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Bending The Learning Curve

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Summary

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Keywords: Learning Curve, Renewable Technologies, Integrated Assessment Models

JEL Classification: Q42, Q55, C55, C26

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Abstract

This paper aims at improving 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 assumption the traditional (OLS) estimates of the learning curve can deliver meaningful predictions in IAMs. We argue that the most problematic of them is the absence of any effect of technology cost on its demand (reverse causality). Next, we show that this assumption 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 reverse causality problem 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 downward for wind power, but possibly upward for solar PV.

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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 (Tavoni et al. 2012, Kriegler et al. 2014). 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 (Messner, 1997; van der Zwaan et al., 2002, Goulder and Mathai 2000, Fisher-Vanden and Ho 2008),¹ often 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, modellers 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 due to the straightforward modelling assumptions they require. The process of learning is described in IAMs using the so-called “learning curve”, namely a simple relation that links cumulated installed capacity of capital embodying a given technology, such as wind turbines or solar photovoltaic (PV) panels, to 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 costs 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 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., 2013).

This paper contributes to this strand of literature by proposing a formal analytical model which sheds light on the learning curve debacle. 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 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 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. However,

¹For a review technical change in climate economy models see Loeschel (2002)

we show and discuss the assumptions which are necessary to ensure that the OLS learning curve estimates can be used in IAMs. 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 develop 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 relax the remaining assumptions on which the use of 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 however believe 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.

The rest of 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, 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 aircrafts 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 (1943) for shipbuilding industry. The empirical relation between cumulating experience on efficiency growth has been formalized theoretically by Arrow (1962) and Rosenberg (1982) with the “learning-by-doing” approach. This gave raise 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 to forecast decrease in technology costs (Zachman 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 cumulated 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 focused on different technologies. Zimmerman (1982) provided learning rate for nuclear power generation, Joskow and Rose (1985) repeated the exercise for the 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 are 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 been often used as a simple tool to form predictions on installation costs using predictions on cumulated capacity supplied by the model themselves.

While the learning curve gained substantial popularity, some authors question its empirical basis. The empirical correlation between technology deployment and its cost is not evidence a causal relation between the two. Two are the main criticisms raised in the literature in this respect. 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 costs reductions of PV panels. He concludes that learning-by-doing effects explain about 10% of the total costs 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, labelled the “two-factor learning curve”, assumes that the log of installation costs is a weighted sum of the log of cumulated capacity (which proxies for experience) and the log cumulated 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 cumulated capacity observed in the data may simply reflect the causal effect of cost reductions on investment in capacity. Nordhaus (2008) 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 (2006) also explore the simultaneity problem with an instrumental variable approach; however they instrument only the installation costs in the equation determining cumulated capacity. Kohler 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. 2013). 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, 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 on the role of learning by doing in reducing installation costs - rather, in the words of Wiesenthal et al. (2013), “the learning curve groups several underlying drivers of cost reduction in 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 cumulated increases on installation costs does not constitute an sufficient argument to abandon 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, 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 main source of concern is not the simplicity of the learning curve model, 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 as-

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 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. Our results suggest that the learning rate utilized in the IAMs should be revised downward for wind power, but possibly upward for solar PV.

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 cumulated capacity (Section 3.2). For 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 behaviour of IAMs.

Let C denote the technology installation cost (in terms of dollars per MW), K the cumulated installed capacity of the renewable technology (in terms of MW) in period 1, I the new capacity installed in period 1, $Y(\cdot)$ the energy production function, P the price of energy (in terms of dollar per MWh). We use K' , C' and P' 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:

$$V(C, K) = \max_I \{PY(K) - CI + \beta(P'Y(K') + C'K')\} \quad (1)$$

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

$$\beta(P'K'^{\alpha-1} + C') = C$$

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

$$\beta(\alpha(1 + g_P)PK'^{\alpha-1} + (1 + g_C)C) = C$$

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 $\ln(K')$, $\ln(C)$ and $\ln(P)$ respectively and \tilde{f} is a generic functions.

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

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

As mentioned, an identical prediction could be derived from the infinite horizon model (see Appendix A1). Similar predictions can also be derived from any IAM which is set up as to maximize the value function of the form given in equation (1).

In reality, observed cumulated 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, Equation 2 can be represented by

$$k = \omega c + \gamma \mathbf{z} + \epsilon \quad (3)$$

where vector \mathbf{z} contains the (log) price of energy, the interest rate and the effect of the policy stringency.

Based on equation (2) we could impose restrictions on parameters ω and γ : e.g. the coefficient on energy price should be the negative of the coefficient on installation costs. However, we do not impose such restrictions to allow for a more general structure of the model. We do so because some IAMs may have different structures than the one described with (1), but still include an equation similar to (3). Thus, we want equation (3) to be as general as possible.

3.2 The Linear Technology Model

Let \mathbf{r} be the vector of factors that determine the installation cost of the renewable technology, which include public and private R&D investments, experience - usually proxied by cumulated installed capacity - and material prices. We will call the elements in $\mathbf{r} = \{r_1, r_2, r_3\}$ the direct drivers of installation cost. These direct drivers depend themselves 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. Conversely, the factors which are not included in IAMs, but have an impact on the elements in \mathbf{r} , e.g. supply of engineers or business cycle, are gathered in vector \mathbf{t} . This structure is pictured in Figure 1.

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

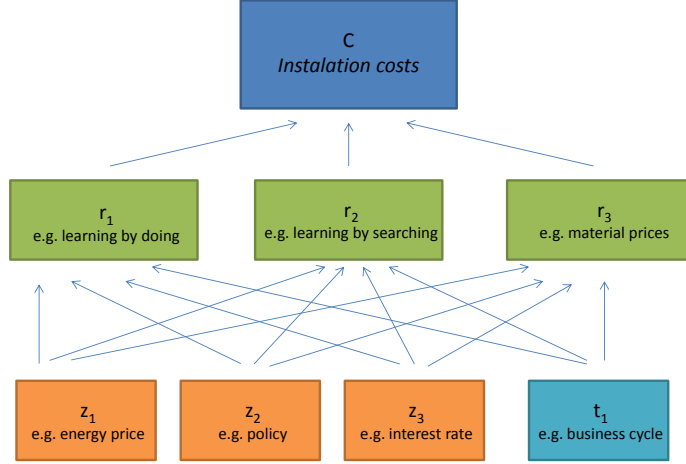


Figure 1: The Structure of the General Linear Technology Model

are indices for factors included in \mathbf{z} and \mathbf{t} . Thus,

$$c = \sum_i r_i(\mathbf{z}, \mathbf{t}) = \sum_i \left(\sum_j \delta_{ij} z_j + \sum_k \nu_{ik} t_k \right)$$

The reduced form of this equation is

$$c = \sum_j \delta_j z_j + \sum_k \nu_k t_k$$

where $\delta_j = \sum_i \delta_{ij}$ and $\nu_k = \sum_i \nu_{ik}$

In vector notation,

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

3.3 The Data Generating Process

Throughout the paper we assume that equation (3) and (4) constitute the true representation of reality. The data we observe is assumed to be generated by this system. In econometric terminology, we take (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 the value function (1) and the

first order condition (2) associated with it. Conversely, they are likely not able 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 equation (2) 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 on 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 modellers, is on predicting changes in installation costs resulting from an increase in one of the factors captured in vector \mathbf{z} - typically we will consider an increase in the energy price. Using our knowledge about the DGP, we can derive what is the the best prediction of installation costs, c , if we are given information on the realized values in vector \mathbf{z} :

$$E(c|\mathbf{z}) = \delta\mathbf{z} + \nu E(\mathbf{t}|\mathbf{z}) = \left(\delta + \nu E(\mathbf{t}|\mathbf{z}) \mathbf{z}' (\mathbf{z}\mathbf{z}')^{-1} \right) \mathbf{z} \quad (5)$$

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

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

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 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 due to learning-by-doing, but rather to other forces which are not modelled within the IAMs . We illustrate the intuition behind this result in 'Scenario II'.

To facilitate illustration and focus on the intuition, we assume that there are only two forces that can potentially influence technology costs reductions: learning-by-doing and learning-by-searching. Thus the two elements in \mathbf{r} are experience k , which can be measured with cumulated installed capacity and the knowledge stock h , measured with the cumulated R&D investment,. We assume that experience and knowledge stock depend only on price of energy thus vector \mathbf{z} contains only one variable, the log of price, and $z = p$. We also assume that all factors in vector \mathbf{t} are constant implying that $\nu\mathbf{t} = t$ where t is a constant . As a result we can express cumulated capacity and knowledge stock as $k = \delta_{kp}p + \nu_k t$ and $h = \delta_{hp}p + \nu_h t$. Finally we assume no misspecification error ($\epsilon = 0$). As

a result of this restrictions, we can describe the DGP with the system of two equations:

$$k = \omega c + \gamma p \quad (7)$$

$$c = \alpha_k k + \alpha_h h = \delta_p p + \nu t \quad (8)$$

where $\delta_p = \alpha_k \delta_{kp} + \alpha_h \delta_{hp}$ and $\nu = \alpha_k \nu_k + \alpha_h \nu_h$. Note that, since t is constant, $Cov(t, p) = 0$ and therefore the true evolution of c as a function of z must follow:

$$E(c|p) = \delta p \quad (9)$$

4.1 The OLS estimate of the learning rate

The traditional approach to estimate the learning rate takes the form

$$c_\tau = \alpha k_\tau + \eta_\tau \quad (10)$$

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

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

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

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 are the implications of a one percent increase in energy price, p , on renewable technology costs. If the IAM includes equation (1) (or its long/infinite horizon equivalent), its solution must satisfy equation (7). Furthermore, if the model includes the learning rate estimated by OLS, the solution must also satisfy

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

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

$$c = \delta p + \text{constant}$$

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 $\delta\%$ reduction in the installation cost of renewable technology. This is exactly in line with the true dynamics in this economy described with equation (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. When learning-by-doing plays no role, and conversely cost reductions are due to learning-by-searching ($\alpha_k = 0$ and $\alpha_k \neq 0$), the estimated slope of the learning curve cannot be interpreted as informing on the causal effect of experience on cost. But we argue that also in this case, the learning curve is a useful tool to predict technology costs in IAMs. Changes in cumulated 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 are 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 do want the learning curve to have negative slope even if the true learning rate is zero.

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 have to capture the effect of all factors, which have the same determinants as cumulated capacity. The analysis above shows that, under some circumstances which we will discuss in detail in the subsequent sections, simple OLS estimator meets this requirement.

Scenario I

Consider a world in which learning-by-doing is the sole driver of technology costs reduction. An increase in installed capacity brings accumulation of experience which in turn reduces costs. Specifically, in this example we assume that $\Delta c = -0.1\Delta k^2$. Cumulated Capacity does not depend on the price of energy, but we assume that it is not affected by changes in the installation costs (i.e we assume

²In 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).

c - log of installation costs			
k - log of cumulated 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)			
period 1	p +10%	k +20%	c -2%
observed slope of the learning curve: 0.1			
period 2	+20%	+40%	-4%
Integrated Assessment Model:			
equations:			
$c = -0.1k + constant$ (learning by doing)			
$k = 2p + constant$ (demand for capacity)			
predictions:			
period 2	p +20%	k +40%	c -4%

Table 1: The Data Generating Process and IAM's predictions in Scenario I.

that $\Delta k = 2\Delta p - 0 * \Delta c$ ³.

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, due to learning effects, in a 2% reduction in installation costs. Further suppose that in period 2 the government introduces a tax that increases 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 (1). If they calibrate the model accurately, the model solution must satisfy the first order condition:

$$k = 2p$$

³In 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.

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.

Scenario II

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

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 10% decrease in installation costs. The drop in costs incentivizes further capacity building, which now grows by a further 20%. Thus, the total change in capacity over the period is 40%. 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: costs are reduced by 20% and total capacity growth is 80%.

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 0.25 (40% increase in capacity coincided with the 10% cost reduction). If the demand structure in IAM is specified and calibrated correctly, the first order condition in IAM will be given by $k = 2p - 2c + \text{constant}$. This equation and the estimated learning curve ($c = 0.25k + \text{constant}$) jointly imply that $\Delta c = -\Delta p$. Thus, scientists would predict a 20% cost reduction after a 20% increase in the price of electricity - in line with reality.

The two examples above show that the reduced form learning rates can be useful for IAMs. The two scenarios we described however have very different implications: one has learning, the other one does not. In the first case, the learning rates capture reality, in the second case they simply capture other forces at work which are not directly modelled in IAMs. If we depart from the stylized examples above, and relax some of the assumptions on which they are based,

c - log of installation costs										
k - log of cumulated 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)										
<table border="1"> <thead> <tr> <th></th> <th>p</th> <th>k</th> <th>h</th> <th>c</th> </tr> </thead> <tbody> <tr> <td>period 1</td> <td>+10%</td> <td>+40%</td> <td>+10%</td> <td>-10%</td> </tr> </tbody> </table>		p	k	h	c	period 1	+10%	+40%	+10%	-10%
	p	k	h	c						
period 1	+10%	+40%	+10%	-10%						
observed slope of the learning curve: 0.25										
<table border="1"> <tbody> <tr> <td>period 2</td> <td>+20%</td> <td>+40%</td> <td>+20%</td> <td>-2%</td> </tr> </tbody> </table>	period 2	+20%	+40%	+20%	-2%					
period 2	+20%	+40%	+20%	-2%						
Integrated Assessment Model:										
equations:										
$c = -0.25k + constant$ (learning by doing)										
$k = 2p - 2c + constant$ (demand for capacity)										
predictions:										
<table border="1"> <tbody> <tr> <td>period 2</td> <td>+20%</td> <td>+80%</td> <td>n/a</td> <td>-20%</td> </tr> </tbody> </table>	period 2	+20%	+80%	n/a	-20%					
period 2	+20%	+80%	n/a	-20%						

Table 2: The Data Generating Process and IAM's predictions in Scenario II.

the learning curve estimates can give rise to significantly biased predictions in IAMs. In the next section, we describe in details 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 Works

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 is not predicted by the IAM has no effect on cumulated 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 has no effect on cumulated 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 modelled in IAMs.

One of these three conditions must be satisfied:

- (i) All factor that are explicitly modelled in a IAM (that is, all factors included the \mathbf{z} vector) are collinear, i.e. $\mathbf{z} = \pi z$ where π 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, $\delta = \eta\gamma$, 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. $\delta = \iota d$ and $\gamma = \iota g$ where ι is a vector of ones and g and d are constant scalars.

Assumption 5. The Linearity of the DGP.

All the parameters in the DGP are stationary, i.e. δ , ν , ω and γ do not vary over time.

5.1 Absence of Reverse Causality

Notice 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 has to capture only the effect of experience and factors that have the same determinants as experience on technology cost. The reverse causality, i.e. the effect of cost on capacity is already captured in a different equation in IAM, namely equation (2). Hence, such effects should not be accounted for twice.

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 as⁴

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

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

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

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

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

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

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

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

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

Comparing this equation with the true relation between c and z stated in equation (13), we conclude that the IAM can deliver predictions that are in line with reality if and only if $\Gamma = 0$, i.e. if and only if $Var(t) = 0$. If $Var(t) > 0$, $\Gamma > 0$ and the effect of z on c is exaggerated. We illustrate this logic with the example below.

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. As before, 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 of 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, that according to their calculations should follow due to the learning effect.

Before we move to more elaborated scenarios, we can derive an optimistic conclusion from the three scenarios presented so far: 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. 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 first order condition included in the IAM, ((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

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

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

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 cumulated installed capacity is determined by different factors than those used to predict cumulated installed capacity in IAMs. In our framework, it implies that, while IAMs assume $k = \delta \mathbf{z}$, in reality (in the DTP) the true cumulated capacity is generated by the function $k = \delta \mathbf{z} + \epsilon$, 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 interdependences, 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 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

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

where $\Omega = -\frac{Var(\epsilon)}{Var(k)}$. In analogy to subsection **5.2**, the combination of the estimated Learning Curve with the IAM's first order condition implies:

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

Thus, again, the use of estimated learning rates in IAMs can deliver predictions that are in line with reality only if $\Omega = 0$, i.e. if $Var(\epsilon) = 0$. The intuition behind this result is explained with the following example:

Scenario IV

Imagine that the reduction in installation costs is driven by the accumulation of knowledge through an R&D process (as in scenario II, we assume here that $\Delta c = -\Delta h - 0 * \Delta k$). Suppose that the knowledge stock depends on the price of energy, $\Delta h = \Delta p$. In contrast, cumulated capacity does not always react to changes in price - e.g. if the price increase comes after a long period of stability, investors will not react immediately as they wish to ensure that higher prices are not temporary. IAMs do not take into account the delay in responses and they predict that $\Delta k = \Delta p$

Suppose that in period 1 energy price increase by 20%. This leads to a 20% increase in the knowledge stock and a 20% reduction in installation costs. However, in period 1 investors do not respond to the price increase and cumulated capacity does not grow. Hence, as researchers observe no immediate correlation between c and k , they conclude that the learning rate is zero.

If researchers specified the equation of demand for capacity in IAM as $k = p$, IAMs prediction on cumulated capacity would carry relevant information about energy prices. Since prices drive research and the level of installation costs, this information about capacity could be successfully used to predict cost reductions. In our example researchers do not exploit this possibility. After period 1, they switch off the learning curve due to the learning rate of zero. In period 2, researchers are asked to evaluate the effect of tax, which increases price by 10%. As the calibrated learning curve is flat, they report that technology costs are going to stay constant. In reality the cost would drop by 10%.

5.4 The Stationarity of the Relation between Controlled Factors

In Section 4, we have assumed that vector \mathbf{z} contains only one variable (namely the price of energy). However, even our simplified model set up to mimic IAM in Section 3 predicts that there are at least two other factors that should be included in the model and which have an effect on investment in capacity: policy stringency and the interest rate. If we allow the vector \mathbf{z} to contain more than one factor, we will have to introduce additional assumptions for the learning curve to produce valid results. The relation between different factors in \mathbf{z} must be constant, that is all the factors must be perfectly collinear. The simple

intuitive reason for this requirement is that the univariate learning curve does not allow us to separately identify the effect of each factor in \mathbf{z} on costs. Below we clarify this point using our theoretical framework.

Imagine that vector \mathbf{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 with

$$k = \gamma_1 z_1 + \gamma_2 z_2 + \text{constant} \quad (15)$$

$$c = \delta_1 z_1 + \delta_2 z_2 + \text{constant} \quad (16)$$

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

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

Combining the estimated learning curve with equation (15) (which is known to the researchers, as we assumed they have correctly specified the value function in their IAM) implies:

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

This reduces to the true equation (16) only in three instances: when the factors in \mathbf{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). The intuition behind this result is explained with the following example.

Scenario V

Suppose that, as in Scenario II, costs can be reduced only by learning-by-searching and the accumulation of R&D knowledge (hence, we assume $\Delta c = -\Delta h - 0 * \Delta k$). The knowledge stock is affected by energy prices, namely an increase in prices stimulates research and the growth of knowledge ($\Delta h = \Delta p$). Cumulated capacity also depends positively on energy prices and, in addition, can be affected by interest rates ($\Delta k = 2\Delta p - 2\Delta R$). As a result, cumulated capacity confounds two signals: one of price and one of interest rates.

Suppose that in period 1, price increases by 20% and the interest rate by 10%. This results in a 20% increase in cumulated capacity. An increase in price has leads to a 20% increase in the knowledge stock. As a result, installation costs drop by 20%. By looking at the increase in cumulated capacity and the decrease in costs, scientists conclude that the slope of the learning curve is 1. At

the beginning of period 2, scientists expect that the increase in energy price will continue at the rate of 10% per period. Scientists wish to evaluate the effect of this price increase on installation costs. If their IAMs are calibrated well, they will predict a 20% increase in cumulated capacity. Furthermore, employing the learning curve with the estimated slope, they will predict a 20% drop in installation costs. In reality, a 10% increase in price leads to a 10% increase in knowledge stock and 10% reduction in installation costs.

Turning away from the example, suppose that \mathbf{Z} is the matrix that contains all the demeaned observations of variables in \mathbf{z} that are available at the time of estimation of the learning curve. Let $\tilde{\mathbf{Z}}$ be the matrix with the expectations about future values of \mathbf{z} 's. If we allow for more than two factors in vector \mathbf{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 (3) and (4) and combining it with the correctly specified equation (3) must satisfy

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

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

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

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

$$E \left(c | \tilde{\mathbf{Z}}, \mathbf{Z} \right) = \tilde{\mathbf{z}}_1 \delta' + constant$$

which corresponds exactly to the functional relation associated with the the DGP. A similar result is obtained if $\delta = \eta\gamma$ and if $\delta = \iota d$ and $\gamma = \iota g$ 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 precesses 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 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 (4). The estimated reduced form model could be included directly in the IAM. The disadvantage of such approach is the loss of generality of the model: since every IAM contains different set of variables in vector \mathbf{z} , the regression and its estimates would not be universal.

6 A Two Stage Estimator of the Learning Rate.

In this section, we present a novel approach to estimate 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 can help overcoming 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:

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

Combining our new learning curve $c = \check{\alpha}k$ with the IAMs first order condition $k = \omega c + \gamma z$ implies:

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

which is exactly the same as (6).

More generally, as long as we maintain assumptions 2, 4 and 5, we could construct the fitted values as

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

where $\hat{\beta} = (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{k}$, \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 brings:

$$\begin{aligned} \check{\alpha} &= \left[((\delta\omega + \gamma)\mathbf{Z}' + \omega\nu\mathbf{T}')\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'(\mathbf{Z}(\delta'\omega + \gamma') + \omega\mathbf{T}\nu') \right]^{-1} * \\ &\quad ((\delta\omega + \gamma)\mathbf{Z}' + \omega\nu\mathbf{T}')(\mathbf{Z}(\delta'\omega + \gamma') + \omega\mathbf{T}\nu') \end{aligned}$$

Lets use \tilde{c} , \tilde{k} and $\tilde{\mathbf{z}}$ 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 $\tilde{k} = \omega\tilde{c} + \gamma\tilde{\mathbf{z}}$ must satisfy

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

The expected value of the prediction is therefore

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

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

7 (More) Consistent Estimates of the Learning Rate.

In this section we present the results of our suggested estimation approach for the learning rates of two key low carbon technologies which are featured in IAMs.

We focus on wind turbines and solar PV panels. Our dataset covers the period 1990 - 2012 for the 34 OECD countries. Energy prices and data on cumulated 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 give countries and giving each implemented instrument a value of one. The policy index 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).

We follow the procedure described in Section 6 above. Specifically, we first regress (the log of) cumulated installed capacity on (the log of) energy prices and on the policy index (which constitute our vector \mathbf{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 total fitted cumulated capacity for each year. This fitted cumulated capacity is then used as an explanatory variable in the second stage regression where (global) installation costs is 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 wind are reported in Table 3 (first stage) and Table 4 (second stage). The first stage regressions for wind technology suggest that policy stringency and energy prices are significant determinants of cumulated capacity. The

⁵accessed 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>

regression with full specification indicates that 1% increase in energy price produces a 3.5% growth in cumulated 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 indeed biased upward. The two stage estimate of the learning curve predicts a 3.7% learning rate (which corresponds to the coefficient of -0.053) if vector \mathbf{z} includes the price of energy and the policy index. It drops further - to -1.5% (i.e. the learning rate becomes negative) - if the vector includes only energy price, but this result is not statistically significant. Table 4 also reports Model 4 for comparison, which is the simple OLS estimates of the learning rate using our sample. In line with the previous findings in the literature, for the period 1990-2012 an implied learning rate for wind power is 4.4%. This estimate is significantly below the estimates of the learning rates for wind technologies available in the literature. However, this is entirely due to the longer time-frame under consideration in our analysis. In fact, Table 5 shows that if we drop the observations after 2007 (hence eliminating the period when installation prices are heavily affected by the upward trend in prices of materials), the estimated OLS learning rate is 16.5%. This last results from is line with the estimates available in the literature. However, even in this case the learning rate estimated using our procedure would be significantly lower, equal to 12.2% in the full specification case. Taking this evidence together, our approach would suggest that the current learning rates for wind used in IAMs should be revised downward. This is due to both our new approach and to the fact that learning seems to have slowed down in the more recent years.

Focusing on solar PV, results of the first and second stage estimation are presented in Tables 6 and Table 7, respectively. Similar to the case of wind, the first stage regression indicates that energy prices and policy stringency are the significant determinants of cumulated capacity. Moreover, our models suggest that the learning rate is higher than the that estimated with the OLS estimator: while the OLS estimates predicts a 12% learning rate (which corresponds o the coefficient of -0.169), the learning rate predicted by our model with full specification (Model 3) predicts a 19% learning rate (which corresponds to the coefficient of -0.254).

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 suggests that in case of wind technology the former effect dominantes. The price of wind turbines appears to have substantial influence on installed capacity. This effect contributes to the correlation between the two variables and biases the estimates of the learning rate upward. This might be due to the fact that wind power is a more mature technology which is almost competitive with traditional fossil generating technologies. In case of solar PV technology, the misspecification bias dominates. This suggest that, in addition to policy and price of energy,

	Model 1	Model 2	Model 3
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
Number of Clusters	32	32	32
Observations	588	588	588

Table 3: First stage regression results for wind turbines technology. Standard errors clustered at the level of countries below the coefficients.

	Model 1	Model 2	Model 3	Model 4
Fitted Cum. Cap.	0.001	-.076**	-0.053*	
	0.048	.032	0.029	
Observed Cum Cap.				-.063**
				0.030
R-squared	0.00	0.22	0.14	0.17
Observations	22	22	22	23

Table 4: Second stage regression results for wind turbines technology. Time-frame: 1990-2012. Standar errors below the coefficients

there are other important determinants of demand for photovoltaic panel or that the response of the demand to policy and price changes is delayed.

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 is when exogenous change in costs of a technology (e.g. due to change in material prices) promotes a change in installed capacity.

	Model 1	Model 2	Model 3	Model 4
Fitted Cum. Cap.	-.165	-.183***	-.187***	
	.255	.040	.043	
Observed Cum Cap.				-.221***
				.045
R-squared	0.03	0.63	0.61	0.65
Observations	14	14	14	15

Table 5: Second stage regression results for wind turbines technology. Time-frame: 1990-2004. Standar errors below the coefficients.

	Model 1	Model 2	Model 3
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

Table 6: First stage regression results for PV panels technology. Standard errors clustered at the level of countries below the coefficients.

	Model 1	Model 2	Model 3	Model 4
Fitted Cum. Cap.	-0.268***	-0.342***	-0.254***	
	0.063	0.026	0.031	
Observed Cum Cap.				-.169***
				0.012
R-squared	0.48	0.90	0.76	0.89
Observations	22	22	22	23

Table 7: Second stage regression results for PV panels technology. Timeframe: 1990-2012. Standard errors below the coefficients.

If we estimate the learning curve using simple OLS, we wrongly attribute this correlation to the effect of installed capacity change on installation costs change 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 high interest rate 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 brings biased results if the effect of the price is different than the effect of interest rate. The fourth instance could arise due to non-linearities. For example, if the earning rate is decreasing with cumulated capacity, then the future effect of cumulated 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 cumulated capacity.

Finally, we update the estimate of the learning curves for wind turbines and photovoltaic panels using this novel methodology. Our estimates of the learning rate for the wind turbines are substantially lower than the previous estimates.

In turn, our estimates suggests that the learning curve for the PV panels has larger slope than the one implied by the traditional estimator.

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 forcing will be the focus of future research efforts.

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Appendix

A1 Infinite Horizon Model

Let k denote the cumulated 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:

$$V(C, K) = \max_I \{PY(K) - CI + \beta V(C', K')\} \quad (17)$$

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

$$V(C, K) = \max_I \{PK^\alpha - C(K' - (1 - \delta)K) + \beta V(C', K')\} \quad (18)$$

The first order condition to firm's optimization problem is

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

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

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

We assume that the firms expects 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

$$V_K(C', K') = \frac{\beta\alpha(1 + g_P)(1 + g_K)^{\alpha-1}}{1 - \beta\alpha(1 + g_P)(1 + g_K)^{\alpha-1}(1 - \delta)} PK^{\alpha-1} + \frac{\beta(1 - \delta)(1 + g_C)}{1 - \beta(1 - \delta)(1 + g_C)} C$$

Combining this with the first order conditions we get:

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

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

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

where

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

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

A2 Conditions for section 5.3

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

$$c = \frac{(\delta_1 + \delta_2\pi)(\gamma_1 + \gamma_2\pi)}{(\gamma_2\pi + \gamma_1)^2} (\gamma_1 + \pi\gamma_2) z_1 + \text{constant}$$

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

$$\begin{aligned} &= \frac{\delta_1\gamma_1\widehat{Var}(z_1) + \delta_1\gamma_1\widehat{Var}(z_2) + 2\delta_1\gamma_1\widehat{Cov}(z_1, z_2)}{\gamma_1^2\widehat{Var}(z_1) + \gamma_1^2\widehat{Var}(z_2) + \gamma_1^2 2\widehat{Cov}(z_1, z_2)} (\gamma_1 z_1 + \gamma_1 z_2 + \text{constant}) \\ &= \delta_1 (z_1 + z_2) + \text{constant} = \delta_1 z_1 + \delta_2 z_2 + \text{constant} \end{aligned}$$

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

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

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