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The role of sustainability characteristics in the diffusion of renewable energy technologies

Fabian Rocha Aponte [a,*], Kirsten S. Wiebe [a], Nikki Luttikhuis [a,b]

[a] Sustainable Energy Technology, SINTEF, P.O. Box 4760 Torgarden, Trondheim 7465, Norway
[b] Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology (NTNU), Trondheim 7491, Norway

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ABSTRACT

This paper aims to investigate the role of sustainability factors in the diffusion of solar photovoltaic (PV) technologies. A combined economic innovation-diffusion model that accounts for additional sustainability aspects is proposed. Two and three-stage least square methods were used for the empirical estimation, and the results were compared to a maximum entropy econometric estimation. The findings indicate that sustainability characteristics (i.e., cell efficiency) have a statistically significant positive effect on installed capacity in all solar PV technologies under analysis. Results show that multijunction PV modules have a learning rate of 17.1%, while Monojunction and the global aggregate have similar learning rates of 19.5% and 19%, respectively. Thin film PV modules have learning rates of 17.9% for the period 1991–2019. Cost reductions in solar PV modules can be largely attributed to learning-by-doing activities, the effects of learning by searching are ambiguous and depend both on the estimation methodology and the period under analysis. The study recognizes the difficulty in measuring sustainability characteristics, such as social aspects of the SDGs or indirect environmental implications but suggest that qualitative research can complement the quantitative analysis.

Introduction

The global transition towards sustainable energy systems is a fundamental requirement to achieve the Sustainable Development Goals (SDGs) outlined in the 2030 Agenda. Within this context, solar photovoltaic (PV) technology has emerged as a crucial renewable energy source due to its economic viability and rapid deployment potential [1]. Despite the significant growth of the PV industry in recent years [2], previous research on diffusion models and learning rates have focused primarily on economic factors such as prices, costs, and installed capacity. However, literature review studies of Kemp &Volpi [3,4], highlight the necessity of incorporating additional factors, including sustainability criteria, in analysing renewable technology diffusion. Sustainability considerations in PV technology are crucial, given their potential to change technology perceptions and acceptance [5]. Accessibility and land-use implications of solar PV have emerged as important considerations for evaluating its diffusion potential. Although solar PV has the potential to provide affordable and clean energy in low-resource settings [6] – i.e. primary sustainability effects –, its installation may lead to trade-offs that compromise natural resources and ecosystem services – i.e. secondary sustainability effects – [7]. Therefore, enhancing the efficiency of solar PV modules has been identified as a critical driver for sustainable diffusion and cost reductions [8,9].

In the literature on technology diffusion, learning curves are commonly used to model the cost changes associated with the adoption of new technologies [10–13]. However, these models often overlook factors beyond cost reductions, resulting in biased estimations of learning rates [4,14–16]. To accurately estimate learning rates and diffusion patterns of sustainable technologies, it is crucial to consider a wide range of factors such as R&D expenses, subsidies/taxes, and other variables. Multi-factor learning curve models that incorporate these factors can help disentangle the causes of cost reductions. Furthermore, taking an endogenous approach to innovation and diffusion can provide insight into the interplay between different phases of new technologies, ultimately leading to more efficient and sustainable outcomes [17].

Overall, studies in the field have contributed to a better understanding of the factors driving the cost reductions in PV technology and the potential for further cost reductions in the future. However, there are still many uncertainties and challenges in estimating the learning rates of sustainable technologies, such as data availability, model specification, and the effects of policies and external factors. A gap is found in the understanding of the role of sustainability aspects in the diffusion process. The lack of investigation into the endogenous relationships

* Corresponding author.
E-mail addresses: fabian.rocha.aponte@sintef.no (F. Rocha Aponte), Kirsten.wiebe@sintef.no (K.S. Wiebe), Nikki.Luttikhuis@sintef.no (N. Luttikhuis).

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Nomenclature

PV	Photovoltaics
R&D	Research and development
TB	Total net benefits
TWH	Tera watt hour
2 SLS	2 stage least squares
3 SLS	3 stage least squares

between sustainability, costs, and diffusion of technologies limits our understanding of the drivers behind the energy transition. Therefore, existing studies may fail to capture the full scope of solar PV diffusion. To address this gap, this paper seeks to empirically examine how sustainability criteria affect the diffusion, innovation, and sustainability aspects of different types of solar PV technologies. In doing so, we use solar PV cell efficiency as a proxy for land use and higher sustainability to model the diffusion for mono-junction cell modules, multi-junction cell modules and thin film cell modules, at the global aggregate level.

To estimate the diffusion, innovation, and sustainability aspects of solar PV the paper extends the model proposed by Söderholm & Klaassen [17] by including solar PV efficiencies. Two-stage least squares and three-stage least squares with instrumental variables are employed to address data availability and the ill-posed nature of the problem. Our study highlights the importance of considering sustainability as a key factor in the diffusion of renewable energy technologies. The positive relationship between efficiency and installed capacity suggests that policies and technological improvements aimed at increasing sustainability can lead to a wider adoption of renewable energy technologies. The inclusion of the sustainability dimension in diffusion models can provide a more comprehensive understanding of the drivers behind the transition towards a sustainable society, which is essential for the design of effective policies. The findings of this study contribute to the growing body of literature on the diffusion of renewable energy technologies and their role in mitigating climate change.

The paper is structure as follows: Next, the authors provide a literature background on technology learning and diffusion applied to renewable energy sources and solar PV. The second section introduces the theoretical model proposed by the authors to investigate the factors that impact the diffusion of solar PV technology. In the third section, the data used for empirical estimation is presented. The fourth section outlines the various empirical approaches utilized to estimate the proposed structural equation model (SEM) described in section two. Section five discusses the results of the empirical estimates and provides analysis. Finally, in section six, the authors present their concluding remarks.

Background

Sustainable technologies are crucial for achieving a green transition. Recent research has focused on the quantitative analysis of innovation and interindustry dependencies [18,19], with technological upgrading being recognized as key to achieving sustainability goals [20]. Adoption, diffusion of sustainable innovations and the study of the factors that drive such innovations is critical for their impact on sustainable development [21,22]. However, adoption of environmentally friendly technologies is still lacking and largely dependent on governmental interventions [23].

The adoption of sustainable innovations is primarily driven by regulation and policy. Companies' motivations for sustainability are primarily compliance-based rather than intrinsic. However, becoming environmentally friendly can ultimately lower costs and provide a competitive advantage [24]. Other drivers include consumer pressure, managerial concern, cost savings, and efficiency [23]. Early movers can gain a competitive advantage through the development of competencies, particularly since sustainability practices are likely to become increasingly important in the future [25].

The rise of sustainability as a concept has led to increased research and attention in the field, with the introduction of Sustainable Development Goals providing further impetus. Sustainable transition is now seen as a key driver of innovation and vice versa. Therefore, exploring the factors that drive the diffusion of sustainable technologies and proposing methods to enhance their adoption is crucial for the green transition. Diffusion and innovation in solar PV technologies has been estimated using different methods, with the learning rate model being the most popular in the literature. A learning rate shows that with each doubling of cumulative capacity, the cost of a technology decreases by a constant percentage. From the learning rate literature in solar PV Nemet [26], identified the main factors influencing cost reductions in PV, such as increased production volume, technological innovation, and learning by doing. Neij [27], combined experience curve modelling with bottom-up assessments to estimate the costs of future power generation technologies, including PV. Other studies have focused on specific aspects of

Table 1
Summary of Literature Review in Solar PV diffusion.

Reference	Approach	Countries/Regions Analyzed
Nemet (2006)[26]	Literature Review	USA, Japan, Germany
Neij, (2008)[27]	Experience Curve & Bottom-up Assessment	Various countries and technolgoies, including wind, solar PV, bioenergy, hydropower
de La Tour et al. (2013)[30]	Experience Curve	Worldwide
Rubin et al. (2015)[15]	Literature Review	Various countries and technologies, including solar PV, nuclear, wind, fossil fuels
Zheng & Kammen (2014)[28]	Roadmap	Global
Kersten et al.(2011)[31]	Literature Review	Worldwide
Mauleón (2016)[32]	Literature Review	Worldwide
Elshurafa et al. (2018)[29]	Learning Curve	Over 20 countries
Marques et al. (2019)[33]	Comparative study	Germany, Spain, Italy, Portugal, and the United Kingdom
Chowdhury et al. (2014)[34]	Case study	Japan, Germany
Curtius et al. (2018)[35]	Empirical study	Germany
Radomes & Arango (2015)[36]	Case study	Medellín, Colombia
Strupeit & Palm (2016)[37]	Case study	Japan, Germany, United States
Do et al. (2020)[38]	Case study	Vietnam
Eleftheriadis & Anagnostopoulou (2015)[39]	Literature review	Greece
Li et al. (2023)[40]	Empirical study	Australia
Adnan & Shahrina (2021)[41]	Literature review	Various
Bianco et al. (2021)[42]	Case study	Italy
Cho et al. (2019)[43]	Case study	Pacific Northwest USA
Grafström & Poudineh (2022)[14]	Empirical study	Europe
Zhang et al. (2022)[44]	Empirical study	China
Ma et al. (2021)[45]	Case study	Solar PV industry

PV technology, such as uncertainties in technology experience curves [15,16] and the importance of government policies, private investments, and R&D efforts for sustainable PV industry innovation [28]. [29] estimated the learning curve of PV balance-of-system components for over 20 countries and provided policy recommendations to accelerate the deployment of PV. Table 1 provides a summary of the main studies of diffusion of solar PV, their approach, and the region under analysis.

Reviewing the literature made clear that the learning rate theory has been extensively utilized to evaluate the cost reduction of photovoltaic technology. Most studies focused on determining the learning rate and examining the factors that influence the cost reduction process. These studies employed different methodologies such as experience curves, system dynamics, and regression analysis, and were conducted across multiple countries and regions. However, most studies did not explicitly consider sustainability factors, which are essential in the current energy transition context. As a result, there is a need for future research to integrate sustainability factors into the analysis of learning curves to gain a more comprehensive understanding of the cost reduction process of photovoltaic technology from a sustainability perspective. Next section provides the methodology we use to apply sustainability factors in the innovation-diffusion theory.

Methodology

This study extends the model of Söderholm & Klaassen [17] to test the hypothesis that technologies with additional sustainability benefits diffuse faster and reduce costs more rapidly. A new variable to represent the sustainability aspects of the technology, accounting for the endogeneity between sustainability, technology diffusion, and costs is introduced. In the following, a summary of the original equations side by side with our changes (emphasized in **bold**) and the reasoning behind the changes is presented.

The model assumes a rational agent/firm/industry that seeks to maximize the present value of total net benefits (*TB*) of adopting the new technology in unit/firm/country *n* at time *t*[46]

$$TB_{nt} = \alpha_0 (CC_{nt})^{\alpha_1} \left(\int_{t=0}^{T} P_{nt}^{f} e^{-rt} dt \right)^{\alpha_2} \left(\int_{t=0}^{T} P_{nt}^{C} e^{-rt} dt \right)^{\alpha_3} \tag{1}$$

$$TB_{nt} = \alpha_0 (CC_{nt})^{\alpha_1} \left(\int_{t=0}^{T} P_{nt}^{f} e^{-rt} dt \right)^{\alpha_2} \left(\int_{t=0}^{T} P_{nt}^{C} e^{-rt} dt \right)^{\alpha_3} (S_{nt})^{\alpha_4} \tag{1A}$$

Where *CC* is the chosen level of installed capacity of the new technology (or industry share of production under that technology or share of production in firm using that technology). P_{nt}^{f} is the price (or mark-up) of the product produced with new technology, and P_{nt}^{C} is the price (or mark-up) of the product produced with the standard technology. In Eq. (1A) we added the variable S_{nt} which is the environmental performance of the new technology. The assumption here is, that the firm/industry/agent receives additional benefits by using a more sustainable technology because of factors like better reputation, a better ethical conscience, new market niches, among others: *"the values of eco-innovation allow companies to counter challenges from competitors in the marketplace"* [47].

The total cost of choosing a given level of installed capacity for a technology *CC* is:

$$TC_{nt} = \beta_0 (CC_{nt})^{\beta_1} (C_{nt})^{\beta_2} (R_{nt})^{\beta_3} \tag{2}$$

Where C_{nt} is the engineering unit cost of the new technology (related to fixed investment costs, machinery, and others). R_{nt} captures the impact of national legislations/incentives on the technology costs. Profit maximizing conditions lead to marginal costs to be equal to marginal benefits, by taking the partial derivatives of Eqs. (1) and (2) with respect to *CC* we can find the optimal level of installed capacity of new technology, which gives the following first order conditions [17]:

$$\alpha_0 * \alpha_1 (CC_{nt})^{\alpha_1 - 1} (P_{nt}^{f})^{\alpha_2} (P_{nt}^{C})^{\alpha_3} = \beta_0 * \beta_1 (CC_{nt})^{\beta_1 - 1} (C_{nt})^{\beta_2} (R_{nt})^{\beta_3} \tag{3}$$

$$\alpha_0 * \alpha_1 (CC_{nt})^{\alpha_1 - 1} (P_{nt}^{f})^{\alpha_2} (P_{nt}^{C})^{\alpha_3} (S_{nt})^{\alpha_4} = \beta_0 * \beta_1 (CC_{nt})^{\beta_1 - 1} (C_{nt})^{\beta_2} (R_{nt})^{\beta_3} \tag{3A}$$

After rearranging and taking the natural logarithm to linearize the equation:

$$\ln C_{nt} = \lambda + \frac{\alpha_2}{(\beta_1 - \alpha_1)} \ln P_{nt}^{f} + \frac{\alpha_3}{(\beta_1 - \alpha_1)} \ln P_{nt}^{C} - \frac{\beta_2}{(\beta_1 - \alpha_1)} \ln C_{nt} - \frac{\beta_3}{(\beta_1 - \alpha_1)} \ln R_{nt} \tag{4}$$

$$\ln CC_{nt} = \lambda + \frac{\alpha_2}{(\beta_1 - \alpha_1)} \ln P_{nt}^{f} + \frac{\alpha_3}{(\beta_1 - \alpha_1)} \ln P_{nt}^{C} + \frac{\alpha_4}{(\beta_1 - \alpha_1)} \ln S_{nt} - \frac{\beta_2}{(\beta_1 - \alpha_1)} \ln C_{nt} - \frac{\beta_3}{(\beta_1 - \alpha_1)} \ln R_{nt} \tag{4A}$$

Where

$$\lambda = \frac{(\ln \alpha_0 + \ln \alpha_1 - \ln \beta_0 - \ln \beta_1)}{(\beta_1 - \alpha_1)} \tag{5}$$

For empirical estimation we simplify the notation as:

$$\ln CC_{nt} = a_0 + a_1 \ln P_{nt}^{f} + a_2 \ln P_{nt}^{C} + a_3 \ln C_{nt} + a_4 \ln R_{nt} + \epsilon_{nt} \tag{6}$$

$$\ln CC_{nt} = a_0 + a_1 \ln P_{nt}^{f} + a_2 \ln P_{nt}^{C} + a_5 \ln S_{nt} + a_3 \ln C_{nt} + a_4 \ln R_{nt} + \epsilon_{nt} \tag{6A}$$

Eqs. (6) and (6A) describe the diffusion of technology as a function of prices, costs, and sustainability parameters. The learning curve is obtained from a Cobb-Douglas cost function [48]. The unit cost of production under the new technology in country/firm/agent *n* in period *t* is:

$$C_{nt}^{C} = \frac{1}{Q_{nt}} \left(k Q_{nt}^{1/r} \prod_{i=1}^{M} P_{nti}^{\delta_i / r} \right)$$

(7)

Where

$$k = r \left[A_{nt} \prod_{i=1}^{M} \delta_i^{\delta_i} \right]^{-\frac{1}{r}} \tag{8}$$

Q is the level of output generated using new technology, P_{nti} are the prices for the inputs required ($i = 1, \cdots, M$) and *r* is the returns to scale which equals the sum of the exponents δ_i. A_{nt} reflect advances in the state of knowledge.

Moreover, the model assumes two factor learning curves derived from the state of knowledge that is defined as [49]:

$$A_{nt} = CC_{nt}^{-\delta_L} K_{nt}^{-\delta_K} \tag{9}$$

Where *K* is the R&D based knowledge stock, and from Eq. (10) we obtain the learning by doing rate associated with the installed capacity and the learning by searching rate associated with R&D.

Replacing the expression of *A* (as in Eq. (9)) in Eqs. (8) and (7) and taking the natural logarithm we obtain the empirical equation for the innovation equation as follows:

$$\ln C_{nt}^{R} = b_0 + b_1 \ln CC_{nt} + b_2 \ln K_{nt} + b_3 \ln Q_{nt} + \mu_{nt} \tag{10}$$

From the parameters, the returns to scale and the learning curves elasticities $\delta_L and \delta_K$ can be obtained as [17]:

$$r = \frac{1}{(1 + b_3)}, \delta_L = b_1, and \delta_K = \frac{b_2}{(1 + b_3)} \tag{11}$$

The learning rates are defined as $1 - 2^{\delta_j}, j = L, K$ which shows the percentage change in cost due to a doubling of cumulative capacity.

The sustainability indicator is a function of technological progress and other explanatory variables. From Eq. (9) *techprogress* $= A_{nt} = CC_{nt}^{-\delta_L} K_{nt}^{-\delta_K}$. Then, sustainability can be described as follows:

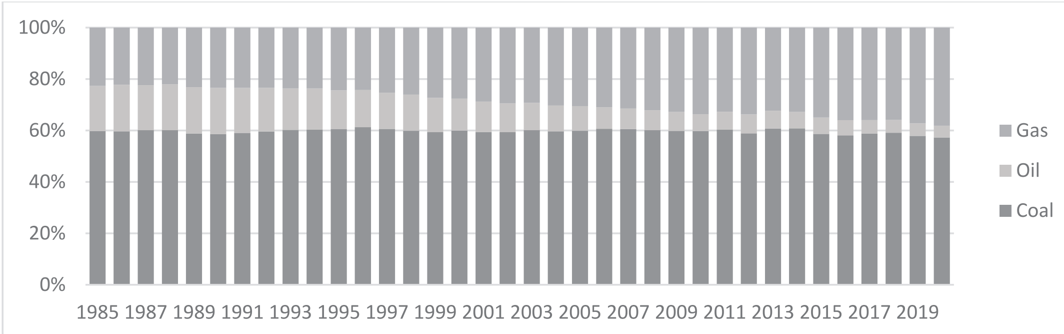

Fig. 1. Weights (shares) of gas, coal and oil in electricity production.

Table 2
Descriptive statistics.

	Variable	Mean	Std. Dev	Variance	years
Solar PV cumulative capacity	CC_total (GW)	72,447	165,316	27846,5	1980–2019
Thin-film cumulative capacity	CC_thin-film (GW)	3,841	7,943	64,221	1980–2019
MultiSi cumulative capacity	CC_MultiSi (GW)	32,595	66,799	4541,373	1980–2019
MonoSi cumulative capacity	CC_MonoSi (GW)	36,010	107,927	11892,59	1980–2019
Production costs using incumbant technology	PC (USD/KWh)	42,324	16,549	273,876	1985–2019
Production costs using sustainable technology	PF (USD/employee)	22,326	4,129	17,051	1991–2019
Solar PV module price	C (USD/W)	13,092	16,223	148,323	1980–2019
Research and development measured by patent applications	K_patent	13953,66	26919,59	724,664,517	1980–2019
Total electricity output	Q_total (TWh)	117,982	224,910	50584,92	1989–2019
Thin-film electricity output	Q_thin-film (TWh)	6,083	10,670	113,849	1989–2019
MultiSi electricity output	Q_MultiSi (TWh)	52,136	87,745	7699,289	1989–2019
MonoSi electricity output	Q_MonoSi (TWh)	59,762	150,539	22662,21	1989–2019
Sustainability: efficiency (total)	S_total (%)	20,897	4,561	19,729	1980–2019
Sustainability: efficiency (Thin-film)	S_thin-film (%)	12,635	3,653	12,282	1980–2019
Sustainability: efficiency (MultiSi)	S_MultiSi (%)	25,975	7,370	53,274	1980–2019
Sustainability: efficiency (MonoSi)	S_MonoSi (%)	24,645	2,995	8,065	1980–2019

$$S = f(A, t, Z) \tag{12}$$

Where Z represent external factors such as environmental regulations, subsidies, etc. Extending Eq. (12) by including the factors of Eq. (9):

$$S = f(CC, K, t, Z) \tag{13}$$

In the log form

$$\ln S_{nt} = \rho_0 + \rho_1 \ln CC_{nt} + \rho_2 \ln K_{nt} + \sum \rho_i \ln Z_i + \omega_{nt} \tag{14}$$

To summarize, the following linearized system of equations is obtained:

$$\ln CC_{nt} = a_0 + a_1 \ln P^f_{nt} + a_2 \ln P^C_{nt} + a_5 \ln S_{nt} + a_3 \ln C_{nt} + a_4 \ln R_{nt} + \epsilon_{nt} \tag{7A}$$

$$\ln C^R_{nt} = b_0 + b_1 \ln CC_{nt} + b_2 \ln K_{nt} + b_3 \ln Q_{nt} + \mu_{nt} \tag{10}$$

$$\ln S_{nt} = \rho_0 + \rho_1 \ln CC_{nt} + \rho_2 \ln K_{nt} + \sum \rho_i \ln Z_i + \omega_{nt} \tag{14}$$

Data

To empirically test the model, seven variables were chosen: Solar PV cumulative capacity (CC), Solar PV price (C), Production costs using standard technology (P^c), Production costs using sustainable technology (P^f), Research and development (K), Output (Q), and Sustainability (S). Data for CC and C were collected from [50,51] and [52]. As data for P^c, was not available, a proxy was developed based on a weighted average of coal, gas, and oil prices. Data for these prices and the global TWh electricity production for 1985 to 2020 were collected from [53] and The World Bank commodity markets pink sheet [54], which was normalized to costs per kWh using information from [55]. The weights for the proxy were calculated based on the global TWh electricity production as displayed on Fig. 1.

To estimate P^f, there is a lack of time series for global levelized costs of electricity generation using solar PV. For renewables, investment and labour costs for maintenance have a greater impact on generation costs compared to fuel input costs for fossil fuels. Approximating investment costs using PV panel costs would lead to a simultaneity/endogeneity problem since these are part of variable C in the model. Instead, this paper use labour costs in the construction industry as a proxy for estimating the development of P^f. Labour cost data is obtained from the UN SNA main aggregates database [56] and Employment by sex and economic activity data from [57] for the Construction industry (ISIC F) for the years 1991 to 2018. For the variable K, the authors use the cumulative patent counts related to all solar PV technologies from the European patents office by filtering the patents using the Y02E10/5 code of the cooperative patent classification system. For Q, the output of electricity in TW from solar PV is obtained from [53]. Regarding the sustainability variable S, module efficiency is used as it is directly related to land use, which is a critical factor for scaling up solar technologies. Cell efficiency data comes from the National Renewable Energy Laboratory [58] and aggregate different solar PV technologies into three main groups: Silicon mono-junction, Silicon multi-junction, and thin-film technologies. Output series for each solar PV technology are generated by computing the share of cumulative capacity year by year and distributing it to global output. The resulting data set is presented in Table 2, which provides descriptive statistics for the variables, and in

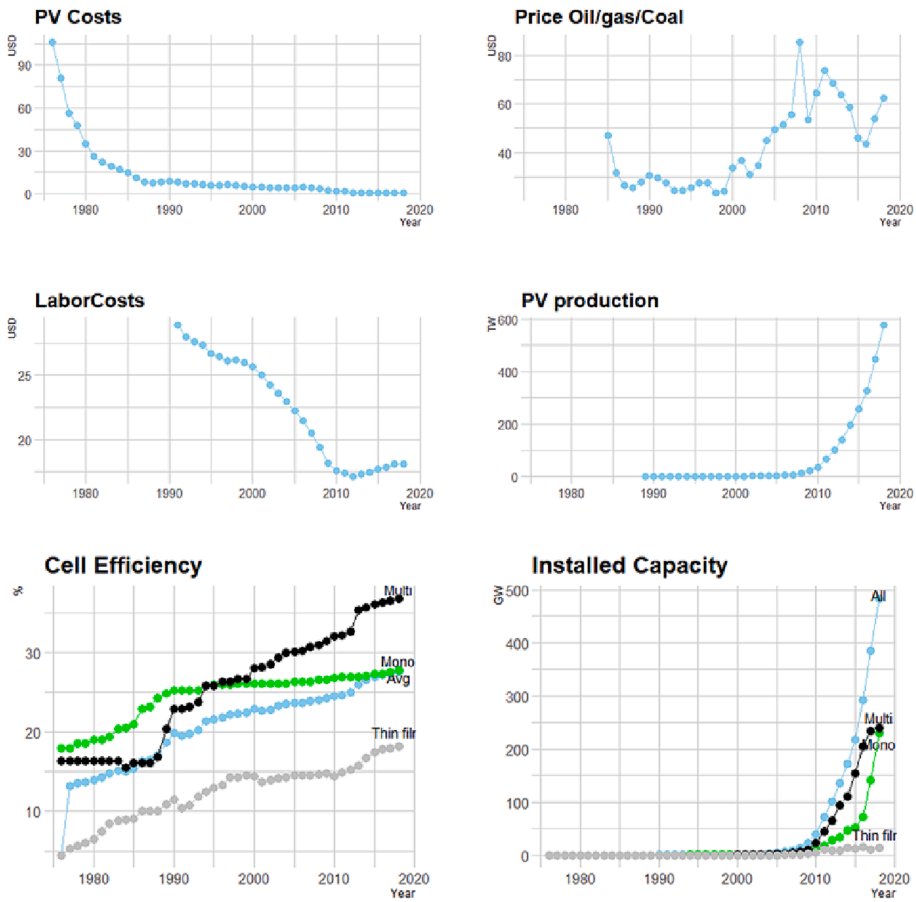

Fig. 2. Time series of selected data for solar PV.

Fig. 2, which depicts the historical evolution of the individual variables over time.

Model estimation

To estimate the proposed sustainability extended model of [17], two-stage least squares (2SLS) and three-stage least squares (3SLS) methods with instrumental variables are chosen as suitable econometric methods. To account for intertemporal effects, the independent variables in each equation and lagged cumulative R&D and total costs are used as instruments in the estimation. The models were estimated for the global average and for each of the three solar technologies. Due to the relatively small sample size and the number of parameters and instruments required to estimate the system of equations, two solutions are selected: multiple imputation techniques to virtually complete the data set, and a maximum entropy estimation approach [59,60] to account for the small size of the equation system.

Multiple imputation for incomplete data sets

Multiple imputation is a statistical technique to handle incomplete data, widely used in health and medical research [61]. The method, developed by Donald B. Rubin [see [62]], generates multiple imputed data sets that capture the variability of missing data, allowing for separate analysis from statistical models[1]. The mice package in R [63] is utilized to impute missing data on labour costs and electricity production of solar PV. The imputation by random forests – a machine learning technique – approach is preferred, generating 20 imputed data sets for the simultaneous equation model. The estimated equations are obtained using 2SLS and 3SLS and reported in section 5.

Maximum entropy approach to estimate a system of equations

The traditional econometric techniques of 2SLS and 3SLS for estimating a simultaneous equation system may not be appropriate in the presence of small sample size as they can produce biased estimates with high variances [59,64,65]. A solution to deal with small samples is to use methodologies based on information theoretic principles. One example is the generalized maximum entropy estimator for a simultaneous system of equations as developed by [59] and extended by [60]. This method uses a reparameterization of the equation system to be estimated with the framework of maximum entropy of [66].

Consider a general SEM model in a matrix form as follows

$$\mathrm{Y}\Gamma + \mathrm{XB} + \mathrm{E} = 0 \tag{15}$$

Where $\mathbf{Y}$ is a matrix of G endogenous variables, Γ is an invertible matrix with structural coefficients of the endogenous variables, $\mathbf{X}$ is a matrix of K exogenous variables with full column rank, $\mathbf{B}$ is matrix of coefficients of exogenous variables, and $\mathbf{E} = (\boldsymbol{\varepsilon}_1 \cdots \boldsymbol{\varepsilon}_G)$ is a matrix of unobserved random disturbances with standard stochastic assumptions.

The reduced form of the model can be expressed as [59]:

$$\mathrm{Y} = \mathrm{X}\left(-\mathrm{B}\Gamma^{-1}\right) + \left(-\mathrm{E}\Gamma^{-1}\right) = \mathrm{X}\Pi + \mathrm{V} \tag{16}$$

Where $\mathbf{V}$ follows the same characteristics as $\mathbf{E}$ in 15. The standard estimation techniques such as 2SLS use the estimated values of $\mathbf{Y}$ in 16 and replaced it in equation 15 to obtain the structural parameters, following [60] we use this to create a nonlinear representation of Eq.

[1] For an extensive description of multiple imputation models see Van Buuren, S. (2018).

Table 3
2SLS and 3SLS estimation results for the imputed dataset and each solar PV technology (1980–2019).

	Total		Mono-junction		Multi-junction		Thin film	
	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS
Capacity eq.								
β_{11}	1.220 (0.000)	1.318 (0.000)	1.356 (0.002)	1.600 (0.000)	0.8155 (0.000)	0.8135 (0.000)	1.405 (0.003)	1.685 (0.000)
β_{12}	−2.054 (0.000)	−1.788 (0.001)	−1.916 (0.100)	−1.394 (0.27)	−3.124 (0.000)	−3.088 (0.000)	−1.546 (0.120)	−1.332 (0.037)
γ_{11}	−1.568 (0.000)	−1.636 (0.000)	−1.566 (0.000)	−1.644 (0.000)	−1.435 (0.000)	−1.447 (0.000)	−1.493 (0.000)	−1.577 (0.000)
γ_{12}	1.711 (0.003)	1.359 (0.02)	1.075 (0.452)	0.324 (0.82)	2.763 (0.000)	2.736 (0.000)	0.242 (0.840)	−0.372 (0.693)
Adjusted R^2 interval	0.989	0.988	0.967	0.963	0.991	0.991	0.923	0.917
Cost eq.								
β_{21}	0.141 (0.694)	0.789 (0.013)	0.268 (0.54)	0.883 (0.083)	−0.567 (0.02)	−0.223 (0.24)	−0.403 (0.000)	−0.331 (0.000)
β_{22}	0.201 (0.799)	−1.209 (0.082)	−0.219 (0.84)	−1.696 (0.16)	1.780 (0.004)	0.945 (0.047)	1.397 (0.000)	1.193 (0.000)
β_{23}	0.521 (0.06)	0.746 (0.012)	0.841 (0.12)	1.246 (0.02)	0.244 (0.5)	0.341 (0.003)	0.177 (0.046)	0.238 (0.006)
γ_{21}	−0.955 (0.07)	−1.702 (0.001)	−1.430 (0.09)	−2.372 (0.01)	−0.113 (0.006)	−0.459 (0.004)	−0.187 (0.028)	−0.312 (0.000)
Adjusted R^2 interval	0.876	0.772	0.846	0.688	0.913	0.878	0.931	0.916
Sustainability eq.								
β_{30}	0.808 (0.02)	0.988 (0.002)	1.526 (0.000)	1.778 (0.000)	1.790 (0.011)	1.039 (0.086)	0.596 (0.126)	0.340 (0.272)
β_{31}	0.318 (0.000)	0.292 (0.000)	0.2269 (0.000)	0.193 (0.000)	0.191 (0.037)	0.291 (0.000)	0.241 (0.000)	0.270 (0.000)
γ_{31}	−0.161 (0.000)	−0.141 (0.000)	−0.1428 (0.000)	−0.116 (0.000)	−0.03 (0.504)	−0.100 (0.050)	−0.106 (0.006)	−0.130 (0.000)
Adjusted R^2 interval	0.856	0.8703	0.621	0.683	0.821	0.797	0.811	0.751

Notes: P-values for the F test are reported in parentheses. In multiple imputation the significance of the statistic can be evaluated as $P = \Pr\left[F_{1,v} > \frac{(\beta^0 - \widehat{\beta})^2}{var(\widehat{\beta})}\right]$ where F is an F-distribution with 1 and v degrees of freedom.

Table 4
Learning rates by PV technology and estimation methodology (Imputed data 1980–2019).

	Total		Monojunction		Multijunction		Thin film	
	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS	2SLS	3SLS
Learning-by- by doing	48%	69%	62%	80%	7%	27%	12%	19%
Learning-by- by searching	0%	−70%	0%	−80%	32%	0%	24,3%	20%

Notes: Zeros are reported when the parameter of interest is not statistically significant.

Table 5
Maximum entropy estimates for solar PV technologies (1991–2019).

	Total	Monojunction	Multijunction	Thin film
Capacity eq.				
β_{11}	0.725 (0.119)	0.618 (0.102)	0.794 (0.140)	0.41 (0.128)
β_{12}	−0.364 (0.121)	−0.486 (0.104)	−0.505 (0.142)	−0.494 (0.131)
γ_{11}	−0.723 (0.068)	−0.754 (0.061)	−0.619 (0.084)	−0.453 (0.077)
γ_{12}	0.315 (0.069)	0.389 (0.063)	0.189 (0.086)	0.0815 (0.079)
Cost eq.				
β_{21}	0.167 (0.017)	0.141 (0.017)	0.125 (0.022)	0.0484 (0.030)
β_{22}	0.164 (0.018)	0.106 (0.018)	0.147 (0.023)	0.137 (0.003)
β_{23}	−0.153 (0.016)	−0.191 (0.017)	−0.116 (0.023)	−0.136 (0.002)
γ_{21}	−0.305 (0.019)	−0.313 (0.024)	−0.27 (0.032)	−0.286 (0.042)
Sustainability eq.				
β_{30}	0.5 (0.003)	0.71 (0.000)	0.485 (0.003)	0.318 (0.005)
β_{31}	0.363 (0.003)	0.334 (0.000)	0.374 (0.002)	0.273 (0.005)
γ_{31}	−0.19 (0.004)	−0.217 (0.000)	−0.161 (0.004)	−0.131 (0.008)

Notes: Standard errors in parentheses.

Table 6
Learning rates by PV technology (1991–2019).

	Total	Monojunction	Multijunction	Thin film
Learning-by-doing	19%	19,5%	17,1%	17,9%
Learning-by-searching	−12%	−10%	−9%	0%

Notes: Zeros are reported when the parameter of interest is not statistically significant.

(16) as follows:

$$Y = X\Pi_{(-)}\Gamma + XB + M \tag{17}$$

Where, $E[\boldsymbol{Y}] = \boldsymbol{X}\Pi_{(-)}$ from Eq. (17), and $M = \mathbf{E} + \mathbf{V}\Gamma$, the (–) notation represents the exclusion of the ith vector for equation $i = \{1, \cdots, G\}$. The parameters of both equations together with the disturbance terms can be reparametrized as convex combinations of reference support points and unknown convexity weights. The GME method, recover the probability distribution of such convexity weights that allows to retrieve

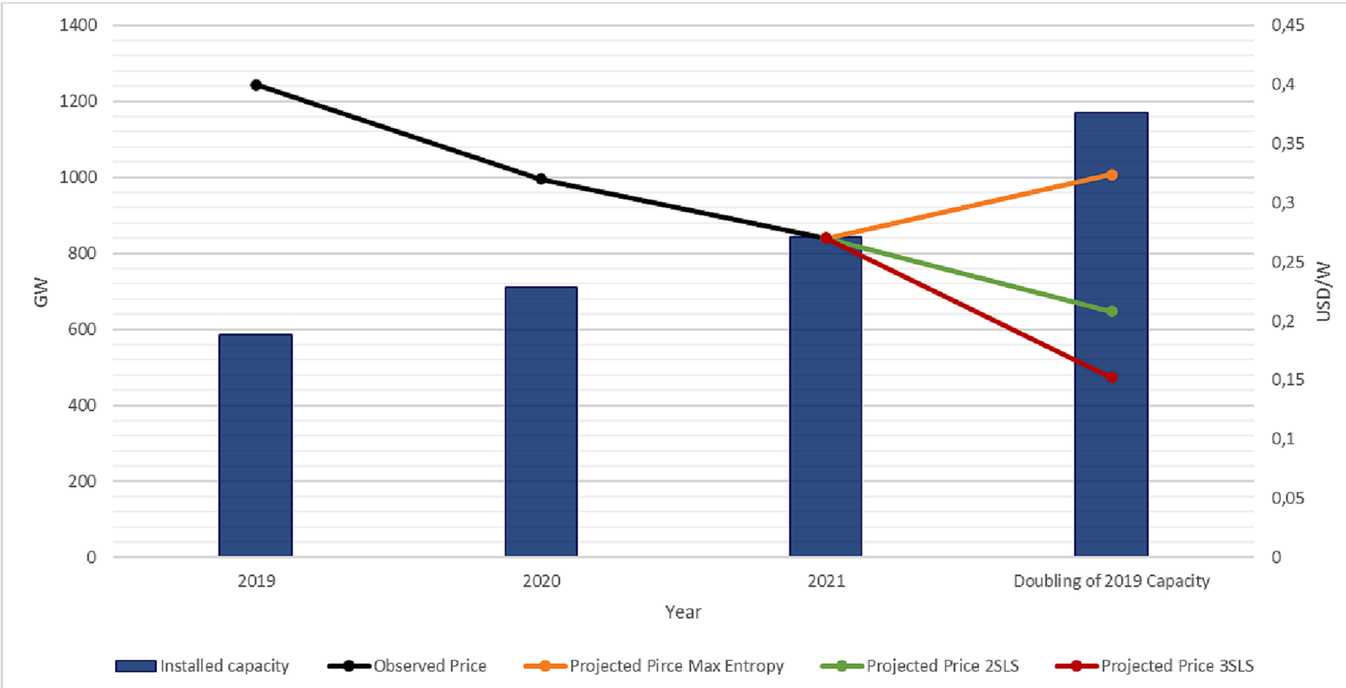

Fig. 3. Solar PV prices, installed capacity, and projections by using the estimated learning rate with different econometric methods(Notes: Data taken from [52]. Prices presented in second axis.).

the parameters of interest for the SEM model. Consider the following reparameterization [60]:

$$\beta = S^{\beta}p^{\beta},\ \gamma = S^{\gamma}p^{\gamma},\ \pi = S^{\pi}p^{\pi},\ v = S^{z}z,\ \mu = S^{w}w$$

Where S^{θ} is a diagonal matrix with M support points for $\theta = \{\beta, \gamma, \pi, z, w\}$ and $p = vec(p^{\beta}, p^{\gamma}, p^{\pi}, z, w)$ is a vector of the unknown probabilities in the space [0,1]. The support points space is chosen to increase the precision of the procedure as suggested by [59] by using five support points for the parameters and the $\sigma 3$ rule for the disturbance terms as $S^{w} = S^{z} = [-3\sigma, \sigma, 0, \sigma, 3\sigma]$. Once the support parameters are defined, the parameters can be expressed, for example, as $\sum_{m=1}^{M} S^{\beta}_{kgm} p^{\beta}_{kgm}$ for the kth β parameter of equation g. The same expression holds for the disturbance terms.

Estimates of π, γ, β are obtained by solving the constraint GME problem [66]

$$\max_{\mathbf{p}}\{-\mathbf{p}'\ln\mathbf{p}\}$$

Subject to the structural equation [60]

$$y = (I_G \otimes X)\left(S^{\pi}_{(-)}p^{\pi}\right)(S^{\gamma}p^{\gamma}) + X^{\beta}(S^{\beta}p^{\beta}) + S^{w}w \tag{18}$$

The reduced form equation

$$y = (I_G \otimes X)(S^{\pi}p^{\pi}) + S^{z}z \tag{19}$$

And the adding up constraints

$$(I_{\eta} \otimes 1'_{M}) = 1 \tag{20}$$

Where I_G is a (GxG) identity matrix, η is the total number of unknown probabilities and $1'$ is a unit vector. This formulation provides a data constraint estimator that optimizes the parameters and disturbances for both the structural model (Eq. (15)) and the reduced form model (Eq. (16)).

Results and discussion

Using the available data, the following equation system is estimated:

$$CC^{i}_{t} = \beta_{11}PC_{t} + \beta_{21}PF_{t} + \gamma_{11}C^{i}_{t} + \gamma_{12}Sust^{i}_{t} + e^{i}_{1,t} \tag{21}$$

$$C^{i}_{t} = \beta_{21}K_{t} + \beta_{22}PF_{t} + \beta_{23}Q_{it} + \gamma_{21}CC^{i}_{t} + e^{i}_{2,t} \tag{22}$$

$$Sust^{i}_{t} = \beta_{30} + \beta_{31}K_{t} + \gamma_{31}CC^{i}_{t} + e^{i}_{3,t} \tag{23}$$

Where CC^{i}_{t} = installed capacity, PC_t = price of competing technology (fossil fuels), $PFVAEMPL_t$ = price of producing with solar technology, C^{i}_{t} = costs of PV modules, $Sust^{i}_{t}$ = efficiency of PV modules, K_t = cumulative patent count as proxy for R&D, Q_{it} = electricity production. The subscript t refers to the time, while the superscript i refers to the PV technology where $i = \{Total, Monojunction, Multijunction, Thinfilm\}$. Finally, the $e^{i}_{1,t}$ are classical disturbances for each equation.

First, the authors estimate the sustainability aspect-extended models with multiple imputed data set and next the maximum entropy estimates are presented and compared. For completeness, the original model from [17] is estimated and results are presented in Appendix B.

The model in Table 3, which includes the sustainability equation and parameters, shows good performance in explaining the variability of the endogenous variables, as indicated by the adjusted R^2. Both 2SLS and 3SLS estimates provide significant parameter estimates with expected signs, although with some variability among PV technologies. The endogenous variables are of particular interest, and the results show that an increase in Costs negatively affects the Installed capacity, as expressed by the γ_{11} estimates, in line with economic theory. The sustainability parameter γ_{12} has a positive effect on installed capacity, except for mono-junction and thin film PV technologies, possibly due to the former approaching its maximum efficiency.

The study finds that the R&D variable has a positive impact on the sustainability measure of PV modules, while the installed capacity has a negative or insignificant effect. For the cost equation, the results reveal a positive or no impact of R&D on cost changes for total and mono-junction technologies, but a negative effect on multi-junction and thin film technologies. The learning-by-doing rate and learning-by-searching rate, calculated as $1-2^{\gamma_{21}}$ and $1-2^{\beta_{21}}$ respectively, indicate the reduction in costs due to experience and R&D activities after a doubling in capacity. Table 4 presents the estimates for each technology and methodology used in the study.

The results show a range of learning-by-doing rates from 7% to 80%, with the highest values observed for mono-junction PV modules, while multi-junction and thin film technologies show lower rates compared to the Total aggregates. Differences in learning rates across the various technologies may be attributed to the longer market presence of mono-junction PV modules. The learning-by-searching rates exhibit higher discrepancies between technologies and estimation methodologies, being positive only for multi-junction and thin film technologies. However, the imputation procedure used to estimate the model with the imputed data sets increases the model variance, which is a potential drawback. Nonetheless, it provides a good overview of the variables of interest and their patterns and behaviours. Next, as a robustness exercise, the sustainability extended model is estimated for the period 1991–2019 by using the maximum entropy methodology.

Table 5 displays the outcomes of the maximum entropy estimation model. The results demonstrate a positive relationship between sustainability and installed capacity for all sub-technologies and indicate that both scale economies and installed capacity have a role in reducing costs. However, the impact of R&D on costs is either positive or not statistically significant, which may be due to the small sample size relative to the number of model parameters or the lack of appropriate R&D proxies. It is possible that R&D has an indirect effect on costs through sustainability and installed capacity, as shown in Table 5, where the coefficient β_{31} has a positive influence on sustainability, which then has a positive impact on installed capacity (coefficient γ_{12}) and lowers costs (coefficient γ_{21}).

Table 6 summarizes the learning rates of each PV technology estimated using maximum entropy estimator. The results show that multi-junction PV modules have the lowest learning rate of 17.1%, while Monojunction and the global aggregate have similar learning rates of 19.5% and 19%, respectively. These rates indicate that for the period 1991–2019, the three sub-technologies experienced similar learning-by-doing rates, with Monojunction PV modules leading the way due to their longer time in the market. The learning rates obtained in this study are consistent with those reported in previous literature, which estimated rates between 10% and 47% for solar PV[15].

Fig. 3 offers valuable insights into the projected prices of solar photovoltaic (PV) panels based on estimated learning rates for the global average. Although the estimation concludes in 2019, the observed installed capacity and prices for 2020 and 2021 are presented for completeness. In 2019, the installed capacity of solar PV panels was 584.69 GW with a price of 0.4 USD/W. According to the estimated learning rates projections, when the market reaches an installed capacity of 1169.38 GW, the projected prices are 0.324 USD/W by employing the Maximum Entropy estimates, 0.208 USD/W with the 2SLS estimates, and 0.152 USD/W with the 3SLS estimates. The highest price projection is found using the Maximum Entropy approach, while the lowest price projection is obtained with the 3SLS technique. Our analysis demonstrates that the 2SLS and 3SLS estimates better approximate the observed market behaviour than the Maximum Entropy estimates.

Certainly, it is important to note that these projected prices should be taken with caution as there are various factors that can affect the prices of solar PV panels beyond the estimated learning rates. For instance, changes in government policies and regulations, technological advancements, shifts in consumer demand, and fluctuations in the global economy can all impact the market dynamics and the corresponding prices. Therefore, while the learning rates methodology is a valuable tool for projecting future prices based on historical trends, it should be considered as one of many factors that may influence the market. Additionally, the accuracy of the projections can be improved by incorporating more data points and refining the model over time.

The present analysis supports the notion that the cost of photovoltaic (PV) modules is declining at a faster rate than previously anticipated. The information provided in the preceding paragraph suggests that the downfall in costs is accelerating, in sharp contrast to earlier projections that attributed the decline up to 2012 to overheated markets and oversupply rather than a genuine cost downfall [32]. In contrast, the microelectronics industry has demonstrated that a high learning rate can persist over several decades, and this is expected to hold true for PV modules as well [32]. The study by [29] estimates a global average learning rate of 16.5% for solar PV costs, which is somewhat lower than our 19% learning rate estimated for the global average of PV modules. However, the study also finds substantial variation in learning rates across countries, with some countries exhibiting learning rates above 30%. Despite the somewhat lower estimated learning rate for solar PV costs, the findings of the [29] study are consistent with the notion that the cost of solar PV systems is declining rapidly. The study's results also highlight the importance of accounting for country-level differences in the pace of cost reductions, as some countries may be able to achieve even more rapid cost declines than the global average. Overall, these findings suggest that the downward trend in solar PV costs is likely to continue for the foreseeable future, albeit with some variation across countries.

The results show that multijunction cells, that are by far the most efficient cells today, have also experienced the largest efficiency increase over the past three decades. For these cells, all our estimations show a highly significant positive effect of efficiency on capacity installations. The same holds for the total model (average/aggregate of all three cell types). When using the imputed dataset, we cannot show a significant relation between cell efficiency and diffusion. This may well be because efficiency is relatively low and not improving as much. Other factors may have more influence on the diffusion than this sustainability factor. When estimated with the maximum entropy approach to control for the small sample size, we find positive significant (at 10%) effects for all cell types. R&D activity (learning-by-searching) seems to have a more significant impact on cell sustainability (efficiency) than on costs reduction directly. Learning-by-searching is also relatively more important for multi-junction cell efficiency improvement than learning-by-doing. Also, both mono-junction and thin-film cells have higher efficiency improvements due to learning-by-doing than multi-junction cells. This means, that R&D activity is especially important for achieving higher sustainability effectiveness.

These results provide valuable insights into the learning rates of different PV technologies and supports the argument that the cost of PV modules is declining at a faster rate than previously anticipated. The findings of this study, along with the remarks [14], emphasize the need to link learning rates methodology with social and political factors to provide a useful tool for assessing the effectiveness of diffusion policies in a changing environment. This paper goes in this direction by incorporating sustainability aspects to capture changes in behaviour from both the consumer and producer perspective. The findings highlight the importance of accounting for sustainability in future studies to better understand the dynamic nature of PV technology diffusion, as discussed above.

Conclusion

This paper aimed to address the gap in the economic literature on inclusion of sustainability factors in the estimation innovation-diffusion models for renewable technologies and empirically tests their effects on the diffusion and costs of solar PV technologies. Specifically, the analysis has yielded the following key findings:

- The model has demonstrated that additional sustainability characteristics of solar PV, beyond GHG emissions reduction, positively influence the diffusion of all three PV technologies analysed.
- The empirical results suggest that these additional sustainability characteristics may indirectly contribute to cost reductions in the technology, although this finding requires further investigation.
- It is observed significant variation in the estimated learning rates, which are dependent on the methodology used.
- The comparative analysis of price projections has revealed that the learning rates estimated using the 2SLS and 3SLS methodologies align more closely with market developments.

Given the lack of data of the different pillars of sustainability, cell efficiency is used to estimate the sustainability aspect of solar PV development. The authors conclude that the hypothesis of the significance of a sustainability factor in the diffusion is supported by the data. This implies that market agents tend to prefer the more sustainable technology options of renewable energy technologies. It also shows the importance of R&D activity to achieve improvements in these "secondary" sustainability factors; with the "primary" sustainability effect of renewable energy technologies being lower GHG emissions during electricity production.

The authors acknowledge the fact that only one possible sustainability factor is used, while other sustainability characteristics, such as more social aspects of the SDGs or indirect environmental implications (e.g. the use of sustainably sourced versus non-sustainably sourced materials) may also play a role. These, however, are hard to measure, and obtaining a time series for econometric analysis is close to impossible. To this end, quantitative research as presented in this paper should be combined with qualitative research methods, where these additional sustainability characteristics can be included in the analysis. This creates a more complete overview of the driving forces that determines the technology diffusion and how these driving forces in turn may influence the diffusion path.

Learning curves have been widely used to predict the future costs of solar PV, providing valuable insights for policy makers, investors, and researchers. However, there are some identified gaps in the literature that need to be addressed to improve the accuracy of these predictions. Firstly, more attention should be given to the geographical variation in learning rates, as different regions may have different drivers and barriers for cost reduction. Secondly, there is a need to improve the transparency and consistency of the learning curve methodology, particularly in the selection of the input data and the curve fitting technique. Therefore, future research should aim to fill these gaps and provide a more accurate and comprehensive understanding of the learning curve dynamics for the diffusion of solar PV. While more research is needed, this paper can conclude that sustainability characteristics of a technology do play a positive role in technology diffusion. It is therefore relevant to include sustainability characteristics to provide a systematic analysis of the impact and design of policies for the energy transition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. . Multiple imputation techniques

Several techniques are available to impute missing data, the most common are based on parametric techniques like predictive mean matching, which uses regression techniques between the missing data and the predictors. However, these methods fail to capture non-linearities and higher dependencies between the missing variable and the predictor variables. In our case, it is possible that the relationship across variables may be non-linear and to the fact that they are closely interrelated, we choose the random forest technique, a non-parametric method that do not rely on distributional assumptions of the data, can work with non-linearities between the variables, and uses the values of the predictor variables to subdivide the data to better fit the data patterns. The complete methodology of random forest can be found in Doove, Van Buuren, & Dusseldorp (2014).

First, inspect the missing pattern in the data as showed in the table below: Table A1.

From the table, it can be seen see that there are 53 missing values, 5 corresponding to the variable PC (Production costs using standard technology), 12 for the variable PFVAEMPL (Production costs using sustainable technology), and 9 for each of the production variables per technology. There are 28 rows with no missing data, 3 with one missing value, 4 with 5 missing values, and so on as indicated by the last two columns of the table. As predictors for the missing data, the authors choose the variables that have complete data sets: PV module costs, PV installed capacity, patent applications, and cumulative patent applications. Thus, it is decided to create 20 imputed data sets with 100 iterations each, the convergence of the imputation technique can be verified by the evolution of the mean and standard deviation of each iteration for the missing values as shown in the figure below.

Fig. A1.

Table A1
Missing pattern of the data set.

CC	C	Cmpatent	patent	S	PC	Q_total	Q_MonoSi	Q_MultiSi	Q_thin-film	PFVAEMPL		
1	1	1	1	1	1	1	1	1	1	1	0	28
1	1	1	1	1	1	1	1	1	1	0	1	3
1	1	1	1	1	1	0	0	0	0	0	5	4
1	1	1	1	1	0	0	0	0	0	0	6	4
1	1	1	1	1	0	0	0	0	0	0	6	1
0	0	0	0	0	5	9	9	9	9	12	53	

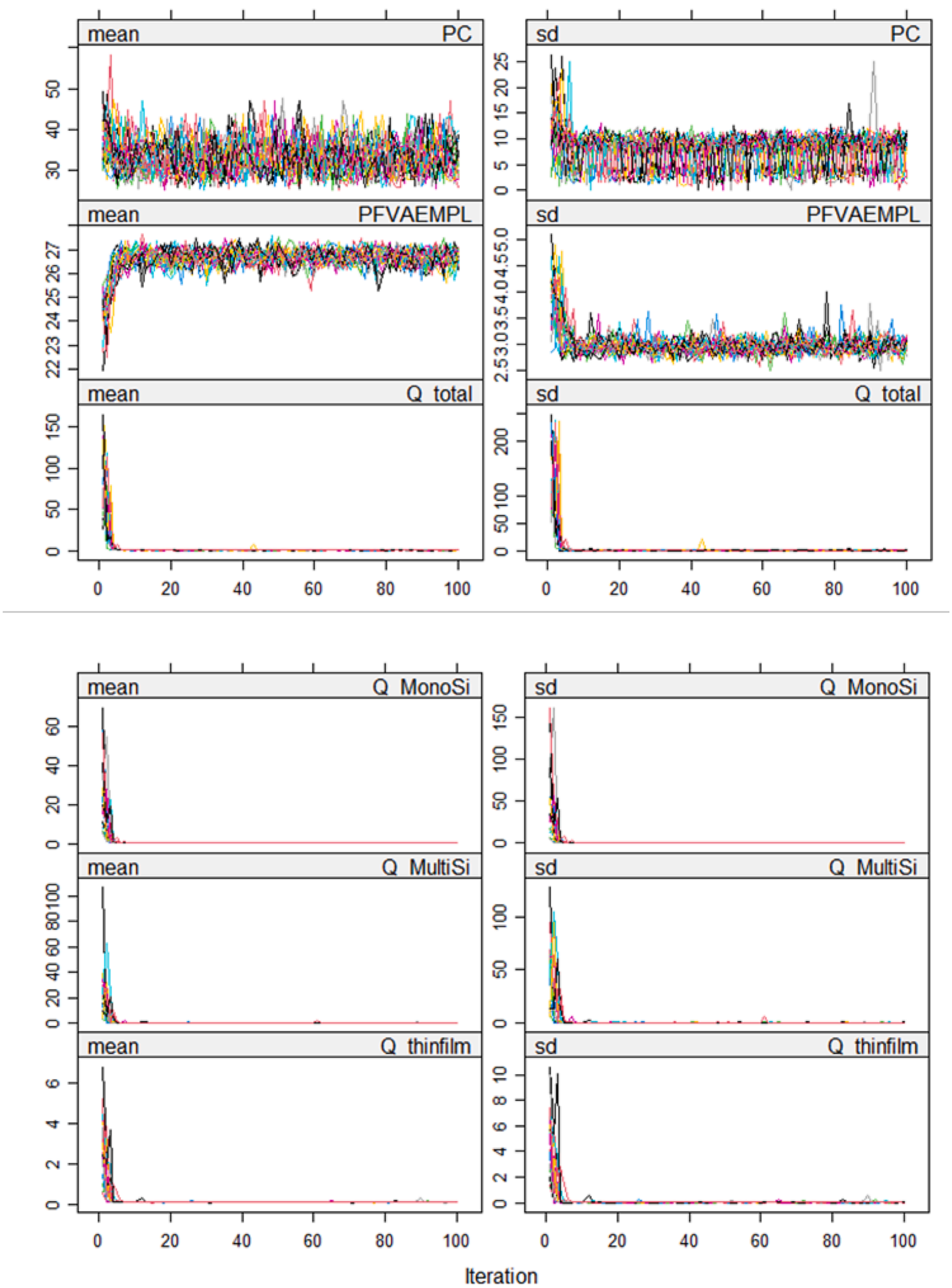

Fig. A1. Trace lines for random forest imputation of variables.

Appendix B. . Innovation-diffusion model without sustainability

Tables B1 and B2.

Table B1
2SLS and 3SLS estimation results for the original model and each solar PV technology (1980-2019).

	Total		Monojunction		Multijunction		Thin-film	
	2sls	3sls	2sls	3sls	2sls	3sls	2sls	3sls
Capacity eq.								
β_{11}	1.583 (0.001)	1.626 (0.000)	1.632 (0.000)	1.719 (0.000)	1.638 (0.000)	1.588 (0.000)	1.383 (0.000)	0.792 (0.000)
β_{12}	-0.6313 (0.001)	-0.685 (0.000)	-1.069 (0.000)	-1.185 (0.000)	-0.891 (0.05)	-0.820 (0.006)	-1.279 (0.009)	-0.438 (0.134)
γ_{11}	-1.954 (0.01)	-1.946 (0.01)	-1.711 (0.007)	-1.677 (0.002)	-2.189 (0.000)	-2.222 (0.000)	-1.590 (0.000)	-1.985 (0.000)
Adjusted R^2	0.984	0.984	0.974	0.976	0.985	0.985	0.927	0.927
Cost eq.								
β_{21}	0.1415 (0.237)	0.486 (0.293)	0.268 (0.541)	2.757 (0.5)	-0.567 (0.02)	-0.012 (0.9)	-0.403 (0.000)	0.263 (0.025)
β_{22}	0.2013 (0.06)	-0.568 (0.577)	-0.219 (0.836)	-6.256 (0.6)	1.780 (0.003)	0.417 (0.5)	1.397 (0.000)	-0.472 (0.15)
β_{23}	0.521 (0.07)	0.800 (0.05)	0.841 (0.11)	3.316 (0.5)	0.244 (0.5)	0.542 (0.007)	0.177 (0.04)	0.1910 (0.07)
γ_{21}	-0.955 (0.008)	-1.494 (0.035)	-1.430 (0.09)	-5.989 (0.5)	-0.113 (0.06)	-0.798 (0.004)	-0.187 (0.02)	-0.843 (0.000)
Adjusted R^2	0.957	0.957	0.966	0.958	0.935	0.937	0.931	0.928

Notes: standard errors in parentheses.

Table B2
2SLS and 3SLS estimation results for the original model and each solar PV technology (1991-2019)

	Total		Mono-junction		Multi-junction		Thin film	
	2SLS	3 SLS	2 SLS	3 SLS	2 SLS	3 SLS	2 SLS	3 SLS
Capacity eq.								
β_{11}	1.697 (0.153)	1.645 (0.152)	1.404 (0.196)	1.228 (0.166)	1.986 (0.160)	1.770 (0.151)	1.848 (0.301)	1.823 (0.300)
β_{12}	-0.798 (0.211)	-0.734 (0.097)	-0.804 (0.269)	-0.561 (0.228)	-1.373 (0.220)	-1.071 (0.207)	-1.963 (0.414)	-1928 (0.413)
γ_{11}	-1.785 (0.099)	-1.811 (0.207)	-1.661 (0.122)	-1.756 (0.106)	-1.824 (0.104)	-1.956 (0.098)	-1.227 (0.194)	-1.241 (0.194)
Adjusted R^2	0.984	0.984	0.974	0.976	0.985	0.985	0.927	0.927
Cost eq.								
β_{21}	0.504 (0.279)	0.557 (0.276)	0.330 (0.149)	0.562 (0.139)	-0.430 (0.356)	-0.200 (0.311)	0.312 (0.226)	0.372 (0.231)
β_{22}	-0.656 (0.632)	-0.773 (0.623)	-0.403 (0.368)	-0.959 (0.342)	1.450 (0.868)	0.894 (0.758)	-0.666 (0.653)	-0.839 (0.667)
β_{23}	-3.218 (0.682)	-3.225 (0.677)	-2.785 (0.507)	-2.708 (0.496)	-1.955 (0.735)	-2.102 (0.652)	-5.465 (1.336)	-5.650 (1.366)
γ_{21}	2.564 (0.569)	2.530 (0.565)	2.189 (0.469)	1.905 (0.455)	1.997 (0.652)	1.981 (0.592)	4.947 (1.193)	5.081 (1.220)
Adjusted R^2	0.957	0.957	0.966	0.958	0.935	0.937	0.931	0.928

Notes: standard errors in parentheses.

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