process became stagnant, awaiting new incentives. Only in 1999 the Tax Relief Extension

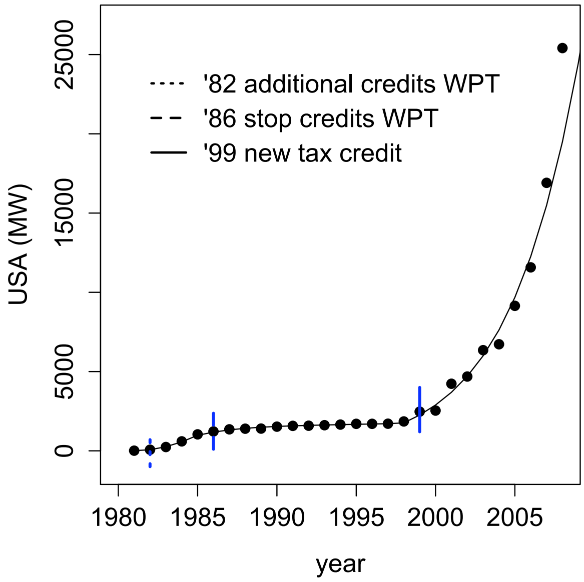
Table 1: Estimates and asymptotic standard errors (in brackets) for GBMs across series. Values of R^2 and $AQ(p,q)$ are also given.

	par.	Europe	US	Germany	Spain	Denmark	Italy
	m	269 692	290 163	27 212	32 187	3 159	33 183
		(223 211)	(359 491)	(711)	(19 395)	(25)	(103 556)
	p	0.0009	0.00003	0.0006	0.0006	0.002	0.0006
		(0.0006)	(0.00004)	(0.0002)	(0.0003)	(0.001)	(0.002)
	q	0.17	0.24	0.35	0.29	0.02	0.38
		(0.04)	(0.05)	(0.03)	(0.18)	(0.06)	(0.11)
	a1	8.63	1.49	13.73	7.15	14.71	6.98
		(0.31)	(0.005)	(0.28)	(1.74)	(0.56)	(1.15)
exp	b1	−0.42	−0.51	−1.12	−0.45	0.20	−0.16
		(0.17)	(0.02)	(0.68)	(0.77)	(0.07)	(0.29)
	c1	1.82	5.32	1.26	1.79	6.61	−0.55
		(0.44)	(0.002)	(0.52)	(1.08)	(12.20)	(0.23)
	a2		5.00			6.50	
			(0.001)			(1.49)	
rect	b2		17.92			12.44	
			(0.0006)			(1.10)	
	c2		−0.96			5.14	
			(0.01)			(6.96)	
	R^2	0.9997	0.9965	0.9995	0.9983	0.9989	0.9986
	$AQ(p,q)$	2.78%	0.11%	1.09%	1.28%	23.98%	1.02%

Act extended, for wind power, the PTC of 1992 until the end of 2001, and this enabled the wind power adoption process to start again. However, since then, only short-term PTC extensions have been passed, and consequently the adoption process has become a “boom and bust” cycle. In fact, since the end of 2001, credits were extended only in March 2002 for two more years, and the late renewal caused the adoption reduction occurred in 2002 (bust), with respect to 2001 (see Figure 2). In 2003, investors started to invest again (boom), while implementation of planned projects slowed down dramatically in 2004 due to, again, the late renewal of the PTC. Since 2004 major attention has been paid to renewing the PTC to control this “on-again/off-again” status, but only a long-term PTC will provide the industry with more stability. The two identified shocks seem to be the effect of policy choices on incentives: in particular, the exponential shock starts when WPT extended ETA tax credit 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 (see Figure 2).

A significant consequence of uncertainty in the American incentive release scheme is that there are fewer US innovators than in Europe. In particular, a boom-and-bust incentive policy cannot be perceived by investors as a strong will of the government

Figure 2: Points correspond to cumulative US wind power data (MW) and the solid line to the fitted GBM.



of pointing in the direction of renewable energies. In fact, in the wind power energy sector, an investor has to be willing to have a return of the investment even ten or fifteen years after the beginning of the financial venture, and this fact is clearly not very popular. Moreover, the next possible profits are reached in a context that is in continuous movement and that does not depend on the choice of a single investor but by a complex scenario based on technological progress, availability of resources, political regimes, choices of economic policy, environmental safeguards and so on. According to this preamble, investments in renewable energies can be considered a bet made by only a few brave investors, at least at the beginning of the process. The difference between the two diffusion processes is strikingly evident, and the US, if compared to Europe, is still at the beginning of the diffusion process. An aspect useful to justify, at least partially, the gap between the US and Europe is the awareness of the different incentives policies adopted in the US and in more than 25 countries in Europe. Nowadays, in Europe there are mainly two 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 allows the interconnection of renewable sources of generation with the electric-utility network and specifies a price that is paid for every kilowatt-hour produced; with RPS, utilities are required to purchase a percentage of the electricity generating capacity from renewable resources, and the produced electricity is often traded with the so-called Green Certificates. The first incentives system appears to be the most effective since the mentioned countries have produced more electricity than any other country. It is never very easy to convert one of the schemes from one country to another, but theoretically if there were favorable legislation and general acceptance, an incentive system such as the Feed-in Tariffs could be very successful, because it safeguards developers, owners, and financiers. The incentive policy in the US is quite different. To promote wind energy development, the US provides tax credits based on installed capital costs. From the beginning of 1990 in advance the tax credits were instead based uniquely on the sale of wind-generated electricity: this mechanism has eliminated from incentives small consumers willing to produce electricity for self-consumption. This questionable incentive policy that leads to a centralization of the technology in the hands of a few is used only in the US. Many American people and associations believe that Tax Credits should be converted into some form of Feed-in Tariffs to develop the wind adoption process as in Europe, and try to put pressure on the government on this topic.

5 European countries

In this section, we introduce the diffusion models estimated for some European countries. The intent is to understand at what stage is the spread of wind power and which are the incentives policies, for Germany, Spain, Denmark, and Italy, that produced an effect on adoption life-cycles.

Taking into account the visual impression of Figure 1, pointed out in Section 2, we perform for Germany, Spain, and Italy a Generalized Bass Model (1) with Equation (3) for $f(\underline{\beta}, t)$ and Equation (4) for $x(t)$ (i.e., one exponential shock) while, for Denmark, model (1) with equation (3) for $f(\underline{\beta}, t)$ and Equation (6) for $x(t)$ (i.e., one exponential and one rectangular shock). The second half of Table 1 shows the estimates, asymptotic standard errors, R^2, and asymptotic cumulative component of innovators $AQ(p, q)$.

For *Germany*, the exponential shock has a positive impact on the model ($c_1 = 1.26$); the shock's effect has been absorbed along time and is placed around $(1987 + a_1) \approx 2001$. Just in 2000, the Renewable Energy Sources Act came into force as a replacement for the Electricity Feed Law, encouraging the activation of many new wind power plants: henceforth, the process of diffusion of wind power technology became more intense and faster until now, when Germany is the world's largest user of wind power. Many features have determined the success of this law: priority for grid connection given to electricity produced from wind power, grid access in either distribution and transmission grid, and power dispatch.

For *Spain*, a positive exponential shock ($c_1 = 1.79$) has been detected arising around $(1991 + a_1) = 1998$, and its effect was absorbed in time ($b_1 = -0.45$). The exponential shock corresponds to the introduction in 1997 of the feed-in-law tariff, which was particularly beneficial for wind power. In 2007, the law was reformed, but it was published only at the end of May, creating uncertainty for investors. Current tariffs are less favorable if compared with the old system, but in 2007, we observed spectacular growth in the adoption process because the new legislation foresaw transitional arrangements for adoption in 2007. However, in 2008 the transitional arrangements for the first year of the new legislation were no longer available and the number of adoptions has been less than one-half compared to 2007.

For *Denmark*, a positive ($c_2 = 5.14$) rectangular shock arises around $(1980 + 6.5) \approx 1986$ and ends around $(1980 + 12.44) \approx 1992$. The exponential shock has been detected to be positive and of considerable impact ($c_1 = 6.61$), and is positioned around $(1980 + a_1) \approx 1995$. Denmark has shown a great sensibility toward the question of dependence on fossil fuels and, since the late 1970s and 1980s, has promoted a energy policy oriented toward the advertisement of renewable energy technologies. In particular, in 1984 government passed legislation that was favorable to wind turbines' owners, and the introduction of these incentives agrees with the beginning of the rectangular shock. The second decisive political action (feed-in-law) was introduced in 1992. The starting year of feed-in-law corresponds approximately with the beginning of the exponential positive shock that was estimated to be 1995. After this period, wind turbines' owners realized huge profits, and the government understood that it was not able to pay out ever-increasing money and utilities became private companies. All these contemporary circumstances led to the adoption in 2003 of a Green Certificates policy that is also preferred by the European Commission. The new incentive policy completely discouraged Danish investors.

For *Italy*, a negative ($c1 = -0.55$) exponential shock has been detected at around $(1995 + a1) = 2002$, and its effect has been absorbed in time ($b1 = -0.16$). The exponential shock corresponds to the introduction of the Green Certificates, and as happened in Denmark, this type of incentive has had a negative impact on the adoption process, which nevertheless has been absorbed in time.

6 Model validation

In this section, we assess the forecasting accuracy of the GBMs proposed in Sections 4 and 5. GBMs were compared, in terms of performances, apart from the BM model, with a Logistic model:

$$z(t) = \frac{m}{1 + c\,\exp(-qt)} \tag{8}$$

and with a Gompertz model

$$z(t) = m \exp(-c \exp(-qt)), \tag{9}$$

where $z(t)$ is the cumulative number of adoptions at time t (to be replaced in the framework of Equation (1)), m the potential market, c and q are parameters, and in particular q is related to the growth speed.

In particular, we check the forecasting performances of each model taken into account through a set of out-of-sample tests that, combined with the goodness of fit of data (in-sample tests) of Sections 4 and 5, can furnish a rating about selected models. The out-of-sample approach consists of splitting data into two parts: models are implemented in the fit period and are checked in the test period. The absolute value differences between the model forecasts for each step ahead and the observations not used in developing the model are the forecast errors. In a rolling-origin evaluation, we fixed the origin t of the forecasting period in 2003 and made forecasts for the next five years until 2008. By rolling t one year ahead, 2004 is included in the fit period, and we forecast four years ahead again until 2008. This procedure is iterated until $t = 2007$, where the last forecast for 2008 is produced (Tashman , 2000). The choice of $t = 2003$ is principally due to the need for at least three forecasts for every step-ahead: in this case, we have five forecasts for 1-year-ahead, four for 2-year-ahead and three for 3-year-ahead. Moreover, we strongly believe that forecasts over long periods are not very reliable because of the nature of renewable energy diffusion data, which heavily depends on periodic policy choices.

Forecast accuracy is assessed with multiple measures (Armstrong & Collopy (1992) and Makridakis et al. (1982)) for two single forecasting horizons: 1-year and 3-year-ahead. We used the square root of the Mean Square Error (RMSE) and the Absolute Percentage Error (APE), where the latter was summarized for each forecasting horizon by the mean (MAPE) and the median operator (MdAPE). We also used an adjustment of the Relative Absolute Error (RAE), proposed by Armstrong & Collopy (1992), for cumulative functions: the random walk is intended as a constant linear growth over years. Armstrong & Collopy (1992) defined the RAE as follows:

$$RAE_{m,t+h} = \frac{|F_{m,t+h} - O_{t+h}|}{|F_{rw,t+h} - O_{t+h}|}, \tag{10}$$

where m represents 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 the forecasting horizon h for model m, and $F_{rw,t+h}$ the correspondent predicted values for the random walk. The idea of a random walk intended as a constant function that assumes over years the value observed at origin t is translated here in a linear function, which grows every year of the increased value observed in t:

$$F_{rw,t+h} = O_t + h\,(O_t - O_{t-1}). \tag{11}$$

The proposed RAE was summarized for each forecasting horizon by the mean (MRAE) and the median operator (MdRAE). Moreover, instead of comparing methods for single forecasting horizons, we also summarized the RAE across different forecasting horizons, by a cumulative sum, giving rise to the CumRAE. Finally, we average all the measures across the six series.

Table 2: 1 and 3-year-ahead forecasting accuracy for the GBM, BM, Logistic, and Gompertz models across countries.

	MAPE				MdAPE				MdRAE			
1-ahead	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-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

It is understood that, a priori, no accuracy measure can be considered better with respect to another (Armstrong & Collopy , 1992); an eventual ranking has to be considered, but it should be referred to a single criterion such as, for example, reliability, outlier protection, construct validity, and so on. To select among forecasting models, we have chosen three accuracy measures, MAPE, MdAPE, and MdRAE, that altogether are reliable also when few sets of series are available and offer protection against outliers. Anyway, all accuracy measures used in the work and not reported here lead to the same conclusion. Note that, although frequently exploited in empirical studies, the RMSE does not appear in the table because of the RMSE's not unit-free nature: we believe (see, among others, Armstrong (2002)) that this aspect could strongly weigh in a study of countries presenting quite different levels of potential markets.

Table 2 reports the forecasting accuracy measures for each country, model, and forecasting horizon. MAPE, MdAPE, and MdRAE are also averaged across countries with the mean operator, and it is revealed that GBMs have the lowest forecasting error over accuracy measures, models, and forecasting horizons. It is apparent that the differences in numeric terms are sizable, especially for MdRAE for 1-year-ahead forecasting horizon. Moreover, looking at the averaged accuracy measures, we can give a ranking among the remaining models: with respect to MAPE and MdAPE, Gompertz comes first, and the Logistic and Bass models follow with small differences, while with respect to MdRAE, the ranking is diametrically opposite. This ranking, in the table, is not always observed for each country. In fact, looking at the figures in boldface in Table 2, we can see that for Spain, for example, the Gompertz model is always the best for 3-year-ahead and the differences, in terms of accuracy, with respect to the other models are significant. Poles apart, the best model for the Danish case is the GBM for both the forecasting horizons, and the discrepancies with the other models are outsize. An intermediate case is that of Germany, which does not appear to have a benchmark model over measures and over forecasting horizons.

Makridakis & Hibon (2000) highlight 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 2 gives enough evidence that GBM, on average, and also in the majority of the country time series, outperforms the remaining simpler models, and the GBM is first in the ranking of performance for all the accuracy measures. In fact, the wind power diffusion process is strongly affected by incentive policies, and consequently, it is difficult to model with methods that do not allow for stationarities or sudden changes in growth.

7 Short-term forecasts

In Section 6, we found that GBMs are the most reliable method across different scenarios. For this reason, we present here short-term forecasts with respect to GBMs for each time series. For Europe, the US, Germany, Spain, Denmark, and Italy, Figure 3 shows the forecasted growth of wind power capacity until 2015, while Figure 4 shows the corresponding predicted life-cycles. For Europe in general, 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 slope of curves in Figure 3, it arises 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 chance of producing electricity from wind, and this great potentiality should be exploited. Among the European countries, with respect to the cumulative MW installed, Germany and Spain stand out as the leaders. However, Figure 4 highlights that while Germany seems to be at the conclusive stage of the life-cycle, Spain is still encouraging the installation of wind power turbines. For Germany, this fact principally depends on the expectations of the revision of the Renewable Energy Sources Act passed in 2008 in order to adapt tariffs to new market conditions and technological developments. German investors are probably slowing down their investments in the wind energy sector, waiting for new and more favorable conditions.

For each time series, Table 3 shows the observed increase rate of MW installed for 2008 (5-year-behind), and the expected MW installed with the corresponding increase rate for 2009 (1-year-ahead) and for 2013 (5-year-ahead). Comparing the predicted 5-year-ahead with the observed 5-year-behind increase rates, we can say that the adoption process will suffer a sharp fall, especially for the US, Spain, and Germany, for which the decrease is predicted to be more than half. This should be the consequence of incentive policies that are becoming less attractive than in the past. Indeed, the intention of governments is in general to gradually reduce the incentives until the technology becomes economically competitive. One-year-ahead forecasts emphasize the increasing disinterest of Germany and Denmark in wind power and the growing interest of Italy. The corresponding increased rate of the US for 2009 is not provided since the large number of adoptions occurred in 2008, underestimated by the model, produces an inconsistent forecast.

Table 3: Observed increase rate of MW installed for 2008 (5-year-behind with respect to 2003) for Europe, the US, Germany, Spain, Denmark, and Italy; corresponding expected MW installed and increase rate for 2009 (1-year-ahead) and for 2013 (5-year-ahead).

	2008 5-year-behind	2009 1-year-ahead		2013 5-year-ahead	
Country	%	MW	%	MW	%
Europe	121%	72 310	14%	114 962	82%
US	300%	24 459	$*$	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%

Note: * not reliable for 2009.

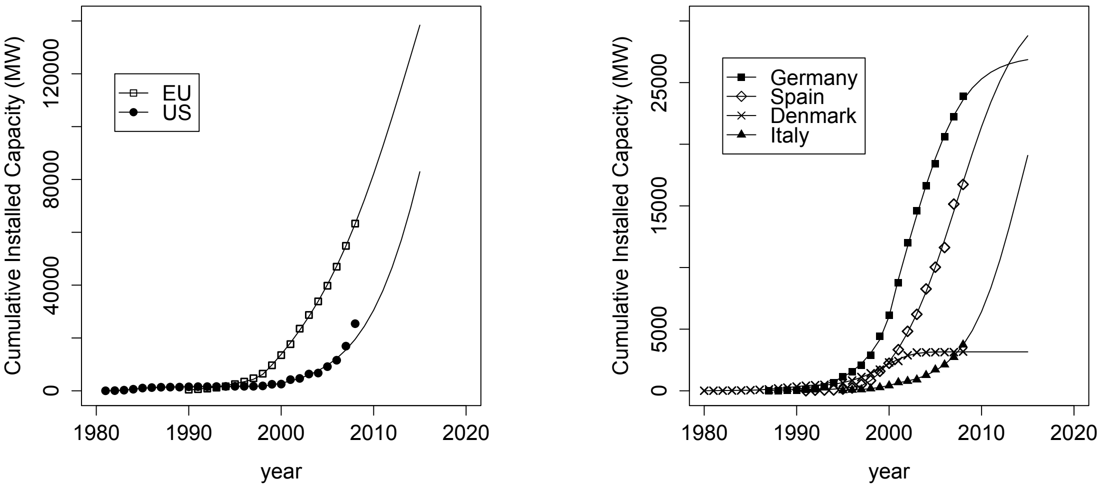


Figure 3: Short-term forecasts (lines), up to 2015, for Europe and the US (left panel), and for the leading European countries (right panel). Points correspond to observations.

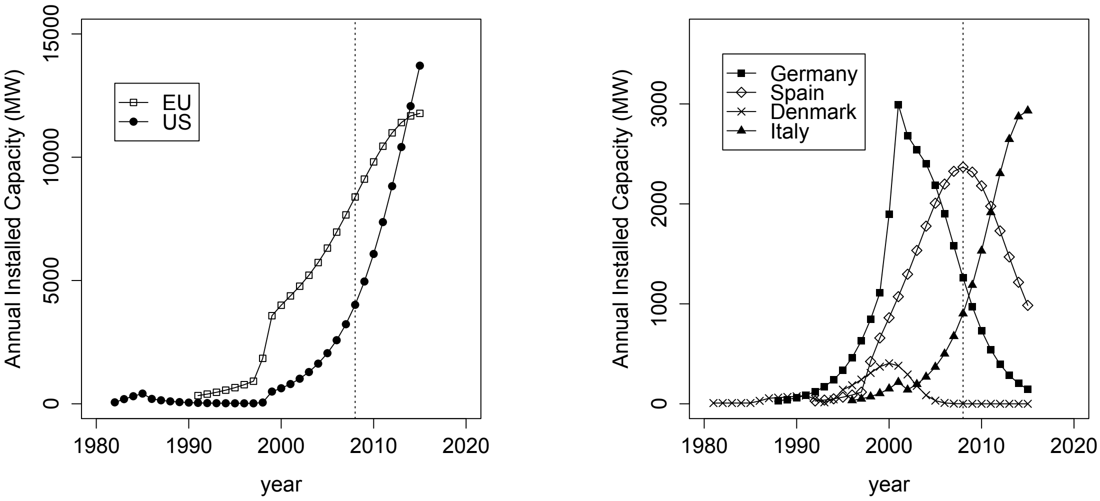


Figure 4: Predicted life-cycle (points and lines), up to 2015, for Europe and the US (left panel), and for the leading European countries (right panel). Vertical bar corresponds to 2008.

8 Conclusions

This paper presents an analysis of the diffusion of wind power technology in Europe, in the US, and in some leading European countries (Germany, Spain, Denmark, and

Italy). Since wind power technology appears to be an innovation strongly characterized by political and legislative interventions to support its spread, we believe is that the GBM is appropriate because it allows the inclusion of the effect of external interventions that significantly modify the diffusion pattern. Indeed, for each time series, the effects of local incentive policies were included in the performed Generalized Bass models through exponential and rectangular shock functions.

In the analysis of forecasting accuracy, the GBMs were compared with the Bass, Logistic, and Gompertz models in the frame of out-of-sample tests with a rolling origin. This method allowed several accuracy measures to be evaluated, among which MAPE, MdAPE, and a revised version of MdRAE, for short-term forecasting horizons (one and three years ahead). The analysis gives enough evidence that the GBM class, on average, and also in the majority of the country time series, outperforms the remaining models, and it is first in the ranking of performance for all the accuracy measures and forecasting horizons. Finally, taking into account the forecasting accuracy results, 1-year-ahead and 5-year-ahead forecasts are provided. It arises that, with respect to the last five years, the adoptions in the next five years will suffer a sharp fall, especially for the US, Spain, and Germany, for which the decrease is predicted to be more than half.

The use of the intervention functions becomes particularly worthwhile because they highlight the apparent relationship between the economic advantages, derived by incentive tariffs, and the increased number of adoptions, in terms of onset time, strength, and duration. With respect to the US, two different interventions have been detected: the first catches the effect of those additional credits extended by the government between 1982 and 1985, while the second shows the effect of the exclusion of wind power from the incentive device until 1998. By comparing the US with Europe, it arises that the US has still a great potentiality in producing electric energy from wind power and that the large gap with Europe depends heavily on the type of adopted incentive policies (for example, in the US contributions are not planned for the self-consumption of small consumers) and from the short-term incentive scheme. Regarding the analyzed European countries, we can say that, while the life-cycle of the wind adoption process in Germany is approaching the final stage, in Spain the process is still at a middle stage, peaking in 2008. The attention to wind power, paid by the latter country, started in 1997 with a particularly beneficial feed-in-law and it is still significant even though the law was reformed in 2007 with less favorable tariffs. Denmark is a brilliant example of the effects of government choices on incentive policy. It is a country that believed in supporting this kind of renewable energy since the 1980s and the feed-in-tariff system of the 1990s makes the wind adoption process booming. However, in 2003 the Green Certificate system passed, and the effect has been of abruptly stopping the adoption process, leading the life-cycle of wind power technology to the very final stage. Italy has a short tradition in wind power technology, although the country has windy areas. The Green Certificate system was approved in 2002, causing a stop in the adoption process. With this incentive policy, the life-cycle of wind power technology is estimated to be still at an early stage.

From this analysis, it also emerges that the asymptotic quota of innovators is low across all countries. This fact sustains the idea that investments in wind power, and in general in renewable energy systems, are perceived as risky, and wide adoption requires ongoing and focused support by local governments. In conclusion, the wind power scenario described by our models is well-drawn and detects that less favorable tariffs lead to an abrupt decrease of the adoption process. If governments strongly believe in renewable energies through appropriate incentive policies and long-term tariffs, the propensity to invest in clean energy should increase; consequently, the dependency on fossil fuels should be reduced, and new job opportunities in the Green Economy could contribute to get through the international crisis.

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