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Market pull instruments and the development of wind power in Europe: a counterfactual analysis.

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Abstract

Renewable energy technologies are called to play a crucial role in the reduction of greenhouse gas emissions. Since most of these technologies are immature, public policies provide for two types of support: technology push and market pull. The latter aims at creating demand for new technologies and at stimulating their diffusion. Nevertheless, due to the complex self-sustained dynamics of diffusion it is hard to determine whether newly installed capacities are imputable to the impulse effect of instruments at the beginning of the diffusion process or to the current support. The paper addresses this problem. A micro-founded model of technology diffusion is built to estimate the impact of the yearly average Return-on-Investment (RoI) on the yearly count of commissioned wind farms in six European countries over the last decade. A counter-factual analysis is carried out to assess the impact of policy instruments on the RoI and, indirectly, on diffusion.

1 Introduction.

In November 2014, the European Union has reaffirmed its ambition to produce 27% of its electricity from renewable sources by 2030. As most renewable energy technologies are not yet mature, increasing their share in the energy mix needs support from public authorities. Indeed, well before the establishment of the European Union Emission Trading Scheme (EU ETS) in 2005, several European countries had already taken the initiative to implement national policies to support the development of renewable energies. They were motivated by both global warming issues and national-specific issues, such as nuclear phase-out and energy independence. In the late 2000s the bulk of European countries had implemented public policies dedicated to the promotion of renewable energies [21]. Among these policies, there is a clear predominance of the market pull approach over the technology push alternative

[24]. The former aims at stimulating the deployment of new renewable energy generation capacities whereas the latter targets the development of innovative solutions. Among renewable energy technologies, onshore wind power became a symbol of national ambitions and is frequently considered as one of the major sources of energy for the future. Now that electricity produced with onshore wind power is close to grid parity after years of public support, more attention is being paid to the balance between environmental gains on the one hand and the cost of support borne by society on the other hand.

This paper contributes to this trend by providing a counterfactual analysis of the impact of market pull policy instruments on the commissioning of wind farms in six European countries (Germany, Denmark, Italy, Spain, Portugal and France). By contrast with the burgeoning literature that analyses the drivers of the development of renewable energy generation capacities with *ad hoc* econometric models ([16]; [17] and [11]), such a counterfactual analysis relies on a structural model of the commissioning of wind farms. Counterfactual analysis is a key concept for the *ex post* analysis of public policies, either to characterise what the business as usual scenario would have been in the absence of the policy or, conversely, to identify what the situation could have been if a given policy had been implemented. For instance, Hamilton, Ruta and Tajibaeva [9] conduct a counterfactual analysis to determine how much produced capital would resource abundant countries have today if they had actually followed the Hartwick rule over the last three decades.

Our counterfactual analysis proceeds in three steps. First, a micro-founded diffusion model of new technologies is developed. The model builds on the work of Kemp [13] who proposed to model the diffusion pathway of a new technology by representing the investment decision at the individual level. His approach sharply contrasts with the usual holistic approach that dates back to the seminal works on technology diffusion of Griliches [7] and Mansfield [15]. In the present paper, the investment is more specifically triggered by the expected return-on-investment (RoI) of a typical wind farm which is referred to as the benchmark value of the RoI. This benchmark value has two components. The first component is the intrinsic RoI (IR) that would accrue from an isolated site. The second component is an additional RoI that results from non-technological learning (i.e. learning from the experience of sites already developed). Differences in climatic conditions or site accessibility, among others, generate heterogeneity across the levels of RoI reached by actual sites. A distribution of actual values of the RoI around the benchmark value (the expected RoI) is thus introduced to capture this heterogeneity. The micro-founded version of the diffusion model proposed in the paper exhibits several interesting and realistic properties: i) the need for a public support to impulse the technology diffusion in the case every wind site is unprofitable; ii) the possibility for the diffusion process to be stopped before the full deployment is reached; ii) the role of the variations of the RoI from year to year and iv) the interplay of two distinct channels of learning (technological learning and non-technological learning).

Second, we describe the methodology adopted to compute the intrinsic component (IR) of the benchmark value of the RoI. This indicator of the profitability is affected by several market-pull policy instruments. Two families of instruments are more specifically distinguished: revenue improving instruments on the one hand and cost alleviating instruments on the other hand. Time series of IR are computed for the six countries. They are sensitive to national policies put in place to support the development of wind power farms, to the dynamics of the cost of wind power technology and to

national economic conditions.

Third, we use yearly data, at the country level, on commissioning of wind power farms to calibrate the diffusion model. The counterfactual analysis then builds on the causal relation between the dynamics of the benchmark RoI and the commissioning of new sites. More precisely, the observed values of IR are replaced by the counterfactual values that would have prevailed in the absence of a given policy instruments in order to generate the counterfactual commissioning of new farms. The results of the counterfactual analysis suggest that up to one third of the new sites commissioned during the last decade would have not been developed without the different policy instruments that supported revenues from wind farms. The figure falls to more or less one percent when considering the impact of policy instruments that aimed at alleviating investment and/or operating costs.

The methods used in this paper are presented in section 2. Subsection 2.1 details the micro-founded diffusion model. The profitability index and its links with the policy support instruments are presented in subsection 2.2. Subsection 2.3 explains how the model is calibrated. Section 3 analyzes the results of the model. In subsection 3.1, the counter-factual analysis of the profitability index is emphasized. Then, subsection 3.2 exposes the counter-factual study of the impact of revenue improving instruments on diffusion. Subsection 3.3 presents a similar study for cost alleviating instruments. Finally, section 4 concludes.

2 Methods.

In this section, a micro-founded model of technology diffusion is presented and the strengths of this approach, compared to the usual holistic approach, are emphasized. Indeed, the micro-founded model has relevant properties that provide a better representation of the diffusion process. The micro-foundation relies on the return-of-investment (RoI) of a typical wind site as a trigger of the investment decision. The retained formula and the role of support instruments on IR are then presented, so as the data and the assumptions made for the computation of times series of IR. The model is then calibrated, with regards of the intrinsic RoI historical values in the six countries. Calibration is intended to fit, as good as possible, the observed time path of the commissioning of wind farms.

2.1 The micro-founded diffusion model.

2.1.1 From holistic modeling to micro-founded modeling of technology diffusion.

The empirical analysis of the diffusion of a new technology found its origins in the pioneering work of Griliches [7] and Mansfield [15]. Originally, it was intended to formally reproduce the S-shaped time path of the rate of diffusion typically observed for many technologies. This analysis is usually said to be holistic as it provides an aggregated representation of individual decisions that are not explicitly analyzed but are assumed to interact through the transmission of information and feedback. The term "epidemiological" is sometimes used in place of the term "holistic" in reference to the dissemination of infectious diseases which also follows an S-shaped curve. If the role of economic and financial incentives was initially disregarded, some authors have sought to remedy to this weakness (see e.g. [5]; [1] and

[2]; [8]). Usha Rao and Kishore [23] propose a survey of applications of this approach to the case of renewable energy technologies. The approach, however, remains devoid of an explicit representation of a process of rational economic decision.

The micro-founded approach to the diffusion of onshore wind power capacities proposed in this article is inspired by the work of Kemp [13], although it was on a different technology. Unlike the holistic approach, the proposed model details the investment decision at the wind farm level. The decision is assumed to rely on a positive profitability, as measured by the RoI, of investing. However, for similar economic conditions and similar cumulative installed capacities, individual projects remain heterogeneous in terms of profitability. This is captured by a distribution of individual levels of the RoI around an expected value that is affected by economic conditions and, among them, different policy instruments to support onshore wind power, but it is also affected by a learning effect. Contrary to the holistic approach, economic incentives and learning are thus tightly linked in the micro-founded model.

2.1.2 Model setting

The model considers the decision of investing at the site level. A country is characterized by a set of sites $n \in \{1, ..., N_{tot}\}$ where N_{tot} stands for the total number of sites. Each site is initially a candidate for a new wind farm. N_t denotes the number of sites that have been developed at time t. Once a site has been developed, the corresponding wind farm operates until a predefined end of life. The decision to develop a site is driven by economic incentives that are common to all sites and are synthesized by the benchmark level of total RoI, μ_t . This benchmark has two components. The first component is the intrinsic RoI denoted by IR_t . It measures the RoI for a reference wind farm, in the absence of learning from sites already developed. Note that we do not constrain the benchmark level of the RoI to be the average return over the whole population of sites. This point will be made more explicit when presenting the calibration of the model. The actual RoI benefits from learning about how to deal with specific local conditions. This second, contextual, component of the RoI is captured by the second term of μ_t and increases proportionally to the share N_{t-1}/N_{tot} of sites already developed. Consequently, μ_t may be written as

$$\mu_t = IR_t + \theta \frac{N_{t-1}}{N_{tot}}.$$
(1)

Where *theta* is positive and represents the coefficient of non-technical learning. Nevertheless, the heterogeneity of sites, due to local peculiarities in terms of meteorological conditions and in terms of accessibility for instance, implies that the RoI fluctuates from one site to another one. In order to capture the heterogeneity of sites without having to collect detailed information site by site, we consider that the RoIs R over the whole population follow a two parameters distribution with a partial density function $f(R; \mu_t, \sigma)$ where μ_t plays the role of a position parameter and σ is the standard deviation. The associated cumulative density function is denoted $F(R; \mu_t, \sigma)$. Figure 1 shows such a distribution.

At a given time t, all sites with a positive RoI R are developed (or have been previously developed).



Figure 1: RoI and the Micro-foundations of diffusion dynamics.

Thus, the proportion N_t/N_{tot} of sites developed at time t is the surface $1 - F(0; \mu_t, \sigma)$ on the right of zero and below the curve representing the density function. If at time t = 0 the density function is null for all positive values of R, the diffusion of wind power can not start. For diffusion to start, it is required that the intrinsic component, IR_t , of the RoI increases. Such an increase may be due either to economic conditions that naturally improve (a higher price of electricity or a reduced generation cost resulting from innovation, for instance) or to public support. At time t, the additional proportion $(N_t - N_{t-1})/N_{tot}$ of sites developed generates a learning effect that results in a higher average total RoI at time t + 1. Ceteris paribus, the higher value of μ_{t+1} compared to μ_t induces a translation of the distribution of R to the right. This effect can be either strengthened or weakened by a change in the intrinsic component of the total return so that the magnitude of the net translation is given by $\Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}}$ with $\Delta IR_{t+1} = IR_{t+1} - IR_t$ and $\Delta N_t = N_t - N_{t-1}$. In case of a negative value of $\Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}}$, the diffusion process stops and will not restart until ΔIR_{t+1} takes a positive value. The dynamics of the development of sites is formally described by the following equation.

$$\frac{\Delta N_{t+1}}{N_{tot}} = \begin{cases} F\left(\Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}}; \mu_t, \sigma\right) - F\left(0; \mu_t, \sigma\right) & \text{if } \Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}} > 0\\ 0 & \text{if } \Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}} \le 0 \end{cases}$$
(2)

This dynamics entails several properties of the diffusion process that make it appealing compared to the holistic approach.

2.1.3 Properties of the diffusion process

As already stressed, a first interesting feature of the dynamics of diffusion described by (2) is that, if the RoI is initially negative for all sites, diffusion needs public support to start. Another interesting feature is that the diffusion can stop before full development, i.e. before $N_t = N_{tot}$. This arises when there is a combination of two elements: ΔIR_{t+1} is negative and $\frac{\Delta N_t}{N_{tot}}$ was small. The first element results from a deterioration of economic conditions, the rise of the price of raw materials used to construct wind turbines or the lowering of public support for instance. The second element may arise from either previous bad economic conditions or, more importantly, from the shape of the distribution of the RoI. Indeed, when many sites have already been developed, the remaining sites have their RoI on the left tail of the distribution represented in Figure 1. Given that the distribution is single peaked, the further they are on the left, the thicker is the tail and, consequently, the smaller is the proportion of new sites developed for a given translation $\Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}}$ of the distribution to the right. It follows that the diffusion process is more likely to be stopped due to a decrease in IR_t when many sites have already been developed. This sharply contrasts with the holistic approach that is not able to explain why the diffusion process can stop before being completed.

Another feature that substantially distinguishes the micro-founded model of diffusion from holistic models is that the dynamics of the proportion of sites developed is as much sensitive to the variations of economic incentives than to their absolute level. The absolute level of economic incentives is crucial to determine the proportion of sites $1 - F(0; \mu_t, \sigma)$ developed at a given date t. As already mentioned above, the current level of economic incentives is captured by μ_t as defined in (1) which, in turn, is a key position parameter of the distribution of the RoI. μ_t also appears in (2) but, even if it takes a high value, it can not generate the development of additional sites, unless $\Delta IR_{t+1} + \theta \frac{\Delta N_t}{N_{tot}}$ is positive. This property is of importance to understand the results of the counterfactual analysis of the impact of public support. More specifically, if the benchmark scenario corresponds to a situation where public support has decreased over the period of study and this decrease is responsible for much of the global decrease of μ_t , then it may be the case that suppressing the support once in all at the beginning of the period would have had a positive impact on the development of new sites compared to the benchmark.

Last but not least, the are two channels for learning in the micro-founded model proposed in the article. The first one is the direct effect of $\frac{N_{t-1}}{N_{tot}}$ on μ_t . It captures non technological learning, such as a better knowledge of, and control on, the required administrative process to build a wind farm or a better understanding of local meteorological conditions. The second effect is indirect and works through the dynamics of the average intrinsic RoI: IR_t . Indeed, *ceteris paribus*, IR_t increases due, for instance, to the decrease of the cost of equipments that results from the traditional learning curve. In other words, the technological learning is treated as exogenous. Mercure et al. [18], for instance, propose a micro-founded model close to the one presented in this article to explain substitution between technologies to produce electricity, but they focus on technological learning only. More specifically, they assume that investment decisions are based on the Levelized Cost of Energy (LCOE), which is a questionable assumption as discussed latter on in this paper, and that the dynamics comes exclusively from the decrease of the cost of equipments that results from the cumulative production of these equipments.

2.2 Policy instruments and the profitability index.

2.2.1 Renewable energy development and the link with the RoI: a short literature review.

For the purpose of modeling, using a single criteria to trigger investment in new generation capacity is a meaningful alternative to the traditional optimization led decision process. As said above, Mercure et al. [18] develop a model of the electricity sector, driven by innovation, where investors make their decision relative to the LCoE of the different generation technologies included in the model. In order to gain realism, the authors apply a probabilistic distribution to these LCoEs, representative of the geographical heterogeneity. However, using the LCoE to approximate the competitiveness of renewable energy power plants and the investment decisions has limits. As emphasized by Joskow [12], the LCoE is a flaw metric that does not take into account the time profile of energy generation and the impact of its intermittency on the market revenue of producers. According to the same author, an alternative is to consider the expected profitability of power plants. In this vein, several studies have been realized using measures of the expected profitability of renewable power plants. We focus on the studies linking profitability and policy instruments supporting renewable energy. Mir-Artigues and del Río [19] highlight the possibility to encompass several economic instruments by using the RoI. They review all the combinations of three types of instruments (revenue improving instruments, investment subsidies and low rate loans) that lead to the same level of RoI. Profitability metrics also make it possible to assess the changes in the design of an instrument. This is done in [6] and [10]. While the former does not build the bridge between the RoI of renewable energy power plants (more precisely, solar power plants in the paper) and the deployment of additional capacities, the latter does. In [10] the Net Present Value (NPV) of total production of a power plant is included in an econometric analysis. In our view, it is a first step to improve our understanding of the determinants of the investment in renewable energy power plants. Jenner et al. [11] estimate a fixed effects model based on the calculation of the RoI of two technologies: solar photovoltaic and onshore wind. By doing so, they estimate the effects of the revenue improving instruments in 26 countries. This study suggests several possible ways of improvement. First, it focuses on revenue improving instruments leaving aside the role of the cost alleviating instruments. Second, yearly LCoE are estimated with help of learning curves, hence assuming implicitly a steady decrease contrasting with the observed data [36].

2.2.2 How do policy instruments impact *IR*?

The following formula is used to compute the intrinsic RoI index of a cohort of producers¹ at time t, IR_t :

$$IR_{Cohort}^{Country} = \frac{\sum_{t=0}^{T} \frac{(P_t Q_t) - (IC_t Cap + O\&M_t Q_t)}{(1+a)^t} - \frac{DC_T}{(1+a)^T}}{\sum_{t=0}^{T} \frac{(IC_t Cap + O\&M_t Q_t)}{(1+a)^t} + \frac{DC_T}{(1+a)^T}}.$$
(3)

Where T is the power plant lifetime, P_t the price at which the electricity is sold at year t, Q_t

 $^{^{1}}$ In the remainder of this article, a cohort of producers will represent all the producers that enter the market the same year, thus reacting to the same economic context.

the generated output, IC_t the investment cost (spread over the first years depending on the loan conditions), Cap the installed power, $O\&M_t$ the operation and maintenance costs and DC_T the decommissioning cost (also spread in the last years of the power plant). In the scope of this analysis, the main strength of IR is to synthesize all market pull instruments that aim at triggering investment in renewable energy power plants. Table 1 presents the evolutions of support policies in favor of onshore wind power in the six countries analyzed here during the corresponding time periods. A more detailed version of this table is given in Appendix A. United-Kingdom is not included in the analysis despite its important installed wind power capacity because the main support scheme in the United-Kingdom were Renewable Obligations, a green certificates system. More specifically, in order to be covered against price uncertainty on the market of certificates, the bulk of renewable energy producers asked for bilateral long-term contracts. The counterpart for risk hedging is that the electricity suppliers captured a significant share of the certificate's price according to [30]. As we do not have access to the characteristics of the contracts, the analysis would be subject to a substantial bias in the case of United-Kingdom. In this article, a distinction is made between two types of market pull instruments. Instruments supporting the revenue part of IR are called *revenue improving* whereas instruments reducing the cost part of IR are said to be cost alleviating. Within these two families there are several instruments. Revenue improving instruments included in the present analysis are:

- *Feed-in Tariff* (FiT): the most frequently used policy instrument for promoting renewable energy. It makes it compulsory for the system operator(s) to buy each kWh of renewable electricity at a fixed rate, independently of market signals. The tariffs are defined for a given period and thus make investments almost riskless.
- *Feed-in Premium* (FiP): an alternative to the previous instrument. The principle is the same except that producers receive a fixed premium on top of the market price. Hence the total payment varies with the price of electricity and investment bear some risk.
- *Tradable Green Certificates* (TGC): a quantity-based instrument for renewable energy deployment. It requires electricity suppliers to supply a certain amount of renewable electricity. In order to demonstrate that they have complied with quotas electricity suppliers must present the corresponding quantity of certificates. For this purpose and for the sake of flexibility, a green certificates market is established, its price being the support to renewable electricity producers (in addition to revenues from the sale of electricity on the gross market).

Cost alleviating instruments included in the intrinsic return are:

- *Investment subsidy*: a reduction of the investment cost. It may cover all or parts of the investment costs (i.e. the turbine, the civil work, etc.).
- *Dedicated loan*: a guarantee of preferential funding conditions for renewable energy producers. In most cases, it relates to loan rate below the market rates. In some cases, low rates are coupled with different reimbursement period lengths or possibilities to extend the repayment period.

• Reduced VAT rate : reduced VAT rates for renewable equipment. According to [26], "reduced VAT rates can be similar as investment subsidies". However, it affects only the turbine price and not the all investment cost.

		Revenue			Cost	
		Improving			Alleviating	
		Instruments			Instruments	
	FiT	FiP	TGC	Dedicated	Investment	Reduced
				Loans	Subsidies	VAT
	Phase 1	Phase 4				
Denmark	(1985 - 1990)	(2003-2007)				
(1985 - 2012)	Phase 2	Phase 5			(1985 - 1989)	
	(1991-1999)	(2008-2013)				
	Phase 3					
	(2000-2002)					
	Phase 1					
France	(2001-2005)					
(2001-2012)	Phase 2					
	(2006-2012)					
	Phase 1		Phase 2			
Italy	(2000-2001)		(2002-2005)			(2000-2012)
(2000-2012)			Phase 3			
			(2006-2012)			
	Phase 1	Phase 1				
Spain	(2000-2003)	(2000-2003)				
(2000-2012)	Phase 2	Phase 2				
	(2004-2006)	(2004-2006)				
	Phase 3	Phase 3				
	(2007-2012)	(2007-2012)				
	Phase 1					
Portugal	(1999-2001)					
(2000-2012)	Phase 2			(2001-2006)		(2001-2012)
	(2002-2004)					
	Phase 3					
	(2005-2012)					
~	Phase 1					
Germany	(2000-2008)			(2000-2012)		
(2000-2012)	Phase 2					
	(2009-2012)					

Table 1: Evolutions of the support instruments for onshore wind power in six European countries

The IR index is an average margin rate for each kWh sold by the producer of the cohort t. It makes sense to consider it as a crucial determinant of the investment decision. However, it suffers from several weaknesses. First, it does not take into account the uncertainty affecting investments in renewable energy sectors (two sources of uncertainty must be mentioned: meteorological uncertainty affecting the plant's productivity and regulatory uncertainty caused by changing policy regimes). Second, it does not fairly reflect the grid connection constraint. Even if the cost of this connection is included in investment costs, there is a wide heterogeneity in this connection cost among installations.

2.2.3 Assumptions and data.

A complete description of assumptions and data used for computing IR is given in Appendix B. Here, the emphasis is on the sources of heterogeneity captured by the index through available data. The first source of heterogeneity is technological. Despite the fact that the wind turbine market is more and more international, several national factors impact the cost of this technology. This technological heterogeneity is partly caught by the data on IC_t which mainly comes from the IEA Wind national reports [35]. It allows for a country specific estimation of wind energy costs and faithfully transcribes their time profiles.

The second source of heterogeneity is geographic, which is of special importance for intermittent energies such as wind power. It can be approximated by using national load factors. Load factors are the ratio between the produced output per year and the maximum theoretical production (measured by the installed capacity). Based on Boccard [4], the productivity of a typical wind site is computed for each country. The main weakness of this strategy is to retain one value per country for the whole period of study. This issue is addressed in the Danish case for which it is possible to estimate a load factor for each cohort in order to capture the technical progress in turbines efficiency from years to years. Due to a lack of data, it is not possible for other countries.

The last source of heterogeneity is economic. The economic background determines several parameters such as loan rates, average risk-free financial returns in the Euro zone (used in this paper as discounting rates) and electricity prices. The latter fulfills three functions in this analysis:

- In the case of FiP, a part of producers revenue comes from the electricity market.
- In the case of FiT (and FiP), when the revenue improving scheme ends, producers only receive the market price.
- For the aim of the counterfactual analysis, we need to compute counterfactual time series of IR_t reflecting what would have been the intrinsic return without policy support. Then, the electricity price makes the producer's revenue.

It must be underlined that the counter-factual analysis investigates the case for a removal of financial support but cannot dispose from the priority access to the grid assumption. Moreover, it is difficult to apprehend the time profile of the electricity generation from wind power that determines producers' revenue. Most of the time, windy hours correspond to off-peak hours, preventing wind producers from recovering their fixed costs [3]. In this analysis only yearly average prices are retained for computing IR_t .

2.2.4 Dynamics of the intrinsic RoI (IR).

The dynamics of the national IR over the covered period are displayed in Figure 2. Several characteristics of IR can be emphasized. First, high levels of profitability are reached for all countries. This feature has already been underlined in the literature (see for instance [11]). However, countries with the higher levels are not necessarily those with the bigger wind power installed capacity. Italy is illustrative of this case. Second, IR is characterized by a strong volatility over time. This volatility results from several factors. First, market pull policies have experienced substantial changes. In most cases, these changes occurred in revenue improving support and resulted from the modification of the length of the scheme, of the level of payment or of the type of instrument. The second source of volatility



Figure 2: Evolution of the observed intrinsic RoI for the six European countries.

is the evolution of the investment costs over time. These costs first followed a decreasing trend due to learning at the beginning of the 2000s. But the raise of raw materials prices and the increase of the demand for wind turbines, resulting in binding production capacities for equipments, induced an increase of investment costs in 2006 and onwards. Since wind power investments are highly capitalistic, IR is also highly sensitive to variations of the investment cost . Finally, the macroeconomic crisis has been reflected in loan rates, discount rates and electricity prices (for FiP and TGC cases), which induced the collapse of the intrinsic return in 2008.

2.3 Model calibration.

2.3.1 Open loop calibration

The purpose of the quantification of the parameters involved in the dynamic equation (2) is to conduct a counterfactual analysis of the impact of different policy instruments on the development of new onshore capacities for wind power. The peculiarity of the counterfactual analysis is that we want to solve the dynamics in open loop, not in closed loop. Indeed, we want to construct a counterfactual time path of the proportion of developped sites, starting from the same initial conditions than those that have actually prevailed, but proceeding with fictitious values of IR. For this purpose, we have to make sure that, at least, the values used for the parameters enable us to correctly reproduce the time path of commissioning observed with the actual values of IR. The open loop approach requires to compute the predicted proportion of sites developed at dates t > 0 on the basis of the initial proportion $\frac{N_0}{N_{tot}}$ at date t = 0. If the dynamic equation (2) was linear, it could be done analytically and we would be able to estimate the parameters with standard econometric methods. The point is that (2) is highly non linear and that we are not able to find a simple and econometrically tractable analytical expression of $\frac{N_t}{N_{tot}}$ as a function of $\frac{N_0}{N_{tot}}$. Therefore, we calibrate the model rather than estimate it with econometric methods. Notwithstanding, we use a root mean square minimization method to calibrate the parameters.

In order to calibrate the model, a grid of possible values of the different parameters is first generated. For each set of parameters' values in the grid, we compute the time path of $\frac{N_t}{N_{tot}}$ over the whole period of the study, conditionally on its initial value $\frac{N_{t0}}{N_{tot}}$ and conditionally on the observed values of IR. The set of parameters' values that minimizes the root mean square error between the simulated proportions $\frac{N_t}{N_{tot}}$ and their actual values is used as the solution. A new minimization, based on a narrower grid with smaller increments between the values of parameters, is implemented until the root mean square error (RMSE) obtained for the solution does not decrease more than an fixed relative value. Parameters subject to this minimization are the coefficient θ of learning, the dispersion parameter σ of the distribution of the RoI and the maximum number N_{tot} of sites that can be used to install a wind farm. Note that, contrary to most technology diffusion problems, we do not know N_{tot} but have to calibrate it like other parameters.

Last but not least, prior to calibrating the parameters we need to specify a distribution function f for the RoI. For the sake of limiting the number of parameters, while allowing enough flexibility, we restrain the analysis to distributions with two parameters, a position parameter tightly linked to μ_t and a dispersion parameter σ . A natural candidate is the Gaussian distribution with expected value μ_t and standard deviation σ . Nevertheless, like all symmetric distributions, it has an important disadvantage: if the initial value of the average total RoI is positive (i.e. $\mu_t > 0$), then at least half of the sites should be developed at the initial date t = 0. This is obviously too restrictive. Therefore, we rather use a truncated (on the right) version of the Gaussian distribution:

$$f(R;\mu_t,\sigma) = \begin{cases} \frac{\varphi(R;\mu_t,\sigma)}{\Phi(R_{\max};\mu_t,\sigma)} & \text{if } R \le R_{\max} \\ 0 & \text{if } R > R_{\max} \end{cases}, with \ R_{\max} > 0 \tag{4}$$

where $\varphi(R; \mu_t, \sigma)$ and $\Phi(R; \mu_t, \sigma)$ are respectively the partial density function and the cumulative density function of the Gaussian distribution with expected value μ_t and standard deviation σ . For given values of θ , σ and N_{tot} , the upper bound R_{max} is calibrated so that the initial proportion of developed sites just coincides with the observed proportion N_0/N_{tot} at time t = 0. This initial condition is formally written as

$$1 - F(0; \mu_0, \sigma) = \frac{N_0}{N_{tot}}$$
(5)

or equivalently

$$\frac{\Phi\left(R_{\max};\mu_{0},\sigma\right)-\Phi\left(0;\mu_{0},\sigma\right)}{\Phi\left(R_{\max};\mu_{0},\sigma\right)} = \frac{N_{0}}{N_{tot}}\tag{6}$$

Due to the truncation, μ_t remains the mode of the distribution but is no longer the expected return. Instead, the expected RoI over the whole population of sites is, according to [27],

$$E[R] = \mu_t - \sigma \frac{\varphi(R_{\max}; \mu_0, \sigma)}{\Phi(R_{\max}; \mu_0, \sigma)}$$
(7)

An alternative specification for the distribution of the RoI is the Extreme Maximum Value distribution. This specification is an interesting alternative because it is initially defined for any real value of the return but, contrary to the Gaussian distribution, it is asymmetric. Like for the Gaussian distribution, if μ_t is the position parameter then the proportion of sites developed at time t = 0 generally exceeds N_0/N_{tot} . To remedy to this problem and satisfy (5), the distribution is also truncated on the right.

Distribution							
function		DK	DE	\mathbf{FR}	IT	\mathbf{ES}	PT
of the RoI							
	N_{tot}	2844.16	39744.9	1756.24	847.543	355.2	652.214
Gaussian	θ	7.29429	29.75	63.5	220.0	59.4529	35.075
	σ	2.30286	24.0714	19.10	91.7151	19.01	12.3443
	RMSE	56.3908	31257.7	93.4763	297.698	6.03882	20.681
	Relative RMSE	0.233851	0.0645403	0.094203	0.227925	0.0334354	0.0397533
	$\operatorname{RMSE}/\operatorname{mean}(N_t)$	0.0785856	12.2531	0.382963	2.88166	0.073852	0.166369
	N_{tot}	2022.4	11113.4	1166.07	515.657	247.858	474.129
Extreme	θ	3.03929	9.16857	29.5014	225.0	26.4986	16.5679
Values	σ	1.352	8.74286	10.6714	110.0	10.90	7.60571
	RMSE	3544.95	30029.4	36.7363	150.064	5.90143	24.4137
	Relative RMSE	0.232967	0.0632444	0.0715909	0.171414	0.0403525	0.0486726
	$\operatorname{RMSE}/\operatorname{mean}(N_t)$	4.94021	11.7716	0.138715	1.45259	0.0721718	0.196397

2.3.2 Values set for the parameters

Table 2: Estimation results by country, depending on the distribution function of the RoI (ISO 3166-2 codes are used instead of countries complete names)

Although previous studies that analyze the development of wind power have used data on installed capacities, it would not be consistent with our micro-founded model of diffusion. Indeed, what is explained by the micro-founded model is whether the investor finds it optimal to develop a site, not which capacity will be installed. The link between the installed capacity and the development of a site is mostly based on technological progress. With this remark in mind, we chose to use the database *The Wind Power* which collects information about wind power sites all around the world². A comparison between the cumulative installed capacities computed from this database for each of the six countries studied in the paper and the cumulative capacities reported on the website of the *European Wind Energy Association*³ shows that the census of sites in the database is almost exhaustive. The date of commissioning is not always reported and the proportion of sites for which this information is available greatly differs from one country to another one (99.58% for Portugal, 98.85% for Denmark, 93.46% for France, 87.85% for Germany, 58.30% for Italy and 15.21% for Spain). We assume that this proportion is stable but there is clearly a risk that results are less reliable for countries with a low proportion, more specifically Italy and Spain.

Parameters of the model are calibrated country by country. The theoretical time path of the count

²For more information on the database: http://www.thewindpower.net/index.php

³http://www.ewea.org/

of developed sites is computed from the dynamic equation (2) multiplied by the parameter N_{tot} which is itself calibrated. By contrast with most empirical studies on technology diffusion, we do not have information on the total number of potential adopters. Nevertheless, N_{tot} can be calibrated like other parameters. Detailed results on calibration are provided by Table 2. The value of the parameters varies greatly from one country to another one, but also from one distribution of the RoI to another one. The Gaussian distribution yields the minimum RMSE for Denmark and Portugal. The minimum RMSE is obtained with the extreme value distribution for the four other countries. Although the RMSE is the minimization criteria, the relative RMSE and the ratio of the RMSE to the mean value of the number of developed sites over the period are also displayed in Table 2. The relative RMSE measures the mean ratio between the quadratic error observed and the cumulative number of developed sites at each date. The relative RMSE and the ratio between the RMSE and mean value of N_t are intended to ease the comparison between countries. Nevertheless, neither of them is perfect. The relative RMSE put a similar weight on each date, whatever the number of sites developed. Yet, a ten percent error on a small number of developed sites is probably less worrying than a ten percent on a large number of developed sites. For its part, the ratio between the RMSE and the mean number of developed sites is sensitive to the general shape of the diffusion. Therefore, in order to complete Table 2, Figures 3 and 4 provide a visual comparison of the observed rate of diffusion of developed sites and the rate of diffusion computed from the count simulated with help of the diffusion model and the computed IR. Figure 3 represents a diffusion process based on a Gaussian distribution of the RoI whereas for Figure 4, an extreme value distribution is used. The diffusion has been simulated only for the period where data required to compute the IR index were available. For all countries, this period ends in 2012 whereas data on newly commissioned wind farms were available until 2014. The period of study starts in 1985 for Denmark, which is the longest period. As a result, the calibration enables to simulate a time path of the diffusion which is particularly close to the observed one. The period starts in 2000 for the other countries (except for France for which it starts in 2001). The observed and the simulated time paths of diffusion are also close to each other for France, Portugal and, to a less extent, for Germany (except at the end of the period). Calibration results in some gaps between the two time paths for Italy and Spain which are also the two countries where the rate of missing dates of commissioning was high and the population of studied wind farms is likely to be less representative of the whole population of developed sites.

Another contribution of Figures 3 and 4 is that they highlight how large is the remaining potential of development. This potential should be interpreted with caution because it relies on the calibrated value of N_{tot} and reflects the social acceptability of wind farms, as much as the physical availability of interesting sites. This explains for instance why France, where the physical potential is likely to be greater than in Germany and where the number of sites developed is much lower, is considered as having reached more than 60% of its potential (with the extreme value distribution that minimizes the RMSE) whereas Germany is still under 40% of its potential (with the extreme value distribution that minimizes the RMSE). Table 3 complements the description of the calibration. It gives information on the main characteristics of the distribution of the RoI. These characteristics derive from the values of parameters displayed in Table 2 and, unsurprisingly, they also greatly vary from one country to



Figure 3: Realized versus estimated diffusion, expressed as a share of the estimated potential (gaussian distribution)

another one. Denmark and Italy appears to be the countries with respectively the lowest and the highest dispersion of the RoI.

3 Results.

The coming subsection is an overview of the evolution of the intrinsic RoI (IR) of the six European countries. Graphics underline the imbalance between revenue improving and cost alleviating instru-



Figure 4: Realized versus estimated diffusion, expressed as a share of the estimated potential (extreme values distribution)

ments resulting from the suppression of each type of support policy. The last two subsections go further in the analysis by presenting the simulation results of two counterfactual scenarios, each one isolating the role of different type of policy instruments on wind farm diffusion.

3.1 Counter-factual analysis of the intrinsic Roi: IR.

The bulk of the counterfactual analysis of the impact of policy instruments on the time path of IR relies on Figures 5 and 6. Figure 5 presents the difference between the national IR with all the support

Distribution							
function		DK	DE	\mathbf{FR}	IT	\mathbf{ES}	\mathbf{PT}
of the RoI							
	t=0	1985	2000	2001	2000	2000	2000
	t=T	2012	2012	2012	2012	2012	2012
	$R_{\rm max}$ at t=0	0.00198937	0.864472	0.318057	2.52105	1.05322	0.395275
Gaussian	Mean at $t=0$	-1.81447	-18.3676	-14.6745	-69.7227	-13.4024	-9.33853
	Mean at $t=T$	1.90174	-16.5917	10.8276	-48.2872	11.4912	2.71064
	Median at $t=0$	-1.52983	-15.3979	-12.3121	-58.3841	-11.0437	-7.81265
	Median at $t=T$	2.18639	-13.622	13.19	-36.9487	13.85	4.23652
	Standard Deviation	1.37771	14.5233	11.3899	54.8194	11.0981	7.3835
	Variation coefficient	-0.75929	-0.790706	-0.77617	-0.786249	-0.828068	-0.79065
	at t=0						
	Variation coefficient	0.724446	-0.875339	1.05194	-1.13528	0.965792	2.72389
	at $t=T$						
	$R_{\rm max}$ at t=0	0.00175972	1.26018	0.286653	5.35938	0.890208	0.372222
	Mean at $t=0$	-0.877959	-4.81241	-6.6251	-1.47547	-5.85131	-4.72623
	Mean at $t=T$	1.53119	-2.8179	9.46394	21.1629	8.23526	2.73457
	Median at $t=0$	-0.815137	-4.43321	-6.15253	-61.8942	-5.3228	-4.38302
Extreme	Median at $t=T$	1.59401	-2.43869	9.96022	11.1062	8.76377	3.07779
Values	Standard Deviation	0.564309	3.81772	4.45032	80.1459	4.39033	3.2409
	Variation coefficient	-0.64275	-0.793307	-0.671737	-54.319	-0.750316	-0.685726
	at t=0						
	Variation coefficient	0.368818	-1.35578	0.470585	2.30045	0.533526	1.18602
	at $t=T$						

Table 3: Characteristics of the distribution of the RoI

instruments and the ones that would have prevailed in the absence of revenue improving instruments. The bigger the difference between the observed time path of IR and the counterfactual time path, the more important revenue improving instruments are in the profitability of wind farms. Figure 6 presents the alternative analysis where cost alleviating instruments are ignored to compute the counterfactual time path of IR. These two Figures underline the prominence given to revenue improving instruments. They also highlight that the strong volatility of IR directly results from the support to revenue. Indeed, the profitability is relatively stable over time when considering only the role of cost alleviating instruments. By contrast, the part of IR that is imputable to the revenue improving instruments is high and volatile. This is consistent with [11].

Among revenue improving instruments, the choice of a peculiar instrument does not predetermine the evolution of the profitability. This is highlighted by the cases of Denmark and Spain. Indeed, both countries chose to implement a premium during a long period (see Table 1), but they exhibit highly contrasted dynamics of IR. We conclude that details in the design of an instrument may be as important as the choice of the instrument.

The case of Denmark also reveals an atypical strategy that consists in generously supporting the investment in wind farm at the beginning of the time period and progressively reducing this support. Actually, this initial impulse on the support has shaped the time path of new commissioning for the whole period.



Figure 5: Intrinsic RoIs (IR) difference between full support and support without revenue improving instruments.



Figure 6: Intrinsic RoIs (IR) difference between full support and support without cost alleviating instruments.

3.2 Impact of revenue improving instruments on diffusion.

Figure 7 illustrates the counterfactual analysis of the impact of revenue improving policy instruments. It is completed by Table 4 which provides some statistics on the impact of suppressing revenue improving instruments. The counterfactual analysis consists in simulating what would have been the development

Distribution							
function		DK	DE	\mathbf{FR}	IT	\mathbf{ES}	PT
of the RoI							
	Mean	-16.42	-10.37	-4.61	-7.02	0.12	-24.29
	Median	0.32	-9.98	-5.18	-7.18	1.05	-25.32
Gaussian	Minimum	-80.54	-14.47	-7.99	-7.93	-0.09	-31.95
	Maximum	24.63	3.39	0.57	-4.98	2.94	-13.81
	Standard Deviation	41.54	3.27	2.81	0.86	1.08	-6.25
	Mean	-32.28	-10.95	-13.70	-5.42	-1.81	-38.34
	Median	-40.79	-10.76	-13.66	-5.92	-1.68	-39.82
Extreme	Minimum	-80.69	-14.99	-19.90	-6.21	-3.45	-41.58
Values	Maximum	12.02	-3.65	-5.60	-3.08	-0.59	-26.06
	Standard Deviation	36.04	3.35	5.32	1.02	0.98	4.64

Table 4: Counterfactual impact of removing revenue improving support (statistics on the simulated cumulated yearly count of commissioned wind farms in % of the actual count)

of wind farms if the revenue improving policy instruments had not exist. For this purpose, the actual values of IR are replaced by their counterfactual values presented just above and the dynamic model described by equation 2 is then rerun, starting at the observed cumulative count of developed sites at the first date of the period of study. The counterfactual analysis thus combines a direct effect and an indirect effect of policy instruments. The direct effect comes from the change of values of IR. The indirect effect is induced by the learning effect incorporated in the total RoI. Indeed, the impact of a change in IR implies that the number of new wind farms commissioned at each date differs from the actual number which, in turn, affects the degree of learning for all future dates. Moreover, as already stressed when discussing Figure 1, the dynamics of the micro-founded model of technology diffusion depends not only on the level of the total RoI, but also on its variations. Therefore, it is not that obvious to anticipate how do the results of the counterfactual analysis for the IR translate in terms of simulated diffusion of wind power.

A striking feature of Figure 7 and Table 4 is that the suppression of revenue improving policy instruments would punctually had have a positive impact on the diffusion of wind power. This is more specifically the case of Denmark from 2000 to 2012 and in a less extent for Spain from 2006 to 2012. The case of Denmark is illustrative of the importance of variations of *IR*. However with regard to the period as a whole, the mean impact of suppressing the revenue improving instruments would have been negative. Moreover, Denmark is even one of the two countries, with Portugal, that exhibits the stronger negative mean impact, despite the one-time positive effects detailed above. By contrast, the diffusion of wind power in Spain would have been almost not affected by a suppression of revenue improving instruments. It may be interpreted as a consequence of the predominance of the role of natural and favourable conditions (the load factor for wind turbine in Spain is among the highest in Europe) compared to economic incentives. The counterfactual analysis also reveals a mitigated impact of revenue improving instruments in Italy whereas this impact is significant in France and in Germany, although smaller than for Denmark and Portugal. It is worth noting however that Italy and Spain are the two countries for which the study does not include all wind farms because the rate of missing dates of commissioning is high. All in one, it turns out that revenue improving policy instruments have had





a significant and positive role in the diffusion of wind power in countries where we have an almost exhaustive information on the dates of commissioning of wind farms.

3.3 Impact of cost alleviating instruments on diffusion.

Figure 8 and Table 5 are similar to Figure 7 and Table 4 but they highlight the counterfactual analysis of the impact of cost alleviating policy instruments on the development of wind farms. It appears from the outset that the impact of cost alleviating policy instruments is much lower than that of revenue

Distribution							
function		DK	DE	\mathbf{FR}	IT	\mathbf{ES}	\mathbf{PT}
of the RoI							
	Mean	73.58	-1.14	0	-0.52	0	-0.36
	Median	19.78	-1.23	0	-0.52	0	-0.39
Gaussian	Minimum	10.16	-1.48	0	-0.65	0	-0.81
	Maximum	446.57	-0.33	0	-0.32	0	0.13
	Standard Deviation	99.19	0.34	0	0.10	0	0.30
	Mean	36.38	-1.18	0	-0.46	0	-1.55
	Median	5.98	-1.28	0	-0.51	0	-1.61
Extreme	Minimum	1.97	-1.54	0	-0.54	0	-2.24
Values	Maximum	505.38	-0.34	0	-0.21	0	-0.57
	Standard Deviation	94.30	0.36	0	0.11	0	0.56

Table 5: Counterfactual impact of removing cost alleviating support (statistics on the simulated cumulated yearly count of commissioned wind farms in % of the actual count)

improving policy instruments. This is in line with what we already observed in the counterfactual analysis of IR. A noticeable and troubling exception is Denmark. Once again, the suppression of policy instruments in this country would have had a positive impact on the diffusion of wind power. Nevertheless, this impact is largely due to the fact that cost alleviating instruments have been substantially weakened from the start of the eighties to the end of the nineties. The slowdown of support has implied a decrease of IR over all that period *ceteris paribus*. In the absence of any cost alleviating instrument, this slowdown would have not occurred and, therefore, the impact on the dynamics of diffusion would have been positive. Denmark aside, the suppression of cost alleviating policy instruments would have had a negative impact, though quite limited. The most impacted countries are Germany and, to a lesser extent, Portugal and Italy (depending on the distribution of RoI considered).

4 Conclusion.

Whether public support to the development of wind power has had a significant impact on this development crucially depends on the type of instrument considered and on the country. The counterfactual analysis of the impact of the different instruments used in several European countries clearly shows that the higher impact comes from instruments that intend to improve revenues of wind farms whereas instruments that aim at alleviating cost of investing in, and operating, wind farms had a rather limited impact. Nevertheless, this mainly reflects the fact that public policies have favored the first type of instruments. The dependence on the country studied is likely to result from the sensitivity of technology diffusion to variations in economic incentives. Indeed, a peculiar property of the micro-founded diffusion model proposed in this article, and implemented for the counterfactual analysis, is that variations of the intrinsic profitability around a trend do not generate the same diffusion that the trend itself. Some countries may have been keen in sending stable signals to investors whereas others have been subject to repeated regulatory changes. Said another way, a sudden and sharp drop of the support can annihilate previous efforts to develop wind power and stop its diffusion process. This result does not mean that public support should never been suppressed but that public authorities should be more





cautious about how to suppress it.

A Appendix A: Historical evolution of the support schemes in the six European countries.

The detailed version of table 1 is given in Tables 6 and 7.

	l	Revenue			Cost	
		Improving			Alleviating ⁴	
	E:T	Fip	TCC	Dodigated	Instruments	Podyaod
	FII	I II	160	Loans	Subsidies	VAT
Denmark (1985-2012) ⁵	Phase 1 (1985-1990) 85% of the Local Retail Price (LRP), taxes excluded Phase 2 (1991-1999) 85% of the LRP, plus 36 €MWh Phase 3 (2000-2002) 58 €MWh for the first 22 000 full load hours. Then a premium of 13 €MWh is given (lifetime, total payment capped to 48 €MWh) Phase 1	Phase 4 (2003-2007) Premium of 13 €MWh (lifetime, total payment capped to 48 €MWh) Phase 5 (2008-2013) 34 €MWh for the first 22 000 full load hours, then 3 €MWh (lifetime)			25% of the IC (1985) 15% of the IC (1986-1988) 10% of the IC (1989) ⁶	
France (2001-2012)	Phase 1 (2001-2005) 83.8 €MWh for the 5 first years, then from 30.5 to 83.8 €MWh for 10 years (depending on the site productivity) Phase 2 82 €MWh for the 10 first years, then from 28 to 82 €MWh for 10 years (depending on the site productivity)			Low rate loans for households. Not included in the study.	Only on a regional basis. Priority is given to households and small power plants Not included in the study.	Reduced rate for wind turbines subject to home renovation work. Not included in the study.
Italy (2000-2012)	Phase 1 (2000-2001) 100 €MWh for 8 years, then 50 €MWh (lifetime). For the year 2001 the payments are 124 €MWh for 8 years, then 69 €MWh (lifetime)		Phase 2 (2002-2005) Market revenue plus the green certificates price (for 8 years) Phase 3 (2006-2012) Support period increases from 8 to 12 years		Only on a regional basis. Not included in the study.	(2000-2010) 10% instead of 20% (2010-2012) 10% instead of 21% ⁷

Table 6: Instruments of support to onshore wind (Denmark, France and Italy)

⁵The sources for the Denmark are [35], [22], [20], [36] and www.ens.dk/sites/ens.dk/files/supply/electricity/conditions-

production-plants/subsidies-generation-electricity/The%20history%20of%20Danish%20support%20for%20wind%20power.docx. ⁶From [36] and [20].

⁷From [38].

⁹According to the Royal Decree 2818/1998, the FiT is guaranteed for five years. However, it contains a provision guarantying unlimited availability of premiums and therefore, indirectly, automatic renewal of purchase contracts [25]. A survey conducted among 40 renewable energy producers demonstrated the minor role of the uncertainty on purchase contracts renewal [25].

 10 The Average Electricity Tariff (AET) reflects the overall average cost of the electricity system. The level of the AET is decided each year by the government, values can be found in national reports on Spain [35].

¹¹To compute the IR index, the premium option is retained since '90% of wind producers have opted for the FIP-support' according to [21].

¹²Cap and floor prices are indexed on the electricity retail price. In 2008, the values were 73.6 €MWh and 87.8 €MWh.

 $^{13}\mathrm{According}$ to the Royal Decree 1614/2010.

 14 According to [33].

 15 According to [33].

¹⁶From [37], [32], [20] and [14].

⁴Instruments not included in the *IR* index are written in italics.

⁸Royal Decree 2818/1998 gives the choice to producers between a FiT and a FiP. Since 'an overwhelming majority of RES plant owners chose the market-based price option', according to [25], only the premium option is considered for the IR index computing.

		Revenue Improving Instruments			Cost Alleviating Instruments	
	FiT	FiP	TGC	Dedicated Loans	Investment Subsidies	Reduced VAT
	Phase 1 (2000-2003) 62.6 €MWh for 5 years ⁹ yearly adjusted depending on electricity price	Phase 1 ⁸ (2000-2003) 28.8 €MWh for 5 years added to the average electricity price			Only on a regional basis. Not included in the study.	
n (2000-2012)	Phase 2 (2004-2006) 90% of the Average Electricity Tariff (AET) ¹⁰ for 15 years then 80%, lifetime	Phase 2 (2004-2006) A premium equals to 40 % of the AET, plus 10% if the production is sold on the market				
Spai	Phase 3 (2007-2012) Tariffs are indexed on the retail price and are guaranteed for 20 years. In 2008 the payment was 75.6 €MWh	Phase 3 ¹¹ (2007-2012) A premium of 30.2 €MWh, indexed on electricity price. A cap on the total payment is introduced ¹² . In 2011 the premium is reduced by 35 % ¹³ .				
-2012)	Phase 1 (1999-2001) 60 €MWh for the first 12 years			$\begin{array}{c} (2001\text{-}2006)\\ \text{Zero rate loans}\\ \text{up to } 25\ 000 \notin\\ \text{of total IC}^{14} \end{array}$		(2001-2001) 5% instead of 17%, (2002-2004)
ortugal (2000-	Phase 2 (2002-2004) 82 €MWh for 20 years Phase 3 (2005 2012)					12% Instead of 19%, (2005-2007) 21%, (2008-2009) 20%, (2010)
ц	(2003-2012) $76 \in MWh$ for 15 years, reduced to $74 \in MWh$ after 2007					(2011-2012) 23% ¹⁵
aany(2000-2012)	Phase 1 (2000-2008) 91 €MWh for 5 years For the following 15 years the payment is adjusted depending on the site productivity. After 2002 the payment decreases annually by 1.5%. After 2004 becomes 86 €MWh for 20 years with an annual decrease of 2%			(2000-2012) Low rate loans up to 50% of the IC, rates are approx. 2 points under the market level ¹⁶	Only on a regional basis. Not included in the study	
Germ	Phase 2 (2009-2012) The payment is 92 €MWh with an annual decrease of 1% As in the first phase producers receive the full payment for the first five years, adjusted for the remaining 15 years					

Table 7: Instruments of support to onshore wind (Spain, Portugal and Germany)

B Appendix B: Assumptions and data

This appendix provides further information about the assumptions made and the data used in this article. It constitutes a detailed version of the subsection 2.2.3.

B.1 Assumptions and data on technological elements

B.1.1 Typical installation and lifetime

The chosen typical installation is a onshore wind turbine with an installed power of 1 MW. Obviously it is impossible to choose an installed capacity that truly reflects the population of wind farms in each of the six European countries. However, the IR index is almost insensitive to the size of installation since it only impacts the decommissioning cost. In fact the challenge was to choose a size which is representative of the most supported technological subset of onshore wind plants in terms of revenue improving policies¹⁷. The retained assumption for the power plant lifetime is 20 years.

B.1.2 Investment Costs (IC)

According to the IPCC [39], IC_t for an onshore wind plant encompass turbine cost, grid connection costs, civil work costs and other costs (transaction costs, land cost, etc.). The main sources are the IEA Wind national reports that provide annual data on IC_t for several countries: Denmark (1985-2012), Italy (2000-2012), Spain (2000-2012), Germany (2003-2012) and Portugal (2003-2012). For the French case, data are rare. The primary source of information is a study made by the French regulatory authority of the electricity sector (Commission de Régulation de l'Energie) [31] which provides data for years 2007 to 2012. The secondary source of information is a study by the French agency for the environment (ADEME) which provides data for IC_t in year 2001 [29]. A linear interpolation is made to estimate missing values. Since this period corresponds to a general decrease of IC_t in the other countries, it is unlikely to hamper our results. For Portugal, IEA Wind reports underline the fact that the values for 2003, 2004, 2005, 2009 and 2010 do not include grid connection cost and civil work. In order to address this issue we increase IC_t values by 17 % based on the IPCC report [39]. Finally the missing values for the first years in Portugal and Germany are estimated by replicating the Danish IC_t trend. This trend is obtained from the data in [28].

B.1.3 Operation and Maintenance Costs (O&M)

O&M costs gather insurance costs, management costs, repair and replacement costs. However, depending on studies, all or parts of these costs are taken into account. In order to avoid any bias when comparing countries, the choice is made to use the same values for the six countries. Data come from the 2010 Wind Technologies Market Report [40].

B.1.4 Decommissioning Cost (DC)

Several ways to apprehend DC_t can be found in the literature. The retained assumptions are that DC_t amounts to 5% of IC_t , as mentionned in the IEA report on electricity cost [34], and that DC_t is paid by producer in the last year of operation of the power plant.

¹⁷Typically, when a FiT is implementing there is a distinction between several subsets of installations depending on the installed power. For example, the tariff will be higher for small power plants and lower for big power plants.

B.2 Assumptions and data on geographical elements

B.2.1 National load factors

The load factor of a power plant measures the ratio between the yearly quantity of generated output and the maximum theoretical load in a year. For an onshore wind turbine it depends on meteorological conditions. Assumptions about the load factor of a wind turbine may vary significantly from a study to another. In this article, the retained values are from Boccard [4] who computes the realized values of the wind power load factors for several European countries. They are reported in Table 8. The study of Boccard only focuses on years 2003-2007, the resulting values are assumed to be representative of the whole period of study.

Country	France	Spain	Italy	Germany	Portugal
Average realized load factors between 2003 and 2007	22.3%	24.8%	19.1%	18.3%	22.7%

Table 8: National load factors for a typical wind power plant

A slightly different strategy is adopted for the Danish case. The availability of detailled data on Danish wind turbines allows us to compute an average load factor for each cohort of producers. The source of data is the *Register of Wind Turbines*, maintained by the Danish Energy Agency. As the average load factor may be volatile from a cohort to another, we use a polynomial trend in order to not overestimate productivity differences. The evolution of the Danish load factor is given in the figure 9.



Figure 9: Realized versus estimated load factors per cohort (Denmark).

B.3 Assumptions and data on economic conditions

B.3.1 Discount rates

The discount rate partially captures the influence of the macro-economic environment on the microeconomic investment behavior. To reflect this causality, yield curves may be used to discount cash-flows. These curves represent the yield from a bond depending on its maturity. The bond that is considered here is a zero-coupon from euro zone AAA rated governments bonds. As a result the discount rate is risk-free, making the *IR* index necessary overestimated. Yield curves data can be found on Eurostat; 20 years maturity bonds are chosen in order to fit with our assumption on wind farms lifetime. For the Danish case, since the study starts before the Euro implementation, Danish bonds yields are used from 1985 to 1999, the source being MPK100: Government bond yields by country, Denmark statistics.

B.3.2 Loan rates and repayment modalities

For every country and every year, we assume that 50 % of IC_t are financed through a loan, reimbursed at a market rate on the ten first years of power plant operation. Loan rates are assume to correspond to the rates for a loan of more than five years from financial and monetary intermediaries to non financial corporations. The European Central Bank provides this information on an annual basis for each country. Usually, data is not available before 2003. We thus assume a 5 % loan rate before year 2003.

B.3.3 Electricity Prices

The liberalization of electricity markets in Europe that began in the 2000s produced an increasing amount of information. Data on the electricity spot price is used whenever it is available. Otherwise, assumptions on the electricity price are made. Sources and assumptions are detailed in the Table 9.

Country	Data and assumptions
Denmark	The Danish system operator (dk.net) provides data for hourly spot price on DK-west and hourly
	wind generation since 2003. Prices used are the yearly average price weighted by the wind
	output. Before 2003 and after 2012 we assume a yearly spot price equals to $50 \in /MWh$.
Germany	Before 2005, we assume a spot price of $30 \in /MWh$. Based on data from EPEX between
	2005 and 2011, yearly average spot prices are calculated. After 2011, we assume a spot
	price of $49 \in MWh$.
France	In France, since 77% of the generated electricity come from nuclear technology the chosen
	value for the spot price is the price of the Regulated Access to the Historical Nuclear
	Electricity, i.e. $42 \in /MWh$. Even if this value was defined in 2010, it is a good
	approximation of the cost of nuclear electricity that represents the main competitor to the
	wind power.
Italy	Before 2005, IEA Wind reports on Italy provided the yearly average market revenue of
	wind producers, a useful information for the IR computation. Between 2005 and 2012
	the system operator (Gestore Mercati Energetici) makes available data on hourly
	spot price. Yearly averages are used. After 2012, a spot price equals to $60 \in MWh$
	is assumed.
Portugal	From 2000 to 2006 regulated tariffs are integrated in IR . After 2006 yearly average
	spot prices are used, from the OMEL (Operador del mercado Energéticos). Then after 2012,
	an assumption of $35 \in /MWh$ is made.
Spain	Since 2000 the OMEL communicates price data. Due to the strong convergence between
	Spanish and Portuguese markets, the same assumption is made about the future spot
	price of electricity.

Table 9: Data and assumptions on national electricity prices.

References

Academic literature.

- BASS, F. M., A new product growth for model consumer durables, *Management science*, 1969, volume 15, pp. 215-227.
- [2] BASS, F. M., The relationship between diffusion rates, experience curves, and demand elasticities for consumer durable technological innovations, *Journal of business*, 1980, volume 53, pp. 551-567.
- [3] BENHMAD, F., PERCEBOIS, J., Wind power feed-in impacts on electricity system, *Cahiers de recherche du CREDEN*, 2014, No. 14.11.110.
- BOCCARD, N., Capacity factor of wind power realized values vs. estimates, *Energy Policy*, 2009, volume 37, pp. 2679-2688.
- [5] CHOW, G. C., Technological change and the demand for computers, *American Economic Review*, 1967, volume 57, pp. 1117-1130.
- [6] DANCHEV, S., TSAKANIKAS, A., Returns on investment in electricity producing photovoltaic systems under de-escalating feed-in tariffs: the case of Greece, *Renewable and Sustainable Energy Reviews*, 2010, volume 14, pp. 500-505.
- [7] GRILICHES, Z., Hybrid corn: an exploration in economics of technological change, *Econometrica*, 1957, volume 25, pp. 501-522.
- [8] GRILICHES, Z., Hybrid corn revisited: a reply, *Econometrica*, 1980, volume 48, pp. 1463-1465.
- [9] HAMILTON, K., RUTA, G., TAJIBAEVA, L., Capital accumulation and resource depletion: a Hartwick rule counterfactual, *Environmental & Resource Economics*, 2006, volume 34, pp. 517-533.
- [10] HITAJ, C., SCHYMURA, M., LÃ-SCHEL, A., The impacts of feed-in tariffs on wind power development in Germany, *Discussion paper of the ZEW*, No. 14-035.
- [11] JENNER, S., GROBA, F., INDVIK, J., Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries, *Energy Policy*, 2013, volume 52, pp. 385-401.
- [12] JOSKOW, P., Comparing the costs of intermittent and dispatchable electricity generating technologies, American Economic Review, 2011, volume 101, No. 3, pp. 238-241.
- [13] KEMP, R., The diffusion of biological wasterwater treatment plants in the Dutch food and beverage industry, *Environmental and resource economics*, 1998, volume 12, pp. 113-136.
- [14] LUTHI, S., PRASSLER, T., Analyzing policy support instruments and regulatory risk factors for wind energy deployment- a developers' perspective, *Energy Policy*, 2011, volume 39, pp. 4876-4892.
- [15] MANSFIELD, E., Technological change and the rate of imitation, *Econometrica*, 1961, volume 29, pp. 741-766.

- [16] MARQUES, A.C., FUINHAS, J.A., Drivers promoting renewable energy: A dynamic panel approach, *Renewable and Sustainable Energy Reviews*, 2011, volume 15, pp. 1601-1608.
- [17] MARQUES, A.C., FUINHAS, J.A., Are public policies towards renewable successful? Evidence from European countries, *Renewable Energy*, 2012, volume 44, pp. 109-118.
- [18] MERCURE J.-F., POLLITT, H., CHEWPREECHA, U., SALAS, P., FOLEY, A.M., HOLDEN, P.B., EDWARDS, N.R., The dynamics of technology diffusion and the impacts of climate policy instruments in the decarbonisation of the global electricity sector, *Energy Policy*, 2014, volume 73, pp. 686-700.
- [19] MIR-ARTIGUES, P., DEL RIO, P., Combining tariffs, investment subsidies and soft loans in a renewable electricity deployment policy, *Energy Policy*, 2014, volume 69, pp. 430-442.
- [20] MULDER, A., Do economic instruments matter? Wind turbines investments in the EU(15), Energy Economics, 2008, volume 30, pp. 2980-2991.
- [21] RAGWITZ, M., WINKLER, J., KLESSMANN, C., GEPHART, M., RESCH, G. 2012, Recent developments of feed-in systems in the EU-A research paper for the international Feed-in Cooperation, 16 pp.
- [22] SOVACOOL, B., Energy policymaking in Denmark: Implications for global energy security and sustainability, *Energy Policy*, 2013, volume 61, pp. 829-839.
- [23] USHA RAO, K., KISHORE, V.V.N., A review of technology diffusion models with special reference to renewable energy technologies, *Renewable and sustainable energy reviews*, 2010, volume 14, pp. 1070-1078.
- [24] ZACHMANN, G., PERUZZI, M., When and how to support renewables? Letting the data speak, Bruegel working paper, 2014.

Books.

- [25] DINICA, V., 2002, Renewable energy policies in Spain, in Handbook of Renewable Energy in the European States-case studies of all Member States, Danyel Reiche (eds).
- [26] GOSWANI, Y., KREITH; F., Energy efficiency and renewable energy, 2011, CRC Press.
- [27] GREENE, W.H., Econometric analysis, 7th edition, 2011, Pearson Education.
- [28] NIELSON, P., LEMMING, J.K., MORTHORST, P.E., LAWETZ, H., JAMES-SMITH, N.E., CLAUSEN, S., STROM, S., LARSEN, J., BANG, N.C., LINDBOE, H.H., *The economics of wind turbines*, EMD International, Aalborg, Denmark, 86pp.

Reports and non-academic studies.

[29] Agence De l'Environnement et de la Maîtrise de l'Enérgie, Premieres conclusions tirées de l'analyse économiques des projets éoliens en terre et en mer, November 2011.

- [30] Carbon Trust, Analysis on policy frameworks to drive future investment in near and long-term renewable power in the UK, *Policy frameworks for renewables*, 2006.
- [31] Commission de Régulation de l'Enérgie, Coûts et rentabilité des énergies renouvelables en France métropolitaine, April 2014.
- [32] De Jager, D., RATHMANN, M., 2008, Policy instruments design to reduce financing costs in renewable energy technology projects, ECOFYS, 2008.
- [33] GHK, 2006, Strategic evaluation on environment and risk prevention under structural and cohesion funds for the period 2007-2013, *National Evaluation Report for Portugal: Main Report*.
- [34] IEA, 2010. Projected costs of generating electricity. IEA/OECD.
- [35] IEA Wind, 1978-2013. Annual Reports. IEA/EWEA/CWEA.
- [36] IRENA-GWEC, 2012, 30 years of policies for wind energy, lessons from 12 wind energy markets, 2012.
- [37] Renewable energy policy review: Germany, 2004.
- [38] Renewable energy policy review: Italy, 2009.
- [39] Special Report of the Intergovernmental Panel on Climate Change, Renewable energy sources and climate change mitigation, 2012.
- [40] U.S. department of energy, 2010. 2010 Wind technologies market report. U.S. department of energy.