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Bending the learning curve☆,☆☆

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ABSTRACT

The aim of this paper is to improve the application of the learning curve, a popular tool used for forecasting future costs of renewable technologies in integrated assessment models (IAMs). First, we formally discuss under what assumptions the traditional (OLS) estimates of the learning curve can deliver meaningful predictions in IAMs. We argue that the most problematic of them are the absence of any effect of technology cost on its demand (reverse causality) and the ability of IAMs to predict all determinants of cumulative capacity. Next, we show that these assumptions can be relaxed by modifying the traditional econometric method used to estimate the learning curve. The new estimation approach presented in this paper is robust to the two problems identified but preserves the reduced form character of the learning curve. Finally, we provide new estimates of learning curves for wind turbines and PV technologies which are tailored for use in IAMs. Our results suggest that the learning rate should be revised upward for solar PV. Our estimate of learning rate for wind technology is almost the same as the traditional OLS estimates.

1. Introduction

Predicting the costs associated with climate mitigation strategies, and the trade-offs between different political interventions to curb CO2 emissions, depends heavily on assumptions about future technology developments and costs (Kriegler et al., 2014; Tavoni et al., 2012). The integrated assessment models (IAMs) which are used for ex-ante policy evaluation embed assumptions about the evolution of the performance and costs of mitigation technologies which are mostly taken as exogenous. The effect of induced innovation has been introduced in some models (Fisher-Vanden and Ho, 2010; Goulder and Mathai, 2000; Messner, 1997; van der Zwaan et al., 2002)[1], often by resorting to the use of learning-by-doing approaches. However, more effort is needed to correctly endogenize technological progress and forecast cost reductions in different low-carbon technologies. To this end, modelers can build on insights from economic theory and on estimates provided by empirical analysis of cost reductions.

Learning-by-doing dynamics, which stem from the empirical observation that as experience in a given technology increases, costs tend to fall, have been successfully embedded in most IAMs on account of the straightforward modeling assumptions they require. The process of learning is described in IAMs by means of the so-called "learning curve", namely a simple relation that links cumulative installed capacity of capital embodying a given technology, such as wind turbines or solar photovoltaic (PV) panels, to the installation costs of such technology.

The simplicity of the learning curve framework represents its strength but also its weakness. While easily implemented in IAMs, the learning curve framework is criticized by many as a simple reduced form relation, and one that does not establish a causal link between choice variables and cost reductions (Nemet, 2006; Nordhaus, 2009). Most notably, from an econometric point of view estimates of the learning rate (the slope of the learning curve) may be biased due to reverse causality and omitted variable bias. Reverse causality arises if cost reductions have themselves an effect on installed capacity. Omitted variable bias arises if an important determinant of costs is excluded from the estimation of the learning curve. The IAM community replies to such concerns by arguing that as long as the aim of the learning curve in climate models is to forecast changes in installation costs rather than to explain their determinants, the reduced form relation is all that is needed (Wiesenthal et al., 2012).

This paper contributes to this strand of literature by proposing a formal analytical model which sheds light on the learning curve debate. We start by arguing that estimation of the true causal effect in a learning curve framework, while of great interest in and of itself, is not

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[1] For a review technical change in climate economy models see Löschel (2002).

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necessarily what is needed for IAMs. The learning curve equation in IAMs and in empirical analysis used to calibrate IAMs should not be interpreted as describing the causal impact of experience on technology costs, rather as a reduced forms of a richer model, which could encompass several forces, such as learning by doing, learning by searching (i.e. accumulation of R&D knowledge) and dynamics of market structure.

Nevertheless, the meaningful application of the learning curve in IAMs requires some assumptions. We list these assumptions and discuss them in a formal framework. These are: the absence of reverse causality, the correct specification of demand for installed capacity in IAMs, a linear relationship between capacity and costs, and two assumptions on the stationarity of the series, as detailed below. We claim that some of these assumptions appear to be unrealistic and as such they limit the applicability of the learning curve in IAMs.

Our analytical model suggests a solution that allows for the use of the learning curve estimates in IAMs if the assumptions on the absence of reverse causality and misspecification are relaxed. This solution does not sacrifice the simplicity of the learning curve model, rather it modifies the econometric approach used to estimate it. We propose a new estimation approach dedicated to the learning curves used in IAMs, which is robust to the reverse causality problem but preserves the reduced form character of the learning curve.

Conversely, we are not yet able to propose a simple solution to relaxing the remaining assumptions on which the use of the learning curve model in IAMs rests, namely linearity and stationarity. Such assumptions cannot be relaxed without replacing the learning curve with a more sophisticated model. This would increase accuracy of the estimates but also increase complexity and thus complicate the use of learning curves in IAMs. We believe, however, that by providing a precise description of these last two assumptions, we open an important debate on the trade-offs associated with developing a more robust but possibly significantly more complex model. Finally, we apply our proposed estimation method to the case of learning in two key low carbon technologies, wind power and solar PV. Our results suggest that the learning rate utilized in the IAMs should be revised upward for solar PV. Our estimate of learning rate for wind technology is almost the same as the traditional OLS estimates.

The rest of this paper is organized as follows. Section 2 provides a brief review of the relevant literature. Section 3 presents our analytical framework, while Section 4 delves into the workings of the learning curve model. Section 5 details the main assumptions on which the use of the learning curve in IAMs rests, and Section 6 presents our new estimation approach. Section 7 discusses our empirical results, and Section 8 concludes by highlighting important implications and future research avenues.

2. The debate on the learning curve

Wright (1936) is the first to have translated the concept of learning in the field of economics. In his study of the aircraft industry, he postulated that experience, as proxied by past production, could help explain reduction in production costs. A similar approach was taken by Searle and Goody (1945) for the shipbuilding industry. The empirical relation between cumulative experience and efficiency growth was formalized theoretically by Arrow (1962) and Rosenberg (1982) with the "learning-by-doing" approach. This gave rise to the very first generation of endogenous growth models explaining long-run economic growth.

On the empirical side, the learning curve became one of the key tools for forecasting decrease in technology costs (Zachmann et al., 2014). The initial approach was that of estimating a reduced form relationship between costs and installed capacity of the form:

$$ln(C) = \alpha_0 + \alpha_K ln(K) + \varepsilon$$

where C is the installation costs (or installation price), K is the cumulative installed capacity, α_K is the slope of the learning curve, α_0 is a constant and ε is the error term. The slope can be translated into a learning rate, which indicates percentage decrease in costs associated with a doubling of capacity: $Learning\ Rate = 1 - 2^{-\alpha}$. Since learning rates cannot be assumed equal across technologies, different studies have focused on different technologies. Zimmerman (1982) provided learning rate for nuclear power generation, Joskow and Rose (1985) repeated the exercise for coal-burning generation units. More recently, researchers have focused on low carbon technologies such as wind and solar, which are considered key components of green growth and climate change mitigation (see for instance McDonald and Schrattenholzer, 2000 and Lindman and Söderholm, 2012).

The learning curve framework has also been widely used in IAMs with the aim of assessing the costs of mitigation under different policy scenarios. In IAMs, the prediction of the future installation costs of non-carbon technologies is paramount both to determine the future energy mix and to evaluate the costs of different climate change mitigation policies. In these models, the learning curve has often been used as a simple tool for making predictions on installation costs by using predictions on cumulative capacity supplied by the model themselves.

While the learning curve has gained substantial popularity, some authors question its empirical basis. The empirical correlation between technology deployment and its cost is not evidence of a causal relation between the two. There are two main criticisms which have been raised in the literature: First, the learning curve disregards other factors that could explain reductions in costs, such as investments in research and development (so-called 'learning-by-searching'), fall in material costs or increasing returns to scale. Nemet (2006), for instance, studies what factors are responsible for the cost reductions of PV panels. He concludes that learning-by-doing effects explain about 10% of the total cost reduction, while the rest is due to other factors. As a result of this criticism, several authors (among others Klaassen et al., 2005 and Söderholm and Sundqvist, 2007) amended the basic learning curve framework to include the most important missing factor: the stock of knowledge accumulated in the R&D process. The new curve, labeled the "two-factor learning curve", assumes that the log of installation costs is a weighted sum of the log of cumulative capacity (which proxies for experience) and the log cumulative public R&D investments (which proxy for the knowledge stock).

The second major problem pointed out by the critics of the learning curve is that of reverse causality. The positive correlation between installation costs and cumulative capacity observed in the data may simply reflect the causal effect of cost reductions on investment in capacity. Nordhaus (2009) presents a simple model which shows that if installation costs are driven by an exogenous trend, OLS estimates are biased and do not capture the true causal effect of capacity growth on reduction in costs. Söderholm and Sundqvist (2007) suggest using an instrumental variable approach to estimate the learning rate correctly. Söderholm and Klaassen (2007) also explore the simultaneity problem with an instrumental variable approach; however they instrument only the installation costs in the equation determining cumulative capacity. Köhler et al. (2006) suggest that the endogeneity problem could be resolved with panel data econometric methods. We follow this suggestion in our study.

The community of IAMs modelers responded to the learning curve criticism with two arguments (Wiesenthal et al., 2012). First, they argue that the one factor learning curve is a useful simplification of reality, one that captures relatively well the process under scrutiny and is extremely useful in advising policy making and design. They argue that other modeling aspects of IAMs embed similar levels of uncertainty and that the reduced form relationship between cost reductions and increased experience (capacity) is not among the ones that suffer from the most severe problems in this respect. In our opinion, this argument is weak, as it confounds model uncertainty with its bias. Moreover, the criticism regarding reverse causality is well-grounded in economic theory, which predicts that as a result of cost decrease demand for a given good (or, in this case, technology, and hence installed capacity) will increase.

The second argument presented by IAMs modelers is, in our opinion, more profound. The modelers note that the aim of IAMs is not a description of economic forces, but rather the formation of predictions about future technology costs, energy mix and costs of climate mitigation. The learning curve in IAMs is not meant to provide insights into the role of learning by doing in reducing installation costs — rather, in the words of Wiesenthal et al. (2012), "the learning curve groups several underlying drivers of cost reduction into one factor that matches empirical data".

Following this second argument, in this paper we argue that the fact that learning rates may not measure the true causal effect of cumulative experience on installation costs does not constitute a sufficient argument for abandoning the learning curve equation in IAMs altogether. We shed some light on the debate surrounding the use of learning curve estimates to calibrate IAMs by proposing a formal analytical model which shows whether, and under what conditions, OLS estimates of the learning rates can be safely used in IAMs. We find that, under some conditions, an omitted variable problem does not prevent a meaningful application of the learning curve in IAMs. In contrast, the possibility of reverse causality does constitute a serious limitation. In addition, we find that the use of the learning curve in IAMs rests on three additional assumptions: the assumption of a linear relationship between capacity and costs, the stationarity of the series, and the correct specification of the demand for installed capacity in the model.

By providing a precise description of each of these core assumptions, we open a debate on the trade-offs associated with developing a more robust but significantly more complex model. We argue that the main source of concern is not the simplicity of the learning curve model, but rather the econometric approach used to estimate learning rates. OLS gives rise to biased estimates, and hence does not provide reliable calibration for IAMs because the very restrictive assumptions on which it relies are not likely to be satisfied. As mentioned in the introduction, our analytical framework suggests that the reverse causality and misspecification error problems can be resolved in a relatively simple way by replacing OLS with a more appropriate estimation technique for learning rates. We use such an approach, which is robust to the reverse causality problem but preserves the reduced form character of the learning curve, to provide new estimates of learning curves for wind turbines and PV panels.

3. The analytical framework

To understand the economic forces that shape the learning curve we need to model the demand and supply curves of the market for a renewable technology. In this section we present a simple, yet reasonably general dynamic model which guides us in this respect. We first show how demand for capacity, as suggested by economic theory, depends on technology installation costs (Section 3.1). We then characterize the interdependence of installation costs and cumulative capacity (Section 3.2). For the sake of simplicity we present here only a two-period model, while we detail the infinite horizon model, which gives rise to almost identical predictions, in Appendix A1.

3.1. The demand for capacity

In this subsection, we use a simple economic model to derive the demand for a renewable technology. The model will serve in Sections 4–6 as a prosthesis that can mimic the behavior of IAMs.

Let C_1 denote the technology installation cost (in terms of dollars per MW) in the period 1, K_1 the cumulative installed capacity of the renewable technology (in terms of MW) in period 1, I_1 the new capacity installed in period 1, $Y(.)$ the energy production function, P_1 the price of energy (in terms of dollars per MWh). We use K_2, C_2 and P_2 to denote capacity, installation costs and energy price in period 2. We also use β to denote the representative firm's (or central planner's) discount rate. The objective function of a firm (central planner) producing energy from the renewable technology is:

$$V(C,K) = max_I\{P_1Y(K_1) - C_1I + \beta(P_2Y(K_2) + C_2K_2)\} \tag{1}$$

subject to $K_2 = (1-\delta)K_1 + I$ and $Y(K) = K^\alpha$. The first order condition of a firm's optimization problem is:

$$\beta\left(P_2\alpha K_2^{\alpha-1} + C_2\right) = C_1$$

If energy price is expected to grow at rate g_P, while technology costs are expected to fall at rate g_C, then

$$\beta\left(\alpha\,(1+g_P)\,P_1K_2^{\alpha-1} + (1+g_C)C_1\right) = C1$$

Rearranging and taking logs:

$$k = -\frac{1}{1-\alpha}c + \frac{1}{1-\alpha}p + \tilde{f}(\beta, g_c, g_P) + \text{constant}$$

where k, c and p stand for the demeaned values of $\ln(K_2)$, $\ln(C_1)$ and $\ln(P_1)$ respectively and $\tilde{f}$ is a generic function.

Since the constant term includes g_C and g_P, which may depend on policies, we shall write

$$k = -\frac{1}{1-\alpha}c + \frac{1}{1-\alpha}p + f(\text{policy}) + \text{constant} \tag{2}$$

As mentioned, an identical prediction could be derived from the infinite horizon model (see Appendix A1).

In reality, observed cumulative capacity is going to differ from the one predicted by the model due, for instance, to model misspecification error. For this reason, we need to include the error term in the equation. In vector form, Eq. (2) can be represented by

$$k = \omega c + \boldsymbol{\gamma}\mathbf{z} + \epsilon \tag{3}$$

where vector $\mathbf{z}$ contains all factors which determine installed capacity in IAM other than installation costs. All variables in $\mathbf{z}$ are demeaned.

IAMs' description of demand is usually more complicated than the simple structure of Eq. (1↑). In the model such as REMIND or WITCH, the cumulative capacity is determined in the central planner's intertemporal optimization process. It can be derived from the first order conditions as a log linear function of installation costs and shadow price of electricity. In models such as IMAGE or POLES, the cumulative capacity is linked to the installation costs, costs of electricity generated with other technologies, and the array of macroeconomic variables, such as level of economic activity, size of population and energy intensity of the economy. One should therefore keep in mind that variables entering vector $\mathbf{z}$ will differ between IAMs. In Section 4, which is mostly demonstrative, we will assume that vector $\mathbf{z}$ includes only price of energy and policy as predicted in Eq. (2)↑. However the general results in Sections 5 and 6 will be derived for any set of variables in vector $\mathbf{z}$.

3.2. The linear technology model

Let $\mathbf{r}$ be the vector of factors that determine the installation cost of the renewable technology, which includes, among others, public and private R&D investments, experience – usually proxied by cumulative installed capacity – and material prices. We will call the elements in $\mathbf{r} = \{r_1, r_2, r_3, \ldots\}$ the direct drivers of installation cost. These direct drivers themselves depend on other factors, which we refer to as the indirect drivers, for instance price of energy, policies, supply of researchers and engineers or demand for materials by other sectors. The set of indirect drivers can include those factors which are used in IAMs to determine installed capacity, i.e. elements of vector $\mathbf{z}$. Conversely, the factors which are not included in IAMs, but have an impact on the elements in **r**, e.g. supply of engineers or business cycle, are gathered in vector **t**. All variables in **t** are demeaned. The example of this structure is pictured in Fig. 1.

Our model is linear, thus each direct driver of installation cost, r_i is a linear function of elements in **z** and **t**, i.e. $r_i = \sum_j \delta_{ij} z_j + \sum_m \nu_{im} t_m$, where j and m are indexes for factors included in **z** and **t**. Thus,

$$c = \sum_i r_i(\boldsymbol{z}, \boldsymbol{t}) = \sum_i \left(\sum_j \delta_{ij} z_j + \sum_m \nu_{im} t_m \right).$$

The reduced form of this equation is

$$c = \sum_j \delta_j z_j + \sum_m \nu_m t_m$$

where $\delta_j = \sum_i \delta_{ij}$ and $\nu_{\mathrm{m}} = \sum_{\mathrm{m}} \nu_{\mathrm{im}}$.

In vector notation,

$$c = \boldsymbol{\delta z} + \boldsymbol{\nu t}. \tag{4}$$

3.3. The data generating process

Throughout the paper we assume that Eqs. (3↑) and (4↑) constitute the true representation of reality. The data we observe are assumed to be generated by this system. In econometric terminology, we take Eqs. (3↑) and (4↑) as a full description of the Data Generating Process (DGP).

In reality, the DGP is partly hidden for IAMs modelers. Hence, we assume that they understand and accurately calibrate Eq. (3↑). Conversely, they are likely unable to fully uncover and model the drivers of the technological progress which reduce the costs of the renewable technology. Instead, they have to rely on the symbiosis of Eq. (3↑) and the learning curve, which they can estimate from the data available to them.

In the following two sections we examine what predictions this symbiosis produces if the data are generated by the DGP. In Section 4 we show that, under some conditions, the symbiosis could indeed deliver correct predictions. In Section 5, we explore in detail what assumptions about the DGP are necessary to ensure that the symbiosis gives rise to such meaningful predictions.

The focus of our exercise, which is meant to mimic the endeavor of IAMs modelers, is on predicting changes in installation costs resulting from an increase in one of the factors captured in vector **z** — typically we will consider an increase in the energy price. Using our knowledge about the DGP, we can derive what the best prediction of installation costs, c, is if we are given information on the realized values in vector **z**:

$$E(c|\boldsymbol{z}) = \boldsymbol{\delta z} + \boldsymbol{\nu} E(\boldsymbol{t}|\boldsymbol{z}) = \left(\boldsymbol{\delta} + \boldsymbol{\nu} E(\boldsymbol{t}|\boldsymbol{z})\boldsymbol{z'}(\boldsymbol{zz'})^{-1} \right)\boldsymbol{z}. \tag{5}$$

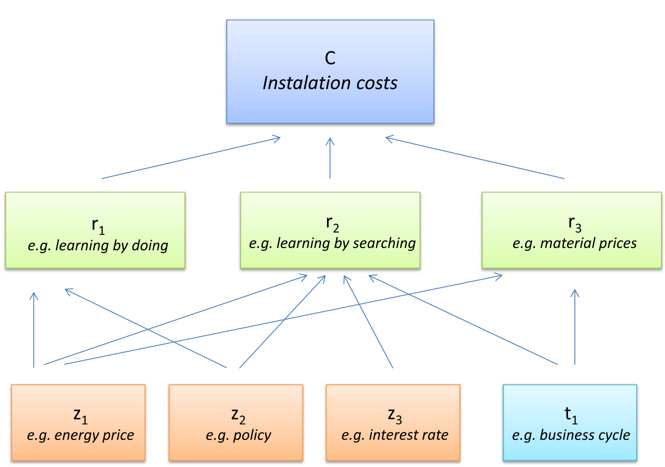

Fig. 1. The structure of the general linear technology model.

If vectors **z** and **t** contain only one factor each (which will be the case in some simplified examples we consider below), then this could be simply restated as:

$$E(c|z) = \left(\delta + \nu \frac{Cov(t, z)}{Var(z)} \right) z. \tag{6}$$

4. How does the learning curve work?

In this section we show two things. First, under specific conditions, the estimation of the learning curve using traditional OLS techniques and the use of the estimated parameters in IAMs may produce valid predictions. We draw on a simple numerical example (Scenario I) to portray the role of the learning curve and its estimation in the formation of IAMs' predictions. Second, we also show that, under clearly specified assumptions, the traditional one-factor learning curve can produce valid predictions even if in reality cost reductions are not the result of learning-by-doing, but rather of other forces which are not modeled within the IAMs. We illustrate the intuition behind this result in 'Scenario II'.

To facilitate illustration and focus on the intuition, in this section we assume that there are only two forces that can potentially influence technology cost reductions: learning-by-doing and learning-by-searching. Thus the two elements in **r** are experience k, which can be measured by cumulative installed capacity and the knowledge stock h, measured with the cumulative R&D investment. We assume that, in accordance with Eq. (2↑), experience and the knowledge stock depend only on the price of energy; thus vector **z** contains only one variable, the log of price, and $z = p$. We also assume that all factors in vector **t** are constant, implying that $\boldsymbol{\nu}\mathbf{t} = 0$ (since variables in **t** are demeaned). As a result we can express cumulative capacity and knowledge stock as $k = \delta_k p$ and $h = \delta_h p$. Finally we assume no misspecification error ($\epsilon = 0$). As a result of these restrictions, we can describe the DGP with the system of two equations:

$$k = \omega c + \gamma p \tag{7}$$

$$c = \alpha_k k + \alpha_h h = \delta p \tag{8}$$

where $\delta = \alpha_k \delta_k + \alpha_h \delta_h$. Note that, since t is constant, $Cov(t,p) = 0$ and therefore the true evolution of c as a function of p must follow:

$$E(c|p) = \delta p \tag{9}$$

4.1. The OLS estimate of the learning rate

The traditional approach to estimate the learning rate takes the form of the regression

$$c_\tau = \alpha k_\tau + \eta_\tau \tag{10}$$

where η_τ denotes the error term in the econometric model. The OLS estimator of the learning rate is then

$$\hat{\alpha} = \frac{\widehat{Cov}(k, c)}{\widehat{Var}(k)}$$

where $\widehat{Cov}(k, c) = \sum_\tau k_\tau c_\tau$ and $\widehat{Var}(k) = \sum_\tau (k_\tau)^2$.

Since we assumed that our DGP is restricted to Eqs. (7↑) and (8↑), the reduced form relation between c and k observed in data is

$$c = \frac{\delta}{\gamma + \delta\omega} k.$$

Hence, simple calculations show that, if the data are generated by our DGP, the estimate of the learning curve slope generated by the

OLS method must be equal to

$$\hat{\alpha} = \frac{\delta}{\gamma + \delta\omega}.$$

4.2. Implementation in the IAM

Suppose now that a IAM tries to explore what the implications are of a one percent increase in energy price, p, on renewable technology costs. The solution of our simple IAM specified in Eq. (1↑) must satisfy Eq. (7↑). Furthermore, if the model includes the learning rate estimated by OLS, the solution must also satisfy

$$c = \frac{\delta}{\gamma + \delta\omega} k. \quad (11)$$

If we combine these two conditions, we find that the solution will satisfy

$$c = \delta p.$$

The model predicts that a one percent increase in energy prices (induced for example by increase in the price of CO2 emission permits) generates a δ% reduction in the installation cost of renewable technology. This is exactly in line with the true dynamics in this economy, as described with Eq. (9↑). Note that our assumptions so far do not imply the existence of learning-by-doing. Rather, with the two examples below, we show that the learning curve can deliver results in line with reality regardless of whether cost reductions are driven by learning-by-doing ($\alpha_k \neq 0$ and $\alpha_h = 0$), learning-by-searching ($\alpha_k = 0$ and $\alpha_k \neq 0$) or both ($\alpha_k \neq 0$ and $\alpha_k \neq 0$). In the first example, the estimation of the learning curve allows to identify the true learning-by-doing effect. In the second example, the estimation of the learning curve slope does not provide information about the true learning rate. However, this does not prevent the learning curve from delivering meaningful predictions which could be used to evaluate policies.

4.2.1. Scenario I

Consider a world in which learning-by-doing is the sole driver of technology cost reduction. An increase in installed capacity leads to accumulation of experience, which in turn reduces costs. Specifically, in this example we assume that $\Delta c = -0.1\Delta k$.[2] Cumulative Capacity depends on the price of energy, but we assume that it is not affected by changes in the installation costs (i.e. we assume[3] that $\Delta k = 2\Delta p - 0 * \Delta c$). The assumptions for Scenario I are summarized in Table 1.

Suppose that period 1 (which could be a multi-year period) witnesses a 10% increase in energy price. Such increase in energy price gives rise to a 20% increase in installed capacity, which results, from learning effects, in a 2% reduction in installation costs. Further suppose that in period 2 the government introduces a tax that increases the price of energy by 20%. This produces a 40% growth of installed capacity, followed by a 4% drop in costs.

Given this, if at the beginning of period 2 scientists were requested to evaluate the impact of a tax (i.e. the impact of an increase in price) on installation costs, they would use observations from period 1 and conclude that a 1% capacity growth is associated with 0.1% reduction in technology costs. Thus, they correctly identify the size of the learning rate. The researchers may also use the model which includes the objective function specified in Eq. (1↑). If they calibrate the model accurately, the model solution must satisfy:

$$k = 2p.$$

Table 1
The data generating process and IAM's predictions in Scenario I.

c – log of installation costs
k – log of cumulative capacity
p – log of energy price

The data generating process

$\Delta c = -0.1\Delta k$ (learning by doing)
$\Delta k = 2\Delta p - 0 * \Delta c$ (demand for capacity)

	p	k	c
Period 1	+10%	+20%	−2%
Observed slope of the learning curve: 0.1			
Period 2	+20%	+40%	−4%

Integrated assessment model

Equations
$c = -0.1\,k$ + constant (learning by doing)
$k = 2p$ + constant (demand for capacity)

Predictions

	p	k	c
Period 2	+20%	+40%	−4%

This equation is going to be accompanied by the learning curve:

$$c = 0.1k.$$

To satisfy both equations, the solution to the model must therefore imply that

$$c = -0.2p.$$

Clearly, the researchers will correctly predict that a tax that increases energy price by 20% must produce a 4% cost reduction, in accordance with the dynamics in the scenario.

4.2.2. Scenario II

In scenario II (Table 2) we shall consider another world. There is no learning-by-doing and so installation costs are unaffected by growing cumulative capacity. However, the costs can be reduced by accumulation of R&D knowledge (thus, if h denotes the log of the cumulative R&D investment, we assume here that $\Delta c = -0.1 * \Delta h - 0 * \Delta k$). The knowledge stock is affected by energy prices, namely an increase in energy price stimulates research and the growth of knowledge ($\Delta h = \Delta p$). As in scenario I, cumulative capacity depends positively on energy price ($\Delta k = 2\Delta p$).

Suppose that in the first period price increases by 10%. The increase in price has two effects: first, it incentivizes capacity building, which as a result grows by 20% and, second, it incentivizes R&D investment. Higher R&D leads to faster technological progress and produces a 1% decrease in installation costs. In period 2, the price of energy, following the tax increase, grows by 20%. The story follows exactly the dynamics in period 1, except that all growths are scaled up: total capacity growth is 40%, R&D knowledge grow by 20% and costs are reduced by 2%

As in the previous scenario, at the beginning of the first period scientists are asked to evaluate the effect of a price increase (namely, a tax) on technology costs. Based on the observations in the first period, they find that the slope of the learning curve is 0.05 (20% increase in capacity coincided with the 1% cost reduction). If the demand structure in IAM is specified and calibrated correctly, it will predict $k = 2p$. This equation and the estimated learning curve ($c = 0.05k$) jointly imply that $\Delta c = -0.1\Delta p$. Thus, scientists would predict a 2% cost reduction after a 20% increase in the price of electricity – in line with reality.

[2] In various scenarios we consider we assume some specific values of the parameters. However, as we demonstrate in the mathematical analysis, the general results do not depend on the values of these parameters (unless this is very clearly stated).

[3] In light of our discussion in Section 3.1, this is a strong assumption. However, we do it as it greatly facilitates the exposition of the role of learning curve estimation in forming predictions in IAM.

Table 2
The data generating process and IAM's predictions in Scenario II.

c — log of installation costs
k — log of cumulative capacity
h — log of cumulated R&D investment
p — log of energy price

The data generating process

$\Delta c = -\Delta h - 0 * \Delta k$ (learning by searching only)
$\Delta k = 2\Delta p - 2\Delta c$ (demand for capacity)
$\Delta h = \Delta p$ (demand for research)

	p	k	h	c
Period 1	+10%	+40%	+10%	−10%
Observed slope of the learning curve: 0.25				
Period 2	+20%	+40%	+20%	−2%

Integrated assessment model

Equations:
$c = -0.25\ k$ + constant (learning by doing)
$k = 2p - 2c$ + constant (demand for capacity)

Predictions

	p	k	h	c
Period 2	+20%	+80%	n/a	−20%

Although in scenario 2 the estimated slope of the learning curve cannot be interpreted as informing on the causal effect of experience on cost, the learning curve remains a useful tool for predicting technology costs in IAMs. Changes in cumulative capacity carry a signal about the underlying economic forces, such as changes in prices or policies. Whenever IAMs suggest that in one period installed capacity is high, we can infer that prices in this period are also high (or policy is more stringent). In this circumstance we shall expect high R&D investment and low technology cost. Consequently we want the learning curve to have a negative slope even if the true learning rate is zero.

These simple examples show that the econometric estimates of the learning curve slope which are fed into IAMs do not have to, and in fact should not, capture only the direct causal effect of experience on cost. Rather, they must capture the effect of all factors, which have the same determinants as cumulative capacity. The above analysis shows that, under some circumstances which we will discuss in detail in the subsequent sections, simple OLS estimator meets this requirement.

If we depart from the stylized examples above, and relax some of the assumptions on which they are based, the learning curve estimates can give rise to significantly biased predictions in IAMs. In the next section, we describe in detail the (strong) assumptions on which the learning rates estimated as customary in the literature rest, and their implications for use in IAMs.

5. When does the learning curve work?

In this section we provide a formal and intuitive discussion of the assumptions that are necessary to ensure that the use of OLS estimates of the learning rate in IAMs deliver meaningful predictions, as is the case in the two stylized examples above. The assumptions are listed here and discussed in detail below.

Assumption 1. The absence of reverse causality.

Any variation that influences technology cost, c, but included in vector $\mathbf{z}$, which is used by IAM to predict cumulative capacity, has no effect on cumulative capacity. This means that either all elements in vector $\mathbf{t}$ are constant (for every k, $Var(t_k) = 0$) or, alternatively, that installation costs have no effect on cumulative capacity ($\omega = 0$).

Assumption 2. Stationarity of the relation between factors controlled and uncontrolled in IAMs.

The relation between those drivers which are accounted for in IAMs and those which are not is constant over time. Put differently, for any pair j and k, $Cov(z_j,t_k)$ is stationary.

Assumption 3. The misspecification errors are constant.

Misspecification errors do not vary over time, i.e. $Var(\epsilon) = 0$

Assumption 4. The stationarity of the relation between factors explicitly modeled in IAMs.

One of these three conditions must be satisfied:

(i) All factor that are explicitly modeled in a IAM (that is, all factors included the $\mathbf{z}$ vector) are collinear, i.e. $\mathbf{z} = \boldsymbol{\pi} z$ where $\boldsymbol{\pi}$ is a vector of constants and z is a scalar.
(ii) For every pair of factors (i,j) included in the $\mathbf{z}$ vector, $\frac{\delta_i}{\gamma_i} = \frac{\delta_j}{\gamma_j}$. Thus in vector notation, $\boldsymbol{\delta} = \eta\boldsymbol{\gamma}$, where η can be any scalar.
(iii) All factors included in the $\mathbf{z}$ vector have exactly the same effect on k and on c, i.e. $\boldsymbol{\delta} = \boldsymbol{\iota} d$ and $\boldsymbol{\gamma} = \boldsymbol{\iota} g$ where $\boldsymbol{\iota}$ is a vector of ones and g and d are constant scalars.

Assumption 5. Precise predictions of IAMs.

IAM's predictions on the future values in vector $\mathbf{z}$ are correct and precise.

Assumption 6. k the linearity of the DGP.

All the parameters in the DGP are stationary, i.e. δ, ν, $\boldsymbol{\omega}$ and γ do not vary over time.

5.1. Absence of reverse causality

Note that in Section 4 we assumed that factors in vector $\mathbf{t}$ were constant. This clearly does not describe reality. In addition to the price of energy, policy stringency and the interest rate, there are number of other factors that determine technology costs and that fluctuate over time in a random fashion. Innovations are rarely deterministic; their number and their value are both random. Similarly, the price of materials fluctuates over time in a random fashion. This implies that the inclusion of the three factors included in vector $\mathbf{z}$ is not sufficient to determine the level of costs without any prediction error.

The presence of this error can result in serious complications in estimating the learning curve. If in the DGP $\omega \neq 0$, any shock in t (e.g. the unexpected arrival of a successful innovation) followed by a shock to cost, would promote growth of installed capacity. This would produce a correlation between the two variables in the data, which is not meant to be captured in the learning curve. In IAMs, the learning curve must capture only the effect of experience and factors that have the same determinants as experience on technology cost.

To illustrate this point with the formal model, suppose that there is only one factor in $\mathbf{t}$, which we label t. We also assume that vector $\mathbf{z}$ contains only one variable. We allow for t to vary over time, that is $Var(t) \geq 0$. In this section we still assume that $Cov(z,t) = 0$ (we discuss this assumption in Section 5.2). The DGP can be summarized then as[4]

$$k = \omega c + \gamma z \quad (12)$$

$$c = \delta z + t. \quad (13)$$

[4] Note that since t has only one factor, ν can be normalized to unity.

In this case, the OLS estimate of the learning curve's slope is going to deliver

$$\hat{\alpha} = \frac{\widehat{Cov}(k,c)}{\widehat{Var}(k)} = \frac{\delta}{\gamma + \delta\omega}(1+\Gamma)$$

where $\Gamma = \frac{\gamma\omega}{\delta}\frac{Var(t)}{Var(k)}$ Thus the estimated learning curve is:

$$c = \frac{\delta}{\gamma + \delta\omega}(1+\Gamma)k.$$

Combining this equation with the IAM's first order condition Eq. (12↑) we find that

$$c = \frac{(1+\Gamma)}{1-\frac{\delta\omega}{\gamma}\Gamma}\delta z$$

Comparing this equation with the true relation between c and z stated in Eq. (13↑), we conclude that the IAM can deliver predictions that are in line with reality for any values of parameters if and only if $\Gamma = 0$, i.e. if and only if $Var(t) = 0$ or $\omega = 0$. If $Var(t) > 0$, then for the usual signs of the parameters ($\omega < 0$, $\delta > 0$, $\gamma > 0$) $\Gamma > 0$ and the effect of z on c is exaggerated. We illustrate this logic with the example below.

5.1.1. Scenario III

Consider a world similar to the one in Scenario II. There is no learning-by-doing, so installation costs are not affected by changes in capacity. However, cost does depend on the stock of knowledge $\Delta c = -\Delta h + 0 * \Delta k$. Assume also that, in contrast to Scenario II, the evolution of that knowledge is totally random. The capacity depends on installation costs and on energy price $\Delta k = -2\Delta c + 2\Delta p$.

In period 1, energy price increases by 10%. Thus capacity increases by 20%. In the same period, a (random) discovery leads to a 10% drop in installation costs. This leads to a further 20% increase in capacity, so overall capacity grows by 40% in period 1. In period 2 a 20% tax increase leads to a 40% increase of capacity. As in period 2 there is no change in knowledge, installation costs remain unchanged.

At the end of period 1, scientists conclude that a 40% increase in capacity is associated with a 10% drop in installation costs. They estimate a "learning rate" equal to 0.25. Suppose they also know – from other sources – that the elasticity of capacity with respect to energy price is 2. As a result they correctly predict a 40% increase in capacity after 20% tax, but wrongly forecast a 10% reduction in installation costs, which according to their calculations should follow from the learning effect.

The comparison of Scenarios I and II with Scenario III suggests that scientists are able to obtain a meaningful estimate of the "learning rate" as long as they base their analysis solely on those instances in which capacity has been affected exclusively by the exogenous shocks. In fact, this conclusion is going to be a starting point for the derivation of the robust estimator presented in the following section.

5.2. Stationarity of the relation between controlled and uncontrolled factors

Assumption 2 states that the covariance between factors in $\mathbf{z}$ and factors in $\mathbf{t}$ must be constant over time. Note that this assumption becomes redundant if Assumption 1 holds under constancy of $\mathbf{t}$. On the contrary, Assumption 2 gains importance if Assumption 1 is satisfied because $\omega = 0$. In this case the estimated learning curve becomes:

$$c = \left(\delta + \gamma^2 \frac{\widehat{Cov}(z,t)}{\widehat{Var}(k)}\right)\frac{k}{\gamma}$$

If we combine this with the IAM's demand for capacity as specified in Eq. (12↑) (with $\omega = 0$), we find that the prediction of the IAM must satisfy:

$$\tilde{c} = \left(\delta + \frac{\widehat{Cov}(z,t)}{\widehat{Var}(z)}\right)\tilde{z}$$

where $\tilde{c}$ and $\tilde{z}$ are the future predictions of c and z.

We can compare this with the true functional relationship between c and z, which can be derived from the DGP as

$$E(c|\tilde{z}) = \left(\delta + \frac{Cov(\tilde{z},t)}{Var(\tilde{z})}\right)\tilde{z}. \tag{14}$$

Thus, the model would correctly predict reality only if $\widehat{Cov(z,t)} = Cov(\tilde{z},t)$, that is if the covariance does not change over time.

The assumption, may appear innocent, but it could be particularly restrictive for evaluating policy scenarios. Recall that the assumption requires $Cov(t,z)$ to be stationary, i.e. unchanging over time. Imagine now that t is a simple time trend and z is the policy variable. In this case the assumption requires policies not to change over time. Clearly this is highly restrictive as the scenarios, which have to be evaluated by IAMs, usually do involve changes in policies.

5.3. Absence of misspecification error

In this subsection we demonstrate that the use of OLS to estimate the learning rates produces biased results if misspecification error varies over time, i.e. if $Var(\epsilon) \neq 0$. Misspecification error arises if observed cumulative installed capacity is determined by different factors from those used to predict cumulative installed capacity in IAMs. In our framework, it implies that, while IAMs assume $k = \omega c + \boldsymbol{\delta}\mathbf{z}$, in reality (in the DGP) the true cumulative capacity is generated by the function $k = \omega c + \boldsymbol{\delta}\mathbf{z} + \epsilon$, where ϵ could be a random variable.

To understand the intuition of why variation in ϵ could cause a problem, recall that in IAMs capacity serves as a signal informing on the level prices or policies, which through various channels, shape the cost of technology. To calibrate correctly these interdependence, we have to rely on the assumption that also the capacity observed in the data is a clear signal of underlying economic forces. The presence of ϵ introduces noise into this signal. If the amount of this noise is substantial, or, equivalently, if observed capacity does not respond to changes in prices or policies as well as the level of capacity generated in IAMs, empirical estimation will suggest that capacity is a poor predictor of costs, although in fact it is not.

For the sake of simplicity, we maintain Assumptions 1 (with $Var(t) = 0$), 4 and 5. In this case, the OLS estimate of the learning curve's slope is going to deliver

$$\hat{\alpha} = \frac{\widehat{Cov}(k,c)}{\widehat{Var}(k)} = \frac{\delta}{\gamma + \delta\omega}(1+\Omega)$$

where $\Omega = -\frac{Var(\epsilon)}{Var(k)}$. In analogy to Subsection 5.1, the combination of the estimated Learning Curve with the IAM's first order condition implies:

$$c = \frac{(1+\Omega)}{1-\frac{\delta\omega}{\gamma}\Omega}\delta z.$$

Thus, again, the use of estimated learning rates in IAMs can deliver predictions that are in line with reality for any parameters values only if $\Omega = 0$, i.e. if $Var(\epsilon) = 0$. If $Var(\epsilon) > 0$, then for the usual signs of the parameters ($\omega < 0$, $\delta > 0$, $\gamma > 0$) the effect of changes in z on changes in c predicted in IAMs is going to be smaller than in reality.

5.4. The stationarity of the relation between controlled factors

In Section 4, we have assumed that vector **z** contains only one variable (namely the price of energy). If we allow the vector **z** to contain more than one factor, then, in general, the univariate learning curve does not allow us to separately identify the effect of each factor in **z** on costs . Below we clarify this point using a theoretical framework.

Imagine that vector **z** contains two variables, z_1 and z_2. Assume that Assumptions 3 and 5 hold. In addition, assume that $\omega = 0$ and $\nu\mathbf{t}$ is constant. These last two assumptions simplify the structure significantly, but still allow us to portray the problem associated with multiple z's. The DGP, restricted in this way, can be summarized as

$$k = \gamma_1 z_1 + \gamma_2 z_2 \tag{15}$$

$$c = \delta_1 z_1 + \delta_2 z_2 \tag{16}$$

The estimates of the slope between technology costs and cumulative capacity, using data that are generated by this DGP, give rise to

$$\hat{\alpha} = \frac{\widehat{Cov(k,c)}}{\widehat{Var(k)}} = \frac{\delta_1\gamma_1\widehat{Var}(z_1) + \delta_2\gamma_2\widehat{Var}(z_2) + (\delta_1\gamma_2 + \delta_2\gamma_1)\widehat{Cov}(z_1,z_2)}{\gamma_1^2\widehat{Var}(z_1) + \gamma_2^2\widehat{Var}(z_2) + \gamma_1\gamma_2 2\widehat{Cov}(z_1,z_2)}.$$

Combining the estimated learning curve with Eq. (15↑) (which is assumed to be known to the researchers) implies:

$$c = \hat{\alpha}k = \frac{\delta_1\gamma_1\widehat{Var}(z_1) + \delta_2\gamma_2\widehat{Var}(z_2) + (\delta_1\gamma_2 + \delta_2\gamma_1)\widehat{Cov}(z_1,z_2)}{\gamma_1^2\widehat{Var}(z_1) + \gamma_2^2\widehat{Var}(z_2) + \gamma_1\gamma_2 2\widehat{Var}(z_1,z_2)}(\gamma_1 z_1 + \gamma_2 z_2 + \text{constant}).$$

This reduces to the true Eq. (16↑) only in three instances: when the factors in **z** are collinear: $z_1 = \pi z_2$, when $z_1$has exactly the same impact on k and c as z_2 i.e. if $\delta_1 = \delta_2$ and $\gamma_1 = \gamma_2$ or when $\frac{\delta_1}{\gamma_1} = \frac{\delta_2}{\gamma_2}$ (Please see Appendix A2 for details).

Turning away from the bivariate example, suppose that **Z** is the matrix that contains all the demeaned observations of variables in **z** that are available at the time of estimation of the learning curve. Let $\tilde{\boldsymbol{Z}}$ be the matrix with the expectations about future values of z's. If we allow for more than two factors in vector **z** and allow $\omega \neq 0$ (although maintaining Assumptions 1, 3 and 5), it can be shown that estimating the learning curve with the data generated by Eqs. (3↑) and (4↑), and combining it with the correctly specified Eq. (3↑), must satisfy

$$E\left(\boldsymbol{c}\middle|\tilde{\boldsymbol{Z}},\boldsymbol{Z}\right) = \frac{(\omega\boldsymbol{\delta}+\boldsymbol{\gamma})\boldsymbol{Z}'\boldsymbol{Z}\boldsymbol{\delta}'}{(\omega\boldsymbol{\delta}+\boldsymbol{\gamma})\boldsymbol{Z}'\boldsymbol{Z}\boldsymbol{\gamma}'}\tilde{\boldsymbol{Z}}\boldsymbol{\gamma}' + \text{constant}$$

where apostrophe denotes the transpose of the matrix or vector. If factors in **z** are collinear, i .e. if $\mathbf{z} = \boldsymbol{\pi}' z_1$ where $\boldsymbol{\pi}$ is a weighting vector with $\pi_1 = 1$, then $\mathbf{Z} = \mathbf{z_1}\boldsymbol{\pi}$ (where $\mathbf{z}_1$ is a vector of demeaned observations on z_1) and

$$E\left(c\middle|\tilde{\boldsymbol{Z}},\boldsymbol{Z}\right) = \frac{\left[(\omega\boldsymbol{\delta}+\boldsymbol{\gamma})\boldsymbol{\pi}'\right]\left[\boldsymbol{z}_1{}'\boldsymbol{z}_1\right]\left[\boldsymbol{\pi}\boldsymbol{\delta}'\right]}{\left[(\omega\boldsymbol{\delta}+\boldsymbol{\gamma})\boldsymbol{\pi}'\right]\left[\boldsymbol{z}_1{}'\boldsymbol{z}_1\right]\left[\boldsymbol{\pi}\boldsymbol{\gamma}'\right]}\tilde{\boldsymbol{z}_1}\left[\boldsymbol{\pi}\boldsymbol{\gamma}'\right] + \text{constant}$$

where objects in the square brackets are scalars. This reduces to

$$E\left(c\middle|\tilde{\boldsymbol{Z}},\boldsymbol{Z}\right) = \tilde{\boldsymbol{Z}}\boldsymbol{\delta}' + \text{constant}$$

which corresponds exactly to the functional relation associated with the DGP. A similar result is obtained if $\boldsymbol{\delta} = \eta\boldsymbol{\gamma}$ and if $\boldsymbol{\delta} = \boldsymbol{\iota}d$ and $\boldsymbol{\gamma} = \boldsymbol{\iota}g$ where η, d and g are scalars.

Note that if learning-by-doing is the sole determinant of technology costs, and if the true value of the learning rate is $1 - 2^{-\alpha}$, then indeed $\delta = \eta\gamma$ with $\eta = \frac{\alpha}{1-\alpha\omega}$, and the assumption is satisfied. However, if one wishes to preserve the reduced form of the learning curve and to allow technology cost to be shaped by other processes than learning-by-doing, then the assumption is fairly restrictive, especially if one wants to avoid restricting the parameters δ and γ. This means that it may be particularly problematic if one wishes to perform a policy exercise within a IAM. If one wishes to explore the effect of a rapid increase in policy stringency, it is difficult to assume that the relation between policy and other determinants of cumulative capacity in IAMs (e.g. energy price) will stay the same as before the policy shock. It seems that the only way to relax this assumption is to replace the learning curve model with a multivariate regression similar in form to Eq. (4↑). The estimated reduced form model could be included directly in the IAM. The disadvantage of such an approach is the loss of generality of the model: since every IAM contains a different set of variables in vector **z**, the regression and its estimates would not be universal.

5.5. Correct and precise predictions of z

Assumption 5 requires that information available to the IAM model is sufficient to correctly predict the future values in vector **z**, i.e. if $\tilde{\mathbf{z}}$ denotes IAMs predictions of vector **z**, then $\tilde{\mathbf{z}} = \mathbf{z}$. This assumption ensures that all variables in vector **z** are exogenous in the sense that they are independent of variation in t: since t cannot be observed by the IAM, IAM can correctly predict **z** only if **z** does not depend on t.

The lack of precision of the estimates will not only result in lower precision in predicting future technology costs, but will also imply that the effect of variation in $\tilde{\boldsymbol{z}}$ on the costs will be systematically biased. To see this, suppose that in the true DGP and in IAM, the cumulative capacity is determined by only one factor, z (which could be, for instance, the price of energy). However IAMs are unable to precisely predict the values of this variable. Instead, they could predict only a part of its variation. In particular, assume that $\boldsymbol{z} = \tilde{\boldsymbol{z}} + \boldsymbol{\eta}$, where $\tilde{\boldsymbol{z}}$ is can be predicted by IAM, while $\boldsymbol{\eta}$ cannot. For the sake of simplicity of the example, assume also that $\tilde{\boldsymbol{z}}$ and $\boldsymbol{\eta}$ are orthogonal.

The best prediction of c given the information on $\tilde{\boldsymbol{z}}$ is given by:

$$E(c|\tilde{z}) = \left(\delta + \frac{Cov(\tilde{z},t)}{Var(\tilde{z})}\right)\tilde{z}. \tag{17}$$

If OLS estimates are based on the true historical values of z, and if Assumptions 1–4 are satisfied, then the effect of $\tilde{\boldsymbol{z}}$ on c in IAM is given by

$$c = \left(\delta + \frac{Cov(z,t)}{Var(z)}\right)\tilde{z}$$

which, given that $z = \tilde{z} + \eta$ is equivalent to

$$c = \left(\delta + \frac{Cov(\tilde{z},t) + Cov(\eta,t)}{Var(\tilde{z}) + Var(\eta)}\right)\tilde{z}.$$

This clearly differs from Eq. (17↑) above.

To understand how restrictive this assumption could be, consider a situation when variation in installation costs affects the decision on the level of feed-in-tariffs, which in turn affects energy price (i.e. the value of z in this example). In this situation t has a causal effect on z. Since, by definition, variation in t is not controlled for in IAM, the model's prediction $\tilde{z}$ cannot take into account the variation in t. Instead, the variation in t will enter the term η. This implies that $Cov(\eta,t) \neq 0$ and the prediction of IAMs is biased.

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6. A two stage estimator of the learning rate

In this section, we present a novel approach for estimating the learning curve parameter for use in IAMs. As discussed in Section 5.1, focusing on the part of cumulative capacity generated by exogenous factors (as modeled in the IAMS) can help to overcome the biggest issue we have identified, namely reverse causality. Suppose that in the regression (10↑), instead of using observed data on cumulative installed capacity, we use its projections based on explanatory variable, z, that is

$$k^* = \hat{\beta} z$$

where $\hat{\beta}$ is an OLS estimator of the coefficient β in the regression $k = \beta z + \xi$.

Using the framework presented above, we can compute $\hat{\beta}$ as follows:

$$\hat{\beta} = \frac{Cov(k,z)}{Var(z)} = \omega\delta + \gamma + \omega\frac{Cov(z,t)}{Var(z)}.$$

If instead of using actual values k, we use its projections k^*, the estimator of the learning curve becomes:

$$\check{\alpha} = \frac{Cov(c,k^*)}{Var(k^*)} = \frac{\delta + \frac{Cov(z,t)}{Var(z)}}{\gamma + \delta\omega + \frac{Cov(z,t)}{(Var(z)}\omega}$$

combining our new learning curve $c = \check{\alpha} k$ with the IAMs prediction $k = \omega c + \gamma z$ implies:

$$\tilde{c} = \left(\delta + \frac{Cov(z,t)}{Var(z)}\right)\tilde{z}$$

which is exactly the same as Eq. (6↑).

More generally, as long as we maintain Assumptions 2, 4 (i) and 5, we can construct the fitted values as

$$\hat{k} = \hat{\boldsymbol{\beta}}\mathbf{z}$$

where $\hat{\boldsymbol{\beta}} = (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{k}$, $\mathbf{Z}$ is a matrix of demeaned observations of $\mathbf{z}$, and $\mathbf{k}$ is a vector of demeaned observations of installed capacity.

In this case, estimating the learning curve with the usual OLS estimator, but replacing observed with the fitted values of installed capacity, yields:

$$\check{\alpha} = \left[\left((\boldsymbol{\delta}\omega + \boldsymbol{\gamma})\boldsymbol{Z}' + \omega\boldsymbol{\nu}\boldsymbol{T}'\right)\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\left(\boldsymbol{Z}(\boldsymbol{\delta}'\omega + \boldsymbol{\gamma}') + \omega\boldsymbol{T}\boldsymbol{\nu}'\right)\right]^{-1} *$$

$$\left((\boldsymbol{\delta}\omega + \boldsymbol{\gamma})\boldsymbol{Z}' + \omega\boldsymbol{\nu}\boldsymbol{T}'\right)\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\boldsymbol{Z}'\left(\boldsymbol{Z}\boldsymbol{\delta}' + \boldsymbol{T}\boldsymbol{\nu}'\right).$$

Let us use $\tilde{c}$, $\tilde{\boldsymbol{k}}$ and $\tilde{\boldsymbol{z}}$ to denote future levels of c, k and $\mathbf{z}$ predicted in IAMs. It can be shown that employing the learning curve $\tilde{c} = \check{\alpha}\tilde{k}$ together with the IAMs first order condition $\tilde{k} = \omega\tilde{c} + \boldsymbol{\gamma}\tilde{\boldsymbol{z}}$ must satisfy

$$\tilde{c} = \left(\boldsymbol{\delta} + \boldsymbol{\nu}\boldsymbol{T}'\boldsymbol{Z}(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\right)\tilde{\boldsymbol{z}}.$$

The expected value of the prediction is therefore

$$E(\tilde{c}|\tilde{\boldsymbol{z}},\boldsymbol{Z}) = \left(\boldsymbol{\delta} + \boldsymbol{\nu}E(\boldsymbol{T}'\boldsymbol{Z}|\boldsymbol{Z})(\boldsymbol{Z}'\boldsymbol{Z})^{-1}\right)\tilde{\boldsymbol{z}}$$

which is exactly the same as Eq. (5↑) if $E(\mathbf{Z}'\mathbf{T}|\mathbf{Z}) = E(\widetilde{\boldsymbol{Z}}'\tilde{\mathbf{T}}|\tilde{\boldsymbol{Z}})$, which is ensured by Assumption 2.

6.1. Difference with respect to IV estimator

The two-stage estimator we propose in this section can resemble the Instrumental Variable (IV) estimator, a common tool in applied econometric studies. Similar to our approach, the IV estimation involves running a two-stage procedure with the aim of isolating the exogenous component of the endogenous regressors and then estimating the causal effect of such regressor on the variable of interest. Applied to the learning curve example, a first stage IV approach models cumulative capacity as a function of carefully chosen regressors, called instruments. The fitted values obtained in this first stage regression are then used as a regressor in the equation of cost.

Despite the similar form, there are important differences between our approach and the IV approach. The two estimators were designed for different purposes. While the IV estimator is meant to identify the causal effect of cumulative capacity on installation cost, our two-stage estimator has been tailored to estimate the reduced form relation between the two and to ensure that the estimated relation will deliver meaningful predictions when incorporated in IAMs. As a result of this, the two estimators require different sets of assumptions, and they may require different sets of regressors in the first stage. In this section we argue that the IV estimator is less appropriate for the estimation of learning curves for use in IAMs than the two stage estimator we propose here.

The first major difference is the criterion for choosing regressors in the first-stage regression. The IV approach involves a careful selection of instruments in the first-stage regression. The only source of correlation between an instrument and installation cost must be through its causal effect on cumulative capacity. This means that the instrument cannot affect installation cost directly or through any other omitted channel — e.g. by affecting material prices, which can then have an effect on installation cost. This also implies that installation cost cannot have an impact on the instrument. If these conditions are not satisfied, the instrument is not valid and the assumptions of the IV approach are violated.

In our proposed approach, there is no room for selecting the regressors in the first stage. Vector $\mathbf{z}$ must contain all variables that, in the specific IAM considered, are used to determine cumulative capacity. One can imagine a perfect instrument, for example availability of wind or number of sunny days in a year, which satisfies the criterion for a valid instrument. However if this instrument is not included in the IAM under consideration, it cannot be included in the vector $\mathbf{z}$ and, thus, according to our method, should not be used as a dependent variable in the first-stage regression.

It is important to stress that the IV approach to estimate learning curve parameters for use in IAMs is not an alternative to the approach we proposed. The IV estimator enables us to identify the causal impact (if any) of cumulative capacity on installation cost. However, the learning curve employed in IAMs are not supposed to capture the causal effect of capacity on costs, rather, as argued above, they need to capture the reduced form relation between the two.

To further understand this difference, consider the following example. Suppose that the cumulative capacity is determined by two factors: wind strength, $\boldsymbol{w}$, and price of energy, p. Assume that $k = p + w$. Next, suppose that dynamics of installation costs are driven by learning-by-doing and the direct effect of energy price — for example energy price affects the cost of wind turbine production. In particular, suppose that $c = -k + p$. Note that wind strength is a perfect IV instrument since it satisfies the exogeneity criteria. Conversely, p cannot be an IV instrument since it affects installation costs not only through its effect on k, but also directly. Consider an IAM, which determines cumulative capacity using energy price only — wind strength is not a variable in the model. Thus $k_{IAM} = p_{IAM}$. The IAM uses the learning curve, $c_{IAM} = \alpha k_{IAM}$ to determine installation costs. If researchers estimated α by using an IV method with wind strength as the instrument, they would find $\alpha = 1$, i.e. the true causal effect of cumulative capacity. Now imagine that in one of the scenarios considered in the specific IAM, the price of energy increases by 1%. Researchers conclude that k increases by 1% and installation costs drop by 1%. This prediction is wrong: in fact a 1% increase in price will have no effect on installation costs, since the two effects – the effect through cumulative capacity and the direct effect – will balance each other out. This example shows therefore that the IV estimate of the learning rate will bias the results in IAMs. A similar problem has been discussed in scenario 2. In that scenario, costs are affected only by accumulation of knowledge; there is no causal effect of changes in experience on cost ($\Delta c = -\Delta h - 0 * \Delta k$). Yet, as explained in Section 3, setting the coefficient of the learning curve equal to zero would result in a misprediction from IAMs.

6.2. Limitations of approach

Although we argue that the estimator proposed in this section is better than the simple OLS or IV estimator, it is important to be aware that it does not solve all limitations of the learning curve, and it still requires some strong assumptions. In particular, the validity of the learning curve predictions in IAMs will still rest on Assumptions 2, 4, 5 and 6.

For instance, as mentioned in Subsection 5.2, Assumption 2 may be particularly restrictive for evaluating policy scenarios. Recall that the assumption requires $Cov(t,z)$ to be stationary, i.e. not changing over time. If t is a simple time trend and z is the policy variable, then the assumption means that policies are assumed not to change over time. Clearly this is highly restrictive as the scenarios which are usually evaluated by IAMs do involve policy changes. Assumption 4 (described in Subsection 5.4) is equally problematic. Unless we put restrictions on the parameter values, the assumption can be satisfied only if variables in $\mathbf{z}$ are collinear. If one wishes to explore the effect of a rapid increase in policy stringency, it is difficult to assume that the relation between policy and other determinants of cumulative capacity in IAMs (e.g. energy price) will be the same as before the policy shock.

The assumption that IAMs are able to deliver the correct predictions on vector $\mathbf{z}$ is fragile too. For instance, consider the case of installation costs affecting feed-in tariffs, which in turn have an impact on the components of vector $\mathbf{z}$ (e.g. electricity price). In this case a variation in t, which, by definition, cannot be controlled for in IAMs, will be transmitted to variation in $\mathbf{z}$, which cannot be predicted by IAMs, hence violating the assumption.

The solution to these problems would be to replace the learning curves in IAMs with a different, more complex and more demanding approach. Note that these problems cannot simply be resolved by a modification of the estimation procedure (for instance, as we show above, the standard IV approach cannot be used in the learning curve context). This is in contrast to Assumptions 1 and 3, which we were able to relax without modification of the form of the learning curve and the structure of IAMs.

One solution to these problems is to replace the learning curve with another model which includes multiple factors (two-, three-factor learning curves). The advantage of this approach is that the amount of variation in vector t will be minimized, which solves most of the problems listed above. The significant disadvantage is that IAMs has to be adjusted to predict not only cumulative capacity but also other factors (e.g. knowledge stock and material prices). While implementing such changes rests in the hand of modelers, we hope that by framing the problem in the formal model, we will facilitate the future debate on tradeoffs associated with such choices.

7. (More) consistent estimates of the learning rate

In this section we demonstrate how our estimation procedure could be used in practice. We estimate the learning rates of two key low carbon technologies which are featured in IAMs: wind turbines and solar PVs. As we noted earlier, the set of regressors in the first-stage must contain only those variables that, in the specific IAM considered, are used to determine cumulative capacity, i.e. variables which are contained in vector $\mathbf{z}$. Since the components of vector $\mathbf{z}$ differ between models, the estimation procedure described in the previous section should be model-specific, i.e. each IAM should estimate its own learning parameters. However, running a separate analysis for each IAM is not feasible within the scope of this study. Instead, we selected a set of variables in vector $\mathbf{z}$ which can reasonably approximate the dynamics of demand for capacity in various IAMs, namely price of energy and policy mix. The variation of energy price reflects key macroeconomic forces: population growth, level of economic activity and energy intensity, which impact demand for capacity in several IAMs (such as IMAGE, POLES, REMIND or WITCH). Low competitiveness of alternative energy sources (e.g. fossil fuels) will also be reflected in high energy price. An inclusion of policy stringency in vector $\mathbf{z}$ results from the fact that nearly all IAMs allow cumulative capacity to be affected by some policies.

Our estimates are a first attempt to implement our procedure and we have to acknowledge several limitations. Most importantly, the validity of our estimates depends crucially on how well our observables (energy prices and the index of policy stringency), reflect the true variation of vector $\mathbf{z}$ in IAMs. For example, if in a IAM cumulative capacity is linked to feed-in-tariffs, and feed-in-tariffs are not well correlated with our policy stringency index, we will find that variation in cumulative capacity predicted in the first stage of our empirical model is different than the variation in cumulative capacity predicted in IAMs. As a result the explanatory variable in the second stage will suffer from the measurement error, which would bias our results. The only way to solve this problem is to ensure that vector of observables $\mathbf{z}$ used in the empirical estimation is as close as possible to the vector $\mathbf{z}$ specified in the IAM. A crucial avenue for refining the estimates in future studies is therefore running the estimation for each model separately.

Second, due to limited data availability, the dependent variable in the second-stage regression is the installation cost reported for the US. This questions the external validity of the model: if the estimates are to be used for other regions, one has to assume that the differences between the installation costs between regions are independent of the differences in energy prices and policies.

Table 3
First stage regression results for PV panels technology. Standard errors clustered at the level of countries below the coefficients.

	Model 1	Model 2 REP	Model 3 REP
Energy price	9.87***		6.19***
	1.34		1.54
Policy index		0.53***	0.32***
		0.06	0.07
R-squared	0.28	0.26	0.39
F-stat.	359.1	349.5	274.0
Observations	457	457	457

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Table 4
Second stage regression results for PV panels technology. Time-frame: 1990–2012. Standard errors below the coefficients.

	Model OLS	Model 1	Model 2 REP	Model 3 REP
Observed Cum Cap.	−0.161***			
	0.013			
Fitted Cum. Cap.		−0.268***	−0.342***	−0.254***
		0.075	0.105	0.058
R-squared	0.88	0.48	0.90	0.76
Observations	22	22	22	22

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Table 5
First stage regression results for wind turbines technology. Standard errors clustered at the level of countries below the coefficients.

	Model 1	Model 2 REP	Model 3 REP
Energy price	9.89***		3.50***
	0.93		0.93
Policy index		0.69***	0.56***
		0.06	0.07
R-squared	0.12	0.40	0.41
F stat.	402.3	1083.4	626.3
Observations	588	588	588

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Table 6
Second stage regression results for wind turbines technology. Time-frame: 1990–2012. Standard errors below the coefficients.

	Model OLS	Model 1	Model 2 REP	Model 3 REP
Observed Cum Cap.	−.051			
	0.031			
Fitted Cum. Cap.		0.001	−.076*	−0.053
		0.052	.039	0.033
R-squared	0.12	0.00	0.22	0.14
Observations	22	22	22	22

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Finally, as discussed in Section 6.2, the unbiasedness of our estimates rests on the Assumptions 2, 4, 5 and 6. Specifically we have to assume that the variation in prices and policies are independent of variation in *t*. This assumption will not be satisfied if energy price and policy index depend on the level of feed-in-tariffs, which are likely affected by the level of installations costs (and hence depend on *t*). Since, as explained in the paper, we cannot rely on the IV estimator, our best option is to minimize the risk that the prices we include in the regression are endogenous. To this end, in the first stage regression we used lagged values of energy prices and policies. We also use an energy price index, rather than an electricity price index. The feed-in-tariff constitute only a small fraction of energy price and therefore the size of its effect on energy price is small. Similarly, our baseline policy index is rather general and depends on the feed-in-tariffs in a relatively small extent.

We focus on solar PV panels and wind turbines. Our dataset covers the period 1990–2012 for the 34 OECD countries. Energy prices and data on cumulative installed capacity are from the International Energy Agency Statistics. Data on installation costs for the wind turbines and solar PV technologies come from the Berkeley Lab and Mints (2014)[5], respectively, and refer to the prices of wind turbines and PV panels in the US. In addition, we include a policy index describing the stringency of renewable energy policies. This is constructed by identifying different policy indexes implementing in any given countries and giving each implemented instrument a value of one. The policy index (REP) is then the sum of the single instruments at any give time. This indicator ranges from 0 to a theoretical maximum of 10 (for details on the index, please see Bosetti and Verdolini, 2013). In the appendix, we present results obtained with two alternative indicators: the Environmental Policy Stringency index and a variable indicating the level of wind (or solar) feed-in-tariffs (FIT), both from OECD (Botta and Koźluk, 2014). One may argue that indeed the Feed-in-Tariffs are the most relevant policy in determining cumulative capacity. However, one should keep in mind that in this study the primary criterion for choosing the policy index in vector **z** is how well it reflects the variation of policies in the IAMs. The modeling of policies in IAMs is very simple, usually focused on the level of carbon tax and rarely capturing the Feed-In-Tariffs. For this reason, there is no objective ranking of the policy indexes, which we use in the paper — instead, the ranking is IAMs specific.

We first regress (the log of) cumulative installed capacity on the lagged values of (the log of) energy prices and on the policy index (which constitute our vector **z**). Since for this stage panel data for all countries and variables are available, we use the Fixed Effect estimator. From the regression we get the fitted values of installed capacity for all 34 countries. We aggregate them to obtain the total fitted cumulative capacity for each year. This fitted cumulative capacity is then used as an explanatory variable in the second stage regression where (global) installation costs are the dependent variable. The OLS estimate from this second stage estimator is effectively a two-stage least-squares estimate, which has been described in Section 6.

Results for solar PV are reported in Table 3 (first stage) and Table 4 (second stage). The first-stage regression indicates that energy prices and policy stringency are significant determinants of cumulative capacity. The second-stage regressions suggest that the learning rate is higher than that estimated with the OLS estimator: while the OLS estimates predict a 12% learning rate (which corresponds to the coefficient of −0.161), the learning rate predicted by our model with full specification (Model 3 REP) predicts a 19% learning rate (which corresponds to the coefficient of −0.254). The results are very similar if we replace our policy indicator with the two alternatives (see the Appendix A3, Tables 7 and 8). We find that the difference between the OLS estimate and our two stage least squares estimate is not statistically significant. However, as we demonstrate below, the difference of estimates for the solar technology learning rates can have a significant consequence for IAM's predictions.

The analysis in the previous section suggests that the OLS and the two-stage estimates are different because the latter is not subject to reverse causality and misspecification biases. Section 5.1 shows that reverse causality leads to an overestimation of the learning rate for IAMs. The misspecification bias should in turn give rise to an underestimation of the learning rate. Our results indicate that in the case of solar PV technology, the misspecification bias dominates. This suggests that, in addition to policy and price of energy, there are other important determinants of demand for photovoltaic panels or that the response to the demand for policy and price changes is delayed.

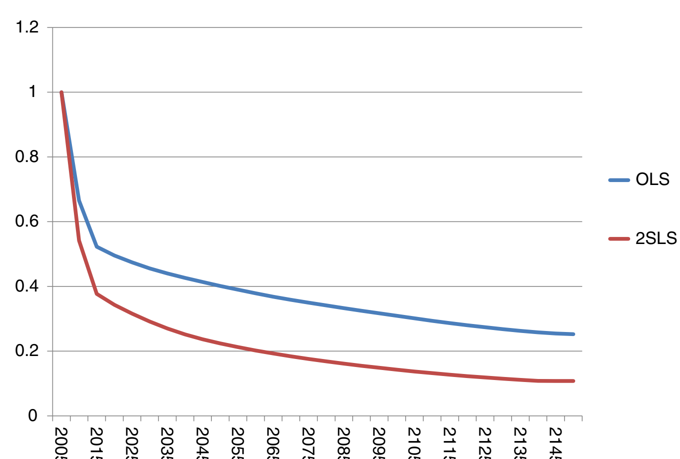

Fig. 2. PV installation costs predicted by the WITCH model under new (red line) and old (blue line) estimates of the learning rates. The new estimates are taken from column 4 in Table 4. The old estimates are taken from column 1 in Table 4. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

[5] Accessed from http://emp.lbl.gov/publications/2012-wind-technologies-market-report and http://emp.lbl.gov/publications/tracking-sun-vii-historical-summary-installed-price-photovoltaics-united-states-1998-20.

Focusing on wind turbines, results of the first and second stage estimation are presented in Tables 5 and 6, respectively . As in the case of solar, the first-stage regressions for wind technology suggest that policy stringency and energy prices are significant determinants of cumulative capacity. The regression with full specification indicates that 1% increase in energy price produces a 3.5% growth in cumulative capacity. The effect of policy stringency is statistically significant, but economically less pronounced — an additional policy leads to half percent increase in capacity.

The results of the second-stage regression suggest that the simple OLS estimator is slightly biased downward. The two-stage estimate of the learning curve predicts a 3.7% learning rate (which corresponds to the coefficient of −0.053) if vector **z** includes the price of energy and the policy index[6]. For comparison, the simple OLS estimates of the learning rate using data for the period 1990–2012 implies that learning rate for wind power is 3.6%. Again, we find that the difference between the OLS estimate and our two stage least squares estimate is not statistically significant.

Note that the results for wind are less stable than those for solar. For instance, changing the policy index drastically impacts the results (Appendix A3, Tables 9 and 10). One likely explanation is the change in $Var(\epsilon)$, $Var(t)$ and $Cov(t,z)$, which affect the size of the difference. For example, if the variation in the policy stringency in recent years was not well captured by our policy stringency index, then $Var(\epsilon)$increased and the negative bias due to imperfect determination of cumulative capacity started to dominate, or even offset the positive bias due to reverse causality.

In addition, the regressions using the most recent data report a very low R-square, which questions the ability of the learning curve to predict future installation costs. In our view, the high sensitivity and low explanatory power is an argument to search for new tools, which could forecast future installation costs in case of wind technology.

As a last step in this section, we compare the predictions of the technology installation costs obtained from the WITCH integrated assessment model under the new and old estimates of the learning rate. We first run the model, using the learning rates obtained from the traditional OLS regression (column 1 in Table 4) for the PV technology. We then rerun the model, using the estimates delivered by our 2SLS estimator (column 4 in Table 4). The results are presented in Fig. 2. The predictions under OLS estimates imply that the installation costs in 2100 will be 25% of the current cost. If we use the new estimates, the predicted installation costs are 12% of the current cost.

8. Conclusions

This paper lists and formally describes some instances in which the learning curve delivers biased results if OLS estimates of the learning rates are used to calibrate IAMs. For each instance, we are able to characterize the direction of the bias. The first instance takes place when an exogenous change in costs of a technology (e.g. due to change in material prices) promotes a change in installed capacity. If we estimate the learning curve by using simple OLS, we wrongly attribute this correlation to the effect of installed capacity change on change in installation costs, and, as a result, the estimate is biased upward. The second instance is the presence of misspecification error, which will generally bias the learning rate downward. The third instance occurs when IAMs include more than one determinant of installed capacity. For example, suppose that the history of high interest rates has played a major role in determining the technology costs through promoting capacity building and R&D investment, while IAMs would predict that the primary promoter of learning-by-doing is energy price. Then the symbiosis of estimated learning curve and IAM yields biased results if the effect of the price is different from the effect of the interest rate. The fourth instance could arise from non-linearities. For example, if the earning rate is decreasing with cumulative capacity, then the future effect of cumulative capacity on installation costs should be lower than in the past.

We show that the learning curve can be robust to the first and the second problems if the traditional OLS estimator of the learning rate is replaced with a more appropriate two-stage approach. The key property of this approach is that it ensures that the estimates of the learning curve do not capture the effect of technology costs on cumulative capacity.

Finally, we update the estimate of the learning curves for wind turbines and photovoltaic panels, using this novel methodology. Our estimates suggest that the learning curve for the PV panels has a steeper slope than the one implied by the traditional estimator. Our estimate of learning rate for wind technology is almost the same as the traditional OLS estimates, however this result is very sensitive to the choice of policy index and sample size.

We also argue that the assumptions on the linear relationship between capacity and costs and on the stationarity of the series cannot be relaxed without replacing the learning curve with a more sophisticated model. This would increase accuracy of the estimates at the cost of increased complexity, complicating the implementation of learning curves in IAMs. Further exploring trade-offs between these two opposing forces will be the focus of future research efforts.

Appendix A

A.1. Infinite horizon model

Let k denote the cumulative capacity of wind turbines, I — flow of new capacity in one period, c — a turbine installation cost, y — wind energy production and, p — its price. The objective function of a firm producing energy from wind (or a central planner) is:

$$V(C,K) = max I\left\{PY(K) - CI + \beta V\left(C',K'\right)\right\} \tag{18}$$

subject to $K' = (1-\delta)K + I$ and $Y(K) = K^{\alpha}$ or simply

$$V(C,K) = max_I\left\{PK^{\alpha} - C\left(K' - (1-\delta)K\right) + \beta V\left(C',K'\right)\right\}. \tag{19}$$

The first order condition to firm's optimization problem is

$$\beta V_{K'}\left(C',K'\right) = C.$$

Using the envelope theorem we can determine the derivative of the objective function with respect to installed capacity:

$$V_K = \alpha PK^{\alpha-1} + (1-\delta)C + \beta(1-\delta)VK\left(C',K'\right).$$

We assume that the firms expect the price of energy and installation costs to grow (or decline) at the constant rates g_P and g_C. If capital is on its balanced growth path, then

$$VK\left(C',K'\right) = \frac{(\beta\alpha(1+g_P)(1+g_K)^{\alpha-1}}{1-(\beta\alpha(1+g_P)(1+g_K)^{\alpha-1}(1-\delta)}PK^{\alpha-1} + \frac{(\beta(1-\delta)(1+g_C)}{1-(\beta(1-\delta)(1+gC)}C.$$

[6] The OLS estimate is significantly below the estimates of the learning rates for wind technologies available in the literature. This is due to the longer time-frame under consideration in our analysis. In fact, Tables 11 and 12 show that if we drop the observations after 2004 (hence eliminating the period when installation prices are heavily affected by the upward trend in prices of materials), the estimated OLS learning rate for wind is 15.7%. These last results are in line with the estimates available in the literature (see e.g. the results for the one factor learning curves in Jamasb (2007), Kahouli-Brahmi (2009) and Lindman and Söderholm (2012)).

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Combining this with the first order conditions we get:

$$\frac{\beta\alpha g_P g_k^{\alpha-1}}{1-\beta\alpha g_P g_k^{\alpha-1}(1-\delta)}PK^{\alpha-1}+\frac{\beta(1-\delta)(1+g_C)}{1-\beta(1-\delta)(1+gC)})C$$

where g_K is the growth of capital. Simplifying and taking logs:

$$k=-\frac{1}{1-\alpha}c+\frac{1}{1-\alpha}p+\text{constant}$$

where

$$\text{constant}=-\frac{1}{1-\alpha}ln\left(\frac{1-2\beta(1-\delta)(1+gC)}{1-(2\beta(1-\delta)(1+gC)}\frac{1-\beta\alpha g_P g_k^{\alpha-1}(1-\delta)}{\beta\alpha g_P g_k^{\alpha-1}}\right)$$

implying that $gK=-\frac{1}{1-\alpha}g_C+\frac{1}{1-\alpha}g_P$.

A.2. Conditions for Section 5.3

The first possibility is that $z_1=\pi z_2$, then

$$c=\frac{(\delta_1+\delta 2\pi)(\gamma 1+\gamma 2\pi)}{(\gamma 1+\gamma 2\pi)^2}(\gamma 1+\pi\gamma 2)z1+\text{constant}$$

which simplifies to

$$c=(\delta_1+\delta_2\pi)z_1=\delta_1 z_1+\delta_2 z_2.$$

The second instance is when $z_1$has exactly the same impact on k and c as z_2 i.e. if $\delta_1=\delta_2$ and $\gamma_1=\gamma_2$. Then

$$c=\frac{\delta_1\gamma_1\widehat{Var}(z_1)+\delta_1\gamma_1\widehat{Var}(z_2)+2\delta_1\gamma_1\widehat{Cov}(z_1,z_2)}{\gamma_1^2\widehat{Var}(z_1)+\gamma_2^2\widehat{Var}(z_2)+2\gamma_1\gamma_2\widehat{Cov}(z_1,z_2)}(\gamma_1 z_1+\gamma_1 z_2+\text{constant})$$
$$=\delta_1(z_1+z_2)+\text{constant}=\delta_1 z_1+\delta_2 z_2+\text{constant}.$$

The third instance is when z_i's impact on k is the same as its impact on c i.e. $\delta_1=\gamma_1$ and $\delta_2=\gamma_2$. Then

$$c=\frac{\gamma_1^2\widehat{Var}(z_1)+\gamma_2^2\widehat{Var}(z_2)+2\gamma_1\gamma_2\widehat{Cov}(z_1,z_2)}{\gamma_1^2\widehat{Var}(z_1)+\gamma_2^2\widehat{Var}(z_2)+2\gamma_1\gamma_2\widehat{Cov}(z_1,z_2)}(\delta_1 z_1+\delta_2 z_2+\text{constant})$$
$$=\delta_1 z_1+\delta_2 z_2.$$

A.3. Regression Robustness check

A.3.1. Alternative measure of policy

Table 7
First stage regression results for PV panels technology. Standard errors clustered at the level of countries below the coefficients.

	Model 2 EPS	Model 3 EPS	Model 2 FIT	Model 3 FIT
Energy price		3.72***		8.921***
		.79		0.565
Policy Index	1.82***	1.37***	0.458***	0.238***
	.08	.12	0.0425	0.0359
R-squared	0.16	0.24	0.232	0.534
F-stat.	496.3	273.3	116.4	220.2
Observations	396	396	411	411

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Table 8
Second stage regression results for PV panels technology. Time-frame: 1990–2012. Standard errors below the coefficients.

	Model OLS	Model 2 EPS	Model 3 EPS	Model 2 FIT	Model 3 FIT
Observed Cum Cap.	−0.161***				
	0.013				
Fitted Cum. Cap.		−0.217***	−0.211***	−0.248***	−0.242***
		.037	.041	0.056	0.055
R-squared	0.88	0.79	0.75	0.45	0.54
Observations	22	22	22	22	22

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Table 9
First stage regression results for wind turbines technology. Standard errors clustered at the level of countries below the coefficients.

	Model 2 EPS	Model 3 EPS	Model 2 FIT	Model 3 FIT
Energy price		2.14***		9.852***
		.75		0.558
Policy Index	1.89***	1.63***	1.285***	0.943***
	.078	0.12	0.190	0.149
R-squared	0.24	0.25	0.09	0.45
F stat.	587.6	302.7	45.7	193.7
Number of Clusters	26	26	26	26
Observations	456	456	499	499

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

Table 10
Second stage regression results for wind turbines technology. Time-frame: 1990–2012. Standard errors below the coefficients.

	Model OLS	Model 2 EPS	Model 3 EPS	Model 2 FIT	Model 3 FIT
Observed Cum Cap.	−.051				
	0.031				
Fitted Cum. Cap.		−.024	−.023	−0.408	−0.0229
		.030	.030	0.494	0.051
R-squared	0.12	0.03	0.03	0.40	0.01
Observations	22	22	22	22	22

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

A.3.2. Alternative time frame

Table 11
Second stage regression results for wind turbines technology. Time-frame: 1990–2004. Standard errors below the coefficients.

	Model OLS	Model 1	Model 2 REP	Model 3 REP
Observed Cum Cap.	−.210***			
	.049			
Fitted Cum. Cap.		−.165	−.183**	−.187*
		.280	.064	.088
R-squared	0.03	0.63	0.61	0.60
Observations	14	14	14	14

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

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Table 12
Second stage regression results for wind turbines technology. Time-frame: 1990–2004. Standard errors below the coefficients.

	Model OLS	Model 2 EPS	Model 3 EPS	Model 2 FIT	Model 3 FIT
Observed Cum Cap.	−.210***				
	.049				
Fitted Cum. Cap.		−0.230*	−0.248	−0.514	−0.441
		0.127	0.160	0.311	0.423
R-squared	0.03	0.43	0.45	0.52	0.28
Observations	14	14	14	14	14

NOTES: *, ** and *** indicate a significance level of 10 percent, 5 percent and 1 percent, respectively.

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