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A System Dynamics Approach to Technological Learning Impact for the Cost Estimation of Solar Photovoltaics

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Abstract: Technological learning curve models have been continuously used to estimate the cost development of solar photovoltaics (PV) for climate mitigation targets over time. They can integrate several technical sources that influence the learning process. Yet, the accurate and realistic learning curve that reflects the cost estimations of PV development is still challenging to determine. To address this question, we develop four hypothetical-alternative learning curve models by proposing different combinations of technological learning sources, including both local and global technological experience and knowledge stock. We specifically adopt the system dynamics approach to focus on the non-linear relationship and dynamic interaction between the cost development and technological learning source. By applying this approach to Chinese PV systems, the results reveal that the suitability and accuracy of learning curve models for cost estimation are dependent on the development stages of PV systems. At each stage, different models exhibit different levels of closure in cost estimation. Furthermore, our analysis underscores the critical role of incorporating global technical sources into learning curve models.

Keywords: photovoltaic; system dynamics; technological learning; learning curve; technological experience; technological knowledge stock

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1. Introduction

Timely and large-scale deployments of solar photovoltaic (PV) technology have emerged as one of the most promising measures to stabilize climate change below the Paris Agreement 2 °C limit and to mitigate the environmental impact of electricity production [1]. By the end of 2022, the global cumulative installed capacity of PV reached 1053 GW [2]. This achievement is primarily attributed to the significant cost reduction in PV technology. Over the past forty years, the prices of PV technology have decreased by more than two orders of magnitude [3]. Moreover, in the last decade, the global weighted-average levelized energy cost for newly commissioned utility-scale PV has fallen by 88%, making it cheaper than fossil fuel in several parts of the world [4]. Although these substantial cost declines benefit the acceleration of PV installation, it remains essential to accurately estimate the cost reduction required for further PV deployment, at the speed and scale that are needed to achieve climate targets, and especially in countries where fossil fuel is still cheaper [5–8].

Technological learning, which refers to the change in cost over time due to technological improvement, is fundamental to driving the cost reduction of PV technologies [9,10]. The improvement and development of PV technology evolves with the introduction of innovative materials, novel designs, and enhanced manufacturing processes, all of which exert a substantial influence on cost reduction [11]. Through the examination regarding cost and technological performance, an in-depth understanding of technological learning furnishes predictive insights into the cost evolution of PV systems [12].

The learning curve model is the most commonly used framework for analyzing the relationship between technological learning and PV cost reduction, which describes how PV cost declines as technological learning increases [13]. The sources of technological learning incorporated into the learning curve model have been recognized as distinct components [14]. Technological experience and technological knowledge stock, which are commonly represented by cumulative installed capacity and research and development (R&D) investment, respectively, are the most common sources of technological learning [15].

A fundamental variant of this model is the one-factor learning curve (OFLC), which considers experience as the single source of technological learning to estimate PV cost development [16]. When the model is expanded to include knowledge stock as the second source of technological learning, it transitions into a more nuanced two-factor learning curve (TFLC). The integration of three or more factors into the learning curve model often encounters significant limitations due to the high level of multicollinearity [17]. Thus, the OFLC and TFLC are preferred for their relative robustness and are the most widely employed formulations in evaluating the relationship between technological learning and PV cost.

The utilization of experience and knowledge stock within the OFLC or TFLC is subject to varied interpretations. Local technological learning, defined as the experience and knowledge stock gained in one specific country or region, is widely used to assess PV cost, especially in studies that focus on one country or region [18,19]. With the development of renewable energies, studies suggest that cost reduction is not only a result of the local learning driven by local experience and knowledge stock but also benefits from the external capacity expansions and R&D expenditures in the international market, referred to as global technological learning [13,20,21]. Especially for PV technology, the installed capacity increases rapidly in various countries worldwide, such as the United States, Germany, and China [22,23]. Furthermore, PV components, such as modules or inverters, are traded globally. A substantial portion of PV components in some countries relies on imports from global markets. Technological learning is a process driven by factors including globally traded equipment and the local accumulation of experience [1,24].

However, in the contexts in which these various technological learning sources and learning curve models have been used in the PV cost estimation analysis, a research gap and an inevitable related question is which model with which sources can more accurately and realistically assess PV cost reduction?

In addition, in the developing process of decreasing PV cost, not only does the technological learning lead to cost reduction, but the cost reduction also influences the changes in experience and knowledge stock. For instance, cost reduction will increase investors' enthusiasm to invest in new PV installations, thus increasing the total installed capacity of PV, and accumulating experience [25]. This indicates that, rather than a linear and static analysis widely used in previous studies, dynamic interaction and feedback structures better explain the relationship between PV cost and technological learning [18,26]. Furthermore, cost reduction and the technological learning process are also affected by variable nonlinear factors such as investors' willingness and policies [6]. These characteristics challenge the previous static linear analyses when investigating the interaction between PV cost estimation and technological learning.

System dynamics (SD) is a powerful approach that mainly describes and analyzes the dynamic system problem with the characteristics of feedback structure and non-linearities between variables, which fits these complex characteristics for analyzing the relationship between technological learning and PV cost [27,28]. Therefore, aiming to explore which technological learning model can more accurately estimate PV cost development, this paper incorporates the SD approach, performing and comparing simulations with four learning curve models, using data from China. The interaction between PV cost and technological learning can be seen as a system. All the influencing factors in this system are incorporated into four learning curve models to estimate the PV cost: OFLC with local experience; OFLC with both local and global experience; TFLC with local knowledge stock; and TFLC with both local and global knowledge stock. The cost development patterns are obtained by simulating the SD approach in these different learning curve models, and the estimation results of different technological learning are investigated.

The contributions of this paper are threefold. First, this paper compares four learning curve models underpinned with a different combination of technological learning sources, including both local and global learning sources, thus providing exhaustive insight into and reference for improved PV cost estimation. Second, compared with previous studies on the learning curve, which only use static analysis, a dynamic evaluation and feedback structure of the technological learning and PV cost development is considered by employing an SD approach. Third, the learning curve models with the SD approach and the research conclusions proposed in this paper provide a valuable resource for investment decision-making and policies regarding PV technology deployment and enrich PV learning theory.

The remainder of this paper proceeds as follows: Section 2 sets the background of the research by introducing the critical theoretical literature related to technological learning and system dynamics studies for PV systems. Section 3 introduces the methodology, and the case used for comparison and analysis. The results are presented in Section 4. Section 5 provides the discussion and conclusion.

2. Literature Review

2.1. Learning Curve and Technological Learning Sources

Table 1 shows that the OFLC, also called the experience curve, is the most popular learning curve model used in the PV cost development analysis [17,29]. Experience is usually the single technological learning source that describes PV cost development [30,31]. In these studies, the cumulative installed capacity is the most frequently used variable as a proxy to represent experience. For instance, reference [32] employed the OFLC to assess the grid parity of PV in China, and experience was represented by the cumulative installed capacity of PV from 2006 to 2014. However, these studies only focused on installed capacity in a specific country as the experience, neglecting global experience and its interaction with local experience, i.e., ignoring that local PV systems can absorb global experience to increase their learning, thereby further influencing the cost. Research by [20] identified that for PV in Thailand, 57% of the total technology cost corresponds to globally sourced parts (e.g., PV modules and inverters), while locally sourced parts account for 43% (e.g., the balance of the system). Ignoring global experience risks overestimating costs and may lead to incomplete or misleading policy. Thus, reference [20] suggested including both global and local experience to more accurately explore PV cost reductions. However, although experience has been represented from different perspectives, some works in the literature have criticized that the OFLC method itself may overestimate the actual contribution of experience, as this model only uses a single parameter to assess the cost and inadequately describes the complex dynamics leading to cost reductions, which leaves out the involvement of another important factor, knowledge stock [33,34].

Table 1. Summary of the relevant learning curve studies for PV using different model formulations and technological learning sources.

Learning Curve Model	Period	Country/Region	Dependent Cost Variable	Experience Metric	LBD Learning Rate (%)	Knowledge Stock Metric	LBR Learning Rate (%)	Ref.
OFLC	2007–2014	USA	Levelized cost of electricity (LCOE)	Cumulative installed capacity	12%			[35]
OFLC	2010–2016	China	Capital cost	Cumulative installed capacity	12.6%			[19]
OFLC	2006–2014	China	LCOE	Local installed capacity	11.7%			[32]

Table 1. *Cont.*

Learning Curve Model	Period	Country/Region	Dependent Cost Variable	Experience Metric	LBD Learning Rate (%)	Knowledge Stock Metric	LBR Learning Rate (%)	Ref.
OFLC	2002–2017	Korea	Cost of PV power	Cumulative PV power generation	18.44%			[36]
OFLC	1992–2015	EU	Cost of c-Si PV module	Cumulative production				[37]
TFLC	2008–2020	USA, Germany, China	Price of PV modules	Local cumulative installed capacity		Global averaged polysilicon prices	26% in USA, 20% in Germany, 33% in China	[3]
TFLC	2008–2020	USA	Capital cost	Local OECD cumulative installed capacity	27.56%	OECD and local R&D expenses	4.72%	[38]
TFLC	2004–2018	China	Initial costs of solar modules	Local cumulative installed capacity	7.85%	Local accumulated R&D investment	13.55%	[39]

Innovation in technology and the related knowledge stock from R&D activities also play a critical role in learning [18,40]. In this context, the TFLC is developed to account for the influence of technological progress and innovation on PV costs [38,41]. The reason for considering the knowledge stock is that R&D connects to technological progress which can lead to breakthroughs in cost reduction. Continuous R&D investments within PV technology promotes technological innovation, including enhancements in technological performance, advancements in materials, and generational shifts in technology. One example of such a transformative shift is the evolution from polymorphic silicon crystal-based PV technologies to thin-film cells. These new thin-film cells are characterized by their minimalistic use of semiconducting material, utilizing approximately 99% less than silicon cells, thereby substantially reducing material costs [11]. With the increasing R&D activities in PV technology in recent years, the TFLC is widely used in recent PV cost analyses. For instance, reference [18] used the government's R&D investment as the source of knowledge stock to analyze how R&D policies impact PV cost reduction. However, such consideration of two factors has also been challenged by some studies, arguing that including two factors in the learning curves hinders its application due to data limitations and high levels of multicollinearity, making it difficult to distinguish the impact of experience and knowledge stock [17,42].

Although there is a substantial body of literature on using technological learning to estimate the PV costs, few studies have considered whether the learning curve model and the technological learning source these studies used are accurate or realistic. It is inevitable that a question emerges: Which learning curve model and technological learning source is more accurate or realistic when estimating cost development specifically for PV technology?

Some studies in the previous literature compared the effect of different technological learning definitions and learning curve models. For instance, reference [15] examined how four types of technological learning can reduce air pollutants' intensity, but they did not focus on the cost estimation. Concentrating on the cost, reference [12] investigated the impact of different technological learning scenarios through the case of renewable energies in the USA, showing that the effect is context-dependent, i.e., the learning curve has different impacts for different renewable energy technologies or different technology maturity stages. However, reference [12] used linear static analysis to explore this question, which means only considering that technological learning leads to cost reduction, neglecting that cost reduction may also influence the learning process.

The relationship between PV costs and technological learning is interactive and dynamic in the process of PV technology diffusion and technological innovation. The influencing factors in this process are complex. The whole process can be seen as a complex system, and feedback structures between factors exist. The increase in installed capacity and R&D investment leads to cost decline; conversely, the cost decline also promotes new PV installations and more R&D activities. It means that cost reduction and technological learning are interdependent and reinforce each other. In addition, PV technology diffusion and R&D activities are affected by several non-linear factors, such as the price of electricity and investors' enthusiasm [34]. When investigating the relationship between technological learning and PV cost, the previous static studies are insufficient to simulate this kind of dynamic process or the non-linear factors.

2.2. System Dynamics (SD)

SD is an approach for understanding the dynamic behavior of a complex system, especially explaining causality between variables, and it has been widely used in energy modeling studies [43]. For instance, reference [44] used SD to investigate the impact of R&D incentives on investment in wind generation. However, regarding the impact of different learning curve models on PV development, few studies considered these dynamic characteristics and used SD to explore this question. Using SD offers a more comprehensive understanding of the relationships between factors in PV technological learning and cost development because it offers the possibility of modeling and simulating complex (energy) systems and analyzing their non-linear behavior over time [45].

Therefore, taking PV systems in China as the case study to investigate which learning curve model is more accurate and realistic for PV cost estimation, we first review the current learning curve models and definitions of technological learning sources, and set up four different hypothetical learning curve models, as shown in Table 2. OFLC-A only considers local experience as the technological learning source, while OFLC-B considers both local and global experience. TFLC-C includes the local knowledge stock in the model in addition to experience; TFLC-D also adds global knowledge spillovers into the model.

Table 2. Four hypothetical learning curve models.

Model	Description	Purpose
OFLC-A	Local experience	To analyze the impact of local experience
OFLC-B	Both global and local experience	To analyze the impact of both local and global experience
TFLC-C	Local and global experience Local knowledge stock	To analyze the impact of knowledge stock based on local R&D investment
TFLC-D	Local and global experience Local knowledge stock and global knowledge spillovers	To analyze the impact of knowledge stock based on both local R&D and international knowledge spillovers

Then, the SD approach is adopted to explore the impact by constructing a causal-loop diagram and a stock-flow diagram to qualitatively describe the PV diffusion process and related non-linear factors. Based on the simulation results from the SD approach, the impacts of different technological learning models are obtained.

3. Method and Data

3.1. Research Framework

The research framework is shown in Figure 1. We first distinguish the formulations of different learning curve models and definitions of technological learning sources. Based on that information, we formulate four hypothetical models to investigate their impact on the PV cost estimations. Then, we run SD simulations of the models to explore the dynamic interactions between PV cost and technological learning. We leverage data on PV from China, including installed capacity, PV cost, R&D investment, and other related parameters, as input technological sources for the four hypothetical learning models.

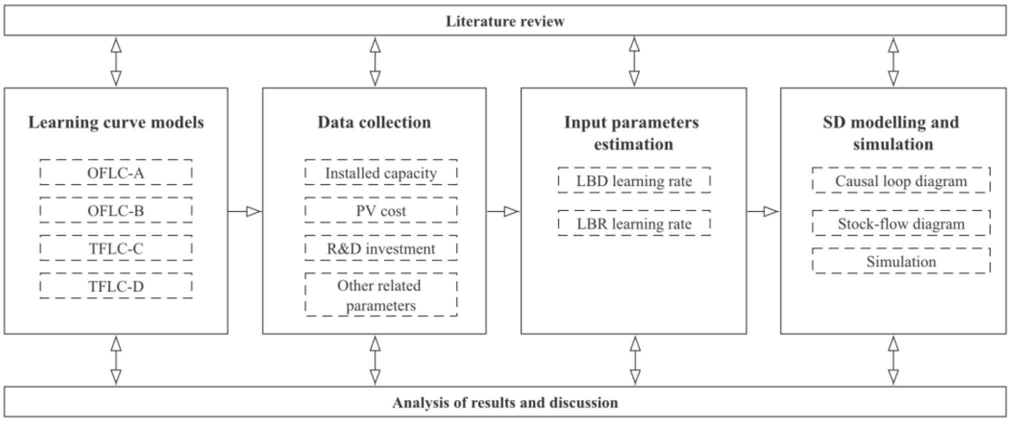

Figure 1. The research framework.

3.2. Learning Curve Model

The learning curve model can be formalized in an exponential correlation between cost and technological learning [46]. To estimate PV cost, two frequently used learning curve models are the OFLC and the TFLC.

The OFLC assumes that the cost of PV follows an exponential decline as experience accumulates, with cumulative installed capacity serving as the most used proxy, also known as "learning by deployment (LBD)" [29,30]. Accordingly, we also adopt cumulative installed capacity as the proxy to represent experience. The relationship between PV cost and experience in the OFLC is shown in Equation (1):

$$C_t = C_0 \cdot (E_t)^{-\alpha} \tag{1}$$

where C_t is the unit cost of the PV system in year t (i.e., costs per capacity); E_t is the cumulative experience; C_0 is the initial unit cost of PV in base year; and α is the rate of cost reduction with increasing experience, which is related to the learning rate [13]. In the OFLC, the learning rate represents the percentage of PV unit cost reduction for every doubling of experience, as shown in Equation (2):

$$LR_{lbd} = 1 - 2^{-\alpha} \tag{2}$$

As discussed in Section 2, in addition to increasing experience, technological learning can occur with knowledge stock accumulation, i.e., through technology innovation and R&D activities that improve technological progress. This is also referred to as learning by researching (LBR). As an extension to the OFLC, the TFLC typically aggregates the impact of both experience and knowledge stock. The relationship between PV cost and technological learning in the TFLC is shown in Equation (3):

$$C_t = C_0 \cdot (E_t)^{-\alpha} \cdot (KS_t)^{-\beta} \tag{3}$$

where KS_t is the cumulative knowledge stock; β is the cost reduction rate with an increase in knowledge stock.

In the TFLC, the LBR learning rate represents the percentage of PV unit cost reduction due to knowledge stock, as shown in Equation (4):

$$LR_{lbr} = 1 - 2^{-\beta} \tag{4}$$

3.2.1. Definition of Experience

In this paper, the cumulative installed capacity of PV is used as the proxy of experience. The experience is modelled in Equation (5):

$$E_t = E_{local,t} + \phi \cdot E_{global,t} \tag{5}$$

where $E_{local,t}$ is the local experience, represented by the local cumulative installed capacity of PV ($IC_{local,t}$); $E_{global,t}$ is the global experience; ϕ is the proportion of global experience to total experience, either 0 or 1 to exclude or include global experience.

Global experience ($E_{global,t}$) flows across countries and has an impact on PV cost development at the local level, which can be depicted as a function of the international installed capacity pool and the absorptive capacity of the given country. The international installed capacity pool is defined as the difference between the global cumulative installed capacity ($IC_{global,t}$) and local cumulative installed capacity ($IC_{local,t}$), while the absorptive capacity of the country is defined as the ratio of $IC_{local,t}$ to $IC_{global,t}$ [12]. Accordingly, the experience of PV gained from the global market is calculated in Equation (6):

$$E_{global,t} = \frac{IC_{local,t}}{IC_{global,t}} \left(IC_{global,t} - IC_{local,t} \right) \tag{6}$$

3.2.2. Definition of Knowledge Stock

Knowledge stock can be modeled as a function of cumulative knowledge stock and the creation of new knowledge, with R&D investment as the proxy to represent knowledge stock [39,47]. This investment in R&D is a pivotal determinant of technological innovation, including the innovation of technological performance, technological transition such as the transition from traditional polymorphic silicon crystals to the emergent generation of thin-film layering techniques, and improvement in manufacturing [48]. These progressions in technology are instrumental in driving down the costs associated with PV systems. Due to obsolescence in the energy innovation process, past knowledge can become inappropriate for current innovation, which means that knowledge stock depreciates with time. In addition, there is a time delay in converting R&D investment into its effect on knowledge stock. These factors are considered when calculating knowledge stock. Cumulative knowledge stock can be modeled in Equation (7) [21]:

$$KS_t = (1 - \delta_t) KS_{t-1} + \lambda \cdot {RD_{local,\, t-g}}^{\mu} \cdot {KS_t}^{\sigma} \cdot {SP_{t-g}}^{\tau} \tag{7}$$

where KS_t is the cumulative knowledge stock; and δ_t is the depreciation rate of knowledge. The second term on the right side is defined as a function of local R&D investment, previous KS, and international knowledge spillovers, which can be seen as creating new knowledge about PV [21]. λ is the lag discount coefficient of R&D investment; μ, σ, τ reflect the elasticities of the creation of new knowledge, which are between 0 and 1. In the case of knowledge stock increasing at the local level, μ is 1, σ is 0, and τ is 0. While including global knowledge flows, knowledge is induced by local R&D investment and international knowledge spillover, and μ is 0.2, σ is 0.55, and τ is 0.15; g is the time lag between R&D activity and its effect on knowledge stock; SP_t is the spillover of international PV knowledge between countries.

The effect of global R&D-based knowledge spillovers (SP_t) is well accepted as measured based on a pool of accessible knowledge from other potential countries, which can be seen as the international knowledge pool. A fraction of this knowledge can be absorbed by the given country, which is defined as the absorptive capacity [49]. The SP_t can be estimated as a function of these two variables [12,21], as shown in Equation (8):

$$SP_t = \frac{RD_{local,t}}{RD_{global,t}} \left(RD_{global,t} - RD_{local,t} \right) \tag{8}$$

The international knowledge pool is defined as the gap between the global ($RD_{global,t}$) and the local R&D investment expenditure ($RD_{local,t}$). The absorptive capacity of the given country is described by the share of the available global knowledge pool that the given country can absorb, i.e., the ratio of $RD_{local,t}$ to $RD_{global,t}$.

The coefficients used in the four hypothetical learning curve models are summarized in Table 3.

Table 3. The coefficients used in the four hypothetical learning curve models.

Model	Technological Learning Sources	ϕ	δ_t	λ	g	μ	σ	τ
OFLC-A	Local cumulative installed capacity	0	-	-	-	-	-	-
OFLC-B	Local and global cumulative installed capacity	1	-	-	-	-	-	-
TFLC-C	Local and global cumulative installed capacity Local R&D investment	1	3%	1	3	1	0	0
TFLC-D	Local and global cumulative installed capacity Local R&D investment and global knowledge spillover	1	3%	1	3	0.2	0.55	0.15

3.3. System Dynamics (SD) Approach

As shown in Figure 2, a causal-loop diagram is first constructed to qualitatively describe the learning and PV cost development process and the cause-and-effect relationships among the main elements. Regarding the relationship between experience and PV cost, with an increase in local and global cumulative installed capacity, the accumulated experience in the installation leads to PV cost reduction. Regarding the knowledge stock, an increase in local and global R&D investment improves the knowledge stock and the technological innovation level, thus reducing the PV cost. In addition, decreasing PV cost leads to an increase in return on investment. Driven by the higher return, the investment willingness and interests of potential PV companies or organizations increase with regard to the new PV installation, promoting the cumulative installed capacity in return, enhancing a feedback loop between PV costs and experience. On the other hand, with higher profits, the potential PV companies or organizations have more funds to reinvest in R&D and increase technological innovation, thereby reducing the PV cost. A feedback loop between PV cost and R&D investment also occurs.

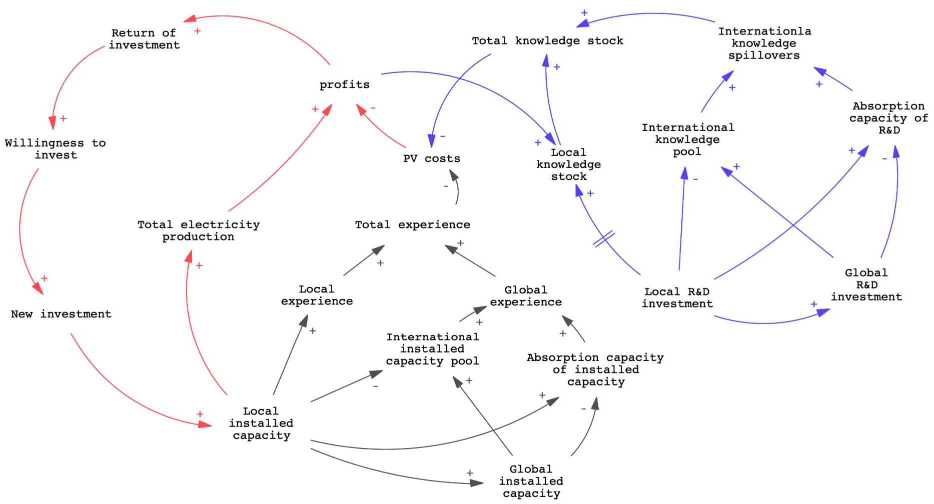

Figure 2. Causal–loop feedback diagram of PV learning and cost development process.

After determining the main modules and factors for the PV learning process, a stock–flow diagram is further constructed to elaborate these factors, as shown in Figure 3. There are three main subsystems in the SD approach: experience expansion subsystem, knowledge stock subsystem and cost and profit subsystem.

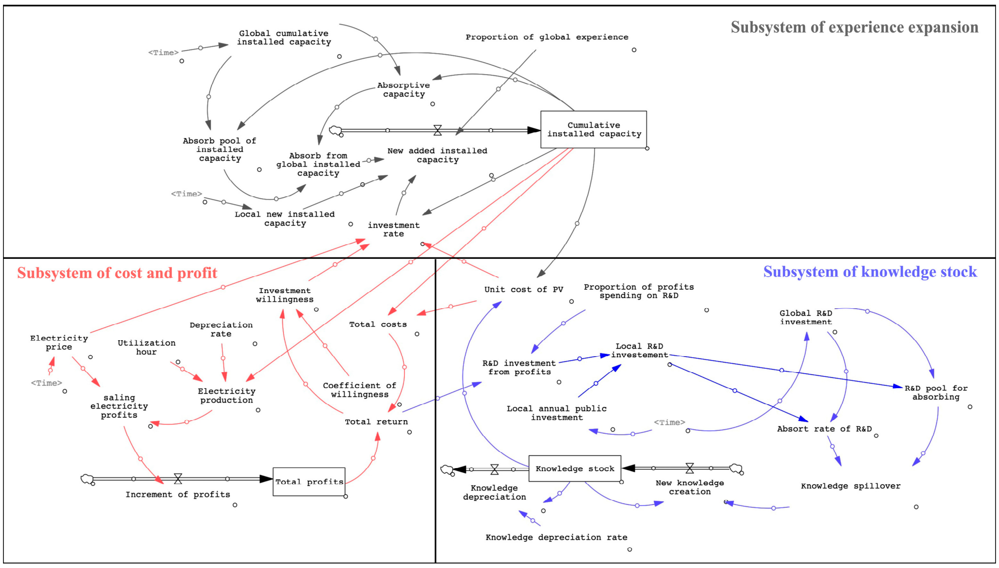

Figure 3. Stock–flow diagram of PV learning process.

3.3.1. The Subsystem of Experience Expansion

The cumulative installed capacity of the PV system is mainly composed of the initial installed capacity and the newly installed capacity, which can be calculated using Equation (9):

$$IC_t = IC_o + \int_0^t IC_{new,t}dt \tag{9}$$

where IC_t is the cumulative installed capacity; IC_o is the initial installed capacity; and $I_{new,t}$ is the newly added installed capacity.

The newly installed capacity depends on the local new installed capacity ($IC_{localnew,t}$), the absorptive installed capacity from the global market ($IC_{globalnew,t}$), and the investment rate (IR_t), as shown in Equation (10), while the investment rate is determined by the investment willingness of the investors (WI) and the cumulative installed capacity, as shown in Equation (11) [26]:

$$IC_{new,t} = IC_{localnew,t} + \phi \cdot IC_{globalnew,t} + IR_t \tag{10}$$

$$IR_t = IC_t \cdot WI \tag{11}$$

3.3.2. The Subsystem of Knowledge Stock Accumulation

The knowledge stock mainly accumulates through new knowledge creation ($KS_{new,t}$) and knowledge depreciation ($KS_{d,t}$), as shown in Equation (12):

$$KS_t = KS_0 + \int_0^t (KS_{new,t} - KS_{d,t})dt \tag{12}$$

New knowledge creation mainly depends on local R&D investment ($RD_{local,\ t-g}$) and absorptive knowledge spillovers (SP_t) from the global market, as shown in Equation (13):

$$KS_{new,t} = \lambda \cdot {RD_{local,\ t-g}}^{\mu} \cdot {KS_t}^{\sigma} \cdot {SP_t}^{\tau} \tag{13}$$

Regarding $RD_{local,\ t-g}$, in addition to public investment ($RD_{pub,t}$), the PV industry also has the option of reinvesting a proportion (ω) of the profit (PF_t) on the PV R&D [18], as formulated in Equation (14):

$$RD_{local,\ t} = \int_0^t RD_{localnew,t}dt = \int_0^t (RD_{pub,t} + RD_{profit,t})dt = \int_0^t (RD_{pub,t} + PF_t \cdot \omega)dt \tag{14}$$

The knowledge depreciation depends on the knowledge depreciation rate (δ_t) and the knowledge stock, as shown in Equation (15):

$$KS_{d,t} = KS_t \cdot \delta_t \quad (15)$$

3.3.3. The Subsystem of Cost and Profit

Profit (PF_t) is mainly measured by the increment of profit ($PF_{in,t}$), obtained through selling the electricity (SE_t), as shown in Equations (16)–(18):

$$PF_t = \int_0^t PF_{in,t} dt = \int_0^t SE_t dt \quad (16)$$

$$SE_t = EP_t \cdot price \quad (17)$$

$$EP_t = (1 - d_e) \cdot IC_t \cdot h \quad (18)$$

where EP_t is the electricity production, which can be calculated by the cumulative installed capacity (IC_t), utilization hours (h), and depreciation rate of PV equipment (d_e); *price* is the PV electricity price.

The return obtained by the investors impacts the investment willingness for new PV investment [50]. The relationship between investment willingness and the return is measured using Equation (19):

$$WI = (PF_t - C_{total,t}) \cdot \psi \quad (19)$$

where ψ is the coefficient of the investment willingness.

3.3.4. Data Collection

To illustrate the effect of these four hypothetical learning curve models using an SD approach, we use data on PV from China. The data sources used for the calculation are listed in Table 4.

China currently has the largest installed capacity of PV in the world. From 2011 to 2022, the installed capacity of PV increased from 2.22 GW to 322 GW [51]. The rapid development of PV in China provides abundant data with which to evaluate the impact of different learning models on PV cost development. The case in China can also provide experience for developing PV in other countries or regions and policy suggestions for the policymakers. Thus, we collect the installed capacity of PV and R&D investment data in China from 2004 to 2022 and other related parameters to estimate the learning curve models and then simulate the SD approach.

Table 4. The summary of variables and the data source used in the SD approach.

Subsystem	Item	Parameter	Value	Ref.
Experience expansion	Local new installed capacity	$IC_{localnew,t}$		[39]
	Global cumulative installed capacity	$IC_{global,t}$		[52]
	Cumulative installed capacity	IC_t		
	Newly added installed capacity	$IC_{new,t}$		
	Absorbed pool of installed capacity	$IC_{global,t} - IC_{local,t}$		
	Absorptive capacity	$IC_{local,t} / IC_{global,t}$		
	Absorption from global installed capacity	$IC_{globalnew,t}$		
	Proportion of global experience	ϕ	0 or 1	
	Investment rate	IR_t		
	Willingness of investors	WI		

Table 4. *Cont.*

Subsystem	Item	Parameter	Value	Ref.
Knowledge stock	Local new annual public investment	$RD_{pub,t}$		[39]
	Global R&D investment	$RD_{global,t}$		[53]
	Proportion of profits spent on R&D	ω	3%	[18]
	Lag discount coefficient	λ	1	[21]
	Elasticities of new knowledge creation	μ, σ, τ	μ = 0.2 σ = 0.55 τ = 0.15	[21]
	Knowledge depreciation rate	δ_t	3%	[54]
	Knowledge stock	KS_t		
	New knowledge creation	$KS_{new,t}$		
	Local new R&D investment	$RD_{localnew,t}$		
	R&D investment from profits	$RD_{profit,t}$		
	R&D pool	$RD_{global,t} - RD_{local,t}$		
	Absorb rate of R&D	$RD_{local,t} \Big/ RD_{global,t}$		
	Knowledge spillover	SP_t		
	Knowledge depreciation	$KS_{d,t}$		
Cost and profit	Electricity price	$price$		[55]
	Utilization hour	h	1163 h	[55]
	Depreciation rate of PV equipment	d_e	6%	[26]
	Coefficient of investment willingness	ψ	10^{-4}	[50]
	Increment of profit	$PF_{in,t}$		
	Profit from selling electricity	SE_t		
	Electricity production	EP_t		
	Total cost	$C_{total,t}$		
	Unit cost of PV	C_t		

4. Results

4.1. The Learning Rate Based on Four Hypothetical Models

The results of the learning curve model and learning rate are summarized in Table 5. Regarding the estimated results, when local experience is considered as the only source of technological learning (OFLC-A), the LBD learning rate is 13.7%. While including the global experience (OFLC-B), the LBD learning rate increases to 14.1%. When the knowledge stock is included in the model, the LBD learning rate decreases to 1.2% (TFLC-C) and 0.8% (TFLC-D). The LBR effect becomes more significant, i.e., the increase in R&D contributes significantly to cost reduction, with LBR learning rates of 34.5% and 30.6% for TFLC-C and TFLC-D, respectively. In addition, it is noted that with the inclusion of the global knowledge spillover (TFLC-D), both the LBD and the LBR learning rates decrease compared to TFLC-C.

Table 5. Estimate results of learning rate and learning curve models for PV in China.

Model	Year	Learning Curve Model	LBD Learning Index (-)	LR_{lbd} (%)	LBR Learning Index (-)	LR_{lbr} (%)	Adjusted R^2
OFLC-A	2004–2018	$C_t = 48.6 \cdot (E_t)^{-0.213}$	0.213	13.7	-	-	0.9574
OFLC-B	2004–2018	$C_t = 57.9 \cdot (E_t)^{-0.219}$	0.219	14.1	-	-	0.9579
TFLC-C	2004–2018	$C_t = 1479.1 \cdot (E_t)^{-0.018} (KS_t)^{-0.610}$	0.018	1.2	0.610	34.5	0.9904
TFLC-D	2004–2018	$C_t = 829.1 \cdot (E_t)^{-0.011} (KS_t)^{-0.526}$	0.01	0.8	0.526	30.6	0.9928

4.2. The Simulation Results of Experience, Knowledge Stock, and Return in Four Hypothetical Models Using the SD Approach

Experience and knowledge stock for PV in China are simulated via the SD approach in four learning curve models. Figure 4a shows the experience based on local installed capacity (OFLC-A) and both the local and global installed capacity (OFLC-B). From 2004 to 2025, the experience increases from 76.7 MW to 466.5 GW in OFLC-A and 2005.5 GW in OFLC-B. The global installed capacity contributes more than 75% of the average experience. Especially from 2008 to 2013, the global installed capacity contributes to more than 85% of the total experience. After 2013, with the rapid development of PV in China, the contribution of the global experience decreases, but it still significantly impacts the learning curve model.

Figure 4b shows the knowledge stock based on the local R&D investment (TFLC-C) and both the local R&D investment and the international knowledge spillover (TFLC-D). In these two models, a proportion of the profit from selling PV electricity is also included as part of the R&D investment. In TFLC-C, the knowledge stock increases from 768 million Chinese Yuan (CNY) (USD 93 million) in 2004 to CNY 169,741 million (USD 23,940 million) in 2025. When considering the global knowledge spillover in the analysis, the knowledge stock increases from CNY 768 million (USD 93 million) in 2004 to CNY 270,001 million (USD 38,081 million) in 2025. The knowledge spillover from the global market contributes to 40% on average of the total knowledge stock.

Figure 4c shows the return under four hypothetical models, which is calculated based on the total cost and profit. Generally, the returns under four hypothetical models all show an increasing trend. Before 2008, the returns are all almost zero. From 2008, with the increase in installed capacity and decrease in cost, the return starts to increase. However, the increasing amount and rate are different. The return under OFLC-B has the highest increase rate of 85%, while for the other three models, the increase rates are 32% (OFLC-A), 60% (TFLC-C), and 58% (TFLC-D). Compared to the model only incorporating local experience, global experience significantly contributes to the return on PV systems. Compared to the TFLCs, although the return amount under OFLC-B is smaller, the increase rate is higher, i.e., the increment in global experience increases the return on the PV systems faster, thus influencing the investors' willingness to invest in new PV projects.

4.3. Cost Estimation Based on the Simulations of Four Hypothetical Learning Curve Models

Figure 5 shows the simulation results of cost development based on four hypothetical learning curve models, in which the real cost of PV is also illustrated for comparison. The cost in all four models shows a decreasing trend but with different decrease rates. For OFLC-A, the cost decreases from 19,283 CNY/kW (2330 USD/kW) in 2004 to 3014 CNY/kW (425 USD/kW) in 2025, with an annual decrease rate of 84.3%. For OFLC-B, the cost decreases from 22,382 CNY/kW (2704 USD/kW) in 2004 to 2412 CNY/kW (340 USD/kW) in 2025, with an annual decrease rate of 89.2%. When including the knowledge stock in the analysis, i.e., TFLC-C and TFLC-D, the cost decreases more significantly than in the OFLC models. In TFLC-C, the cost declines from 23,767 CNY/kW (2871 USD/kW) to 735 CNY/kW (104 USD/kW), with a decrease rate of 96.9%. In TFLC-D, the cost declines from 23,997 CNY/kW (2899 USD/kW) to 983 CNY/kW (139 USD/kW), with a decrease rate of 95.9%. In these four learning curve models, the cost result based on TFLC-C decreases fastest and with the highest decrease rate.

In comparing simulation results with real data in the period before 2011, the cost simulation result derived from the TFLC-C exhibits the closest alignment with the real data. Between 2011 to 2018, the results showed that the OFLC-A provides the most congruent fit with the real PV cost. After 2018, the TFLC-D model fits the real data best among these four learning curve models.

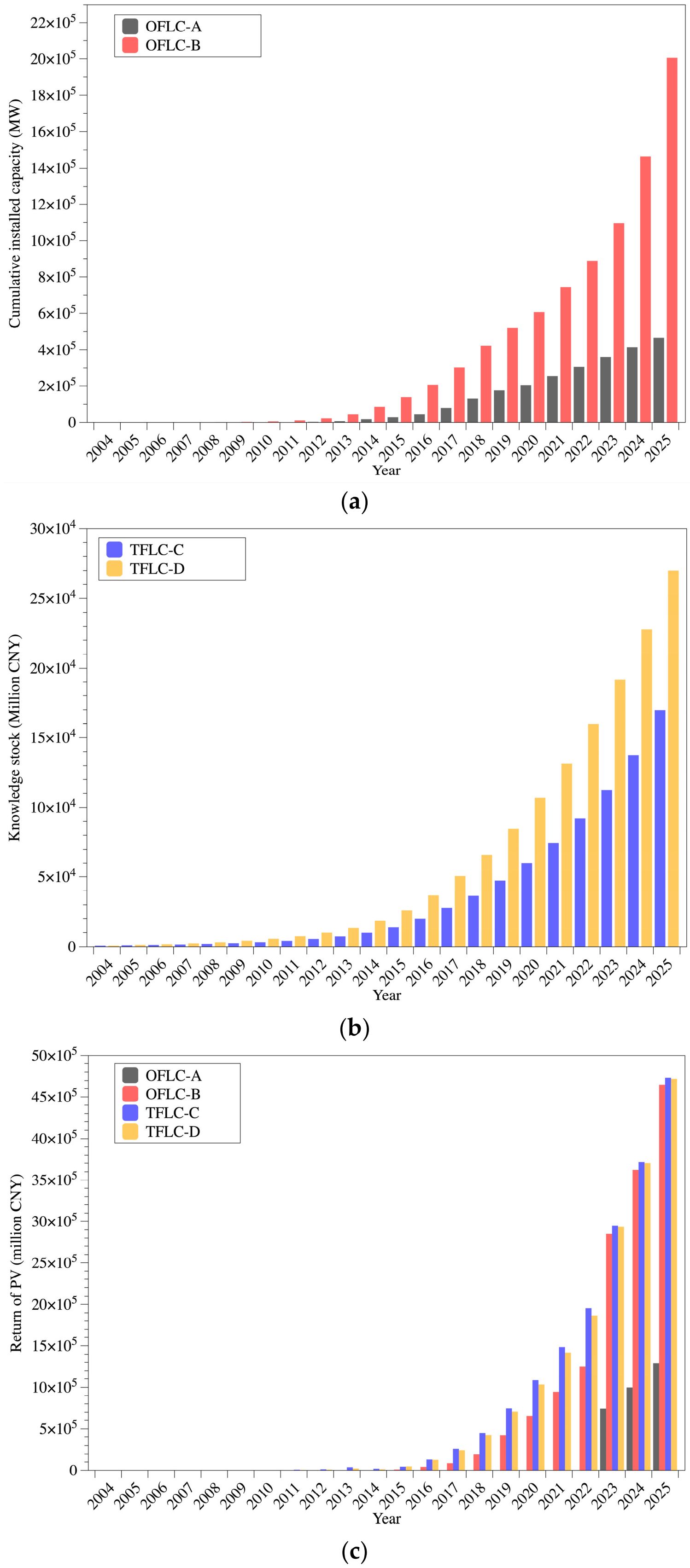

Figure 4. The results of experience under OFLC-A and OFLC-B (**a**); knowledge stock under TFLC-C and TFLC-D (**b**); and return under four learning models (**c**).

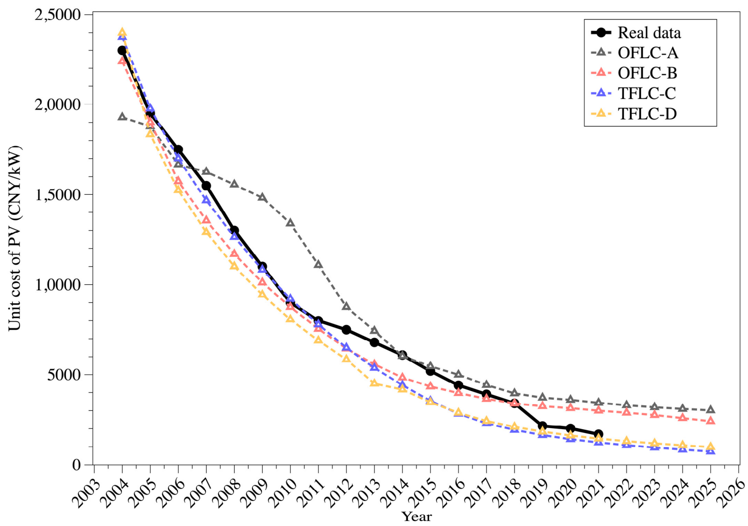

Figure 5. The PV cost results based on the SD simulation.

5. Discussion and Conclusions

In this paper, we developed four hypothetical learning curve models using a combination of different technological learning sources, including local and global installed capacity and R&D investment. We simulated the models via the SD approach. The SD approach was used to capture the complexity of related non-linear factors and to present the dynamic interactions between PV cost and learning sources that can occur in the PV technological learning process. This should contribute to the accuracy of PV cost estimations. The four models underpinned with the SD approach drew on data from China. It provides several relevant findings that answer the following question: Which learning curve model and technological learning source is more accurate or realistic when estimating cost development specifically for PV technology?

First, the findings suggest that the suitability and accuracy of learning curve models for cost estimation are dependent on the development stages of PV systems. In the period before 2011, the cost simulation results yielded from TFLC-C most closely fit the real PV cost data. According to the study conducted by Zhang et al. [56], the cumulative installed capacity of PV systems in China before 2011 was still small, and PV development was still in the early stage. This means that during the nascent phase of China's PV deployment, a learning curve model that integrates both the scaling of installed capacity and local R&D investment most effectively captures the trajectory of PV cost development. While after 2011, China adopted a nationally uniform feed-in tariff (FIT) program, which is a regulatory mechanism that requires power grid enterprises to purchase electricity from PV production at a predetermined price, thereby ensuring the economic viability of PV-generated electricity [57]. With the implementation of such a policy, the installed capacity of PV systems in China has increased rapidly since then. During the period from 2011 to 2018, the cost development of PV systems most aligns with the simulation cost result from OFLC-A, which employs local installed capacity as a proxy for technological learning. After 2018, the cost from simulation TFLC-D most closely fit the real cost data. In 2018, the Chinese government published the "Notice on matter of PV power generation", which is referred to as the "531" policy. This policy reduced the subsidies and FIT price for PV systems; however, it caused great shock to the PV industry in China, resulting in a slowdown in the growth rate of PV installation [58]. Thus, during this more mature stage, the effect of local installed capacity on cost reduction faced limitations. The TFLC-D, which adds international knowledge spillover into the learning curve, provides a more accurate reflection of PV cost development.

Second, the findings highlight the importance of consideration of the global learning sources (i.e., global installed capacity and knowledge spillover) in PV cost reduction estimation. At the early stage, as the local installed capacities of PV systems are relatively small compared to the international market, the cost reduction is significantly driven by the installed capacity from the international market. As PV technology matures, the contribution from international R&D endeavors emerges as the paramount driver of cost reduction. For the case of China in this study, the development of PV technology occurs later than in developed countries, such as the United States or several countries in Europe. The advanced R&D for PV technology in these countries propel technological advancements, thus exerting a consequential impact on the cost reduction of PV systems within the Chinese market. An accurate cost estimation of PV systems should take global learning into account.

Third, the SD simulation approach provides a more accurate PV cost estimation than the regression method. Regression models are based on the linear relationship between the dependent and independent variables [39,59,60], which is their weakness compared to the SD approach, which can quantitively capture the multiple non-linear factors and feedback loops that can occur in a real technology learning system, rather than only considering the dependent and independent variables [54,61,62]. For instance, in the SD approach in this study, the subsystem of cost and profit provides the information of total profits, the investment willingness of the investors, and electricity price, showing how cost reduction in return impacts the expansion of installed capacity and the increase in technological innovation, which is not a characteristic of regression-based technological learning studies. An SD approach to PV technological learning analysis, therefore, significantly improves the robustness of the learning curve model for more cost-efficient PV deployment.

Although valuable insights have been presented in this paper, the analysis has some potential limitations. First, investigating the more accurate learning curve models from an SD perspective showed the impact of various learning sources on PV cost estimation in China. While the current research is limited to the Chinese context as a case study to demonstrate the model's applicability, future research could explore an extension of this model to other countries or regions. Furthermore, the approach adopted in this study could serve as a tool for future analysis to construct comparative research between countries, yielding cost estimation patterns across diverse economic, political, and geographic contexts. Second, in this paper, we only consider the development of PV. However, in future studies, the model may be extended to other technologies such as wind or hydrogen, or it could be used to compare the effect of different learning curve models on different technologies' cost development.

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