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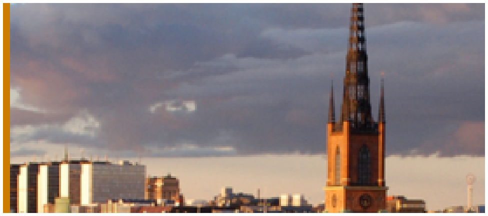

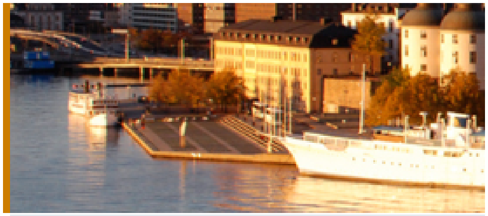

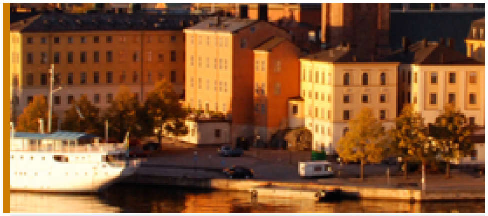

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Up-front investment costs of renewable energy technologies in a dynamic context

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Motivation and background information

Following the current trend of ambitious RES targets within the European Union as well as abroad, the design of the applied promotion schemes becomes continuously more important. In order to improve design criteria towards more effectiveness and efficiency in the recent past several studies have been published where conducted scenarios have been discussed in detail. A key parameter for such estimations, and in specific for the *Green-X* model which is applied here, is the future development of RET investment costs during the observed time period. Historically, the determination of investment costs has been derived endogenously based on a current level and technological improvements due to learning by doing. Recent observations have shown that investment costs of most RET have not strictly followed scientific expectations but some deviations are in context to other market situations. Therefore, Yu et al (2010) discusses crucial parameter of technological learning especially for the Photovoltaic technology. Principally, three different periods have been identified with respect to the historic PV module price development; see Figure 1.

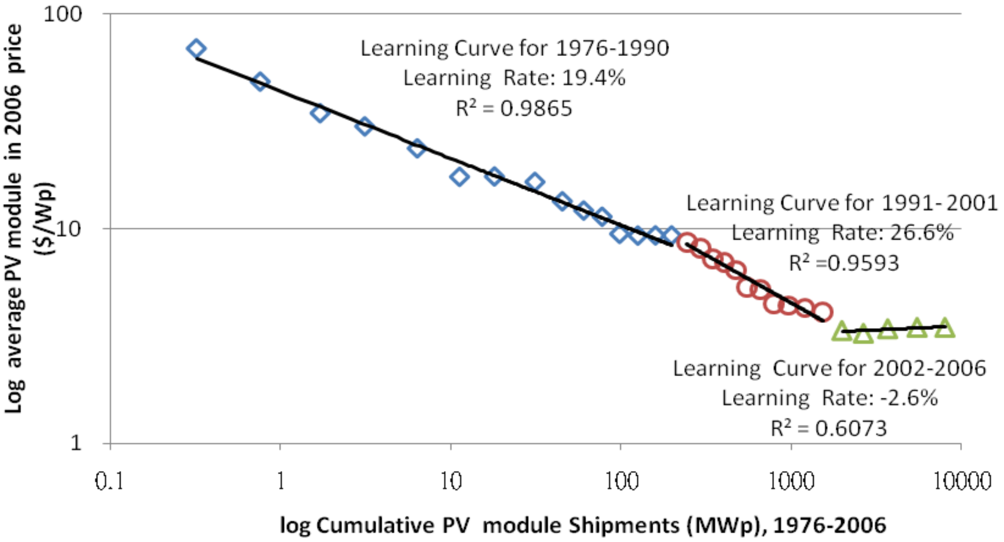

Figure 1 Technological learning rate for the Photovoltaic modules in the time period from 1976-2006 (Source: Yu et all, 2010)

As a consequence of above, the determination of learning curves is very sensitive to the observed time period on the one hand and to the starting point of observation on the other hand. According to the theory of technological learning based on cumulative production, only one learning rate exists for each technology. This point launches the motivation for further research in the estimation of future costs developments based on historic observation. Among others, Yu et al (2010) identified the impact of raw material and energy prices on energy technology costs in addition to technological learning. With respect to the example of Figure 1, relevant price decrease of silicon have been noted in the nineties whereas, due to several reasons, strong price increases of silicon are observed since 2004, leading to an overall increased Photovoltaic module price.

However, it is the task of this work to improve future investment cost estimations of RET within the *Green-X* model. Since this model only focuses on the energy sector, in particular the renewable energy sector, other parameter than energy related ones cannot be considered although they hold an important impact on investment costs as well. In this respect, market power of manufactures is not considered in the dynamic future cost estimations for RET presented below. This issue raises the topic of costs versus prices of raw materials which are representing the main materials of RET. On the one hand raw material costs are mostly not available and on the other hand their future development is difficult to estimate. Consequently, *Green-X* endogenously derives raw material prices based on the future development of energy prices. This approach then allows for shaping more efficient and effective support schemes for future RET investments within the model.

Methodology

This paper addresses the impact of raw material prices on investment costs of renewable energy technologies. In particular, future scenarios are conducted based on empiric evidence of correlations between raw material prices and RET investment costs.

General concept:

The **general concept** to assess the impact of energy and raw material prices on investment costs of RES technologies comprises the following steps:

- **Identification of the correlation between energy and raw material prices:** The impact of energy prices on raw material prices needs to be identified in order to calculate raw material costs in dependence of energy prices but neglecting market impacts that usually define the raw material prices.
- **Data adjustment:** In order to explicitly separate the effect of technological progress and raw material price impacts a data adjustment of historic data on investment costs for RES technologies appears necessary for the subsequent econometric assessment.
- **Econometric assessment:** Based on above an econometric assessment can be conducted whereby the impact factor of dynamic raw material price changes on RES technology investment costs will be derived
- **Impact assessment:** As a final step, a quantitative assessment of the impact of energy / raw material prices on the future development of investment costs for RES technologies can be conducted.

Thus, following the concept sketched above, we start in the subsequent section with the discussion of the correlation between energy prices and raw material prices / costs. In order to allow a serious future raw material price development accompanied by the fact that a modeling of raw material prices is beyond the scope of the applied model *Green-X*, only the energy price related drivers of raw material prices are considered. In this context, the raw material cost data of this study, rather refer to the production cost of raw materials than to their market prices. Therefore, other drivers such as market demand as well as political (fiscal) interests or transport issues are neglected. Thus, in the following section we talk about raw material costs.

Generally, only the steel-, concrete- and silicon price are considered in this study, whereas their future development was calibrate within the model based on empiric data. Consequently, the data gathering process of both, raw material prices and energy prices was of key importance for the overall project result. Furthermore, regression analyses are conducted depicting the relation between material and energy price as well as future expectation of different trends are considered. However, with respect to future energy price, as driver for the endogenously calculated raw material prices, exogenous assumptions are taken into account, see NTUA, 2010. More precisely, the crude oil, natural gas and coal price is taken from PRIMES, whereas the electricity wholesale price an endogenous result of *Green-X* linked to the crude oil, natural gas and coal prices.

First, the steel price development is envisaged. Below, Eq(1) describes this relation in mathematical formulas, whereas p_{coal} represents the relative coal price and c_{steel} the relative steel costs.

$$\begin{aligned} \forall p_{coal} \leq 1.575 &\Rightarrow c_{steel} = 0.5567 * e^{0.86 * p_{coal}} \\ \forall p_{coal} > 1.575 &\Rightarrow c_{steel} = 1.5811 * \ln(p_{coal}) + 1.4308 \end{aligned} \qquad \text{Eq(1)}$$

Generally, regardless the steel making process, coking coal is the largest contributor in steel production. However, with respect to prices coke price increased significantly in 2009 due to production shortages when coal price decreased already again. Since this paper focuses on commodity costs – neglecting such events as described for coke, the coal price is more convenient for deriving a relation between energy prices and the steel costs. Moreover, a constant increase of the steel costs with increasing coal prices is according to experts unlikely due to production type changes and associated material input changes.

Next, silicon is addressed, whereas the main energy driver is electric power. In contrast to the steel price it is not only the electricity price but also the electricity consumption which drives the cost of silicon. Hereby energy consumption in silicon production decreased significantly in early years of the observation period, starting in 1976 and electricity prices only increased slightly. However, until the early 2000 years silicon for the Photovoltaic industry was only a waste product of the silicon production of the electronic industry. With increasing demand of Photovoltaic modules new silicon production facilities were required and a different grade of silicon was developed – the solar grade[1]. Generally, silicon prices followed their production costs with some exceptions, as in 2004 when prices increased strongly due to a high demand and too less silicon production sites.

$$\begin{aligned} \forall p_{energy} < 0.224 &\Rightarrow c_{silicon} = 0.8538 * p_{energy} + 0.18 \\ \forall p_{energy} \geq 0.224 &\Rightarrow c_{silicon} = 0.3553 * \ln(p_{energy}) + 0.903 \end{aligned} \qquad \text{Eq(2)}$$

The formula Eq(2) describes the relation between the energy costs p_{energy} for silicon production to the related silicon costs $c_{silicon}$, according to the approach of this study where no other

[1] Before only electronic grade silicon was used, showing a higher degree of purity and is therefore characterized by a higher electricity consumption in production.

than energy related drivers for commodity costs are considered. However, the introduction of the logarithmic function in formula Eq (2) of the energy costs indicate some qualitative saturation of the silicon price with increasing energy costs due to other impact factors, as i.e. a decreasing demand of silicon with increasing energy costs.

Finally, concrete prices influence investment costs of RET to some extent, whereas especially cement production, as a very energy intensive process, bridges the relation to energy costs. Generally, cement production is characterized by high energy consumption, especially high process heat demand. Depending on the site, this energy is provided by coke or biomass energy and eventually also natural gas. In this study, biomass energy prices and coke prices are considered as drivers of the endogenously calculated concrete costs.

Depending on historic biomass energy prices (forestry products) and coke prices, concrete costs are derived according to the formula Eq(3) wherein $c_{concrete}$ represents the costs of concrete, p_{coke} the coke price and $p_{biomass}$ the biomass energy price.

$$c_{concrete} = 29.845 + 0.255 * p_{coke} + 0.453 * p_{biomass} \qquad \text{Eq(3)}$$

Although, historic biomass energy prices and coke price showed similar trends in this time period, whereby in absolute terms coke price increased much stronger, the combination of this two parameter results in a much better fit than when only considering one of the two energy prices for the regression analysis.

Modeling the impact of the commodity costs, discussed above, on RET requires a new approach of estimating future cost developments of RET. In this context, the multi factor learning curve has been implemented with basically two factors, the impact the commodity costs (steel, silicon and concrete costs) as well as technological learning based on cumulative production. Depending on the specific energy technology the most important materials are considered in the model, according to Eq(4).

$$c(x_t) = c(x_0) \cdot \left(\frac{x_t}{x_0} \right)^{-b} \cdot \prod \left(\frac{CP_0}{CP_t} \right)^{LCP} \qquad \text{Eq(4)}$$

In Eq(4) the product of the first two terms represents a certain cost reduction based on technological learning b with each doubling of cumulative installations x_t/x_0 and the last term indicates the positive or negative impact LCP of raw material prices on RET investment costs, depending on the raw material price C_{P0}/C_{Pt}. Since this approach only pursues to measure the impact of commodity costs, having a high share of the total investment costs, other materials as copper, glass of aluminum are neglected in this study[2]. In this context it might be argued that an overestimation of the impact of considered raw material price on RET investment costs will be achieved. However, due to the fact, that for the future development of raw material prices only the energy price driven part of the raw material prices – the raw material costs – are taken into account, an overestimation is avoided. Especially, because raw material costs represent the minimum future price development[3] of the single commodity and there-

[2] However, since aluminum and copper production are also energy intensive processes it is unlikely that these costs would impact RET investment costs differently than steel, silicon or concrete prices.

[3] This approach assumes that no manufacture will sell its produced commodity below its production costs.

fore the here calculated impact of a commodity on RET investment cost is at least as strong as presented. Other studies (Yu et al, 2010) introduced an extra term, modeling the impact of the sum of other parameters. However, this study only focused to prove the historic development and consequently determined the other commodities as the difference between the impact of selected commodities plus the learning effect to the real historic observation. Therefore, this approach does not allow future forecasts up to 2030 and hence is not suitable for this study.

In order to determine the impact factor LCP of commodity costs on RET investment costs, a regression model is established and calibrated according to historic observations. Hence, the outcomes only reflect the impact of the commodity costs and technological learning effects, but do not necessarily meet the real historic investment costs due to facts of neglecting other, market driven price effects as mentioned above. Consequently the given energy price forecasts enforce that the impact factor LCP in Eq(4) holds a negative sign in every moment.

However, this paper builds on constant, exogenous technological learning rates which are derived from historic observations of RET investment costs or refer to the existing *Green-X* database. Allowing for defining exogenous – not regression based – technological learning rates of RET requires to select a time period where no other influence than technological learning took place. Such a time period was between 1975 and 2003 - see Figure 2, when the CEPC Index (Chemical Engineering Plant Cost Index)[4] developed in the same range as the steel price. Such an exogenous definition of the learning rate[5] is also necessary in this study since not all required data is available for each technology from its initial introduction to the energy market.

Moreover, the regression analysis – for identifying the impact factor LCP - is applied to historic commodity prices and the investment costs of RET[6] which needs to be corrected for the technological learning rate in prior. This learning correction is a necessary precondition in order to determine the pure impact factor, LCP, of the commodity prices on RET investment costs without taking into account other technological improvements of the various RET in the selected time period.

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[4] Originally, the CEPC Index represents the historic development of costs in the chemical engineering sector which, however, in most components are similar to the power sector and therefore the CEPCI is a suitable parameter for this study.

[5] Since a technological learning rate is defined for the period of introducing a new technology until the current date and it cannot change over time. Therefore, the period of determination of a learning rate must be very long and additionally it is very sensitive to the starting point.

[6] Commodity prices as well as RET investment costs, are considered in Euro 2006 values.

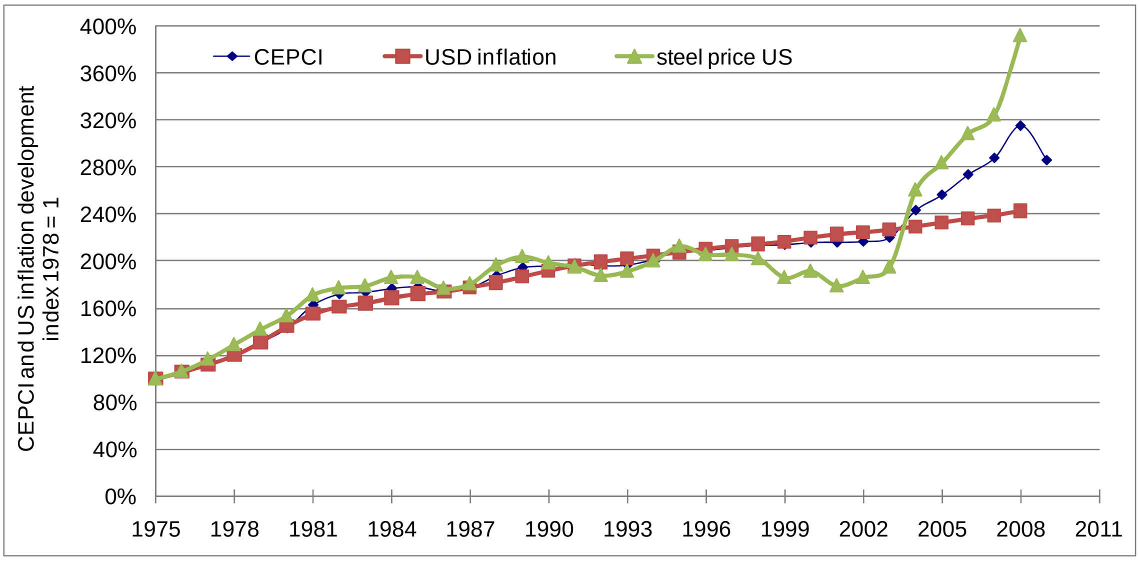

Figure 2 Historic development of the CEPC index (Chemical Engineering Plant Cost Index), ths US inflaction and the steel price in nominal terms from 1975 to 2009

Figure 2 depicts that in the period from 1975 to 2003 hardly any influence of commodity prices was noticed on engineering components. Therefore, on the one hand this confirms that exogenous technological learning rates are appropriate to be assumed and the technological learning effect can be defined outside the regression analysis. On the other hand, it approves that a pure correction for technological learning of RET investment costs in this period is appropriate as data preparation for the regression analysis identifying the LCP factor. In order to sum up the details for this study: conducting a multi regression analysis for determining both - the commodity price impact and technological learning rate for this selected period - endogenously would return the same result for the learning rate as when exogenously defined. But, since technological learning rates are constant over time, they can be defined independently from the regression analysis. Furthermore, RET investment costs are corrected for this learning effects for the time period of volatile commodity prices and hence the pure impact factor, LCP, of each commodity can be defined. Thus, Figure 2 in combination with feed note 5 confirms that from 1975 to 2003 a technological learning rate can be defined without considering raw material prices, and the impact of raw material prices can be derived from the learning corrected RET investment cost in the period beyond 2003. Combining these two impact parameters in Eq(4) allows estimating RET investment costs.

Econometric assessment:

Next, the regression analyses for the selected RET are in depth discussed. First, Figure 3 indicates the model regression curve of the relation between the relative wind investment costs compared to the relative steel costs. Additionally, the historic relation between wind onshore investment costs and the steel price in the period 1999 to 2009 is depicted.

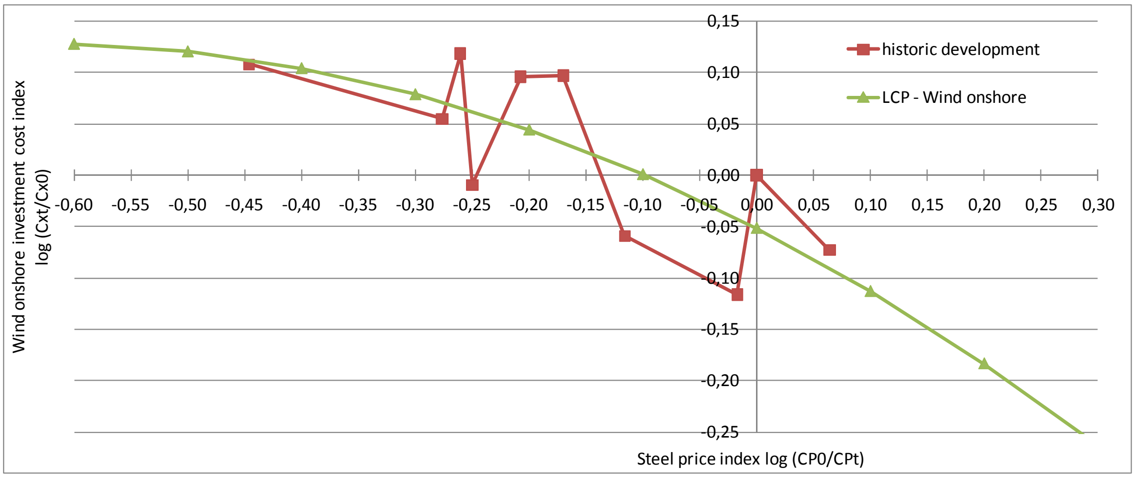

Figure 3 Impact factor LCP for the steel price impact on wind onshore investment costs as well as historic observations between 1999 and 2009

In the recent past, most records are noticed at negative $\log\left(\frac{CP0}{CPt}\right)$ (x-axis), caused by an almost constant increase of the steel price in this time period. Again, a plausible relation between steel costs and wind investment cost developments results in a negative sign for the logarithmic change of the steel price and in a positive sign for the relative wind investment costs, and vice versa. A detailed look at the regression curve points out, that increasing steel price only increases the wind investment costs to a certain extent, whereas decreasing steel prices have a stronger impact on wind investment costs. This can be explained that in times of high steel prices different kinds of steel alloys are used or even some material substitutions of different components take place. In mathematical formulas the impact factor, $LCP_{WI\text{-}ON}$, of the steel costs on wind onshore investment costs is described according to formula Eq(5):

$$LCP_{WI-ON} = \frac{\log\left(\frac{INV_{WI-ON(t)}}{INV_{WI-ON(0)}}\right)}{\log\left(\frac{c_{steel(0)}}{c_{steel(t)}}\right)} \qquad \text{Eq(5)}$$

In the formula Eq(5) $INV_{WI\text{-}ON(t)}$ represents the investment cost of wind onshore technologies at the current time whereas $IN_{I\text{-}ON(0)}$ indicates the investment cost at the beginning of the research. The same notification is applied for the steel costs c_{steel}. With respect to the investment costs of the current time (t), they are in prior corrected for the technological learning effect as explained above.

In contrast, a slightly different situation appears for wind offshore energy. Principally, this study assumes that no other major differences compared to wind onshore exist than, the type of foundation and the offshore grid infrastructure inclusive transformer platform. Therefore, investment costs of wind offshore energy technology are divided into two components, one representing the wind onshore turbine and one with the mentioned extra installations regarding wind offshore. However, modeling the impact of commodity costs on the extra component of wind offshore turbines requires extending the approach to two commodity costs, steel costs and concrete costs. Consequently, the same methodology as discussed above is applied, but in order to determine the impact factor $LCP_{WI\text{-}OFF}$, the regression analysis is extended to two parameter regression[7]. This results in two impact parameters, one for steel LCP_{steel} and one for concrete $LCP_{Concrete}$, plus an additional constant term. Therefore, the cumulated impact of the two commodity costs on wind offshore investment costs without considering technological learning is explained by formula Eq(6):

$$c_{WI-OFF} = 64.405 * \left(\frac{c_{steel(0)}}{c_{steel(t)}}\right)^{-0.179} * \left(\frac{c_{concrete(0)}}{c_{concrete(t)}}\right)^{0.277} \quad \text{Eq(6)}$$

In order to calculated the overall development of wind onshore investment costs, formula Eq(6) needs to be inserted into the last term of formula Eq(4). However, in formula Eq(6) $C_{WI\text{-}OFF}$ represents the extra component costs of wind offshore compared to wind onshore technologies without taking into account the technological learning effects. The constant term only results of the multi parameter regression analysis. The overall wind offshore technology costs can be derived by combining Eq(6) and Eq(4) plus adding the component costs of the calculated wind onshore investment costs for the specific years. Generally, the impact of steel costs is much stronger than from concrete costs.

A similar approach as for wind onshore technology is applied for the Photovoltaic technology. According to Schumacher et al (2010) the most important raw material is silicon, whereas others as glass, aluminum or steel play only a minor role. Since Photovoltaic is a more novel technology than wind technologies, the data preparation for the regression analysis, especially the correction for historic learning effects is key. Additionally, high silicon prices were noticed in 2004 and beyond[8], which distort the determination of the impact parameter $LCP_{silicon}$ to certain extent.

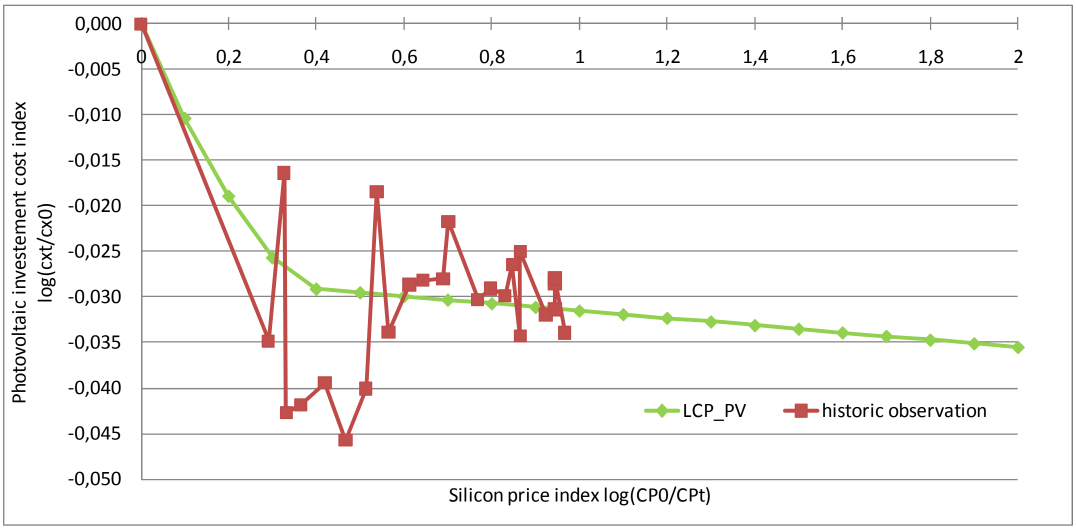

Figure 4 Impact factor LCP for the silicon price impact on Photovoltais investment costs as well as historic observations between 1976 and 2007

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[7] The regression analysis is conducted with Excel, which requires linearizing the parameters before running the regression, wherefore a logarithmic function is used.

[8] Due to a tremendous increase of demand of silicon accompanied by production shortages. Until 2004 silicon supply for the PV industry was covered by waste products from the electronic industry.

Above, Figure 4 depicts the relation between the relation between the relative development Photovoltaic investment costs depending on the relative development of the silicon costs in logarithmic scale. Additionally, the historic evidence Photovoltaic investment cost depending on silicon prices is illustrated. Some bigger deviations appeared in history due to above mentioned effect of strong difference between silicon costs and prices. However, the impact factor $LCP_{silicon}$ holds a negative sign in every moment, meaning a positive correlation between the silicon costs and the Photovoltaic investment costs. This interpretation is also apparent form the mathematical relation, presented in Eq(7):

$$LCP_{SILICON} = \frac{\log(\frac{INV_{PV(t)}}{INV_{PV(0)}})}{\log(\frac{c_{silicon(0)}}{c_{silicon(t)}})} \qquad \text{Eq(7)}$$

Since the regression is calibrated by data of a long time period, early relations between investment costs and silicon prices are considered as well as more recent relations. In this context it is obvious that with decreasing Photovoltaic investment costs, the influence of silicon costs decreases caused by a more efficient usage of the raw material – see Figure 4. Finally, inserting the impact factor $LCP_{silicon}$ from Eq(7) into the formula Eq(4) delivers the future investment costs of Photovoltaic.

In order to complete the depiction of the different methodological approaches of the some RET, biomass energy is addressed here as well. Principally, Schumacher et al (2010) concluded that independent from the type of biomass plants, steel and concrete prices hold the most significant impact on their investment costs. This fact requires a multi parameter regression analysis, as presented for wind offshore energy, whereas the mathematical relation of the small-scale biomass investment costs is presented in Eq(8):

$$c_{BM} = 0.3321 * (\frac{c_{steel(0)}}{c_{steel(t)}})^{0.353} * (\frac{c_{concrete(0)}}{c_{concrete(t)}})^{0.485} \qquad \text{Eq(8)}$$

The same notification as explained above is used here, whereas c_{BM} represents the investment costs of Biomass energy, influenced by the concrete and steel price, but without the consideration of technological learning – which is anyhow limited in the advanced biomass technology sector. With respect to Eq(8) it will be noticed, that the regression analysis delivers only a badly satisfactorily results, since data is very limited on historic small-scale biomass energy investment costs. Moreover, hardly any data is available with respect to medium and large scale plants. Even though only limited historic data points are available, the regression of Eq(8) allows to estimate the trend of the impact of volatile energy prices on RET investment costs. Nevertheless, several research still needs to be undertaken to firstly improve the regression analysis of the different biomass technologies and secondly the future predictions of concrete costs depending on energy prices need to be further improved as well.

Results new methodology

First, results with respect to the endogenously derived commodity costs, only reflecting the net impact of energy prices on the commodity prices, are discussed. Therefore, historic as well as future projections of steel-, silicon and concrete costs are discussed.

Based on the historic analysis presented above, future projections of the commodity costs until 2030 are derived. In this context, energy price developments refer to the PRIMES reference scenarios of 2010, NTUA (2010). Furthermore, electricity wholesale prices are derived under consideration of the energy prices and the related energy demand of the above mentioned scenarios (NTUA, 2010). These projections are depicted in Figure 5 below.

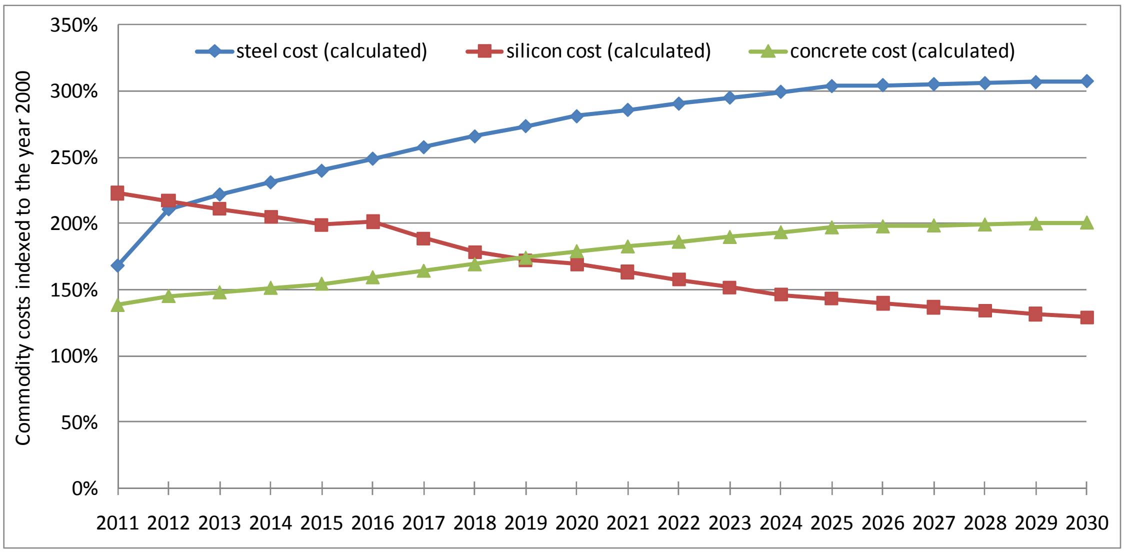

Figure 5 Future projections of the steel-, silicon and concrete costs according to energy prices forecasts of the PRIMES reference scenario, NTUA 2010 expressed in index of 2000 values

With respect to the steel price projections in Figure 5 a stronger increase is expected within the coming years, which declines in the later years. On the one hand it is expected that with increasing energy, especially coal, prices more efficient production processes will be developed and therefore the impact of energy prices on steel costs will decline. On the other hand, the impact of coal prices on steel costs will decrease due to material substitutions in terms of switching towards more novel production processes (i.e. from BOF to EAF).

In contrast, concrete costs will continuously increase until 2030 and only level off close to 2030 due to some efficiency improvements. Again, the development of concrete costs, driven by the energy input price for cement production, is very sensitive to the location of the production site. Hence, cement production supplied by coke heat might affect concrete costs stronger than cement production supplied by biomass energy.

Finally, silicon costs are expected to decrease again leading to values before the silicon demand increase occurred, as Figure 5 depicts. On the one hand the shift from electronic grade to silicon grade silicon is now ongoing, and this trend will be continued resulting in less electricity consumption of silicon producers. On the other hand, also the production of silicon grade silicon still offers a high energy efficiency potential. Apparently, the trend of less energy consumption is partly compensated by increasing electricity prices, based on the assumed energy prices.

However, applying the multifactor learning approach to RET considers both, the technological learning effect of each RET as well as its impact of the main raw material prices. First, according to the approach discussed above, future projections for wind onshore technology until the year 2030 are derived and presented in Figure 6. Obviously the impact of steel price explains the historic observation of wind onshore investment costs to a major part since technological learning effects are compensated and investment costs even increase in between.

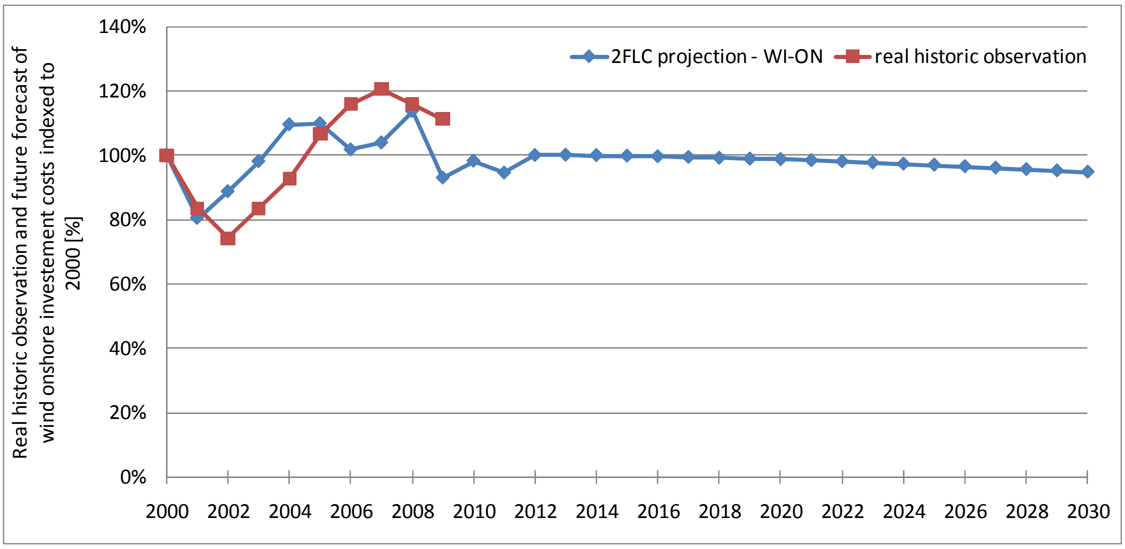

Figure 6 Wind onshore investment costs based on the mutli factor learning approach and historic evidence indexed to the year 2000 (in constant EUR) for the time period 2000 to 2030

Important to note is, that in Figure 6 historic wind onshore investments are compared to future predications based on steel cost impacts. Therefore, calculations cannot meet the historic observations totally but they show the same trend. With respect to future predictions, a rather constant development is calculated caused by the exogenous scenarios[9] of energy prices. In relation to wind onshore investment cost of the year 2000, costs declined in the beginning of the decade but increased shortly afterwards due to increased steel costs/prices which peaked between 2006 and 2008. Since 2008 a decrease of investment costs due to reduced raw energy prices, caused by the economic crisis etc is noticed. Within the period 2010 to 2030 a rather constant development of wind onshore investment costs is predicted when steel costs almost compensate the effect of technological learning. Generally, a constant learning rate of seven percent with each doubling of capacity is considered over the total time. Due to the impact of steel costs, an overall cost reduction in 2030 compared to 2000 is achieved of about 5.23 percent, equaling a learning rate of the standard one factor learning curve of LR=1.2 percent.

Next, wind offshore is discussed. In contrast to wind onshore energy, not only steel costs influence the investment costs but also concrete costs, caused by the extra investments for foundation and the offshore infrastructure. Therefore, investment cost projections of wind offshore build on above presented results of wind onshore with an additional term modeling the extra investments of wind offshore according to formula Eq(6).

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[9] Since these scenarios are conducted on a yearly basis until 2030, no intermediate volatilities caused by exogenous events (i.e. economic crisis, production shortages, etc.) can be considered

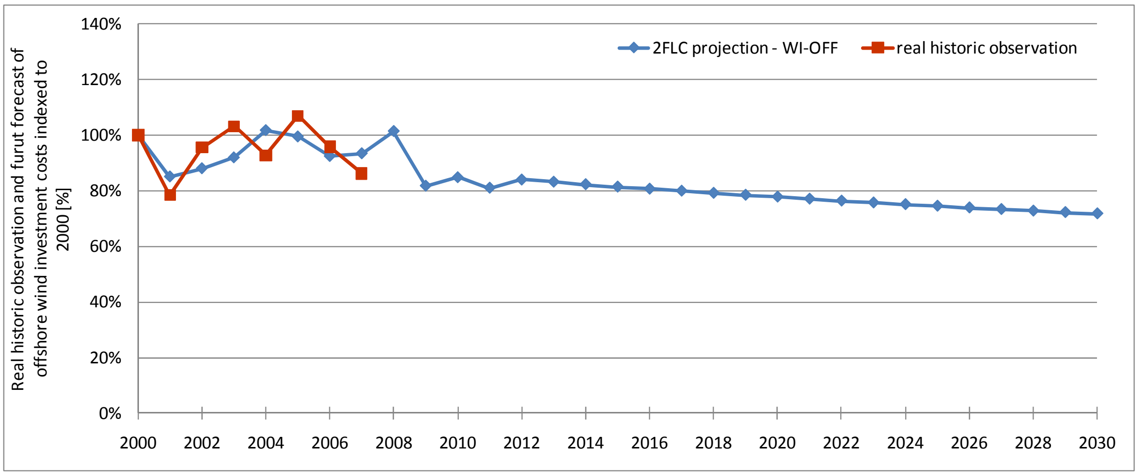

Figure 7 Wind offshore investment costs based on the mutli factor learning approach and historic evidence indexed to the year 2000 (in constant EUR) for the time period 2000 to 2030

Figure 7 above presents the future expectations of wind offshore costs, taking into account technological learning as well as the impact of steel and concrete costs. Additionally, the historic evidence for the period 2000 to 2007 is depicted. Comparing Figure 6 to Figure 7 depicts that wind offshore costs are less sensitive to steel costs since their additional investment costs are stronger influenced by concrete costs, which have been more constant throughout the last decade. Generally, derived projections of wind offshore investment costs follow historic observation to a high degree. However, as already indicated above, future expectations show less volatility than projections for the past decade due to the assumed, less volatile energy prices in the future. Nevertheless, since wind offshore potentials are so far less exploited than wind onshore potentials, the technological learning effect is only partly compensated by the impact of raw material costs. Hence, assuming a learning rate of nine percent for the extra investment of wind offshore technologies, an overall cost reduction of 28.3% between 2000 and 2030 can be achieved[10].

In contrast to the wind energy technologies, Photovoltaic investment costs are negatively impacted by commodity costs, especially silicon costs. Thus, considering silicon costs in addition to technological learning even reduces future investment costs of Photovoltaic modules. The overall projection of future Photovoltaic investment costs, according to formulas Eq(4) and Eq(7) is illustrated in Figure 8.

10 With respect to the definition of a one factor learning approach, this would result at an overall learning rate of 1.2%, as for wind offshore. However, since wind offshore is less exploited so far, technological learning effects are stronger influencing the overall result, as depicted in this paper.

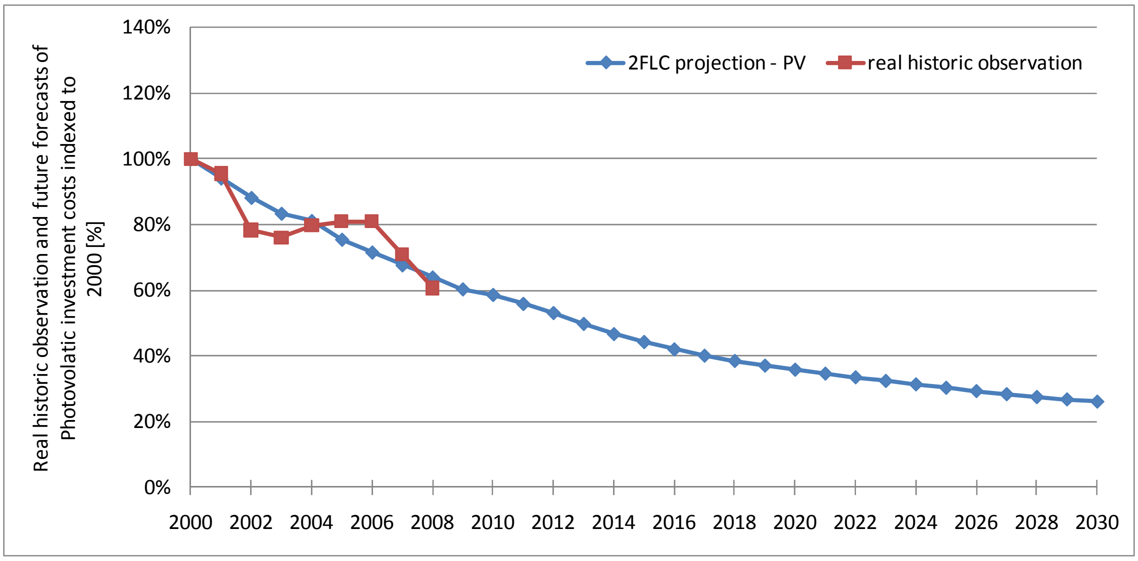

Figure 8 Photovoltaic investment costs based on the mutli factor learning approach and historic evidence indexed to the year 2000 (in constant EUR) for the time period 2000 to 2030

As already indicated for other technologies above, Figure 8 compares real historic Photovoltaic investments to projections of Photovoltaic investment costs based on technological learning and silicon costs[11]. However, as silicon costs and price showed volatile trends in the last decade this volatility is also notable in the projection of Photovoltaic investment costs. Nevertheless, this impact of silicon costs is only weak compared to the influence of technological learning of this technology. Since, it is a rather new technology learning effects are still strong, caused by a high learning rate of 16% and the fast growing market with fast doublings of installations. As Figure 5 indicates, silicon costs are expected to decrease, Photovoltaic module investment costs will decline to about only 26 percent of the investment costs of the year 2000. This equals a technological learning rate with the ordinary, one factor learning curve approach of about 16.3%.

Finally, small scale solid biomass energy plants are addressed. With respect to biomass energy plants several different plant types exists and moreover a broad range of different scales is installed. Depending on the type and the scale of the plant, historic investments varied strongly. However, due to little data availability this paper only addresses small-scale, solid biomass plants[12]. Figure 9 depicts the results for the biomass sector.

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11 This aspect is especially crucial in the case of silicon costs versus silicon prices for the period between 2003 and 2008, when silicon price increased strongly due to market driven mechanism.

12 Please see therefore, below the suggested improvements for futher research of this topic.

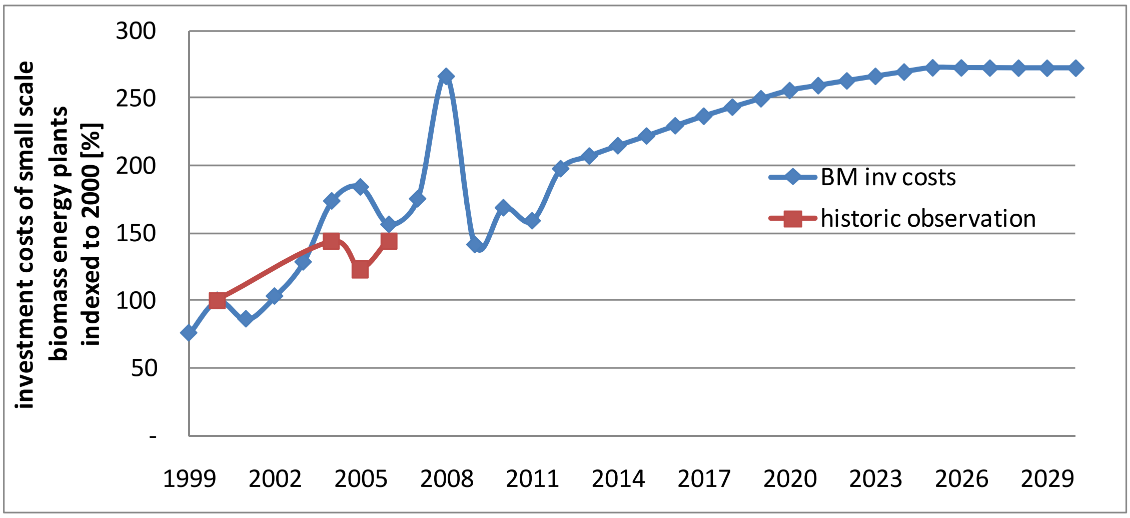

Figure 9 Small scale biomass plant investment costs based on the mutli factor learning approach and historic evidence indexed to the year 2000 (in constant EUR) for the time period 1999 to 2030

With respect to Figure 9, the historic trend of investment costs of small scale biomass plants can described with the applied methodology of this paper. However, in absolute terms still a high gap occur between historic observations and calculated investments. This fact is caused by poor data availability of concrete costs which hold the most significant impact on this technology. Generally, the biomass technologies are already a very advanced RET and consequently showing only minor effects of technological learning. Therefore, the technological learning hereby is totally compensated by the commodity cost impact. In this study a learning rate of 3.5% is assumed, but due to the already high exploited potential its impact is rather limited. Therefore the impact of commodity costs totally compensates the technological learning effect of small scale solid biomass energy plants.

Conclusions

In order to sum up this paper, some conclusions and recommendations are drawn here. In principle the multi factor learning curve approach allows to model RET investment costs more precisely and therefore also follows the historic observations. Moreover, concentrating on the impact of commodity costs rather than of commodity prices on RET investment costs prevent to overestimate the influence of commodities. In contrast, neglecting market mechanisms with respect to commodity prices represents a simplified modeling approach and does not reflect real developments. Generally, identifying commodity costs is very sensitive to the input data and therefore the data collection is a crucial task of this work. In this respect, it must be noted that results presented here, refer to an ongoing process of research and will be constantly further improved. On the one hand, statistical test need to be conducted in order to prove the robustness of the identified regression models and on the other hand especially concrete prices and costs as well as biomass energy investment costs need to be updated. The latter need to be divided into more different clusters, either sorted by scale or by type. However, results have shown the importance of considering next to technological learning also commodity costs, but the preparation of input data is of key importance.

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