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Learning Curves Analysis for Solar PV

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Summary

Introduction

This project studies the development of solar photovoltaic technology through the analysis of learning curves, with particular focus on the trend followed by solar PV module costs in the 2000-2017 period. Learning curves analyse the effect of learning as the technology is developed.

State of the art

The most common way to represent the cost reduction of a technology is a potential function, making it linear through a log-linear function. Learning curves equations represent the relationship between accumulated capacity, which is the driver, and cost. The model can be improved by splitting the different components of the module, with different LR. Also, two drivers (not only capacity) can be decoupled through a Two-factor learning curve, analysing its individual influence over the cost.

Determining factors

Two possible factors are proposed that could influence the solar PV learning curve: interest rates and silicon cost. Through a qualitative analysis, annual installed capacity and module costs have been compared to interest rates. Nevertheless, the results obtained were not consistent enough to provide a coherent solution. Silicon has also been analysed, as it is the main resource for solar PV module manufacturing. Results show that module costs are highly influenced by silicon costs, and its shortage between 2005 and 2008 which provoked module costs increase.

Model elaboration, results and conclusions

Three models have been developed: the first one corresponds to a basic model with one factor (capacity), and one period (2000-2017). It gives coherent results, but needs better adjustment as silicon costs fluctuation is not taken into account. The second one is also a model with one factor, but with three periods, in order to isolate the silicon fluctuation during the second period (which includes the silicon shortage). Its main drawback is that it wastes the information of period 2. Finally, a Two-factor learning curve is proposed, in order to decouple silicon costs and accumulated installed capacity. This model proofs that silicon costs is as important as capacity for module cost reduction and provides a decoupled learning rate. With this model, the solar module cost is forecasted to be 0.45 USD/Wp.

Model	Period/factor	β	LR	R2	Mod. Cost 2030 (USD/Wp)
OFLC (1 period)	-	-0.33	20.9%	0.687	0.49
OFLC (3 periods)	1	-0.268	17%	0.87	1.39
	2	-0.2	13%	0.576	0.63
	3	-0.62	34.9%	0.91	0.212
Two-factor LC	Capacity	-0.283	17.8%	0.93	0.45
	Si Cost	0.289	-22%	*	

Figure 0.3. Summary Results

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1. Introduction

The Project consists in an analysis of the learning curves of renewable energy sources, and in particular PV energy, which is the most visible example of cost reduction in this context.

The climate change problem alongside the goal to attain a more independent energy mix has boosted the development of low-carbon technologies, which are not dependant on primary sources that need to be imported, through a set of energy policies whose main objective is to make the implantation of these technologies economically viable. In the European Union, the goal is to reduce carbon emissions in the order of 80% by 2050.

The main problem in the development of these new technologies is that in conventional technologies the investment has already been amortised, making them more profitable and competitive, whereas the start-up investment for learning innovative technologies has to be done. In order to boost the development of new technologies, support policies have to be elaborated, so that conventional technologies do not lock-in, and economic and environmental progress in the energy sector can be achieved.

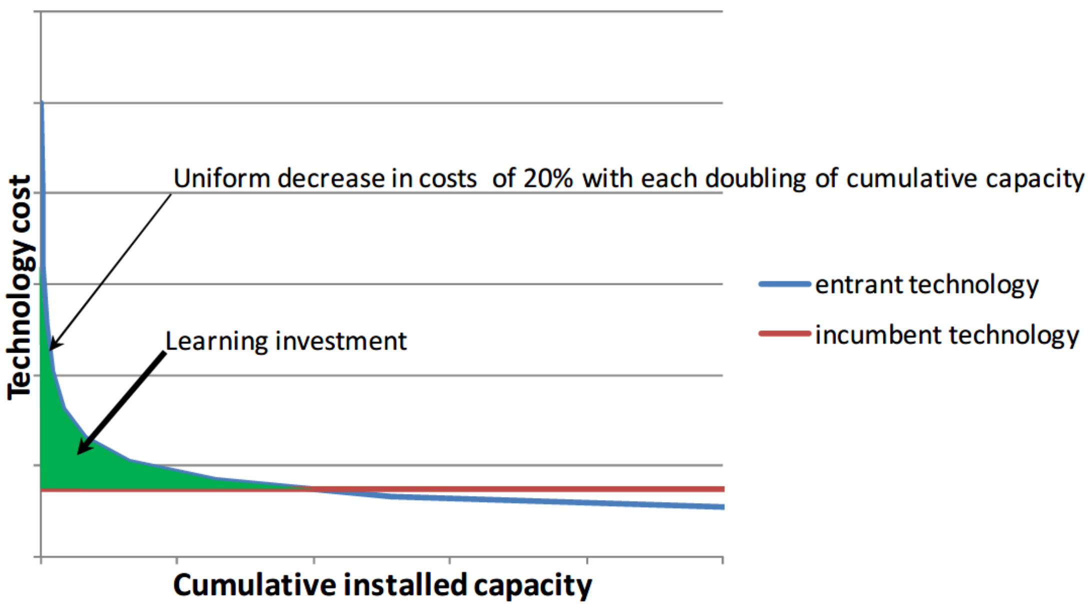

Figure 1.1. Entrant and existing technology development [3].

Some examples of support policies can be found in the EU and USA. In particular, several policies have been designed with the objective of promoting innovative technologies in the energy sector. This long-term goal came up after the oil crisis in 1973, in which European countries and the USA became aware how dependent their energy mix was from fossil fuels imported from countries outside. Apart from energy independence, another important driver is the climate change issue, which needs to be compensated with the promotion of technologies that don't affect the environment. In the European Directive 2009, the 2020 target of 20% was established, and in 2018, a 32% target by 2030, through the Clean Energy for All Europeans Package.

These policies have to be studied so that every goal is attained in the most efficient way. Therefore, it wouldn't be optimal to boost a technology that will not be sustainable and competitive in the long-term. Therefore, learning curves are used in order to analyse the impact of capacity increase over the cost of installing the technology. With this, it is possible to understand if it makes more sense to support this increase in capacity, or it is worth investing in the technology through R&D. This is useful for helping institutions decide which policy would be better off for the energy sector, or for the development of a particular technology (such as PV), that are willing to boost an innovative technology, so that they know if it would be better to invest in the improvement of production processes by means of capacity promotion policies, or in R&D.

Learning curves analyse the effect of learning as the technology is developed, so that accumulated learning due to accumulated capacity makes a technology to have a cost reduction pattern in production. Studies in photovoltaic technology have proposed a 20% of cost reduction for doubling the capacity output. This reduction can be mainly explained by one factor, or by two, or even more, making the model too complex. One-factor learning curves base the explanation of cost reduction to the learning accumulated as capacity is increased, while Two-factor learning curves include usually the R&D factor (but other factors could be proposed such in this thesis), which takes into account the investment realised in such technology.

This project tries to analyse the cost reduction pattern of Photovoltaic Energy with a learning curve, studying the different possible models and which one fits better for the project's objective.

For instance, special focus will be made on the interest rates, as they can make PV projects be more expensive or cheaper, depending how costly money is at that moment in the market. This means that, as Photovoltaic technology is a capital intensive industry, and projects need a high amount of investment (before making any money), developers need to borrow money from the banks (or other financial institutions). This amount of money will be lent in exchange of interest rates that shall be given back to the lending institution. Therefore, if these interest rates are lower, investment in the project is lower (less debt has to be returned), and PV cost is lower.

In the project, firstly, state-of-the-art is discussed. Then the arguments and explanations of different factors that could influence the model are exposed: interest rates and silicon cost. Afterwards, the results of the models are presented. Finally, the conclusions are discussed, as well as the possible future work.

2. State-of-the-art

This section tries to review the development of learning curves and the implantation of the improved One-factor learning curve model. Even though there is large literature concerning technological change, here a general review with is carried out.

As explained in the introduction, technical change is gradual and goes through different stages. Schumpeter defined these stages as Invention-Innovation-Diffusion (Schumpeter, 1934). With respect to this, Invention refers to the creation of new ideas, innovation to further development of the already generated ideas, and finally diffusion is the widespread adoption of new products [1].

Jamasb and Kohler (2007) review the literature on learning curves and discuss its role in the low carbon energy policy. Learning is part as this technical change as explained in Wright (1936), where workers are more efficient as they produced more units, which reflected the phenomenon called "learning by doing" observed in manufacturing processes. When, afterwards, it was extrapolated to other sectors such as power plants, the independent variable of the model shown in Equation (2.1), includes all the factors that affect the cost trajectory of such technology [4]. Even though most of these studies were mainly oriented to manufacturing plants, since 1990 learning curves started to be applied for energy technologies.

2.1. Types of models

The most common way to represent the cost reduction of a certain technology is (2.1), which measures the cost improvement from a power function of cumulative installed capacity. The exponent of the function defines the slope, which is precisely the learning coefficient (β), used for calculating the actual cost of production and the learning rate. In the following equation, C represents the cost of technology, α the normalization parameter with respect to the initial conditions, and Q the cumulative capacity of technology.

$$C = \alpha \cdot Q^{\beta} \tag{2.1}$$

Log-linear function is the most common curve for implementing the learning curve of the equation above, since it makes the curve be linear, so it is easier to understand its meaning. It can be formulated as:

$$\log(C) = \alpha + \beta \cdot \log(Q) \tag{2.2}$$

Learning rate can be formulated as the percentage of cost reduction for every doubling of installed capacity:

$$LR = 1 - 2^{-\beta} \tag{2.3}$$

An improvement of this model can be achieved by means of splitting the total cost of the technology in different components, so that a deeper analysis can be achieved. The main advantage of this improved model is to identify the components that experience a cost reduction by means of learning, and those which don't, such as commodity prices. Therefore, these components may have different learning rates.

$$C(Q) = \lambda C(Q_0) \left(\frac{Q}{Q_0}\right)^{-\beta} + (1-\lambda)C(Q_0) \tag{2.4}$$

$$LR = 1 - 2^{-\beta} \tag{2.5}$$

Where λ is cost share of the component at t=0, Q is the cumulative output, C is the cost and β is the learning parameter, which determines the learning rate LR.

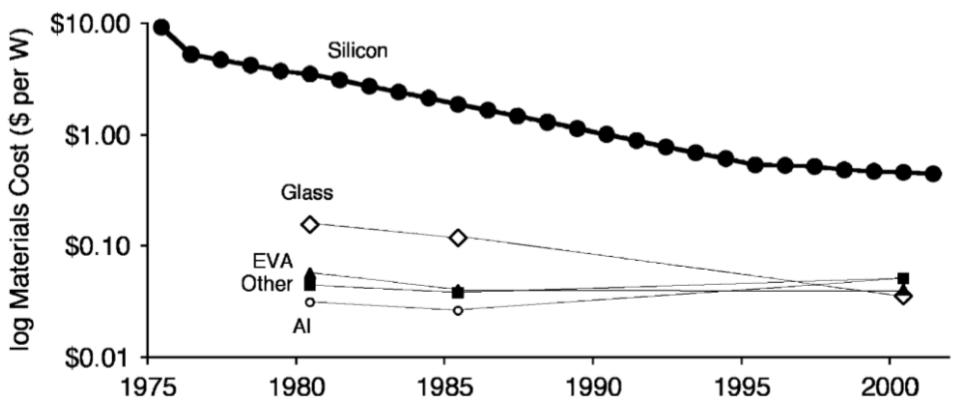

Figure 2.1. Materials and components costs of solar PV modules [2].

Nemet (2005) propose a model that considers different factors and components of PV plants such as plant size, module efficiency, wafer size, yield, market share for poly-crystalline cells, silicon cost, and silicon consumption, and finds out that the most important factors in PV learning curves are the size of the plant, the efficiency of the cell and the cost of the silicon, but only explain around 60% of the cost reduction pattern, explained by other factors.

Rubin et al. (2015) overviews the learning rates for different technologies and propose a learning rate of 20%,i.e., the cost is reduced in 20% as installed capacity is doubled. This argument is supported by different studies gathered together, as it can be seen in Figure 2.2.

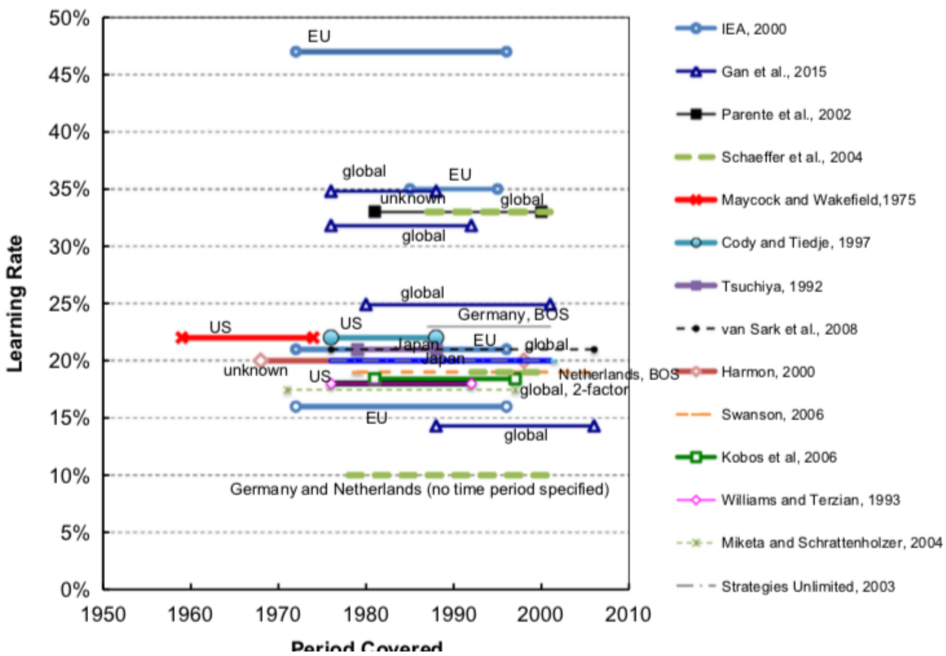

Figure 2.2. Learning rates for solar PV in different studies [4].

One factor learning curve achieves a high level of simplification of the costs, grouping all the drivers into one learning rate. But this is also one weakness, as the drivers could also be divided so that the influence of individual drivers are analysed. This is the objective of the two-factor learning curve. It splits the most important learning factors of the technology, usually capacity and R&D, even though in this thesis capacity and silicon cost will be proposed as factors. The expression is:

$$C = \alpha \cdot Q^{\beta_{Cap}} \cdot C_{Si}^{\beta_{Si}} \tag{2.6}$$

Where $beta$ factors are the learning coefficients for each driver, and α is the normalisation coefficient. This expression can be transformed into logarithmic form:

$$\log(C) = \log(\alpha) + \beta_{cap} \cdot \log(Q) + \beta_{Si} \cdot \log(C_{Si}) \tag{2.7}$$

2.2. Considerations

Some considerations have to be taken into account in order to define a learning curve model. Within these considerations, it can be possible to choose between different possibilities. Wiesenethal (2012) discuss the different considerations to make for designing the model.

One of them is the election of modelling the curve with costs of production or market prices. Costs represent the learning curve itself, that depends on the accumulated installed capacity, whereas market prices, which actually represent the diffusion of the technology, can differ from these costs. At this extent, using cost data is preferable than using price data, as the latter is affected by market fluctuations. Still, it is true that materials purchased from third parties are also affected by the market, and therefore affect costs.

Another issue that affects the learning curve is of global or local model. It is an important issue to consider whether PV technology is developing at the same rate globally, or regional specific factors differentiate the development. On the one hand, there are different trends on the policies that governments approve that support more or less PV energy. In addition, cost of the components may be change. On the other hand, it is true that regional technological progress can be quickly imitated or adopted by other regions, making technologic developments be global in the medium term.

It is also important to define if it is necessary to determine if there is a limit to the learning of the technology in the future. This limit can be represented through a floor cost, which represents the level where the cost of a technology is highly reduced down to a level that is not logic.

2.3. Limitations of Learning Curves

Apart from this considerations, Wiesenthal also discuss some of the challenges of learning curves to asses their support in the policy decision making in the context of the EU strategies. Because, even though learning curves are very useful, they have some major drawbacks and limitations that should be taken into account.

- Treatment of the data used in the model, because the models are based and rooted on the historical development of the technology. As the data used for elaborating the model is obtained from the costs of the past, the model will follow a pattern rooted on these values, and don't need necessarily to follow. In addition, the selection of the data can significantly change the results of the study, so that choosing different starting and ending points in time or include or exclude outliers vary the final learning rate.

- Horizontal transfer of knowledge between different technologies and sectors, which is very difficult to measure. This, alongside the correlation between different factors, makes it difficult to obtain coherent results if the model is too complex. The solution to this is to take into account the possible correlation between the factors selected, and the origin of the data when acquiring it.

- Sudden discontinuities in the historical development of a technology can affect its learning curve. This challenge can be solved by splitting the learning curve into different curves with different learning rates, as Nemet [2] does in his study. As it will be seen later, in this study possible discontinuities will be studied through interest rates and the cost of silicon.

- Considerable changes in the quality of the product can distort the purpose of the learning curve. For this reason, among others, the data shall be carefully acquired to make sure the "product" is the same as more capacity is installed.

3. Determining factors for the model

In this section, two main factors will be observed in order to calibrate the most adequate model: interest rates and silicon cost. Firstly, a qualitative analysis is made in order to see the relationship between Solar PV module costs and the interest rates at the moment when that capacity was installed. The silicon cost through 2000-2017 time frame is observed, in relationship with the module costs. This qualitative analysis shall give the possible influence these factors have on the costs of the module, so that the models elaborated later are as adjusted as possible.

When acquiring the data for modelling the learning curve, it is possible that the learning rate of the technology does not follow a constant learning rate through the studied period. In fact, a driver could exist that establishes a sudden discontinuity between two (or more) periods in the learning curve. These periods shall be identified in order to set different learning rates for each of them, because otherwise the model would not be coherent. Thus, the model can be partitioned in several periods and studied separately, taking into account the different drivers. In this project two main possible factors are studied as possible drivers of a sudden discontinuity in the solar photovoltaic technology costs: interest rates and silicon cost.

Comparing these two factors and the cost of solar PV modules, a sudden discontinuity of these factors could have forced the costs of solar PV to reach a sudden increase or decrease. In a qualitative way, the influence of these factors will be analysed.

3.1. Interest rates

Energy is a very capital intensive sector that requires high investments to generate electricity. Most of the investment is always borrowed by the owner of the plant and given back through the principal of the debt and an established interest rate. Interest rates have a great importance in energy investment projects, as costs of capital are affected and therefore the expected interest rate of return expected. Besides, competitiveness of green versus brown technologies is at stake if it is difficult and expensive to find accessible debt.

For instance, as world interest rates have started to increase – 10-year rates in the U.S., have climbed from 2.2% in July 2016 to more than 3.5% in early 2018 – , more expensive debt would be a second challenge for renewable energy sources. A new era may be beckoning in which solar and wind costs are lower, but financing is more difficult to get, and more expensive [6].

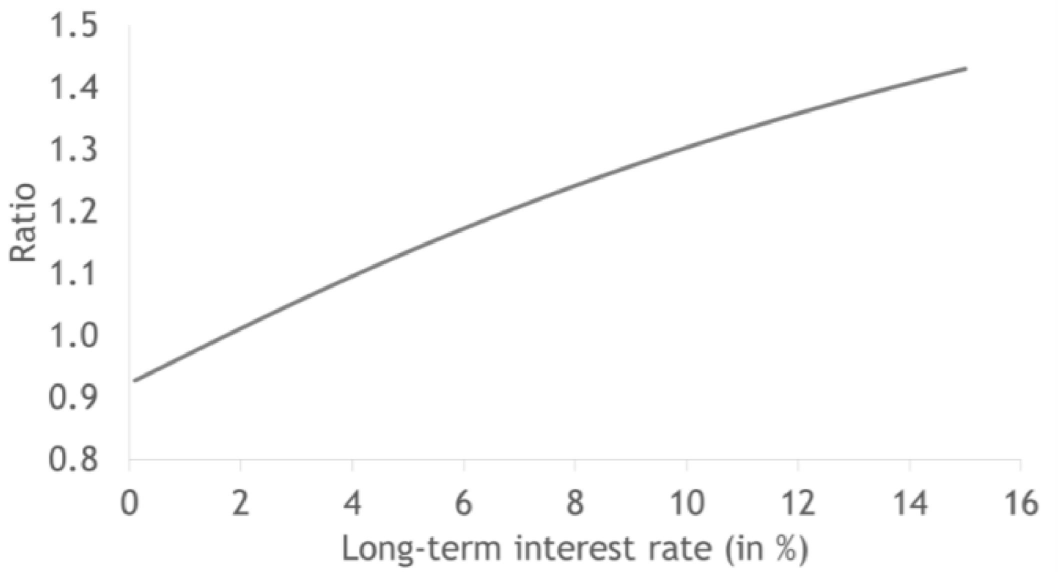

Figure 3.1. Sensitivity of interest rates in Solar PV technology

Interest rates affect costs of energy, as it can be seen in Figure 3.1 for Solar PV. As interest rates increase, it is more difficult and expensive to obtain debt, and the cost of the project increases. For example, with the increase of US bonds explained before, the cost of a solar PV project could increase around 10%. This is why interest rates can strongly affect the costs of the technology and should be analysed. When these interest rates are more or less constant, they slightly affect the cost of PV. Nevertheless the problem arises when a sudden discontinuity exists that affects the learning curve model. With this discontinuity, the cost of the technology has a sudden change and the learning rate is not useful to study the cost reduction pattern.

The methodology to follow is to compare the interest rates of the different regions of the world where Solar PV technology has increased more, and, taking into account the installed capacity in these regions, study the effect of these interest rates in the overall cost of the technology,so that a qualitative analysis is made in order to see if a sudden discontinuity correlation between both exists.

The regions where Solar PV technology has developed most are Europe, China, USA, Japan, India and Latin America, as it can be seen in Figure 3.2. Next the interest rate of each of these regions is going to be computed with the installed capacity in that region, in order to see the how it changes as the interest rates are lower. It is obvious that, as interest rates are lower and money is less expensive, the overall costs of a photovoltaic project are expected to be lower. Maybe, a sudden jump can be found in the chronological development of the technology that will help to elaborate a more precise model. In the following lines the regions with more importance in the solar PV sector will be analysed: first a short overview of the policies that

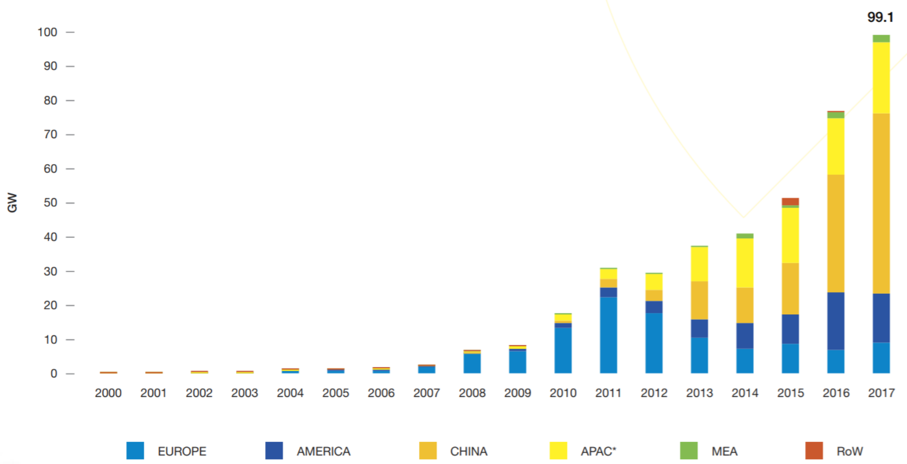

Figure 3.2. Evolution of global annual Solar PV installed capacity [7]

each of the regions have implemented is presented, in order to understand the start of RES. Then, the interest rate - installed capacity study is done.

3.1.1. European Union

3.1.1.1. Overview of Policies

Europe progress has been with not much growth in the last years due to the changing support schemes for RES. Most of the European Member States decided to boost renewable energy through the Feed-in Tariffs in the past, which led to a very high growth in the first decade of the 21st century. Nevertheless, as solar PV is more and more competitive, fixed support schemes are not necessary anymore, and these are changing towards sliding Feed-in premiums and auctions.

The EU started to promote renewable energy in the second half of the 1980s, even though the first Renewable Energy Directive was presented in 2001 by the European Commission through 2001/77/EC, proposing a minimum of 12% of renewable sources by 2010. The directive elaborated and presented in 2009, 2009/28/EC, had the objectives of 20% RES by 2020, with a 10% in the transport sector, individual MS targets and National RES Action plan, with the EC having the supervisory authority to overview the MS decisions and policy adoptions. The "Clean Energy Package for all Europeans" was presented in 2018 and sets a 32% Renewable Energy target for 2030 for the whole EU, with no indications at national level, giving the MS the freedom to to fulfil the targets by their own decisions making in terms of regulation, fiscal incentives or public financing. The Package also sets the conditions for support mechanisms to promote RES.

3.1.1.2. Interest Rate Analysis

With the objective of trying to understand the drivers of the boost of solar PV in the EU, Figure 3.3 shows the interest rates in the European Union and the annual installed capacity of solar PV. Even though in the first years of the century installed capacity grows as interest rates are lower, after 2011 interest rates show a decrease but installed capacity does not expand, in fact it decreases. Therefore, in the EU interest rates seem no to be a critical factor for the sensitivity of solar PV annual installed capacity. Policy factors, such as the gradual phase-out of FiTs in 2011 onwards and their adjustment (which led to less generous support schemes) in the European Union seem to be much more decisive.

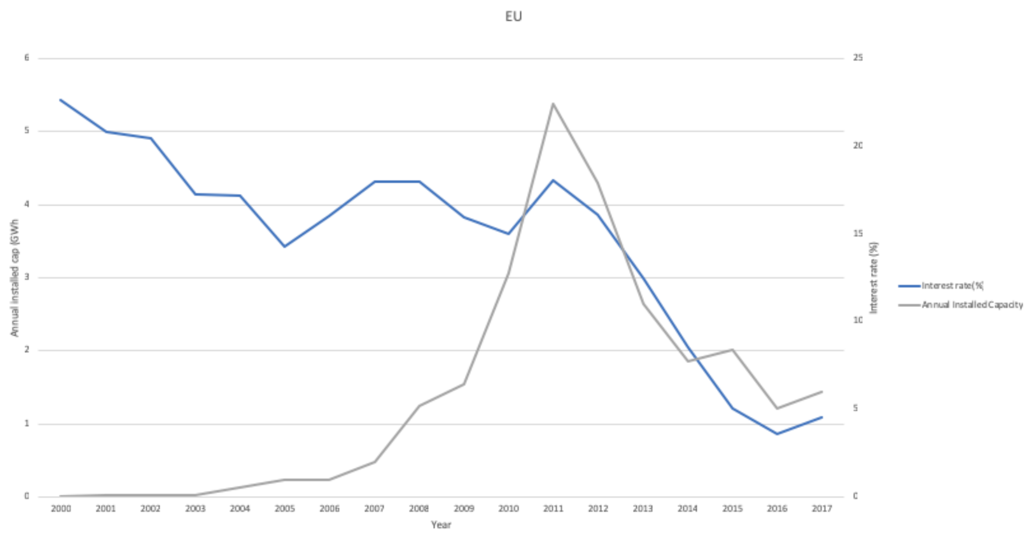

Figure 3.3. European Union interest rates vs annual installed solar PV capacity

3.1.2. United States of America

3.1.2.1. Overview of Policies

United States hold the second position in annual installed capacity in solar PV technology, even though it has contracted nearly a 30% in the last year.

U.S. is the pioneering country in the development of solar PV technology, when it started to develop non-conventional technologies, through the creation of the National Energy Act, with the objective of depending less in fossil fuel energies in the 1970s crisis. In the 1980s, it was slowed down because of the low prices of oil and the electric power market restructuration. Then in 2009, through the American Recovery and Reinvestment Act, renewable energies programs are elaborated that help PV development. However, the US energy policy is generally regulated at a state level; there is no specific target for PV at federal level, even though some states have developed more the solar PV such as California. The country has a goal of 33% of retail electricity sales from renewable energy sources by 2020.

3.1.2.2. Interest Rate Analysis

In the United States the interest rates represented in Figure 3.4 seem to follow a more reliable trend than in the EU. The Figure shows that as interest rates are lower, more solar PV projects are deployed in the US, specially from 2008 onwards. Around 2015, when interest rates increase, i.e, it is more expensive to borrow money to start up projects, installed capacity decreases. The reason why in the US there is higher correlation between interest rates and installed capacity than in the EU is because in the former there hasn't been any support scheme reform as there has been in the EU.

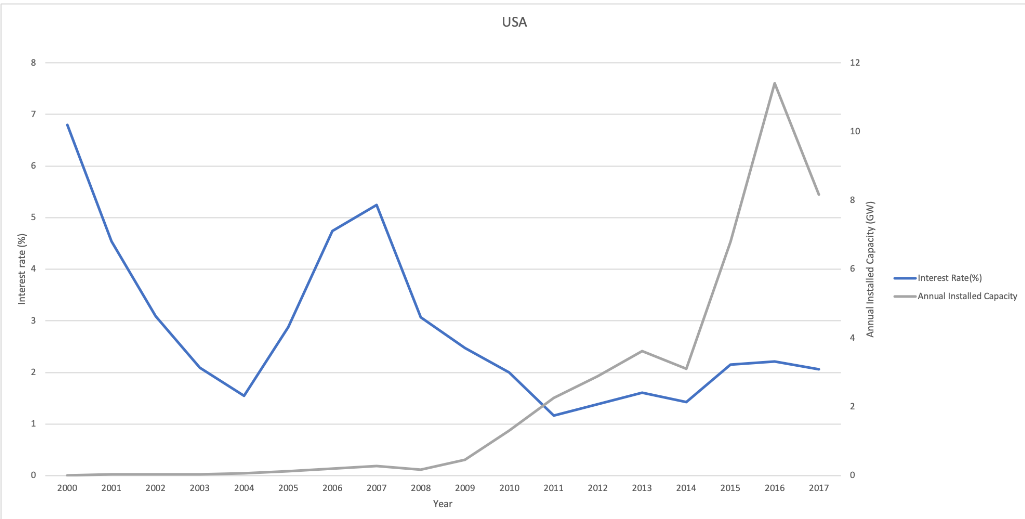

Figure 3.4. United States interest rates vs annual installed solar PV capacity

3.1.3. China

3.1.3.1. Overview of Policies

China has been the region with the largest added capacity last year, with more than 50% of the world new capacity, and since 2013 has been the region with most cumulative installed capacity (after overtaking Germany). It surpassed by far the expected minimum objective set by the government in 2016, which was achieving a total installed capacity of 105 GW, that by now it is already at 131 GW. This great development go hand in hand whith the efforts made by the government on the promotion of Renewable Energy Sources. The plans for development of REs started in 2000 with the "2000-2015 Main Points of Development Planning of New Energy and Renewable Energy Industry", and the "Renewable Energy Law of the PRC" in 2005, which legally established the renewable energy as a priority for energy policies. In fact, a special renewable commission (NDRC) started developing the "5 year plans" specifically for renewable energy. Support mechanisms such as tax relief, feed in tariffs and detail planning, alongside with cheap interest rates have boosted solar PV technology in the country. Nowadays, the NDRC still promoting renewable energy through guidance systems and other measures.

The government has just set the new Feed-in Tariff adjustments after months of uncertainty, which is expected to slow down the demand due to the surpass on the expected objectives, but anyways China accounts for more than half of worldwide solar manufacturing and demand, will be country with the fastest growth, and their influence in the developments will have a major impact in the solar PV sector.

3.1.3.2. Interest Rate Analysis

The interest rates in China have been stable in the last twenty years, with a slight decreasing slope. Thus, it is true that installed capacity increases as interest rates are lower, but there is not a strong relationship between both. This can be explained by the support policies that have been developed in China for the last 20 years, with the supported interest rates for RES, tax reliefs and FiTs.

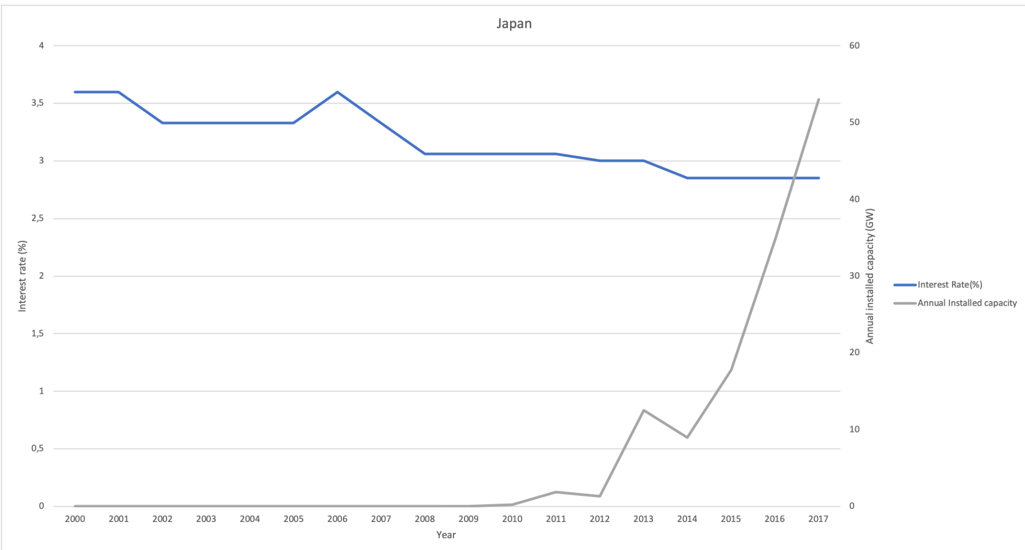

Figure 3.5. China interest rates vs annual installed solar PV capacity

3.1.4. Japan

3.1.4.1. Overview of Policies

Japan is the second most important solar PV market in Asia and the fourth worldwide, in terms of installed capacity. It was the country with most capacity in the first years of the 21st century, achieving a capacity of 1.13 GW in 2004, the largest in the world by that time (then it was surpassed by Germany in 2005).The Sunshine program was the first big move to develop Solar PV technology in Japan, with the objective of diversifying the generation mix and reducing the dependency on oil. Then, Japan also set up a long term road map in 2004 called "PV2030", trying to set the necessary guidance for solar PV technology. After the Fukushima accident in 2011, the government decided to implement a support scheme of Feed-in tariffs for RES, that boosted PV installed capacity granting developers with 80GW. The FIT hedged investors and provided the stability for developers to invest in the sectors. By 2016, 25 new GW had been installed, and another 40GW were on the way. This measures made Japan become the second biggest market after China.

The FIT has been adjusted as solar PV becomes more competitive in Japan, and it has been lowered from 40 Japanese yen (about USD 0.40)/kWh to JPY 24 /kWh [10]. this has reduced investment in the rest of the licensed installed capacity for solar PV. This has also discouraged investment in the remaining licensed solar capacity. The government is considering the possibility to move from feed-in tariffs to auctions to improve the cost of support schemes for solar PV.. Even though, as the FIT was not well designed, it fell intro trouble, leading to a contraction in installed capacity last year. Nevertheless, a new auction mechanism has been introduced, which will help reducing costs in the projects.

3.1.4.2. Interest Rate Analysis

In Japan the interest rates do show a quite strong relationship with the installed capacity, as it can be seen in Figure 3.6. Nevertheless, in 2015, with the reform in the Feed-in Tariff support scheme, when an adjustment was made, a strong recession is visible in installed capacity, even though interest rates still follow a decreasing trend. Therefore, even though interest rates are important for the development of annual capacity increase for solar PV, other factors, such as policies, are much more critical.

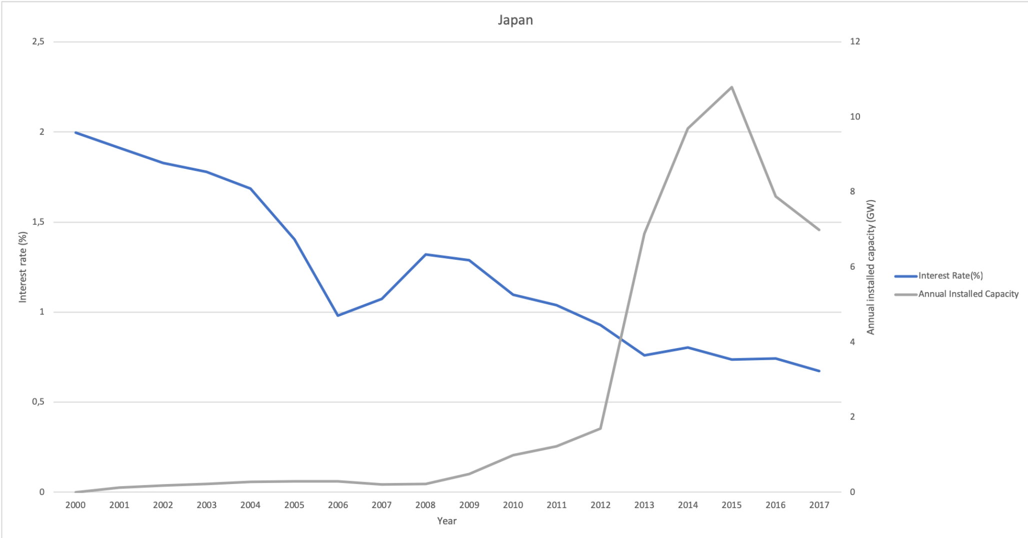

Figure 3.6. Japan interest rates vs annual installed solar PV capacity

3.1.5. LATAM

3.1.5.1. Overview of Policies

Latin America is starting to be a hub for solar PV growth and is expanding quickly, but nowadays is still a small portion of the yearly additions. New tenders for big projects through PPAs have been presented during 2017 in Chile, Brazil, Argentina and Mexico, and also distributed solar PV is having a remarkable growth in Brazil and Mexico, where net metering and high prices tend to ease the switch to self-consumption. Chile and Brazil are the top leading countries in the region in solar PV installation: Brazil added nearly 1GW in one year, and Chile is solving its transmission problems for new additions [17]. In 2017, the total solar PV cumulated capacity installed was around 5 GW.

Latin America is the only region of the ones analysed that either is not a country or an union of countries with common policies (the EU), so a brief overall description in the progress of RES and solar PV in the region will be discussed in the following lines. Latin America started its progress in regulation and promotion of renewable sources after the oil crisis of the 1970s when the ProAlcool biofuels programme was presented in Brazil in 1975 and geothermal regulation in Costa Rica and Nicaragua. Since then, there has been a long way towards nowadays' policies: 13 out of 20 countries have introduced auctions for RES, and others measures such as fiscal incentives (18), net metering (10) grid preference (13). Most of these countries have introduced a legal framework for the promotion of RES, and national targets for achieving a minimum amount of the generation mix by a certain date [16]. Feed-in tariffs in LATAM have not enjoyed the success of other regions, and failed in its implementation in Argentina, Brazil or Ecuador, which are phased out nowadays, and other countries use them in a limited way or as an addition to auctions.

3.1.5.2. Interest Rate Analysis

Figure 3.7 shows the development of annual installed capacity in Latin America and the interest rates, which where collected from Chile, as it is the country with the highest progress in solar PV among the LATAM countries (Brazil nowadays is the one with biggest installed capacity but installed it in almost one year). Solar PV started to boost with some years of retard in comparison with the rest of the analysed regions, around 2013, and the annual installed capacity has increased since then. Interest rates show a remarkable decrease in the last decade, and coincide with the boost of solar PV in the region, letting from 2013 onwards to develop solar projects at a feasible cost of borrowing money. The relationship between low interest rates and annual installed capacity seems reasonable in the region, starting with the changing trend of interest rates in 2013, and the initial solar PV developments. Since then, interest rates have followed a negative trend and solar PV an exponential growth.

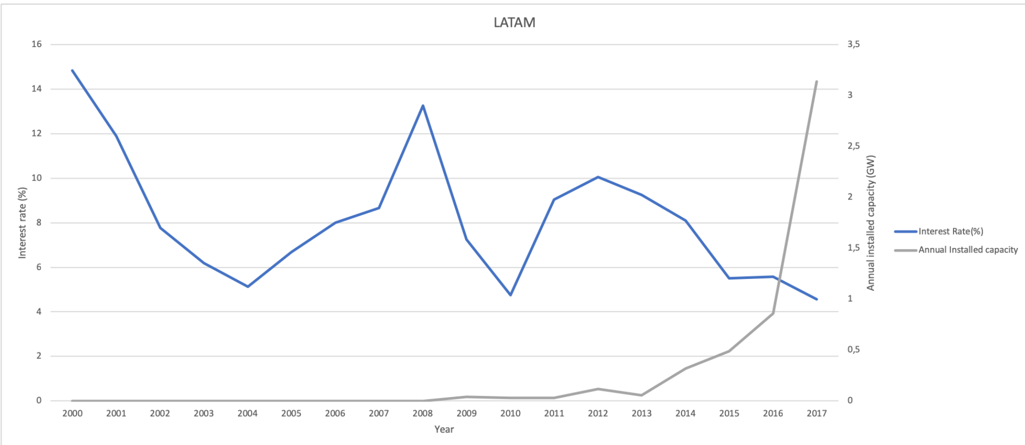

Figure 3.7. LATAM interest rates vs annual installed solar PV capacity

3.1.6. India

3.1.6.1. Overview of Policies

India is taking advance in the recent years in the promotion of RES, and solar PV in particular, through an ambitious plan with a target of 175GW of installed RES capacity by 2022, from which 100GW are solar energy, reaching the third place in the global ranking with 9,8% of the total acumulated installed capacity [17] . India has set presented some initiatives and policies talking about the priority and need in the promotion of renewable energy sources in the last years. One of the first of these policies is the Electricity Act of 2003, by which cogeneration and RES should be promoted by the State and easy access and connection to the grid should be provided, and also de-licensed stand-alone generation and distribution systems in rural areas [14]. Also the National Rural Electrification Policies of 2005 and 2006, in which solar PV in rural areas is promoted. The New Tariff Policy of 2006 set a minimum quantity of energy has to be from RES and the faster adoption of RES through auction methods (amended in 2016) [15].

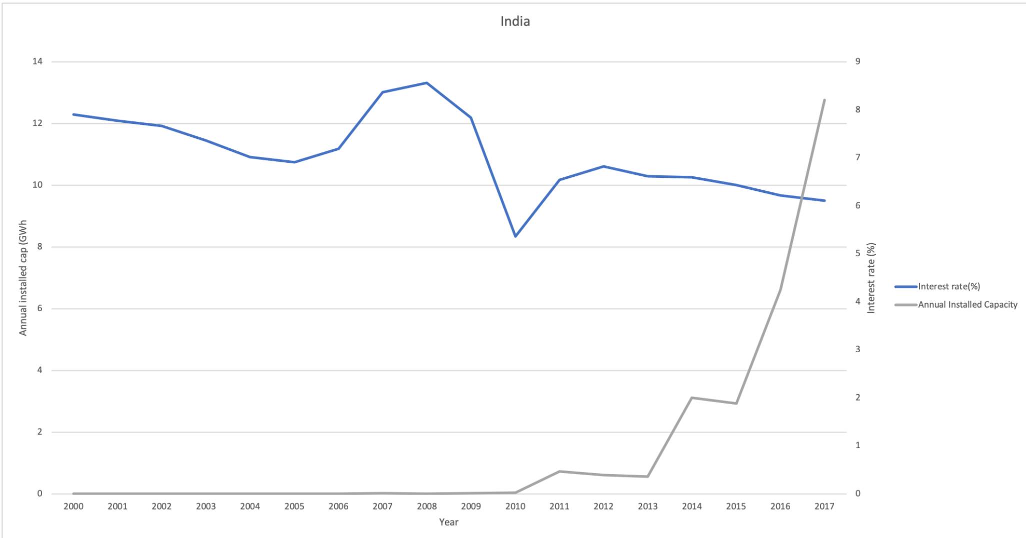

Figure 3.8. India interest rates vs annual installed solar PV capacity

The Ministry of new and renewable Energy (MNRE) developed an incentive scheme for the promotion of solar energy (PV and Concentrated SP) in 2008. The incentive is a generation-based incentive which awards solar power plants with a maximum of 12Rb./kWh. Other promotion initiatives at State level are being promoted, mainly through Feed-in tariffs. In 2010, the Solar National mission was presented, which aimed at the installation of 20GW of grid connected solar power and 2GW of off-grid solar power by 2022.

3.1.6.2. Interest Rate Analysis

The late integration of solar PV in India, practically from 2010 onwards, can be seen in Figure 3.8, where interest rates have followed a decreasing trend as solar PV boosted in the country. In fact, a valley in 2010's interest rates coincide with the start of solar PV installation in India. Even though the interests have decreased as solar PV installation increases, the trend is not strong enough to see a clear relationship between both. Basically because interest rates have behaved with certain stability while solar PV has grown with exponential magnitudes over the last years. Different policies and support schemes can have influenced more in India than the interest rates trends for the massive development of photovoltaics.

3.1.7. Global Weighted Average and Comments

The objective of this section was to study the possible relationship between the interest rates and the development of the installed capacity of solar photovoltaics over the last 20 years. Under a qualitative analysis, it could be possible to see if a certain trend was followed, or even if a sudden discontinuity in interest rates could have led to a jump in the installed capacity in a certain region, or even worldwide. In the previous sections, regional analysis has been carried out with more interesting results in some regions than in others. However, apart from the regional analysis, a global study has also been elaborated, taking into account the interest rates of all the analysed regions and compute them in depending on the weighted capacity that this region has over the rest of them. During the first years of the 21st century, Japan, EU and USA have had more weight, as their capacity contribution is higher, but in the second decade (2010-2017), China's interest rate is the most important one, due to its massive contribution of annual installed capacity.

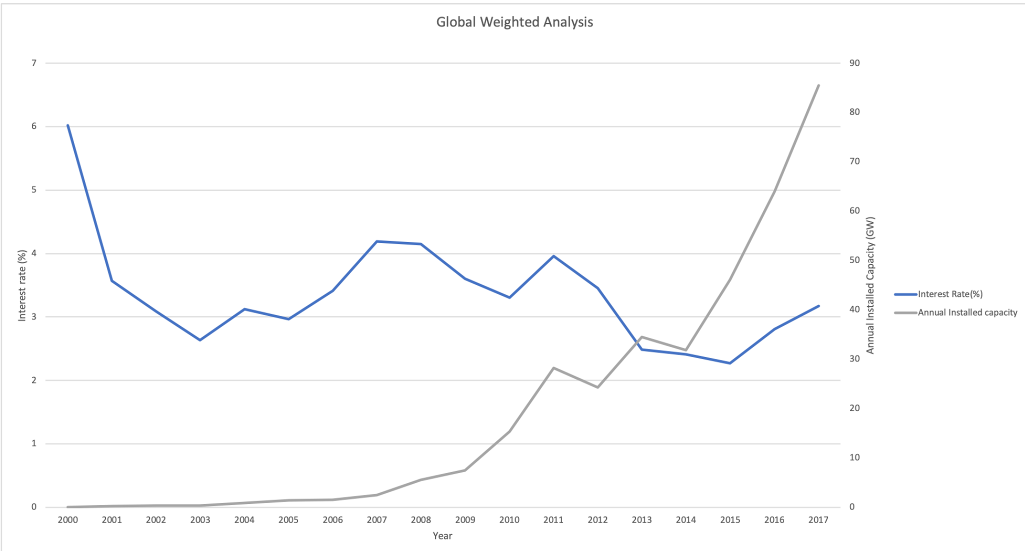

Figure 3.9. Global Weighted interest rates vs annual installed solar PV capacity

Figure 3.9 represents the global yearly installed capacity with respect of the interest rates. Observing the graph, interest rates have been more or less stable throughout the period (2000-2017), with a slightly decreasing trend in the period 2011-2015, after the crisis, when interest rates started to be lower. This period coincides with the boost of solar PV worldwide, which could be explained partially by the cheaper borrowing of money for the development of solar PV projects. Since 2015, interest rates have started to increase again, but by that time solar PV annual installed capacity had already boomed, with an exponential trend, particularly in China.

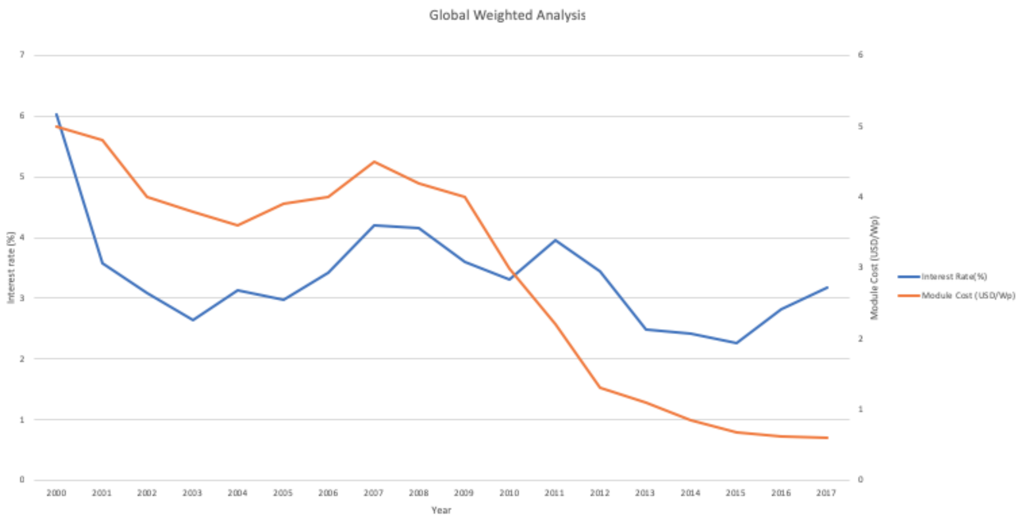

Figure 3.10. Global Weighted interest rates vs solar PV module costs

As it can be seen in Figure 3.10, there is not a clear relationship between the costs of the modules and the interest rates. In the first half of the time frame, the trend is the same but then the relationship is not strong enough. Even though the analysis has also been done with installed capacity, as a regional study could be done, the important variable is the module costs.

Nevertheless, even though it has been demonstrated that interest rates do have a correlation with yearly installed capacity (and the module costs of Figure 3.10) and even more in RES projects, the relationship between both is not strong enough, and the trend that installed solar PV follows doesn't always coincides with the trend that interest rates set. Some clear conclusions can be extracted from this study:

- Interest rates have much to do with solar PV projects, as capital intensive projects require huge investments, usually acquired with debt. Cost of debt changes according to the interest rates, as it is cheaper to borrow money when interest rates are lower. RES projects have more sensitivity than other sources of energy when considering interest rates, as seen in Figure 3.1.
- Even though interest rates have demonstrated to be correlated to annual installed capacity of solar PV, the relationship is not strong enough to come up with coherent conclusions. It is true that at some periods in time in some regions, the trend was strong, but not in others, or in the global analysis of Figure 3.9. This happens basically because there are other factors, such as support schemes, policies or silicon cost (as is studied in the next section) that are much more critical than interest rates. The module cost's relationship with interest rates haven't given enough evidence to proof that there is a strong relationship between these two variables. Even though most of the study has been done with installed capacity, module cost is a critical variable to study.

- To sum up, the study of interest rate as a determining factor for solar PV module cost is not strong enough to demonstrate it.

3.2. Silicon Cost

3.2.1. The importance of Solar-grade Silicon

Over 90% of solar PV cells market is composed by silicon-made cells, and the decreasing cost of silicon is critical for the growth of solar PV sector. Silicon is the main component for the development of solar cells, and it has to be processed to attain the required purity for solar PV appliances, usually starting from metallurgical-grade silicon. The purity of the silicon used in metallurgical processes in the industrial sector is 98%, also known as metallurgical grade silicon (MG-Si). Another application of silicon is used in the chips in the electronic industry (transistors, diodes...), but the purity needed is 99.9999999% (9N, eight nines), so more expensive purification processes are needed. The silicon with this purity is called electronic-grade silicon (EG-Si). Finally, the purity needed for solar photovoltaic applications is 99.9999% (6N, six nines), known as solar-grade silicon (SoG-Si). The purity required for solar cells is lower than the one for the electronic industry, and therefore, its production is cheaper[12].

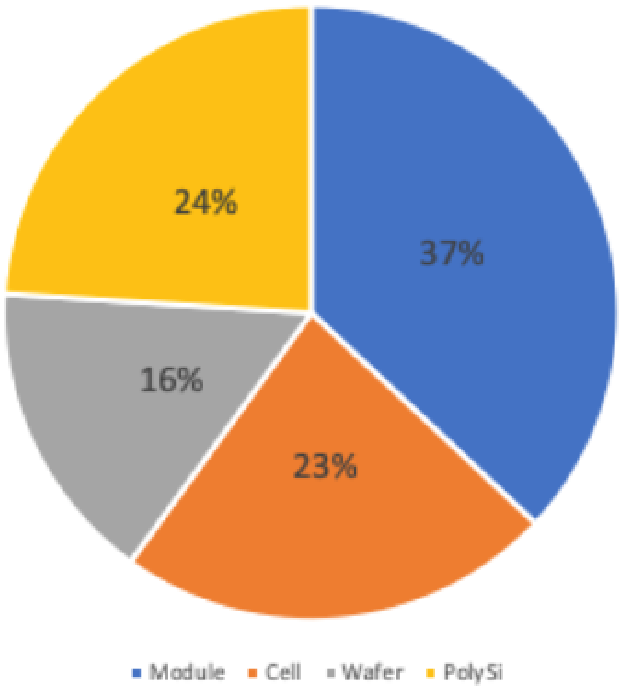

Figure 3.11. Module cost breakdown

As it can be seen in Figure 3.11, silicon cost matters in the overall cost of a module, and its fluctuation can affect significantly. The other costs are more predictable as are not changing as fast as the silicon is doing, and this is the reason why the analysis on this section is focused particularly on this material.

Until 1997, the polysilicon used for solar cell production came from ultra pure virgin electronic grade poly-silicon, also called Electronic-grade Silicon, usually made up from rejects and scraps of the electronic chip industry. Alongside the fall of the electronic industry and the higher demand in solar PV modules, because of the growth of the solar photovoltaic sector, a shortage of electronic scrap to supply solar PV happened, so producers had to buy normal Electronic-grade polysilicon to build the solar PV modules. This polysilicon is highly purified and therefore very expensive. Finally, in the mid of the 00 decade, new economic solutions arose, and the poly-silicon process was adapted to Solar-grade poly-silicon, with a lower cost, and suitable for solar PV cells. These adapted processes are the Siemens chemical process directly for solar-grade silicon, and other alternatives that are starting to gain weight such as the upgraded metallurgical process, or the fluidized bed technology, but as it can be seen in Figure 3.12, Siemens is the most common technique.

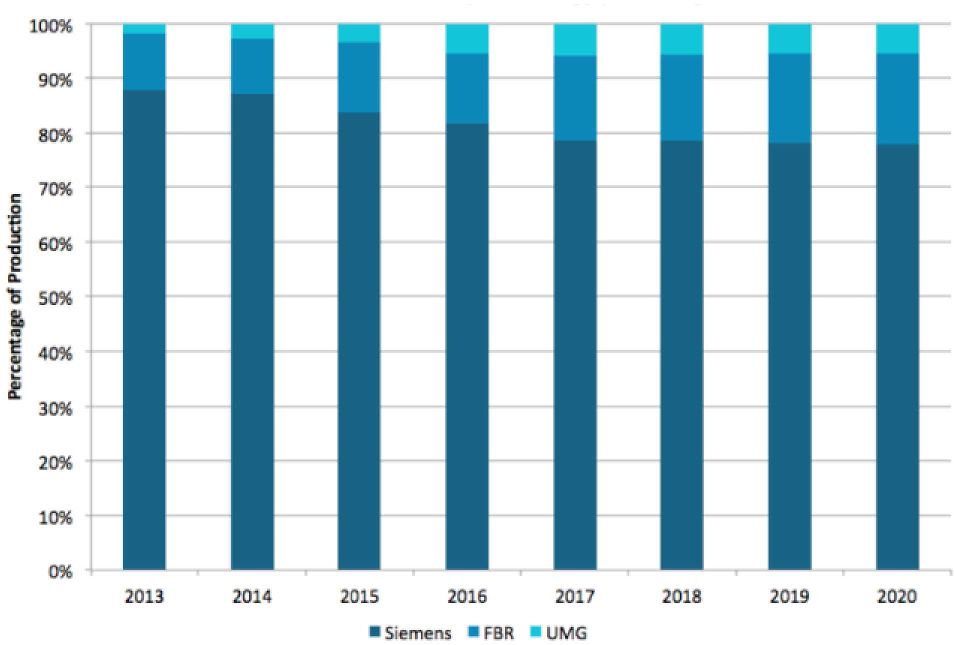

Figure 3.12. Market share of Polysilicon module production by technology. Source: IHS technology.

In the process for the manufacturing of silicon photovoltaic modules, the first step is the mining of quartz sand. The silica contained in the quartz sand reacts in an electric arc through carbon electrodes (coal, wood, charcoal...) in order to obtain the MG-Si. Then it can be purified in a higher level up to SoG-Si (6N) or an even more purified EG (9N) to meet the minimum requirements of each of appliances. There are two main methods to carry out the purification process: the Siemens process and the modified Siemens process. Basically, the Siemens process trichlorosilane gas decomposes and deposits additional silicon onto silicon rods at 1100–1200 C, whereas in the modified conversion silane is used as feedgas and the decomposition temperature is around 800 C. The final product Solar-grade Silicon, is composed by a mixture of electronic-grade silicon, off-spec EG-Si and dedicated SoG-Si. In the first part of the 21st century, off-spec EG-Si and silicon scraps from electronic-grade silicon production were the main sources for the photovoltaic industry, but the importance of dedicated SoG-Si has been increasing as PV industry grows [13].

3.2.2. Poly-Silicon cost analysis

With the description made on silicon and its development over the last decades,i.e, why in the mid 00s a shortage and consequent increase in spot prices of silicon led to a increase in solar PV manufacturing price. Then, with the application of economical processes and the commercial introduction of solar-grade silicon, it decreased exponentially. The objective of the study is to analyse a possible sudden discontinuity in the mid 00s, so that two different learning curves should be elaborated instead of one. In addition, the trend of the silicon prices is going to be compared to the ones of the solar PV total prices.

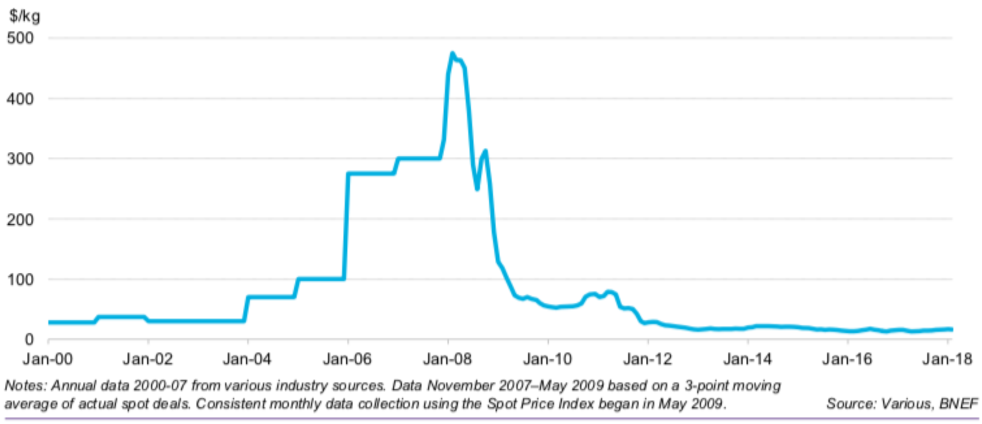

Figure 3.13. Prices in the Spot market of silicon

As it can be seen in Figure 3.13, due to the shortage, and latter use of EG-silicon, prices in the market grew strikingly between January 2006 and January 2008, up to a spot price of 475 $/kg of silicon. Then, because of the use of solar-grade silicon with less costly methods and the adaptation of the production process specifically to solar PV industry, prices started to become more competitive. Modules reduced its costs by 80% between 2010 and 2016, and during this period 87% of the accumulated installed capacity occurred. It is obvious that module costs depend on the silicon costs in the spot market, as modules' main material is silicon. With the shortage of the mid 00s, module costs started to increase. Figure 3.14 shows the trends of both module and silicon costs and it can be easily seen that they follow the same curve and that the correlation between both is high. Even though nowadays more ways to produce solar PV modules are being developed, such as thin-film, around 90% of the modules are still being developed with silicon. This is why modules are so dependant on silicon prices of the spot market.

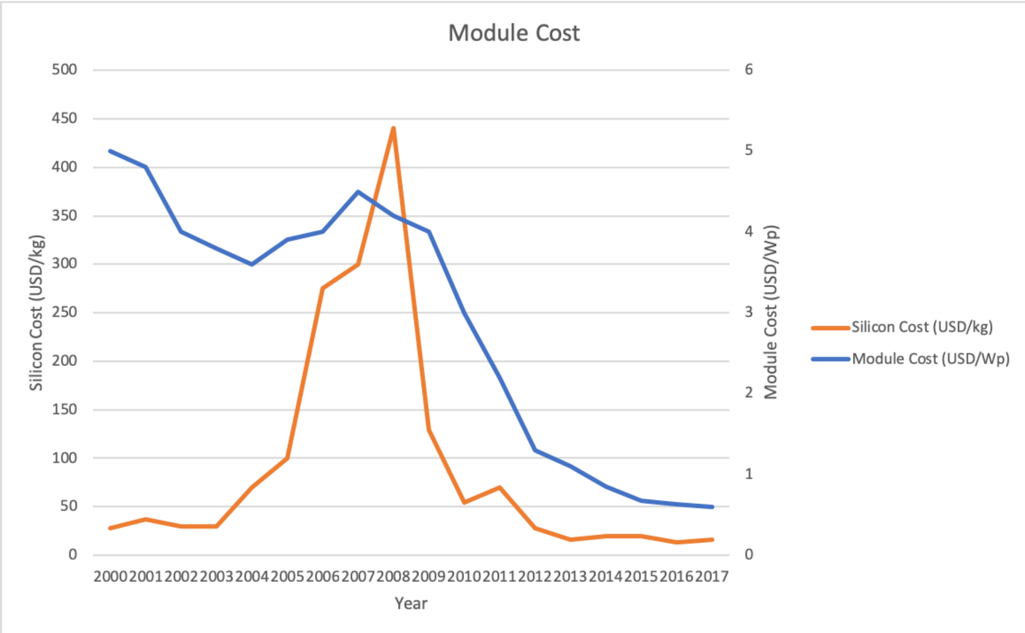

Figure 3.14. Module costs (USD/Wp) versus SoG Silicon Costs (USD/kg)

In order to elaborate a learning curve for module costs, the sudden discontinuity caused by the shortage of EG-silicon scraps can be managed through the division of the LC into two: before and after the silicon shortage of 2008. Thus,the model will be partitioned into two time periods with different learning factors: the first period goes from 2000 to 2006, and the second period starts in 2007, just after silicon prices start to decrease, until 2017.

4. Learning Curve Model

The final part of the study consists on the elaboration of the learning curve for solar PV polysilicon modules, with respect to the installed capacity. In this section, three main parts can be differentiated:

- First, a learning curve is going to be considered as a whole, without taking into account external factors that could affect the behaviour of the module costs such as the silicon, studied in the previous section.
- Then, a three period learning curve is proposed, with a division in 2004, and another in 2011. Therefore, three different learning curves with different learning rates are presented. The main objective of this model is to achieve to isolate the silicon fluctuation in the second period (2004-2011).
- Nevertheless, as some problems arise with the second model, a third model is proposed, with two different factors (and just one period). This model is more complex but decouples better the silicon cost fluctuation.

Even though the model with just one period will prove to be reliable and coherent, a solid motivation to propose a three period model can be also found in the validation criteria of learning curves, that could have problems, or even be inappropriate if the technology is nonlinear (in logarithmic form), or if cost increase after initial decrease due to learning [18]. This could be argued that is what happens to solar PV (Figure 4.1) during the silicon shortage of 2007. This is why both models are studied.

Before analysing these, some common considerations are studied for the development of the learning curves. The methodology to follow for the elaboration of the curves can be summarised as follows:

- **One-factor Learning Curve models** (OFLC models with one and three periods)
  1. Deploy the module costs and the cumulative installed capacity for solar PV in logarithmic form. This is necessary, as the data in linear form follows an L shaped trend (as can be seen in Figure 4.1), which can be easily linearised using logarithmics.
  2. The next step is to obtain the equation of the regression line of the module costs with respect to the cumulative installed capacity. This regression line is a straight line in logarithmic form, and a curve in linear form. The line (or curve) is the learning curve, i.e, how much does the costs of the modules are reduced every time capacity is doubled.

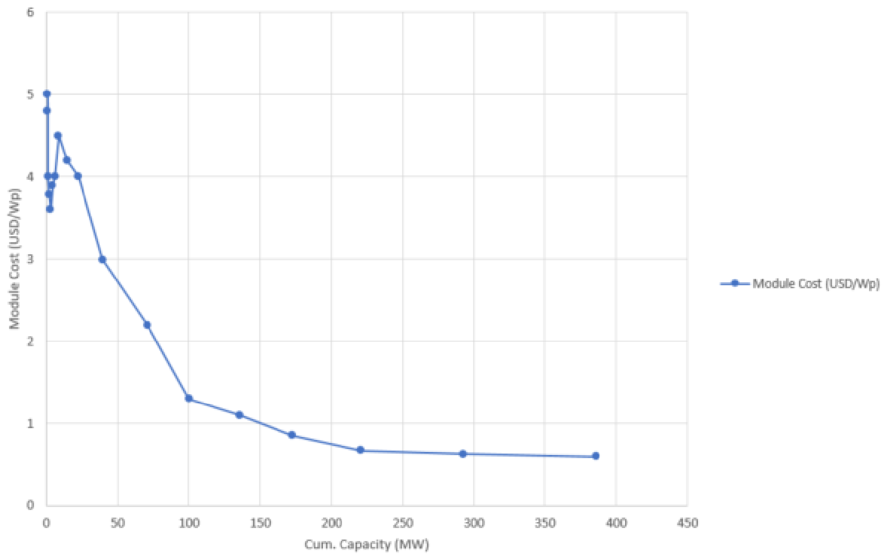

Figure 4.1. Module Costs against Cumulative Installed Capacity in linear scale

3. With the equation of the regression line, parameters α and β can be obtained from the slope and the intercept. It is necessary to remember the learning curve equations formulated in Section 2, which are (P is module price and V installed capacity):

$$C = \alpha \cdot Q^{\beta} \tag{4.1}$$
$$\log(C) = \log(\alpha) + \beta \cdot \log(Q) \tag{4.2}$$
$$LR = 1 - 2^{\beta} \tag{4.3}$$

   Where equation (4.1) refers to the linear form (which should be an L-shaped curve), (4.2) is its logarithmic equivalent, used to obtain the parameters out from the regression line, and finally (4.3) refers to the learning rate, which can be obtained from β. The learning rate calculated represents the cost reduction trend for the modules as solar PV installed capacity is doubled. The calculations explained herein are detailed in Annex I.

- **Two-factor Learning Curve Model** (the third model)

1. As in the previous methodology, it is necessary to deploy the module costs, the cumulative installed capacity for solar PV, and the silicon costs in logarithmic form. The silicon costs will be the "second" factor, apart from the capacity.

2. Develop the regression model with two factors, that will end up being a plane, instead of a line, in a three-dimension graph. The equation of the plane means

the relationship between module costs and the factors: silicon costs and installed capacity. The equation of the plane follows this form:

$$C = \alpha \cdot Q^{\beta_{Cap}} \cdot C_{Si}^{\beta_{Si}} \tag{4.4}$$

$$\log(C) = \log(\alpha) + \beta_{cap} \cdot \log(Q) + \beta_{Si} \cdot \log(C_{Si}) \tag{4.5}$$

$$LR = 1 - 2^{\beta} \tag{4.6}$$

Where β coefficients are related to the influence of each of the two factors.

3. Finally, from the equation of the plane, learning rate coefficients can be obtained through the β coefficients, using the expression 4.6.

A summary of the results of the calculations are showed in the next Table. The results are used and explained in the following sections.

Model	**Period/factor**	β	**LR**	**R2**	**Mod. Cost 2030 (USD/Wp)**
OFLC (1 period)	-	-0.33	20.9%	0.687	0.49
OFLC (3 periods)	1	-0.268	17%	0.87	1.39
	2	-0.2	13%	0.576	0.63
	3	-0.62	34.9%	0.91	0.212
Two-factor LC	Capacity	-0.283	17.8%	0.93	0.45
	Si Cost	0.289	-22%	*	

Table 4.1. Results of the learning models

4.1. One period Learning Curve

This learning curve only considers one period, from 2000 to 2017, as if no external factors, such as the costs of solar-grade silicon described in Section 3.2, are taken into account. This analysis is done as if the learning rate from 2000 to 2017 is constant and unique for the whole period. The proposed LC model is a one-factor model, considering the module costs as one variable, without other factors (two-factor LC).

The main reasons to have chosen this model are several. In the first place, it is chosen because the data is much more accessible, and reliable, than the other model types, which can lead to build not very reliable models with redundant data. For instance, R&D investments are really difficult to measure. This argument is strong enough to reject a Two-factor learning curve with research and development data. Improved one-factor LC components' data are not difficult to obtain and are quite reliable. Nevertheless, the cost reduction trend for solar PV is strong enough to discard the separation of the total cost into the underlying components, and analysing them separately. It is a feasible option, but for this study it has been considered that the model would be too complex in comparison with the benefits obtained for improving the model.

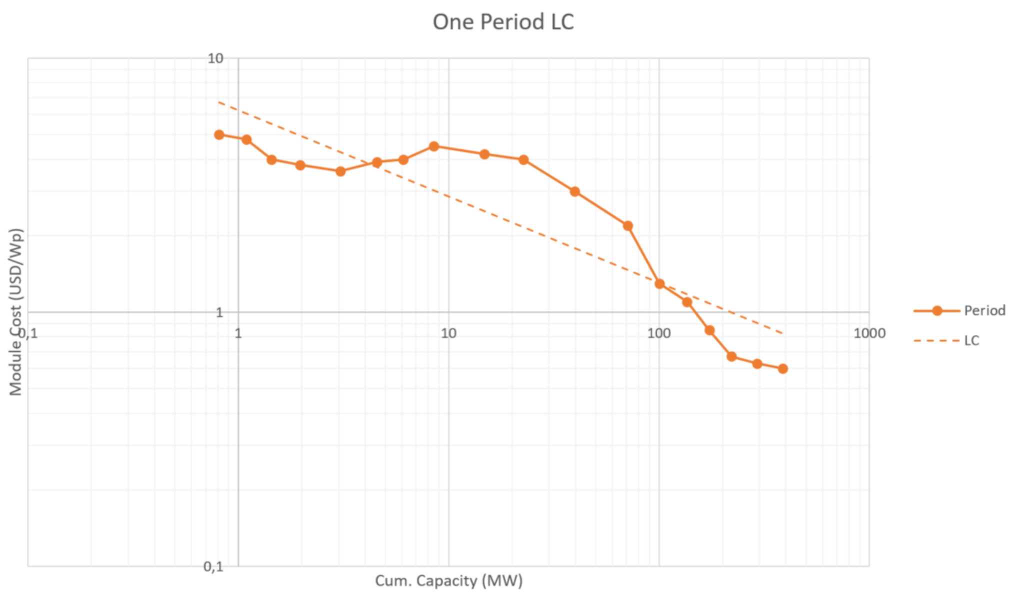

Figure 4.2. One period Learning Curve in logarithmic scale

Figure B.5 shows the Learning Curve in logarithmic scale, with an evident cost reduction pattern as capacity increases. The LC is a straight line in the logarithmic scale. With the pertinent calculations, the Learning Rate obtained is 20.9%, i.e., cost in modules is reduced by 20.9% as capacity is doubled. Most of the studies reviewed in Section 2 propose a 20% LR for Solar PV, which is near the 20.9% proposed in this analysis, proving to be a coherent result. The R2 analysis elaborated gives for this model a coefficient of 0.687, meaning that nearly 70 % is explained, which is reasonable, but information is missing.

According to IRENA forecasts, solar PV capacity will reach 1,760 GW by 2030. Computing this capacity in this learning curve (Figure B.5), the solar PV modules would have a cost of 0.493 USD/Wp.

4.2. Three Period Learning Curve

As explained in Section 3.2, silicon shortage in 2007 increased silicon prices, and affected solar PV industry. Then, its later adaptation to the solar PV market through solar-grade silicon production let solar PV decrease again. Therefore, a sudden discontinuity happened in 2007, which had nothing to do with the module technology. Because of this, and in order to improve the adjustment of the model, a split of the curve into three is proposed, with different learning rates. The main objective of this division is to deal with the silicon fluctuation between 2004 and 2012, when prices boomed and went down again, so that the real learning for the modules is less affected by this fluctuation. In principle, the learning rate before the adaptation from electronic-grade silicon to solar-grade silicon will be lower than afterwards, when the photovoltaic industry got to adapt to produce modules, and real technological "learning by doing" was more remarkable. But this phenomenon can only be explained when silicon costs stop decreasing, from 2011 onwards. Therefore, the most interesting periods are the first and the third ones, as silicon cost is constant and learning can be studied independently of silicon costs fluctuations in the market.

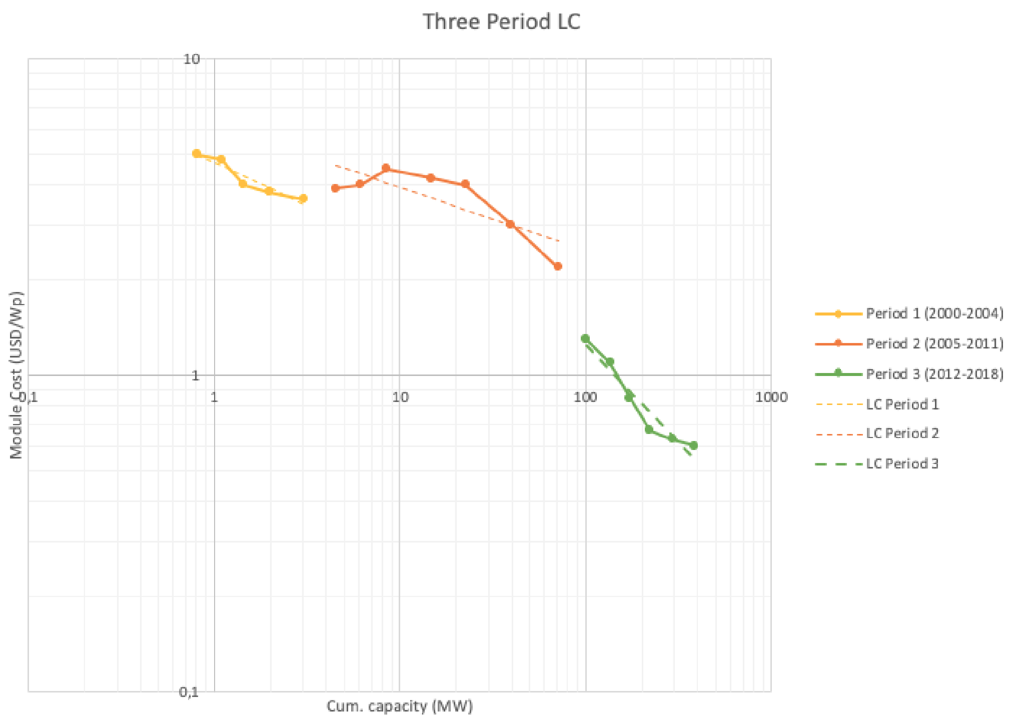

Figure 4.3. Three period Learning Curve in logarithmic scale

In Figure 4.3 the learning curves for the three periods are plotted. The adjustment for the LC through the division of the time frame, improves the model, that partly achieves to isolate the silicon cost variations. A more detailed analysis is carried out in the next Sections.

4.2.1. Time Period 1: 2000-2004

The first period is characterised by the start of the solar PV industry, using basically the electronic-grade silicon from the scraps of the electronic industry to manufacture the modules. Its price is initially high, but tends slowly to learn, letting the costs of the module reduce due to "learning by doing", until the silicon shortage of 2007 (this shortage is further discussed in Section 3.2). This period starts in year 2000, and finishes at the aforementioned shortage in 2004, when module costs started to rise again due to the silicon costs variation. In order to "isolate" this learning, the first period tries to reflect the development of the solar PV modules learning during its first steps of the century.

Figure 4.3 shows the first period learning curve (in yellow). This LC has a learning rate of 17.9 %, which shows a slower learning pattern of solar modules in this period, comparing it from the 20,9 % analysed in the previous section, and much further away from the third period analysed in the next paragraph. The correlation coefficient R2 is 0.87, which shows a high correlation in this period, because the module costs in this period do follow a straight line, and therefore the regression is well adjusted. During this period the silicon cost was more or less constant, as it came from a mature industry such as the electronic sector, and the demand was not very high yet in solar modules. Because of this, the learning curve can be mainly explained by the "learning by doing" of the sector, not as the second period, which is mainly influenced by silicon costs.

4.2.2. Time Period 2: 2005-2011

The second period starts just after the silicon costs start to rise in 2005, goes across the shortage until 2008, and experiences the exponential decrease in silicon costs when the industry finally adapted to solar-grade silicon. Herein after, the decrease in the module costs is huge, but it is not due to the learning, but because of the silicon cost decrease, which carried out a considerable cost reduction in the costs of the solar PV modules. As can be shown in the results of Table 4.3, the LR is 13%, much lower than the popular 20 % of learning. This can be explained by increase and later decrease of the module costs during this period, which makes the LR be not well adjusted, in fact, adjusted R2 coefficient is 0.576, a quite low number.

This period does not conceive a coherent learning curve, as the data used does not follow a linear trend, first increasing and then decreasing hugely. The learning rate obtained is not representative of what happens in this period, because the regression model is not well adjusted (due to the irregular trend of the data). This period was just used as a way to isolate the silicon fluctuation.

4.2.3. Time period 3: 2012-2017

This period occurs after the silicon cost stabilisation in 2012, when its market was more mature, so "learning by doing" could be easily studied, and the learning rate of the solar PV modules was quite independent from the fluctuation of silicon costs. Figure 3.14 shows that from 2012 onwards, silicon starts to be constant while module costs keep on reducing.

Results on Table 4.3 show that the learning rate in this period is the highest out of the three periods, with 34.9 % of LR, and an adjusted R2 coefficient of 0.91, showing a very good adjustment of the learning curve. Learning Rate in this period show that according with this model, the "learning by doing" of solar PV module manufacturing is much higher than in the initial capacity investments in 2000 (first period). This can be related to the better adaptation of resources for the solar PV industry in the last years, and the fast learning this has provided to the sector.

There is a considerable difference within this period, only noticeable when using the logarithmic scale, and two sub periods could be defined, with the gap in 2015. This sub division has not been considered, but it is important to remind that other factors could have major influence in the solar PV development, such as economies of scale, policies, Chinese subsidies... In fact, if a sensibility analysis is done and the third period starts in 2013, the LR changes from 34.9% to 24.4% which is less aggressive in terms of cost reduction, and provides more reasonable results. Nevertheless, relying on a LR that only takes into account data from 2013 to 2017 does not seem very reliable.

First year	LR
2011	34.9 %
2013	24.4 %

Table 4.2. Sensitibity analysis on the third period

Even though this model with three periods is coherent, and the results give light to the real behaviour of the solar PV industry, the main drawback consists on the isolation of the second period. This isolation has two main difficulties: the first one is that most of the data used for the period 2000-2017 is contained in this period, and is wasted; and the second one is that in the second period there was also a huge learning in the industry, as in that period the solar module sector adapted, and this model does not take it into account. It isolates it. Therefore, even though the results are coherent and useful, another model is proposed which tries to decouple capacity and silicon through two factors without isolating one entire period.

Regarding the IRENA outlook for 2030, and considering the forectast of 1760GW of accumulated installed capacity, this model provides a module cost of 0.212USD/Wp. It would be interesting as future work to see if a floor cost is needed, as it might happen that this solution is not technically feasible.

4.3. Two-Factor Learning Curve

As discussed in the previous Section, a more complex model is necessary to decouple the silicon costs from the learning rate due to installed capacity,i.e. the "learning by doing" rate (in this case it would be "learning by installing"). This difficulty can be dealt with a model with two factors: one is the accumulated installed capacity of solar PV worldwide, the same as the previous models, while the other factor is the cost of silicon. Using the silicon as another factor lets the model explain the influence of both factors on the module cost.

The results of this models are showed in Table 4.3. The LR of the capacity is 17.8%, a positive number. This result means that the costs of the modules are reduced due to the installation of solar PV modules. The result is coherent with the other models and with the expected result. This LR is lower than the rate from the average models of PV (which is 20%) because the silicon cost reduction is decoupled from the "learning by doing". The LR of the silicon cost is a negative number, -22.2%, which also makes sense, meaning that as the silicon costs increase, the costs of the module also increase, and the rate by which the costs increase is a 22.2% for doubling the costs of the silicon. The plane obtained with the regression model with two factors comes from the expression of (4.5), where:

$\alpha = 1.698$
$\beta_{Cap} = -0.283$
$\beta_{Si} = 0.289$

Notice that both $betas$ are nearly the same. The relationship between them gives the percentage of cost explained by each of the two factors.

Factor	β	**Coefficient**	**% of Cost explained**
Capacity	β_{Cap}	0.283	49.44%
Silicon Cost	β_{Si}	0.289	50.56%

Table 4.3. Cost explanation in the Two Factor LC Model

These results show that both factors explained nearly the same percentage of the costs of solar modules. Substituting these coefficients in (4.5), the plane is obtained:

$$log(C) = 1.698 - 0.283 \cdot log(Q) + 0.289 \cdot log(C_{Si})$$

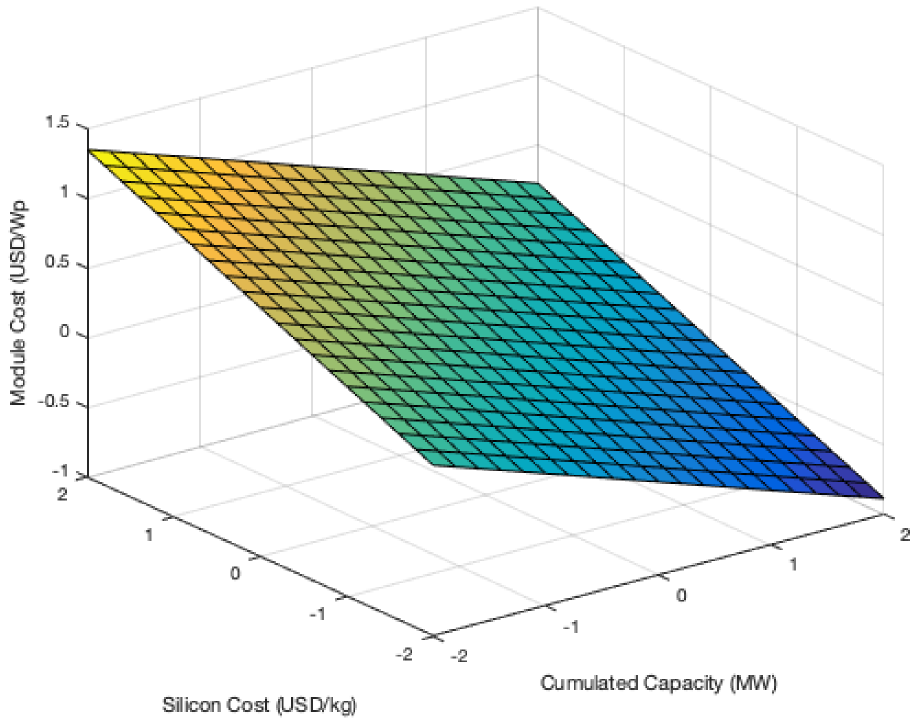

Figure 4.4. Two factor Learning Curve (Plane)

The regression plane can be represented through a 3D graph, with the two factors in the horizontal axis, as independent variables, and the module costs in the vertical axis, as the dependent variable. This plane is the learning curve, with two factors. It is important to notice that the numbers in the graph are in logarithmic form.

The results make sense, and back up the expected results: as capacity increases, module costs will decrease in a lower rate than in the conventional models, because of the decoupling of silicon costs, while module costs will increase as silicon cost increase. In addition, the model is well adjusted with an adjusted coefficient R2 of 0.93.

Finally, as done in the previous models, for a 1760 GW installed capacity (forecast for 2030), and leaving the silicon cost at its price of 2017, the solar PV module cost would be 0.45 USD/kg, according to this model.

5. Conclusions and Future Work

In this Section the main outcomes of the thesis are discussed, with respect to the methodology followed and the results obtained. As it is an open project, also possible future work is proposed to enhance the model an provide a better learning curve.

On the one hand, even though it is demonstrated that interest rates have some influence over the development of solar PV cost reduction, the analysis carried out couldn't proof that they could influence the pattern followed by solar PV industry in the XXI century, or at least that this influence was not strong enough to make solar modules follow a certain trend. On the other hand, the analysis on silicon costs gave clear evidence that this factor was determinant for the module costs, and that the shortage affected in a considerable way the development of this industry. The adaptation of the industry to solar-grade silicon was an important factor to consider.

In addition, the results of the models have given coherent results, and the efforts to improve the adjustment and calibration of the model have been successful. The first model, the OFLC model with one period gave coherent results, with a 20.9 % of LR (within the average of other solar PV Learning Curve studies). As silicon costs influenced the module costs and they fluctuated, the division of the time frame into three periods tried to isolate this fluctuation. Results have shown that the learning has improved in the third period over the first one (17% against 35%). This Learning Rate is much higher than the average learning rates of solar PV, and the rest of the LR of this thesis. This can be explained by the two sub periods that can be found: the first one, between 2011 and 2013, has a faster decrease in cost than the second one. There are factors that remain outside of the model, such as economies of scale in the manufacturing processes of solar PV modules, or subsidies granted in the Chinese market that influence a higher learning. It is also important to notice that, even though the cost of silicon does not decrease as fast as in the second period, in the transition between the second and third periods, there still is a slight decrease which could affect this high LR. Among the other factors, this influence of silicon cost reduction in the beginning of the third period could be critical. In fact, if the third period starts in 2013, the LR rate is reduced to 24.4%, a much more conservative LR, but not very reliable as is only supported by 4 years of data. The main conclusion of this second model is that, even though the model proved to be able to isolate the silicon fluctuation, the information that the second period could give was wasted, so a model with two factors has also been proposed.

This two-factor LC model tried to decouple the silicon costs over the installed capacity of solar PV modules, so that the module costs could be explained independently by both. The results have shown that the influence of both are nearly the same over the module costs, giving coherent results that proved that as capacity increases module costs are reduced, and as silicon costs increase, module costs increase too. A remarkable finding of this model is that the "learning by doing" rate of installed capacity was lower than in the previous models, and lower than the proposed LR by most studies (other studies have an average of 20 %), being 17.8%. This result means that the decoupling of silicon costs in this model has been successful, and that not all the cost reduction is due to learning.

To sum up, the results given by the different provide coherent Learning Rates, particularly the Two-factor model, that successfully decouples the fluctuating silicon costs. This model can be considered to be the most complete of the three models used. The study of the three models provides a full understanding of the development of the solar module industry in the last 20 years, and the critical influence of silicon in its cost reduction pattern. Thus, solar PV has a learning rate, but is lower than the usually proposed 20 %.

Finally, as a way to continue this analysis some future work can be proposed. A way to better understand the real influence of silicon costs could be to analyse if there has been a decrease in the quantity used of silicon per Wp, and to take into account the increased efficiency of the modules. These considerations could introduce modifications in the results obtained, and in the influence of silicon over module costs. Other important factor that should be analysed is the economies of scale, mentioned in the project, as the variable cost of manufacturing per Wp decreases. Finally, a more detailed study of support policies and Chinese subsidies to the industry is proposed, as its influence could be critical.

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A. Terminology

*	**Meaning**
OFLC	One factor learning curve
TFLC	Two factor learning curve
C	Module Cost
C_{Si}	Silicon Cost
Q	Cum. Installed capacity
α	Normalisation parameter
β	Learning parameter
β_{Cap}	Capacity learning parameter (TFLC)
β_{Si}	Si Cost learning parameter (TFLC)
λ	Cost share of a component
LR	Learning rate
EG-Si	Electronic grade silicon
SoG-Si	Solar grade Silicon
FiT	Feed in Tariff

Table A.1. Terminology

B. Regression Analysis

In this Section the regression analysis of the models used are presented:

OFLC with One Period

Resumen

Estadísticas de la regresión	
Coeficiente de correlación múltiple	0,896641
Coeficiente de determinación R^2	0,803964
R^2 ajustado	0,791712
Error típico	0,1561
Observaciones	18

ANÁLISIS DE VARIANZA

	Grados de libertad	*de cuadra*	*Promedio de los cuadrados*	*F*	*Valor crítico de F*
Regresión	1	1,598929	1,598929276	65,61782197	4,71459E-07
Residuos	16	0,389877	0,024367302		
Total	17	1,988806			

	Coeficientes	*Error típico*	*Estadístico t*	*Probabilidad*	*Inferior 95%*	*Superior 95%*	*nferior 95,0%*	*Superior 95,0%*
Intercepción	0,794277	0,064921	12,23445176	1,5537E-09	0,656650143	0,931904426	0,65665	0,931904426
Variable X 1	-0,339164	0,04187	-8,100482823	4,71459E-07	-0,427923261	-0,250404212	-0,427923	-0,250404212

Figure B.1. Regression Analysis for OFLC with one period

OFLC with Three Periods

Resumen

Estadísticas de la regresión	
Coeficiente de correlación múltiple	0,951576312
Coeficiente de determinación R^2	0,905497477
R^2 ajustado	0,873996636
Error típico	0,022391183
Observaciones	5

ANÁLISIS DE VARIANZA

	Grados de libertad	Suma de cuadrados	Promedio de los cuadrados	F	alor crítico de F
Regresión	1	0,014411832	0,014411832	28,745184	0,0126982
Residuos	3	0,001504095	0,000501365		
Total	4	0,015915927			

	Coeficientes	Error típico	Estadístico t	Probabilidad	Inferior 95%	Superior 95%	nferior 95,0%	uperior 95,0%
Intercepción	0,671060982	0,013356635	50,2417681	1,736E-05	0,6285542	0,7135678	0,6285542	0,7135678
Variable X 1	-0,268331627	0,050048298	-5,361453543	0,0126982	-0,4276076	-0,1090556	-0,4276076	-0,1090556

Figure B.2. Regression Analysis for OFLC with three periods: Period 1

Resumen

Estadísticas de la regresión	
Coeficiente de correlación múltiple	0,804491369
Coeficiente de determinación R^2	0,647206364
R^2 ajustado	0,576647636
Error típico	0,070919614
Observaciones	7

ANÁLISIS DE VARIANZA

	Grados de libertad	Suma de cuadrados	Promedio de los cuadrados	F	alor crítico de F
Regresión	1	0,046134388	0,046134388	9,1725912	0,0291271
Residuos	5	0,025147958	0,005029592		
Total	6	0,071282346			

	Coeficientes	Error típico	Estadístico t	Probabilidad	Inferior 95%	Superior 95%	nferior 95,0%	uperior 95,0%
Intercepción	0,795032585	0,083388237	9,53410948	0,0002148	0,5806763	1,0093889	0,5806763	1,0093889
Variable X 1	-0,200652224	0,066251842	-3,028628607	0,0291271	-0,370958	-0,0303464	-0,370958	-0,0303464

Figure B.3. Regression Analysis for OFLC with three periods: Period 2

Resumen

Estadísticas de la regresión	
Coeficiente de correlación múltiple	0,9637721
Coeficiente de determinación R^2	0,928856661
R^2 ajustado	0,911070827
Error típico	0,041272383
Observaciones	6

ANÁLISIS DE VARIANZA

	Grados de libertad	Suma de cuadrados	Promedio de los cuadrados	F	alor crítico de F
Regresión	1	0,088959745	0,088959745	52,22452	0,001945
Residuos	4	0,006813638	0,00170341		
Total	5	0,095773384			

	Coeficientes	Error típico	Estadístico t	Probabilidad	Inferior 95%	Superior 95%	nferior 95,0%	uperior 95,0%
Intercepción	1,333945393	0,197109087	6,767548946	0,002487	0,786683	1,881208	0,786683	1,881208
Variable X 1	-0,618437769	0,085577339	-7,226653373	0,001945	-0,856039	-0,380837	-0,856039	-0,380837

Figure B.4. Regression Analysis for OFLC with three periods: Period 3

Two Factor LC

Resumen

Estadísticas de la regresión	
Coeficiente c	0,96924696
Coeficiente c	0,93943966
R^2 ajustad	0,93136495
Error típico	0,08960758
Observacion	18

ANÁLISIS DE VARIANZA

	Grados de libert	*ra de cuadrad*	*lio de los cua*	*F*	*ılor crítico de F*
Regresión	2	1,86836334	0,93418167	116,343434	7,3521E-10
Residuos	15	0,12044277	0,00802952		
Total	17	1,98880611			

	Coeficientes	*Error típico*	*Estadístico t*	*Probabilidad*	*Inferior 95%*	*Superior 95%*	*nferior 95,0%*	*uperior 95,0%*
Intercepción	0,23003016	0,10429227	2,20562998	0,04342628	0,00773645	0,45232388	0,00773645	0,45232388
Variable X 1	-0,282934	0,02592093	-10,915275	1,5601E-08	-0,3381832	-0,2276849	-0,3381832	-0,2276849
Variable X 2	0,28933152	0,04994755	5,79270644	3,5479E-05	0,18287083	0,39579221	0,18287083	0,39579221

Figure B.5. Regression Analysis Two Factor LC