Renewable and Sustainable Energy Reviews 94 (2018) 224–233

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Economic policy instruments and market uncertainty: Exploring the impact on renewables adoption

Jorge Blazquez*, Nora Nezamuddin, Tamim Zamrik

King Abdullah petroleum Studies and Research Center (KAPSARC), PO Box 88550, Riyadh 11672, Saudi Arabia

ARTICLE INFO

Keywords:
Renewable policy
Market uncertainty
Renewable technology adoption curve
Investors' behavior

ABSTRACT

The success of any renewable policy can be measured through three parameters: total cost, aggregate installed capacity of renewable technology deployed over the lifetime of the policy and speed at which renewables are adopted. Using these three parameters, this study allows us to explore how policy instruments perform under different market conditions taking into account the impact of price volatility and uncertainty of those investments. This study has a financial perspective, omitting political, institutional and economic barriers that impact on renewable technology deployment. In particular, this paper develops a generator of potential renewable projects, using Spanish onshore wind data. The economic environment for those projects is set using a stochastic future evolution of European electricity prices. Finally, for each project this study calculates, under the five different policies, the expected present value and when is the best moment to commission the project. A relevant insight for policymaker is that, in reality, there is no 'best policy instrument', since there are tradeoffs among different policy instruments. Governments must prioritize between the total deployment of renewables, speed of adoption and cost of policies. Our findings show that feed-in tariff, in particular the contract-for-difference, is the policy that yields the fastest adoption of renewables. However, it is also the most expensive policy. The investment credit is the cheapest policy, while at the same time has the slowest pace of adoption with the largest number of laggards.

1. Introduction

Governments and policymakers seek to promote renewable technologies through policies that simultaneously achieve a large amount of renewable projects commissioned, expedite the adoption of these technologies and minimize the cost for the taxpayers or electricity consumers. This holistic approach to define the 'success of a renewable policy' is original, since many articles tend to identity renewable policy success with the deployment of renewable technology, such as Kilinc-Ata [1], Buckman [2], Carley [3] and Jenner et al. [4] among others. There are, then, three variables that define the success of a policy. First is the cost of the policy, second is the amount of renewables deployed over the timeframe of the policy and third is the speed of adoption of renewable energy. Renewable policies cannot achieve all three objectives at the same time. There are trade-offs between cost of a policy, speed of adoption and total deployment. In this study, we explore these tradeoffs using a model that evaluates the expected net present value of renewable investments under five of the most popular policy choices.

In this context, our study seeks to understand how different policy instruments affect renewables adoption amid market uncertainty. Using real Spanish onshore wind data, a stochastic model is developed to understand how investors behave in real market situations. From the point of view of investors, the key finding of this study is that some policy tools favor the deployment of renewable technology while others favor a higher speed of adoption, but there is a tradeoff between these two objectives.

Investments will normally be made if there is an attractive combination of yield and risk. However, policies set by governments usually do not take into consideration investors' behavior under uncertainty. Governments implement policies under the assumption that they will be attractive for investors, regardless of future market conditions. In other words, policies designed for a specific market condition can be unsuccessful if market conditions do not hold, as Bauner and Crago [5] highlights for solar PV technology. The topic of economic policy effectiveness under uncertainty has been studied from different perspectives. In a pioneer study, Brainard [6] explains the theoretical implications of uncertainty for the selection and design of the optimal policy tool. Policymakers faces two source of uncertainty: uncertainty about the of evolution external variables and uncertainty about the response of the economic agents. In the field of renewable energy

* Corresponding author.
E-mail addresses: Jorge.blazquez@kapsarc.org (J. Blazquez), Nora.nezamuddin@kapsarc.org (N. Nezamuddin), Tamzam@gmail.com (T. Zamrik).

https://doi.org/10.1016/j.rser.2018.05.050
Received 19 May 2017; Received in revised form 23 April 2018; Accepted 21 May 2018
1364-0321/ © 2018 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/BY/4.0/).

policy, Mentanteau et al. [7] examine the efficiency of a set of alternative policy tools, taking into consideration uncertainties regarding costs of technologies and learning effects. Barradale [8] focuses on the USA production tax credit and the boom-bust cycle in wind generation investments. These cycles are closely linked to the short-term renewal and expiration cycle of this policy instrument. This study suggests that these cycles are not generated by absence of this policy tool, but rather by the uncertainty over its return. White et al. [9] focus on policy uncertainty, explaining that unexpected policy changes make more difficult to attract investments. In addition, there are some non-economic elements that can impact on renewable deployment. Attitudes of investors towards new technologies, technology concerns [10], institutional conditions [11] or policy barriers [12] play a critical role in the deployment of renewable technologies, adding uncertainty on the effectiveness of a specific policy instrument. In this context, it is important to highlight that this study has a financial approach to renewable technologies, omitting relevant non-economic elements that could impact on expected deployment.

Five policy instruments are considered including contract-for-difference feed-in tariffs (constant price tariff), Floor feed-in tariffs (price floor tariff), floor & cap feed-in tariff (price cap and floor tariff), feed-in premium and investment credits. We define policies that achieve the same economic profit for an average renewable project in a deterministic setting. This methodology, which ignores uncertainty, is a standard approach used to determine the level of financial support for renewable technologies. Once these set of policies are defined, we explore how investors react to each of these policies in a realistic stochastic environment. After which, we look at the total deployment of the technology, the speed of adoption and the total cost to the government.

The policy with the highest speed of adoption is the contract-for-difference, since this instrument removes all volatility for investors. At the same time, the contract-for-difference is the most expensive policy in terms of megawatts of installed capacity. Investment credit is the cheapest policy and it achieves a high success ratio in terms of total deployment of renewables. The remaining policy instruments fall between these two policies in terms of cost, total deployment or speed of adoption.

In most cases, policies are designed with the objective of achieving a certain amount of total deployment within a set duration and, at the same time, minimize the cost for taxpayers or final consumers. In our opinion, compared to total deployment, the speed of adoption plays a secondary role for policymakers. Hence, our view that investment credits are the appropriate policy instrument to promote renewable energy under current market conditions. However, as it is pointed out by Bean et al. [13] investment credits require a large upfront payment by the government, making this policy more difficult to implement politically.

The rest of the article is organized as follows: Section 2 describes the data, the policy instruments and the methodological approach, Section 3 presents and discusses the results, and Section 4 collects the conclusions.

2. Materials and methods: data, policies and model

2.1. Overview

A general overview of our analytical framework is the following (The structure of the model is summarized in Fig. 1):

1. Under the description of projects, we built a 'project generator' based on the characteristics of the Spanish onshore wind projects committed between 2006 and 2013. Generating a stochastic sample of 1000 'realistic' projects.
2. Under the wholesale electricity prices section, we define an electricity price generating process that reproduces the characteristics of the main European markets.
3. Under the policy levels and description section, we define five policy instruments that, in a deterministic setting, provide the same economic profit for the representative project, i.e., the average Spanish onshore wind project.
4. For each of the 1000 projects and each policy instrument we calculate the expected net present value during the timeframe of the policy, which is 10 years. Using this information, we find the best moment to commission each project.
5. Finally, the study is set up by comparing the results of the five policy instruments in terms of total deployment of renewables technology or success ratio (defined as total renewables installed over total potential projects), the speed of adoption of these technologies defined by laggards (projects commissioned in the last month of the policy timeframe over total projects commissioned) and early adopters (projects commissioned in the first year over total projects commissioned) and the total cost of the policies in billion Euros (EUR/MW deployed).

2.2. Description of data and project generator

This analysis uses real Spanish onshore wind data collected from Bloomberg New Energy Finance (BNEF). The dataset includes financial and operational information on 318 onshore wind projects implemented in Spain between 2006 and 2013. Projects selected for the dataset are limited to those with a minimum installed capacity of 15 MW (MW) or more. The projects represent 10,732 MW of installed capacity, 83% of the total 12,885 MW installed in 2006–2013, according to the *BP Statistical Review of World Energy 2014*.

For each project we compute the levelized cost of electricity (LCOE), using the weighted average cost of capital (WACC) as the discount rate. The initial results of our analysis indicates that the LCOE of the projects have considerable variation from 36 €/MWh to 193 €/MWh. To avoid excessive dispersion in LCOE, this study uses the interquartile LCOEs. This means that the upper and lower cost limits in the spectrum are not considered. Based on the data, the projects in the analysis are normally distributed with an average LCOE of 72 €/MWh and a standard deviation of 8.6 €/MWh. Additionally, the WACC of the projects is normally distributed with an average of 7.2% and a standard deviation of 0.4%. The average installed capacity of each project is 33.7 MW and the average capacity factor is 25%. The maturity of the projects is 20 years.

Given these parameters, we randomly generate a population of 1000 projects that are equal in capacity. This approach attempts to tackle the problem of lack of granularity in costs that some research on renewable technology face [7]. In addition, a decline in the cost of technology occurs given a progress ratio[1] of 0.97. This progress ratio is calculated to fit the evolution of the LCOE of onshore wind technologies between 2009 and 2014, using data from the BNEF report, *H2 2014 Global Levelized Cost of Electricity Update.* Obviously, the future cost of renewable technology is quite difficult to forecast, but simple approaches to gaze into the future have been attempted by Neij [14] and Witajewski-Baltvilks et al. [15].

In our analysis the projects can be developed at any moment and once a project is commissioned the LCOE cost is locked in for the lifetime of the project. Therefore, once projects are developed they do not benefit from further cost reduction in the technology.

A representative wholesale electricity price for Europe is created using the average of monthly data from Germany, France, Italy, Spain and Nordpool market for January 2006 to March 2015. The wholesale traded electricity prices evolve as a geometric Brownian motion with a volatility of 39%. The Brownian process has a drift, which is set at 1.5% annually, and it is consistent with the expected evolution of inflation in Europe, given the mandate of the European Central Bank. The initial

[1] The LCOE of a particular project in time t is equal to $LCOE_t = LCOE_{t=0} {}^* t^{\ln(progress\ ratio)/\ln(2)}$.

Download English Version:

https://daneshyari.com/en/article/8110400

Download Persian Version:

https://daneshyari.com/article/8110400

Daneshyari.com