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Can technological learning significantly reduce industrial air pollutants intensity in China?—Based on a multi-factor environmental learning curve

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ABSTRACT

This paper introduces a methodology to examine the effect of technological learning on industrial air pollutants intensity in China. It is based upon the theory of learning curves and environmental learning curves. In this way it is possible to estimate the effect of technological learning on industrial air pollutants intensity in two steps. First, we build a multi-factor environmental learning curve model to investigate the relationship between technological learning and industrial air pollutants intensity. At the second stage of the analysis, we assess whether and how different types of technological learning can reduce industrial air pollutants intensity based on a mediating effect model. The results show that there is a causal relationship between technological learning and industrial air pollutants intensity. Moreover, different types of technological learning have the same influence way on industrial air pollutants intensity: learning-by-doing can significantly reduce industrial air pollutants intensity through energy efficiency; and the same is true with learning-by-researching and learning-by-importing. In addition, different types of technological learning have different influence degree on industrial air pollutants intensity: learning-by-doing is the leading contributor to the reduction in industrial air pollutants intensity, while the contribution of learning-by-researching is the smallest.

1. Introduction

The issue of emission reduction of industrial air pollutants is a major environmental concern of most developing countries due primarily to the air pollution at both the national and the global level. Generally, there are mainly two ways to control the emissions of industrial air pollutants, one is to control the emissions in the process of production (Wang et al., 2017), the other is the end-of-pipe treatment of industrial air pollutants (Frondel et al., 2007). Compared to the end-of-pipe treatment, the former one is a kind of proactive method based on cleaner production technology (Depret et al., 2015; Zailani et al., 2015), and is advocated by most countries because of its consistency with the idea of sustainable development like "green", "innovation" and "coordination" (Frondel et al., 2007). However, there are still some questions that need to be further explored in the study of cleaner production technology for the abatement of industrial air pollutants emissions, for example, can technological learning significantly reduce industrial air pollutants emissions?

Technological learning is a way of improving the performance of a given technology and the rate of technological improvement is usually depend on parameters in learning curves (Broek et al., 2009). Learning curves are the most common framework for assessing technological learning and cost reduction (Wei et al., 2017). Currently, the learning curve model has been considered a popular method for addressing various cost-related issues from production cost predictions to energy technology cost predictions. The influences of experience from learning-by-doing and learning-by-researching are among the independent variables that have been most often modeled (Clarke et al., 2006; Gillingham et al., 2008). A large body of studies show that such types of technological learning as learning-by-doing and learning-by-researching have a significant effect on the cost reduction trend of new energy source technologies (Huang and Liu, 2008; Lecca et al., 2017; Lindman and Söderholm, 2012).

More recently, the investigation of learning curves has been

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extended to the field of environmental economics (Han et al., 2008; Yu et al., 2016; Guo et al., 2016). For example, Yu et al. (2016) establish an environmental learning curve model for estimating the carbon abatement potential of economic sectors in China. They estimate the carbon abatement potential by assessing the learning coefficients of independent variables like energy intensity, per capita value added and fuel consumption mix. Guo et al. (2016) estimate the abatement potential of provincial carbon intensity by evaluating the learning coefficients of per capita GDP, the proportion of the tertiary industry in GDP and energy intensity. In sum, the core idea of these environmental learning curves underlies the analysis in this paper. That is, the abatement potential of industrial air pollutants emissions may be estimated by using the environmental learning curve model. However, the independent variables employed by these studies (energy intensity, per capita GDP, etc.) failed to reflect the effect of different types of technological learning, such as learning-by-doing or learning-by-researching, on emission reduction potential. This paper fills this gap by investigating the direct and indirect effect of different types of technological learning on industrial air pollutants emissions.

China is particularly suitable for such an analysis, since over the last decade the country has experienced an emission-intensive development pathway, becoming the world's largest air pollutants emitter. For instance, 338 municipal cities and provinces in China are monitored in 2015 according to the new Environmental Air Quality Standard, only 73 cities achieved the target in terms of the number of days with acceptable air quality (Yuan et al., 2017). Indeed, China's emission amounts of pollutants (e.g. SO_2, NO_x and PM2.5) have increased greatly with the rapid development of the economy, which has been a serious problem and is associated with adverse effects on human health and people's life quality (Chen et al., 2017; Sun et al., 2016). It is therefore important that the potential of technological learning to reduce China's industrial air pollutants emissions be tested empirically.

This paper contributes to existing literature in two ways. First, we establish a multi-factor environmental learning curve model, with learning-by-doing, learning-by-researching, learning-by-importing and scale effect as independent variables, and air pollutants intensity as a dependent variable. This allows for an analysis of the relationship between technological learning and air pollutants intensity based on the provincial panel data of China over 2001–2014, which may help us to know whether there is a causal relationship between technological learning and industrial air pollutants intensity. Second, we build a mediating effect model to distinguish between the direct and indirect effect of different types of technological learning on industrial air pollutants intensity, taking energy efficiency, energy structure and industrial structure as mediator variables. It is reasonable to assume that a wider variety of factors is involved in the process of technological learning (Wei et al., 2016). Thus, decomposing the total effect of technological learning into direct and indirect ones offers additional insights on whether and how technological learning can reduce industrial air pollutants intensity. This may provide a more comprehensive perspective for the literature on technological learning.

The rest of the paper is structured as follows: Section 2 contains a literature review related to the learning curve and environmental learning curve; Section 3 provides a theoretical analysis on the direct and indirect effect of technological learning; Section 4 focuses on describing the methodology; Section 5 reports and discusses the empirical results; Section 6 summarizes the paper and concludes with potential policy implications.

2. Literature review

The learning curve was first proposed by (Wright, 1936), which mainly describes the relation between cumulative output and labor time cost per unit product. As a popular tool for forecasting future costs, the learning curve has been constantly improved and its change is twofold. On the one hand, the model specification has shifted from single-factor learning curves to multi-factor learning curves that contain multiple independent variables. In addition to cumulative output that reflects learning-by-doing (Mcdonald and Schrattenholzer, 2007), the multi-factor learning curves involve cumulative R&D expenses or R&D based capital stock that reflects learning-by-researching (Jamasb, 2007; Söderholm and Klaassen, 2007), scale effect (Nemet, 2006; Söderholm and Sundqvist, 2007), changes in input prices and many others (Nemet, 2006). On the other hand, the application field of learning curves is also extended from product-level technologies to energy demand-supply technologies (Arrow, 1962; Kobos et al., 2006; Lindman and Söderholm, 2012). Besides forecasting cost reduction trend of products, the learning curve has been increasingly applied to predict the cost reduction trend of new energy source technologies, such as wind power and photovoltaic power (Ibenholt, 2002; Kobos et al., 2006; Rout et al., 2009; Xu et al., 2017; Yu et al., 2011). As a result, the technological learning captured by a learning curve is widely accepted as a mechanism through which technology costs reduction can occur.

While the learning curve has gained substantial popularity, there is a debate on whether it can accurately depict the cost reduction trend of a given technology (Rout et al., 2009; Yeh and Rubin, 2012). Klaassen et al. (2005) attempted to develop a more accurate model of learning curve for more precise prediction. They estimate a two-factor learning curve model and conclude that cost reduction depend on both cumulative production and R&D investment. Such consideration, however, has been challenged by some authors who argue that the cause of the cost decline may possibly root in price (e.g., the cost of wind power is closely associated with the price of wind turbines) (Nordhaus, 2013; Witajewski-Baltvilks et al., 2015). Moreover, others suggest that precise cost prediction for a technology depends not only on the model itself, but also on the learning rate as well as factors that affect learning (Li et al., 2012; Rubin et al., 2007). This is because the uncertainty in the assumed learning rates plays a crucial role in the production–cost development and model outcomes (Rout et al., 2009).

Despite this complexity, the technological learning mechanism originated from learning curves provide a theoretical basis for us to investigate the technological change driven by learning-by-doing, learning-by-researching and other factors (Pan et al., 2007). Since these types of technological learning can trigger reductions in the cost of technologies (Rubin et al., 2007), it is rational to assume that learning-by-doing, learning-by-researching and other factors might also lead to reductions in unit environmental cost (i.e., air pollutants intensity).

Environmental learning curve is a bottom-up model which is often used to estimate the abatement potential of CO_2 and air pollutants. It is a curve that can describe the trend of unit environmental cost, and better reflect the development of cleaner production technology. Even though there is a substantial body of literature on learning curve, only a handful of studies focus on environmental learning curve. Han et al. (2008) built an environment learning curve to estimate the abatement potential of SO_2 in 28 provinces of China, with per capita GDP as an independent variable, and SO_2 emissions per ten thousand yuan output value as