Renewable Energy 103 (2017) 522–536

Contents lists available at ScienceDirect

Renewable Energy

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

The price evolution of wind turbines in China: A study based on the modified multi-factor learning curve

Yang Yu [a, b, *], Hong Li [c], Yuyuan Che [d], Qiongjie Zheng [e]

[a] Business School, Ningbo University, No. 818 Fenghua Road, Jiangbei District, Ningbo, Zhejiang Province, 315211, PR China
[b] School of Economics and Trade, Ningbo Institute of Technology, Zhejiang University, No. 1 Xuefu Road, Ningbo, Zhejiang Province, 315100, PR China
[c] School of Economics, Peking University, No. 5 Yiheyuan Road, Haidian District, Beijing, 100871, PR China
[d] Department of Agricultural, Food, and Resource Economics, Michigan State University, 446 W. Circle Drive, East Lansing, MI, 48824, USA
[e] Nanjing Academy of Social Sciences, No. 43 Chengxian Road, Nanjing, Jiangsu Province, 210018, PR China

ARTICLE INFO

Article history:
Received 11 January 2016
Received in revised form
8 October 2016
Accepted 28 November 2016
Available online 28 November 2016

Keywords:
Wind turbine price
Learning-by-doing
Learning-by-researching
Scale effect
Input-price effect
Wind curtailment

ABSTRACT

It is surprising to observe that China has led the wind turbine price reductions across the world. To explain turbine price changes, the theoretical mechanism applied for technologically advanced countries is insufficient to demonstrate the performance of turbine manufacturing from technology adoption to indigenous innovation and during wind curtailment shocks. The paper constructs a multi-factor learning model in the framework of the Cobb-Douglas function to examine the distinctive China turbine price evolution in 1998–2012. The core factors: the learning-by-doing, learning-by-researching, economies of scale in turbine size and quantity and input-price effects of labor, capital, steel and fiberglass/resin, are recognized and qualified in accordance with industrial and market characteristics. The results show that the learning effects are the most important factors associated with the larger turbine price reductions in China and most likely weakened by the price effects of inputs. The scale effects are important to understand the innovative performance uncaptured by learning effects and negative price responses to production adjustments during curtailment shocks. The labor cost is statistically insignificant but geographically important. To strengthen the price and manufacturing competitiveness of turbines in China, policies should be adjusted to maximize benefits from these effects and minimize negative impacts of wind curtailment.

1. Introduction

As the largest single cost component of a wind system, the swinging price trend of wind turbines has aroused great academic interests in the literature. It is supposed that technological learning effects contributing as major forces to turbine price reductions are diminishing in the long-run and tend to be offset by upward changes of input price and module size [1]. China, as a newly-emerging wind market, is distinctive for the trend of much sharper price reductions in 1998–2013, slight price fluctuations in 2003–2007 and unexpected price rebound in 2012–2013. The literature we reviewed has not given a satisfactory explanation on these major price movements.

With the production localization and mass deployment of wind turbines over 1998–2013, China had a 65% decrease in the real turbine price, a decrease larger than any other countries for the same time span. From 2007, China has been the lowest wind turbine price holder in the world market. In this period, China locally-made turbines for commercial applications increased from zero to 15 GM annually and accumulated close to that of EU-15 or 29% of the world market. The local plants grow from small-size assembling ones to ten times larger than foreign counterparts in China and they are competing on the independently developed superpower turbine models. With such aggressive production expansions and technology progress in China turbine manufacturing, the theoretic grounds to explain price changes in turbine technology innovators are not appropriately enough for those from technology adopters to innovators.

The global-wide turbine price rise is in the input price climbing period of 2002–2008, but not all input markets are globally integrated. China is one of few exceptions to large price movements,

* Corresponding author. Business School, Ningbo University, No. 818 Fenghua Road, Jiangbei District, Ningbo, Zhejiang Province, 315211, PR China.
E-mail address: yuer3339@163.com (Y. Yu).

http://dx.doi.org/10.1016/j.renene.2016.11.056
0960-1481/

with only 5% price volatility in comparison with 50% plus in traditional technology leading countries. On the other hand, the unexpected China turbine price rebound in 2012–2013 is followed after the outbreak of nationwide wind curtailment in 2010 which is much more significant and persistent than in other countries. The power system is unprepared to tackle the flexible operations for additional large-scale wind power and rebalance the power generation across areas. It is further incapable to properly integrate wind, of which the majority has been built and will continue to be centered in distant, resource-rich north areas where the peaking capacity and transmission capacity are highly insufficient and time-consuming to be expanded. The rate that wind is curtailed even exceeds 60% in some farms. In response, China annual installed and produced turbine capacity declined for the first time in 2011–2012 and the price appeared to change against the curtailment rate. These facts imply that the turbine price driving forces are more complicated in China and the empirical basis needs to be modified.

This paper intends to discuss these unique features of wind turbine price evolution in China and provide empirical evidence to evaluate them. The exploration of this issue helps to clarify the origin of China turbine price changes, explain the development of turbine technology and understand the importance of coordinated developments between turbine sector and power market. With the improved understanding of China turbine price evolution, it is also constructive for the industry and government to make strategic planning or policy adjustments to improve the competitiveness of turbine manufacturing in China.

The complication of this work includes the construction of theoretical and empirical models, identification of price driving forces and tests of factor effects. A modified multi-factor learning curve (MFLC) is built in the framework of the Cobb-Douglas (CD) function, of which the theoretical foundation goes beyond simple learning effect and for the improved technology performance with optimal resource allocation. A broader set of turbine price factors is identified in accordance with industrial and China market characteristics over different time periods, which is conducted to minimize technological or geographic mismatch in wind turbine manufacturing. The empirical results are compared between models and across countries to argue for the modeling fit and geographic distinctions in China wind turbine price evolution. To support our research work, the following review is carefully done to clarify the approaches and controversies in turbine price studies.

1.1. The type and construction of learning models

The learning curve is the most widely adopted method to measure the effects of technology learning on the costs of wind technology [2]. The key publications are distinctive in terms of approaches to top-down or bottom-up interpreting the cost or price changes. The former approach is formulated on the empirical basis and the latter is constructed in the theoretic framework of economic or engineering rules.

The basic one-factor learning curve (OFLC) and two-factor learning curve (TFLC) take production experience and innovative learning as sources for the improvement of technology performance [3]. The effects of learning-by-doing (LBD) and learning-by-researching (LBR) are applied with an aggregate outlook to the problem of cost reductions in wind turbines. They can be expressed as follows:

$$C_t = C_0\left(\frac{CQ_t}{CQ_0}\right)^{-b} \tag{1}$$

$$C_t = C_0\left(\frac{CQ_t}{CQ_0}\right)^{-b} KS_t^{-d} \tag{2}$$

$$LBD = 1 - 2^{-b} \tag{3}$$

where C_t and C_0 are the turbine cost at time t and zero, and CQ_t and CQ_0 are the corresponding cumulative capacity. KS_t is the knowledge stock at time t, and b and d are the indices of LBD and LBR. Equation (1) presents the LBD effect through cumulative productions. Equation (2) integrates the LBR effect through innovative activities. And equation (3) is used to calculate turbine cost reductions with the doubling of cumulative production. The basic learning models are criticized for the exclusion of non-learning forces and the omission of possible discontinuities in the curve when the price is adopted as the proxy variable of cost. For the price learning curve, it is usually regarded that for more than five years, the price margin will not change much under market competition and the estimation is valid for the price and also for the cost trend [4].

Since basic learning models can't explain turbine price fluctuations in 2002–2008, the MFLC modeled with bottom-up assessments is inspired to take cost analysis along the production process [5,6]:

$$\Delta = \sum \Delta C_{kf,t} \tag{4}$$

where ΔC_t and $\Delta C_{kf,t}$ are the total and disaggregated cost changes at time t. Cost factors such as labor and material price, manufacturer profitability and warranty provisions are statistically examined in the literature. From the disaggregated perspective, the MFLC can be better derived in the economic framework of cost minimization in which inputs are fully utilized to maximize outputs. The function is set for wind power in Qiu and Anadon [7]:

$$\begin{aligned} C_t &= ZCQ_t^{-b}KS_t^{-d}\prod p_{i,t}^{e_i}\prod CV_{j,t}^{f_j} \\ P &= Z^*CQ_t^{-b}\prod p_{i,t}^{e_i}\prod CV_{j,t}^{f_j} \end{aligned} \tag{5}$$

where C_t is the wind power cost, Z is a constant, p_i is the price of inputs and CV_j represents other spatial control variables. The price function is derived from the cost. Although the modeling is better grounded, the function and result cannot be directly applied to wind turbines. The mismatch between inputs and outputs of different wind systems will lead to the biased or even invalid conclusions [8].

An alternative to MFLC is a component-based assessment under the engineering framework [2]. The cost function is the engineering-based scale model (or combined with the learning curve). The scale effect at the level of turbine models is specifically introduced into the function. It is expressed in Coulomb and Neuhoff [9] as follows:

$$c_t(D,H) = CQ_t^{-b}\sum C_{ci,t}^{e_i}\left(D, D_{ref},\ H,\ \mu\right) \tag{6}$$

where $c_{ci,t}$ is the unit cost of turbine component i at time t, D, D_{ref}, H and μ are the key technical scaling descriptors of rotor diameter, reference diameter, tower height and cost proportion varying with the mass. The cost of components differs in the forms of exponential functions (e^i). The empirical results provide evidence for the existence of diseconomies of scale in the turbine models above 600 kW [9]. The calibration of the modeled cost to the market price-adjusted cost is proposed and applied in Fingersh et al. [20] and Mone et al. [21]. But the effect of productive scaling is still