DISSERTATION

Investment costs of renewable energy technologies under consideration of volatile raw material prices

ausgeführt zum Zwecke der Erlangung des akademischen Grades eines Doktors der technischen Wissenschaften

begutachtet von

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Abstract

The global commitment towards a more sustainable future energy supply portfolio yields several new technical, economical and political challenges. Thus, understanding the drivers of energy technology investment costs is of key importance for an ambitious future renewable energy supply mix. In particular, energy and raw material prices as well as technological learning by doing effects hold fundamental impact on the energy technology investment costs. Therefore, adopted methodological approaches in energy models are required.

The theoretical literature of dynamic energy technology investment cost modeling focuses in general exclusively on technological learning by doing effects. Thereby, the historical investment cost development is explained by a constant decrease with each doubling of cumulative installations. More recent literature raises the question on a certain bias of the learning by doing effect caused by other exogenous effects. In this context, the impact of energy and raw material prices is revealed.

Consequently, the core objective of this thesis is to identify the impact of energy and raw material prices on the investment costs of energy technologies. Thus, the key drivers in terms of primary energy prices of most relevant raw material prices are quantified based on empirical evidence within econometric models. Hence, the simultaneous impact of these raw material prices and technological learning effects on energy technology investment costs is identified in econometric models, too. This allows modeling the endogenous feedback from energy prices to the investment cost of energy generation technologies being responsible for future energy prices.

Results depict a significant impact of coal and natural gas prices on steel and concrete prices. Silicon prices are largely depending on expenditures for electricity consumption. However, an important contribution of wind onshore investment costs is explained by steel prices, whereas offshore wind investment costs are additionally affected by concrete prices. Steel and concrete prices show an even slightly stronger impact on small-scale biomass CHP investment costs. In contrast, the silicon price holds a marginal impact on Photovoltaic investment costs only. Similar results are derived for small-scale hydro power investment costs, where energy and raw material prices do not explain their development significantly. In general, technological learning by doing effects are largely compensated by the impact of raw material prices in the case of wind and small-scale biomass CHP technologies.

In terms of electricity generation costs, the strong impact of energy and raw material prices on biomass CHP investment costs is partly compensated by the fuel costs. However, due to the technological similarity of biomass and coal fired CHP plants, conclusions highlight that even in times of increasing energy prices, wind energy generation costs can drop below conventional generation costs and Photovoltaic generation costs result in only slightly higher levels in 2030.

Kurzfassung

Das globale Bekenntnis zu einem zukünftigen, nachhaltigen Energieversorgungsmix bringt einige technische, wirtschaftliche und politische Herausforderungen mit sich. Folglich ist die Identifikation von Einflussfaktoren auf Investitionskosten der Energieerzeugungstechnologien von zentraler Bedeutung. Im speziellen üben Energie- und Rohstoffpreise als auch technologische Lerneffekte einen fundamentalen Einfluss auf deren Investitionskosten aus. Daher sind Energiemodelle auf erweiterte methodische Ansätze angewiesen.

Die theoretische Literatur der dynamischen Modellierung der Investitionskosten von Energieerzeugungstechnologien fokussiert nahezu ausschließlich auf technologische Lerneffekte. Darin ist die historische Entwicklung der Investitionskosten durch eine konstante Kostensenkung mit jeder Verdopplung der kumuliert installierten Leistung erklärt. Jüngere Literatur erhebt die Frage nach einer bestimmten Verzerrung des Lerneffekts, bedingt durch andere exogene Einflüsse. In diesem Zusammenhang wird der Einfluss von Energie- und Rohstoffpreisen aufgeworfen.

Folglich ist die Kernaufgabe dieser Arbeit die Identifizierung des Einflusses von Energie- und Rohstoffpreisen auf die Investitionskosten von Energieerzeugungstechnologien. Die Haupteinflussfaktoren im Hinblick auf Primärenergiepreise der relevanten Rohstoffpreise werden basierend auf empirischen Analysen mit Hilfe von ökonometrischen Modellen quantifiziert. Des Weiteren werden die Einflussfaktoren dieser Rohstoffpreise als auch die simultanen Effekte des technologischen Lernens auf die Investitionskosten der Energieerzeugungstechnologien analysiert. Das erlaubt eine endogene Modellierung der Einflüsse von Energiepreisen auf die Investitionskosten zukünftiger Energieerzeuger.

Ergebnisse zeigen einen signifikanten Einfluss von Kohle- und Gaspreisen auf Stahl- und Betonpreise. Siliziumpreise hängen stark von den Bezugskosten des Elektrizitätsverbrauchs ab. In Bezug auf onshore Windkraftanlagen zeigen Investitionskosten starke Abhängigkeit vom Stahlpreis wobei Investitionskosten von offshore Windkraftanlagen zusätzlich vom Betonpreis beeinflusst werden. Stahl- und Betonpreise zeigen sogar einen noch stärkeren Einfluss auf Investitionskosten von biomassebefeuerten Kraftwärmekopplungsanlagen. Im Gegensatz dazu zeigen Siliziumpreise nahezu keinen Einfluss auf Investitionskosten von Photovoltaik. Gleichermaßen sind Investitionskosten von Kleinwasserkraftwerken nicht durch Energie- und Rohstoffpreise erklärbar. Im Fall von Wind- und KWK-Investitionskosten werden technologische Lerneffekte durch steigende Energie- und Rohstoffpreise kompensiert.

In Bezug auf Stromgestehungskosten werden die starken Energie- und Rohstoffpreiseinflüsse auf biomassebefeuerte KWK Investitionskosten teilweise durch die Brennstoffpreise kompensiert. Die technologische Ähnlichkeit von biomasse- und kohlebefeuerten KWK-Anlagen erlaubt Rückschlüsse, dass auch in Zeiten steigender Energiepreise die Stromgestehungskosten von Windkraftanlagen unter das Niveau von konventionellen Anlagen fallen werden. Stromgestehungskosten von Photovoltaik werden im Jahr 2030 nur unwesentlich darüber liegen.

Executive Summary

Motivation

The future development of energy technology investment costs is fundamental input information to energy simulation models. On the one hand, investment decisions are based on scenario calculations and, on the other hand, policy support schemes are determined in consequence of technology investment costs. The standard approach of dynamic investment cost modeling takes into account technological learning by doing curves. A constant decline of investment costs with each doubling of cumulative installed capacity is considered for each technology.

However, in recent past several additional exogenous impacts on energy technology investment costs have been observed. Besides economies of scale or learning by searching effects based on cumulative R&D expenditures, commodity price impacts are of even more significant relevance. In this respect, the pure impact of primary energy prices as well as steel, concrete and silicon prices on the investment costs of renewable electricity generation technologies is of crucial importance. Furthermore, the dynamic interaction between the commodity prices and the investment costs gives an indication on the sensitivity of specific energy technology investment costs on volatile energy and raw material prices. Especially, this volatile character of energy and raw material prices requires considering their impact on technology investment costs in energy models. Thus, accompanying technological learning by doing effects and energy and raw material price impacts in the assessment of energy technology investment cost determinations allows for a precise forecast of their future development.

Research objective

This thesis analyzes an endogenous feedback from energy prices, forming the market where renewable energy technologies must compete, to the investment cost of renewable energy technologies. In particular the following questions are addressed:

1. Which commodity prices are of key relevance for the investment costs of the selected energy technologies?
2. What are the main drivers of the identified commodity prices in terms of primary energy sources?
3. What is the quantitative relation between primary energy prices and commodity prices?
4. What is the quantitative relation between these commodity prices and energy technology investment costs?
5. What effect does learning by doing have on the investment cost in quantitative terms?
6. Are there any coherencies from renewable to conventional energy investment costs?
7. How robust are energy technology investment costs against energy price volatility?
8. What are the implications of the results derived for the electricity market?

Method of approach

First, econometric analyses quantify the impact of primary energy prices on the development of steel, concrete and silicon prices. This assessment is based on historical data taking into account the effect of costs versus prices as well as other impact parameters like economic growth. In a next step, technological learning by doing rates are defined based on existing literature. This assessment of learning by doing rates is carried out in a time period when no impact of energy and raw material prices on energy technology investment costs has been identified in real units.

Building on a constant learning rate allows deriving the pure impact of commodity prices on investment costs of energy technologies. Econometric models explain the commodity price impact by considering growth rates, logarithmic values and time lagged impacts. Furthermore, applying the multi factor impact approach estimates the investment cost development by taking into account the technological learning effect and the impact of energy and raw material prices. Finally, future scenarios are derived based on these models, assuming no major technological changes in the production process of these energy generation technologies.

Theory

The first scientific publication in this field discussed the labor cost decrease of airplane frame productions (Wright, 1936). In particular, a constant cost decrease was quantified with each doubling of cumulative output. Later, the Boston Consulting Group (BCG, 1968) extended the approach to more parameters whereas the expression experience curve was introduced. More recent literature argues for a certain bias of learning by doing effects solely based on cumulative production (Nordhaus, 2008). Therefore, several research studies have been published in the context of learning by searching where costs decline by a constant percentage with cumulative R&D expenditures (Miketa et al, 2004; Berglund et al, 2006; Kouvaritakis et al, 2000 or Klassen et al, 2005). Moreover, aspects of national versus global learning (Lindmann et al, 2011) and the distortion due to different financial support schemes in the learning progress (Söderholm et al, 2003) are taken into account in scientific studies. Finally, the impact of energy and raw material prices become a key criterion in modeling the dynamic investment cost development of energy technologies (Nemet, 2006; Yu et al, 2010 and Panzer, 2012).

The impact of primary energy prices

First, with respect to steel making processes different approaches are implemented whereas the ordinary Basic Oxygen Furnace still represents the largest share. However, this process relies to about 74 percent on coal and coking coal inputs. Therefore, the steel price development in Figure 1 is modeled as a function of coal prices. In particular, the coal price growth rate impact indicates the high share of coal products in steel production. In contrast the impact of the coal price growth rate of the previous year represents the coal price impact on coke production used in steel-making processes. However, major impact of delayed coal prices occur due to the fact that high volumes of coal are traded on long term contracts.

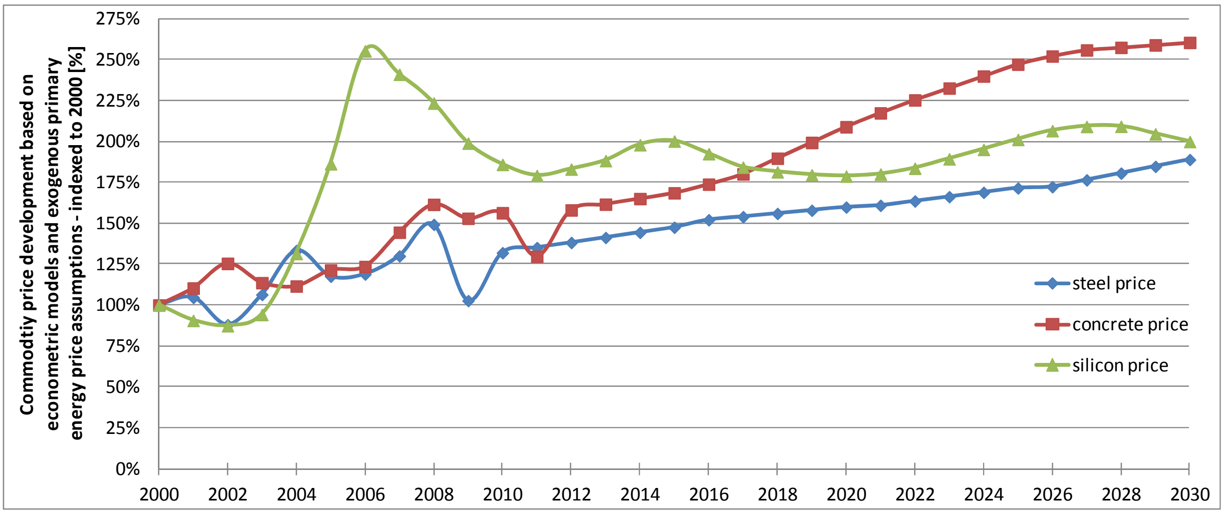

Figure 1 Comparison of steel, concrete and silicon price development in the historical context and future prospects derived from econometric models concentrating on the primary energy price development. Source: Own calculation.

Next, the concrete price development is dominated by the cement price which is strongly impacted by coal, coking coal and natural gas prices. The direct impact of the coal price reflects energy use for heat production in clinker burning. Additionally, the time lagged impact of the coal price results from the pre-preparation of coking coal where coal plays a determining role. With respect to the gas price, highest impacts are identified for two year time lagged prices. On the one hand, high volumes of gas are traded on long term contracts and, on the other hand, small on-site storages facilities lag the impact of gas prices in addition.

Finally, the silicon price development is considered. In contrast to other raw materials, in the case of silicon prices not only the electricity price development but also the related electricity consumption had strong impacts on the historical development. Therefore, the silicon price is depending on the electricity expenditures, the product of electricity price and consumption, of the same year as well as of the previous year. The feedback of the previous year implies that technology development is a discrete development and consequently different silicon production facilities with different energy consumption characteristics have an impact on the silicon price.

Generally, the volatile character of the commodity prices, depicted in Figure 1, is explained in full detail by energy prices. However, future estimations are based on exogenous energy price assumptions (Capros et al, 2011). Additionally, technological changes in the production of these commodities might partly distort the derived relation between energy and commodity prices.

Energy technology investment costs – drivers and impacts

In order to explain the dynamic development of energy technology investment costs a multi factor impact model has been applied, considering technological learning by doing effects as well as energy and raw material price impacts. Therefore, the major drivers of these investment costs in terms of raw material prices have been quantified in econometric models. Figure 2 depicts an overview of on- and offshore wind energy, Photovoltaic and biomass CHP investment costs from the years 2000 to 2030. On the one hand, the impact of raw material price characterizes the volatility observed in the recent past. On the other hand, different technological learning effects partly compensate increasing investment cost effects.

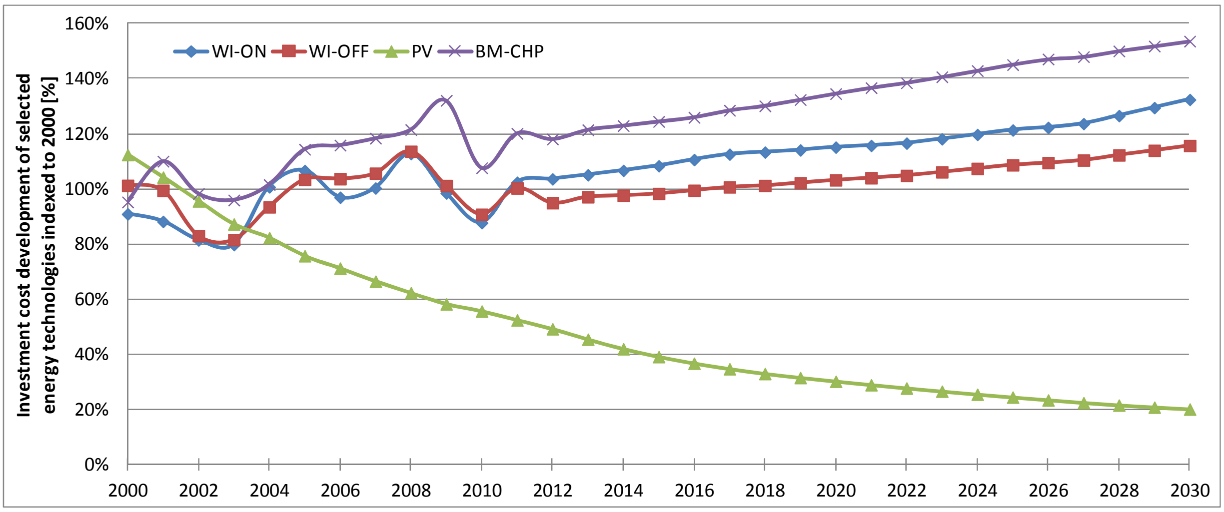

Figure 2 Depiction of on- and offshore wind, Photovoltaic and biomass CHP investment costs based on econometric models taking into account the commodity prices. Illustrated in the time period up to 2030 in relative units indexed to the year 2000. Source: Own calculations.

In terms of wind onshore investment costs, about 42 percent up to 58 percent, depending on the scale of the wind energy turbine, are caused by steel inputs. On the one hand, a direct impact of current steel prices is identified in the model. On the other hand, also a direct impact of the previous year's steel price is recognized. The time lagged impact occurs from long term contracts of steel supply for wind technology manufactures but also the long time period of admission procedures is responsible for the delayed impact. However, Figure 2 depicts that the technological learning effect will be completely compensated by the impact of steel prices. Consequently, wind onshore investment costs will, according to this scenario, increase by about 25 percent until 2030 compared to nowadays (2011).

In contrast, offshore wind technology is from a technological viewpoint very similar to onshore wind energy converters. However, the foundation of offshore wind energy converters differs significantly from onshore technologies. Consequently, the focus is put on the dynamic development of investment costs of the additional equipment of offshore wind energy plants.

Previous research highlighted an impact of commodity prices of 45 to 55 percent in terms of investment costs. Generally, a direct impact of the steel price is identified whereas the concrete price influences the investment costs one year delayed. Among others, this issue is caused by the fact that wind offshore installations usually require a longer planning and admission procedure. Therefore, one year delayed concrete prices are taken into account in actual installations but steel price are mostly considered in real times. Similar to the onshore technology, forecasts of investment costs are expected to increase by about 16 percent compared to nowadays (2011) and, therefore, totally compensate technological learning effects.

Next, Photovoltaic investment costs are addressed. This thesis concentrates on investment costs of crystalline silicon installations. Therein, silicon prices are responsible for about 13 to 27 percent of the total investment costs of Photovoltaic installations. Thus, a direct impact of silicon prices on the investment costs of Photovoltaic installations is identified, whereas an additionally delayed impact of the silicon price of three years ago has important influences too. Historically, silicon from the electronic industry has been used in the Photovoltaic industry and, therefore, no delay of the silicon supply for Photovoltaic production has occurred. In contrast, the production shortage of silicon in peak time of Photovoltaic demand reduced the actual silicon supply and enforced a delayed silicon price impact. In contrast to other energy technologies, the silicon price impact is very limited and the strong technological learning effect drives the Photovoltaic investment costs towards a 62 percent reduction in 2030 compared to nowadays (2011).

In the context of small-scale biomass CHP investment costs, an impact of steel and concrete prices on the overall investment costs is identified at about 20 percent on average. However, both commodity prices hold an one year delayed impact which is caused by the fact that the planning procedure mostly requires a longer time period. A constant term in the model represents the part of the investment costs being independent of energy and raw material prices. Generally, a slightly lower quality of the investment cost estimation is achieved than for above discussed technologies. This issue is caused by the site-specific requirements on CHP technologies. Nevertheless, biomass CHP investment costs show only a moderate learning by doing effect and, therefore, are expected to increase significantly. However, the investment costs reflect only one part of the relevant electricity generation costs on the market.

Finally, small-scale hydro power investment costs depend only to each five percent on steel- and concrete costs. Moreover, detailed analyzes have resulted in very insignificant contributions of raw material prices at the estimation of hydropower investment costs. With respect to the two modeling approaches, neither the technological learning theory nor the multi factor impact approach result in a precise estimation of small-scale hydropower investment costs. Thus, only investment costs of similar site characteristics can be taken into account for estimating their future development. Furthermore, it is sufficient to apply the ordinary technological learning methodology since hydropower investment cost show a strong robustness against commodity price volatility. Therefore, energy and raw material prices do not provide additional information to the model.

Conclusions

This thesis considers renewable energy technologies for electricity production which generally show electricity generation costs above current market prices. On the one hand, increasing energy prices might lower the gap between market prices and renewable electricity generation costs. On the other hand, increasing energy prices impact the selected energy investment costs differently and, therefore, might distort the merit order of the energy technologies. In order to address the implications of the completed results for electricity markets, rough estimations of investment costs of conventional coal fired CHP plants are conducted.

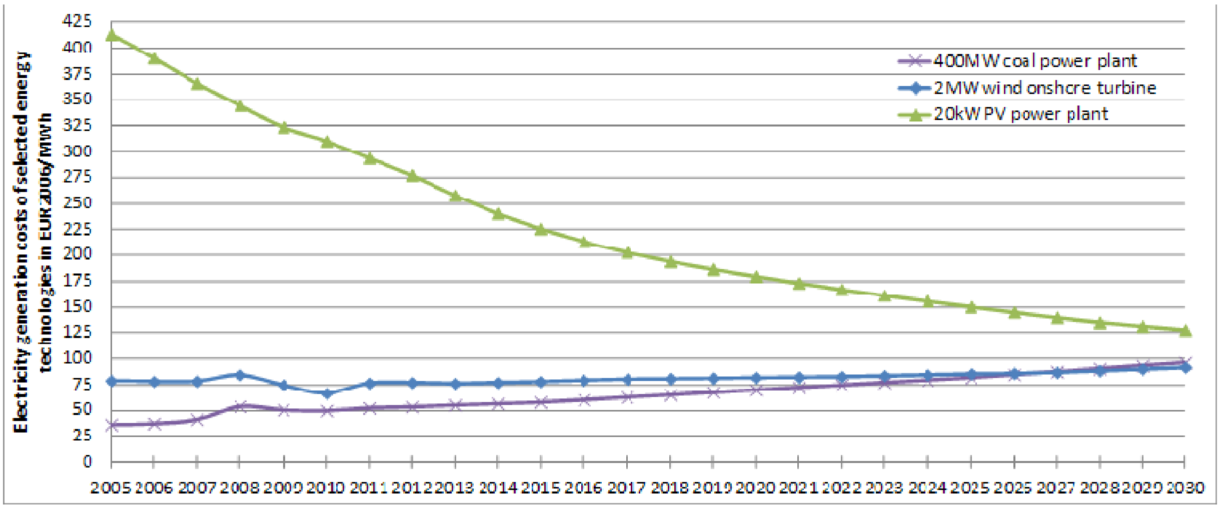

Figure 3 Levelized annual electricity generations costs in EUR2006/MWh, considering the impact of energy and raw material price on investment costs of selected energy technologies. Economic assumptions: (discount rate 6.5 percent, deprecation time 15 years (RES) respectively 30 years (coal) as well as CO2 prices (Capros et al, 2011). Source: Own calculation

Figure 3 indicates significantly increasing coal power electricity generation costs up to the year 2030. This increase is driven by 50 percent of raising fuel prices, 30 percent CO2 price increases and the rest is caused by investment cost increases. With respect to the year 2008, the peak of the energy and raw material price impact is significantly noticed with a relaxing period beyond. Moreover, wind onshore electricity generation costs show an almost constant development until 2015 with slight fluctuations in the period 2008 to 2011. According to this scenario, in the year 2025 wind onshore generation costs reach the breakeven point to coal fired electricity generation costs. In contrast, Photovoltaic electricity generation costs are expected to decrease in same magnitude as historically observed until 2020. The scenario result shows that grid parity of Photovoltaic installations is achieved around the year 2017 but their generation costs will not decline to the level of conventional plants until 2030.

Recommendations and outlook

Generally, the derived methodology results in a very supportive approach at the estimation of energy technology investment costs. However, specific technological characteristics control the quality of the analyses significantly. Nevertheless, on the one hand, estimations of selected energy technology investment costs have been derived for the recent historical development. In this context, the volatile character of historical investment costs is very precisely described by the derived models. In particular, good approximations are achieved in the case of wind and Photovoltaic energy investment costs, whereas for solid biomass CHP investment costs only moderately acceptable results are achieved. In the case of small-scale hydropower investment costs, no significant impact of energy and raw material prices has been identified. On the other hand, future scenarios are calculated by the model, quantifying potential future pathways of the investment costs depending on energy price assumptions up to the year 2030.

However, the multi factor impact modeling approach enables a discussion on the implications of raising primary energy prices in future. Thus, the modeling approach quantifies the feedback from energy prices to the investment costs of energy technologies. However, additional results indicate that raising energy prices increase investment costs and therefore also their electricity generation costs. Moreover, investment costs of, in terms of capacity, more mature (renewable) energy technologies are stronger impacted by energy and raw material prices than technologies at a currently moderate market share. Thus, technologies like Photovoltaic benefit from a more robust character against increasing energy prices.

In the context of financial support schemes of renewable energy generation hardly any consideration of increasing investment costs caused by raising energy and raw material prices has been observed so far. Nevertheless, a general link of financial support schemes to the growth rates of energy and raw material prices appears inadequate. Results have shown that a potential overcompensation of generation costs for some energy technologies would be the consequence of such a direct link. However, considering the development of annual electricity generation cost changes, caused by energy and raw material price, in adjustments of support levels is a key criterion for an efficient but sufficient future support of renewable energy sources. Furthermore, especially in the early stage of a technology development a high support of R&D activities increases the learning effects. Moreover, based on the results of this thesis, strong learning effects dominate over energy and raw material price impacts. Consequently, technology investment costs become more robust against the energy price volatility.

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1 Introduction

Understanding the drivers of energy technology investment costs[1] is of key importance towards an ambitious future renewable energy portfolio. Thus, this thesis quantifies most relevant impacts of selected energy technology investment costs. First, this section highlights the motivation and background information of this research. Second, the core objective of the thesis is discussed with respect to its research questions, important side conditions and limitations. Third, the method of approach is presented in terms of the major tasks with respect to the research question. Finally, an overview of the structure of this thesis is pointed out.

1.1 Motivation

The global commitment towards a more sustainable future energy supply portfolio yields several new technical, economical and political challenges. Consequently, in the year 2009 the European Commission published the Directive 2009/28/EC (European Commission, 2009) aiming for a 20 percent renewable energy target in the year 2020. In this context, fundamental contribution is expected from renewable energy sources in general and renewable electricity in particular (IEA, 2011). However, nowadays only a small share of renewable electricity generation already competes on international electricity markets whereas the rest is still incentivized by financial support schemes. Nevertheless, these implemented support schemes of renewable energy technologies must be strengthened towards more efficiency and effectiveness in order to meet the policy target by the year 2020. This is a necessary precondition in order to guarantee an enhanced future renewable energy development at moderate consumer expenditures, incentivizing this development.

Thus, necessary information for the design of efficient support options provides a precise forecast tool of future investment costs of renewable energy technologies. Main drivers of these investment costs must be identified and incorporated into energy models. Therefore, models deriving a future pathway of energy technology investment costs require new, additional methodological approaches. With respect to the status quo, most energy models solely consider investment cost decreases caused by technological improvements, the learning by doing effect. The broad variety of known methodological approaches allows taking into account several important drivers and, therefore, deriving more precise estimations.

Recent market observations have shown that not solely technological learning by doing effects influence energy technology investment costs but volatile energy and raw material prices hold an even more significant impact (Chupka et al, 2007). Of high relevance in this respect is the pure

[1] The expression “investment cost” refers to the monetary expenditures an investor has to bear for the installation of the technology.

impact of primary energy prices as well as steel, concrete and silicon prices on the investment costs of renewable electricity generation technologies. Furthermore, the dynamic interaction between the different impact parameters provides an indication of the sensitivity of specific energy technology investment costs in case of volatile energy and raw material prices.

1.2 Core objective

This thesis analyses the dynamic development of (renewable) energy technology investment costs. Specifically, it assesses their key drivers in a historical and future context. Thus, the impact of technological learning and volatile energy and raw material prices is quantified. In particular, the following research questions are addressed in detail:

1. Which commodity prices are of key relevance for the investment costs of the selected energy technologies?
2. What are the main drivers of the identified commodity prices in terms of primary energy sources?
3. What is the quantitative relation between primary energy prices and commodity prices?
4. What is the quantitative relation between these commodity prices and energy technology investment costs?
5. What effect does learning by doing have on the investment cost in quantitative terms?
6. Are there any coherencies from renewable to conventional energy investment costs?
7. How robust are energy technology investment costs against energy price volatility?
8. What are the implications of the derived results for the electricity market?

Hence, an endogenous feedback from energy prices, forming the market where renewable energy technologies must compete, to the investment cost of renewable energy technologies is modeled within this thesis.

1.3 Method of approach

The general concept to assess the impact of energy and raw material prices on investment costs of energy technologies basically comprises four steps. First, the identification of the correlation between energy and raw material prices is carried out. This allows deriving future raw material prices as a function of energy prices. Second, the historical investment cost data is adjusted in order to explicitly separate the effect of technological learning and raw material price impacts. This adjustment of historical data on investment costs for energy technologies is carried out according to theory defined in literature. Third, an econometric assessment is conducted, wherein the impact of dynamic raw material price changes on the energy technology investment costs is determined. This assessment takes into account the simultaneous impact of several commodity prices as well as their growth rates or time delayed impacts. Finally, an impact assessment of energy and raw material price influences on the future development of investment costs for selected energy technologies is conducted. Consequently, sensitivities of the selected energy technology investment costs with respect to energy price changes are discussed. Moreover, implications of the derived results for the electricity markets are addressed in detail, too.

Furthermore it is important to note that, on the one hand, R&D knowledge, economies of scale[2] and market price effects hold an impact on energy technology investment costs, too. On the other hand, apart from energy supply technologies commodity prices additionally influence energy infrastructure investment costs. Nevertheless, these impacts are beyond the scope of this thesis and provide input for future research. Therefore, this thesis solely focuses on the impact of technological learning by doing effects as well as energy and raw material price impacts on energy technology investment costs.

1.4 Structure

This thesis is organized as follows:

Chapter 2 gives a review of existing literature. Therefore, the historical and future perspectives of renewable electricity generation are addressed. Moreover, energy modeling approaches are discussed in general and renewable energy modeling in particular. Thereby, special emphasis is given to the technological learning by doing approach. Consequently, the state of the art of technological learning rates is depicted in detail. Finally, investment costs of selected (renewable) energy technologies are in the focus of an in-depth assessment, concentrating on its main drivers in the context of primary energy and raw material prices.

Next, **chapter 3** discusses the methodological approach of this thesis. In a first step, the principal interaction between energy prices, commodity prices and renewable energy technology investment costs is addressed. Especially highlight is the multi-factor modeling approach of this dynamic interaction. A theoretical discourse of econometric analysis is given in the following subchapter, depicting elementary rules of linear regression models as well as statistical background information. Finally, the boundary of this research is discussed, highlighting methodological challenges and exogenous assumptions.

In **chapter 4** the historical development of energy and raw material prices as well as investment costs is discussed in detail, focusing on their main drivers. Additional emphasis is put on the impact of economic growth on the development of raw material prices. An in-depth analysis on the impact of prices versus costs of renewable energy technologies is carried out, enabling correct interpretations of the following research.

[2] In this context, economies of scale explicitly refer to up-scaling of single energy technology installations.

On the one hand, **chapter 5** elaborates on different raw material production processes and their major energy inputs. On the other hand, the impact of primary energy prices on raw material prices is quantified according to econometric models. In this respect, the results are discussed and interpreted in the mathematical context whereas the focus is put on the energy context. Finally, future scenarios on raw material price developments are derived and debated. However, supporting argumentation for the importance of the isolated consideration of energy price impacts on raw material price developments is presented. Scenarios focus on the steel price, concrete price and silicon price development until the year 2030.

Chapter 6 focuses on a detailed assessment of energy technology investment costs highlighting their main impact parameters. Special emphasis is given to the quantification of raw material price influences as well as to the effect of learning by doing. Generally, renewable energy technologies are selected, whereas particularly wind onshore, wind offshore, Photovoltaic, Biomass Combined Heat and Power (CHP) as well as small-scale hydropower plant investment costs are considered. Hence, econometric models are developed explaining the historical development of investment costs and are used accordingly in order to derive future scenarios. Additionally, sensitivity analyses of energy price assumptions allow for drawing conclusions on the robustness of the different technology investment costs.

A comparison of the main characteristics identified in the historical context as well as their estimations in the future context is given in **chapter 7**. The investment cost development is discussed and the quality of the applied modeling approaches is compared. Moreover, the robustness respectively the sensitivity of the selected energy technology investment costs against volatile energy and raw material prices is depicted. Furthermore, the implications of the derived energy technology investment costs for the electricity market are taken into account. In this context, electricity generation costs of specific technologies are determined based on standard economic assumptions.

Finally, **chapter 8** draws conclusions from the key findings of the thesis. Consequently, an assessment of the methodological improvements as well as their limitations is discussed. Moreover, the implications of the developed modeling approach for renewable energy technology investment costs forecasts are addressed. Furthermore, a technical outlook as well as a political outlook opens a qualitative discussion on future developments. Eventually, still open questions are raised.

2 Status quo – Review of existing literature

This thesis builds on the status quo of energy modeling. Consequently, a review of existing literature is given in this chapter. First, the historical and future perspectives of renewable electricity generation are addressed. Second, energy modeling approaches are discussed in general and renewable energy technologies modeling in particular. Special emphasis is thereby given to the technological learning by doing approach. The general theory as well as different aspects and concerns are compared. Furthermore, the state-of-the-art of technological learning rates is depicted in detail. Finally, investment costs of selected (renewable) energy technologies are in the focus of an in-depth assessment, concentrating on its main drivers in the context of primary energy and raw material prices.

2.1 Renewable electricity development – historical and future perspectives

Generally, historical renewable electricity generation in the European Union is dominated by large scale hydro power. However, this thesis solely focuses on renewable technologies with promising future perspectives. Therefore, large scale hydro power is not depicted in the following figures. Generally, the historical new renewable electricity development was incentivized by financial support schemes (Ragwitz et al, 2011). Moreover, strong regional differences among the European Member States occurred, showing a significant development in some Member States and hardly any deployment in others. Additionally, in terms of technological development a wide regional spread is observed between the Member States.

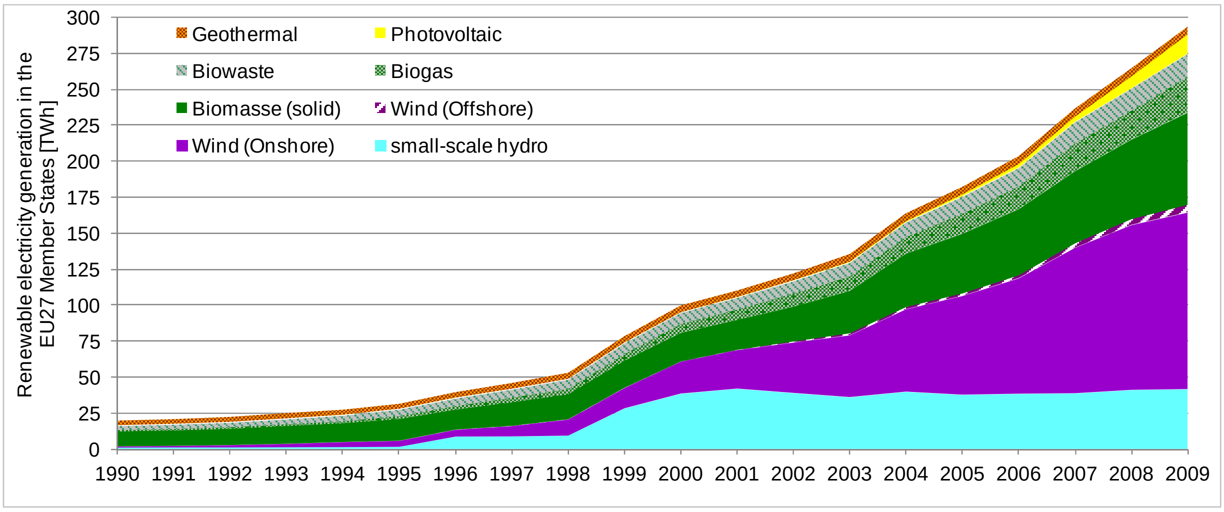

Figure 4 Historical development of renewable electricity generation of selected technologies (excluding large-scale hydropower) in the time period from 1990 to 2009; depicted in TWh. Source: (Eurostat, 2011b).

Figure 4 illustrates the historical renewable electricity development from year 1990 to 2009. In the early nineties, new renewable electricity generation was dominated by biomass fired power plants. Strong annual growth rates of small-scale hydropower and wind onshore plants launched a significant annual increase of renewables in the electricity sector until nowadays (Eurostat, 2011b). Within the last decade, the contribution of solid biomass energy increased significantly, whereas small-scale hydro power generation roughly stagnated. With respect to Photovoltaic electricity important growth rates are observed in the recent past. Nevertheless, currently (2009) wind onshore electricity represents the major share of new renewable electricity generation.

In the context of the future renewable electricity development a potential ambitious pathway depending on the relevant background assumptions (Panzer et al, 2009) is depicted in Figure 5. A strong development of onshore wind until the year 2030 is expected to continue. Major growth rates are foreseen for the wind offshore and solar energy technologies. Especially Photovoltaic will play an important role in 2030. Additionally, solid biomass, biowaste and biogas will largely contribute to an enhanced future renewable electricity generation. Electricity from solar thermal and tide and wave plants are expected to enter the market beyond 2015. Nevertheless, wind energy, on- and offshore, solar energy and bioenergy will be the largest contributors by 2030.

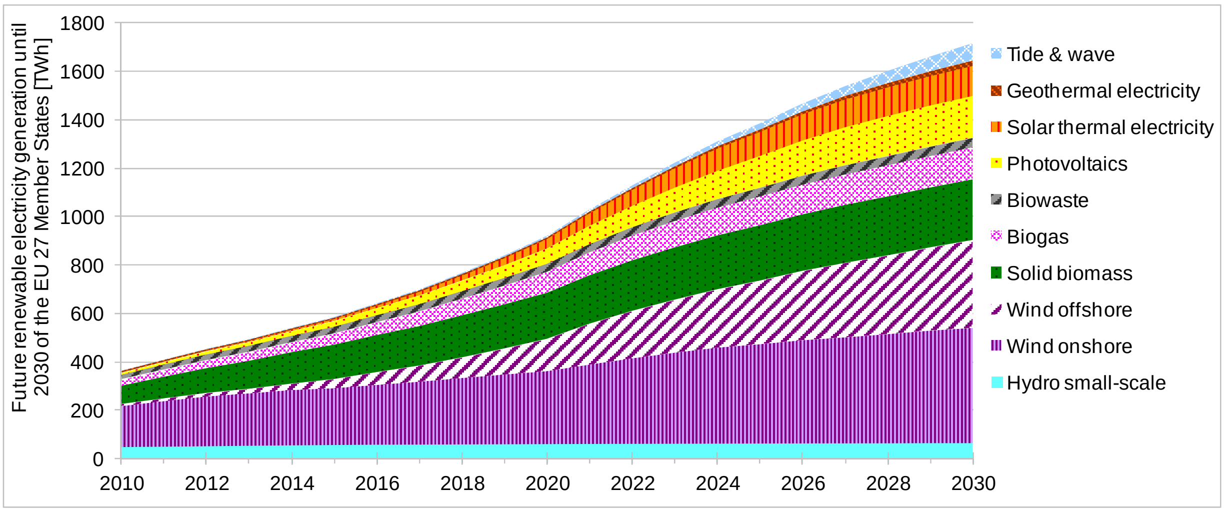

Figure 5 Ambitious future pathway of renewable electricity development in the EU27 Member States according to scenario assumptions (energy market prices, non-economic market barriers, conventional energy supply portfolio; depicted in TWh. Source: (Panzer et al, 2009).

Generally, the future development of renewable electricity generation is depending on many different aspects. Therefore, assumptions on policy measures, future demand projections, realizable future exploitation potentials or the conventional electricity generation portfolio have a strong impact on the derived scenarios. Thus, Figure 5 represents a potential pathway based on the assumed input parameters under the given scenario objective, achieving the RES Directive 2009/28/EC (European Commission 2009) in 2020. A broad set of future energy scenarios exist in literature (Resch et al, 2009; Panzer et al, 2009; IEA, 2008, IPCC, 2012, Capros et al, 2011). On the one hand, these scenarios are very different in their objective which needs to be taken into account in their interpretation. On the other hand, the considered technology disaggregation as well as the time frame and the geographical coverage vary significantly among them.

2.2 Energy modeling approaches

In the context of above, several different future energy scenarios exist in literature, whereas their specific characteristics need to be taken into account carefully at their interpretation. However, these characteristics require different modeling approaches. First of all, it is distinguished between prophetic, deductive and normative model types. Principally, prophetic scenarios object to answer the question "What will happen?" in a short term time frame. This type of scenarios assumes that the socio-economic structure as well as the technology will not change in the time scope of the scenario. Next, deductive scenarios allow for some changes in terms of the socio-economic structure as well as the technological change in the mid-term time frame. Therefore, the research objectives focus on the question "What will happen if?". Lastly in contrast, normative scenarios address the question "What needs to be happening for?". Consequently, normative scenarios have a long-term time frame wherein the socio-economic structure is not defined and technology evolution is able to be described (Weber, 2010).

Depending on the objective types of the energy scenario discussed, the scenario developing process and the system boundaries have to be determined. This identifies the applied participatory approaches as well as the regional aspect, the exogenous assumptions and the energy sector selection. Moreover, in this context an important issue is the general modeling methodology. On the one hand, econometric models (Greene, 2012) are often used as energy foresight tools, since they are very robust in the short term forecast due to their statistical calibration. Additionally, techno-economic models are applied for several simulation scenarios. This type of models is bottom-up oriented and structured in sub-models in order to give an aggregated final outcome. On the other hand, optimization models have been developed in order to illustrate future scenarios optimized to certain targets under pre-defined boundary conditions (Panzer et al, 2009b).

In order to cope with the objective of a specific energy scenario development a model is derived according to the above discussed attributes. However, scenarios lead to misinterpretations if a model is used for other than the original purposes[3] (Château, 2008). Consequently, assessing future energy scenarios requires the right selection of the methodological approach according to the scenario objective.

Moreover, in order to allowing deductive and normative models for precisely addressing their objective in a dynamic context, different theories are discussed in literature. Besides the general diffusion theory of technologies, more recently stochastic approaches are often taken into account in energy models. Additionally, the technological learning by doing theory is considered within several energy models. In this context, the general diffusion theory discusses the

[3] In this context, purposes mean either scenario objective, timeframe, regional coverage or the methodological approach.

penetration of technologies in competitive markets. This diffusion typically follows an S-curve pattern. In the initial phase of the technology deployment a modest market penetration is considered whereas in the following a faster market penetration is realized, caused by decreased costs due to technological improvements and market competiveness. Close to the full deployment of the technology the market penetration slows down again (Grübler et al, 1999). In contrast, the stochastic approach builds on a random combination of incidents in order to discuss the consequences for the objective of the energy scenario. Therein several potential input parameter combinations depict the range of scenario results. This type of scenarios is often used to address a future renewable energy development and its impact on the conventional energy market (Weber, 2010). Finally, technological learning effects are of crucial importance in dynamic energy models. Investment costs of energy technologies decrease over time by a certain but constant percentage with each doubling of cumulative installation. This implies the learning by doing effects in terms of improvement in production and installation of the energy technologies (McDonald et al, 2001). The next chapter is dedicated to discuss the technological learning theory in more detail.

2.3 Technological learning theory

The learning by doing effect addresses the technology cost reduction caused by substantial improvements of technology production and installation due to increased experience. The first scientific publications discussed the labor cost decrease of airplane frame productions (Wright, 1936). In particular, a constant cost decrease was quantified with each doubling of cumulative output. Furthermore, this identification was used to predict future airframe production costs. Later, the Boston Consulting Group (BCG, 1968) extended the approach to more parameters whereas the expression experience curve was introduced. The mathematical formulation of the constant cost decrease of a specific item with each doubling of its cumulative output is indicated in formula Eq. 1.

$$c(x_t) = c(x_0) * (\frac{x_t}{x_0})^{-m} \quad \text{Eq. 1}$$

$$LR = 1 - 2^m \quad \text{Eq. 2}$$

$c(x_t)$	Investment cost per unit in the year t
$c(x_0)$	Investment cost of the first unit
x_t	Cumulative installed capacity in the year t
x_0	Initial cumulative installed capacity in year 0
m	Learning by doing index
LR	Learning rate

Consequently, the investment costs of a technology in the year t is determined by the investment costs of the first unit and the technology development since the first unit has been installed with the power of the learning by doing index. The learning rate can be derived from the learning by doing index according to formula Eq. 2. This issue indicates the sensitive impact of the input data. Generally, difficulty occurs in the determination of the first unit, not representing the prototype and especially in quantifying the investment cost of the first unit. In this respect, another sensitive impact holds the consideration of module investment costs versus installation investment costs. The latter considers the learning effect of installation additionally whereas the first only takes into account production improvements. Moreover, a period of at least three powers of magnitude in cumulative production must be taken into account when deriving a learning curve. Thus, temporary strong or weak technology improvement developments are balanced. Additionally, the regional aspect of the technology development should be taken into account, if learning takes place on regional or global level. Finally, the impact of costs versus prices represents a crucial difference in estimating the learning rate.

In order to apply the technological learning by doing approach to models deriving future scenarios, an important matter is the constancy of the learning rate. A supporting argument of a constant learning rate is the fact that despite of a constant learning rate the learning effect decreases at a higher market penetration level due to a longer time period for doubling the cumulative output than in the initial phase. The stronger learning effect in the initial market phase of a new technology implies the higher potential of improvements of novel technologies (Junginger, 2011). Moreover, research directly impacts the investment costs most significantly in the initial market phase of a novel technology but is not related to cumulative production and therefore, does not change the learning by doing rate. A similar argumentation is found in literature (McDonald et al, 2001), although therein a specific market growth rate is required in order to guarantee the constant learning by doing rate.

Moreover, other parameters as R&D expenditures, economies of scale and raw material price impacts are not represented in cumulative production but do influence the investment costs additionally. A similar argumentation is given in literature (Nordhaus, 2008) that learning rates are generally upwards biased due to the consideration of different impacts in learning effects. Especially in energy models this becomes crucial when future investment decisions are taken based on overestimated learning effects. Nordhaus (2008) quantified the major difference when considering learning by doing effects and exogenous technological change impacts combined or separately in terms of correlation by only 0.009. Thus, a separate implementation of the different cost impacts allows energy models for a more precise forecast of the investment costs.

First, learning by searching is often taken into account in addition to learning by doing. Learning by searching addresses cost decreasing effects based on technological improvements caused by (public) R&D expenditures. These effects mostly dominate in the initial market phase. However, a constant learning index is assumed here, since R&D expenditures decline with increasing maturity of the technology and, therefore, lower the effect of learning by searching. Several researches have been published in the context of learning by searching (Miketa et al, 2004; Berglund et al, 2006; Kouvaritakis et al, 2000 or Klassen et al, 2005). In principal, a two factor learning curve approach has been applied in these studies, considering learning by doing and learning by searching simultaneously. On the one hand, Miketa et al. (2004) argue that R&D expenditures generally hold a significant impact on investment cost whereas Berglund et al. (2006) summarize that R&D expenditures have a time lagged impact. Moreover, historical R&D expenditures potentially depreciate over time and, therefore, lower its total impact.

In general, the adequate approach for the implementation of technological learning curves into energy models depends on many aspects. A critical assessment of some aspects is discussed by Söderholm et al. (2007). Moreover, research identified the importance of regional versus globally generated experience. In the case of wind power in Sweden, obviously a strong difference in the learning rate[4] appears depending on the consideration of national versus global cumulative deployment (Lindman et al, 2011). In contrast, support schemes of (renewable) energy technologies often accelerate their development and consequently stronger learning effects significantly decrease the investment costs. However, inefficient support schemes also discourage technology producers in terms of competiveness pressure and, therefore, innovations and improvement potentials are realized slower, hampering the technological learning effect (Söderholm et al, 2003). Consequently, support schemes are an additional attribute influencing the technological learning rate.

Finally, energy and raw material price impacts distort the technological learning effect additionally. Scientific work concentrates on the Photovoltaic energy investment costs and its impact of silver and silicon costs (Nemet, 2006 and Yu et al, 2010). Furthermore, related activities are conducted for wind onshore investment costs and the impact of steel prices (Folz, 2008). An econometric assessment of the impact of various raw material prices and technological learning effects on different (renewable) energy investment costs is discussed by Panzer (2012).

Additionally, research focuses on a separate consideration of learning impacts of different technology components. On the one hand, only some components are driven by technology learning effects and therefore the rest represents a certain minimum cost of the total technology. On the other hand, specific components are implemented in different technologies and therefore, show a slower doubling of cumulative development (Ferioli et al, 2009). Finally, the discussed impact parameters are considered in a top-down or bottom up approach. Essentially, the main

[4] A doubling in Swedish cumulative production is by far faster achieved than a global doubling.

difference is that a bottom-up approach addresses the single impact parameters based on fundamental data as supply chain or demand. In contrast, the top-down approach builds on a conceptual description in terms of aggregated economic data (Kahouli-Brahmi, 2008).

2.4 State of the art of learning rates

The theory of technological learning has already been developed for more than 80 years. Consequently, several different studies exist, especially on the energy technology sector. Due to the previously discussed issues of learning rate impacts a broad range is given in literature. Several scientific articles (Kahouli-Brahmi, 2008; Junginger et al, 2010b or Hoefnagels et al, 2011) summarize historical as well as more recent results. Table 1 indicates an overview of ranges of technology specific learning rates as well as the time frame and the region of their identification process. Generally, learning rates are depicted in terms of their investment costs. However, no such data is available for small-scale hydropower and coal power plants, which are represented in terms of the learning rate of their levelized generation costs.

Table 1 Overview of learning rates found in literature for selected energy technology investment costs and in brackets selected learning rates used in this thesis. Source (Hoefnagels et al, 2011 and Kahouli-Brahmi, 2008)

Range found in literature	LR	Time frame	Price data region	Capacity
Wind onshore	**7% *(-1 - 19%)***	**1981-2004**	Global	Global
Wind offshore	**10% *(-13 - 19%)***	**1991-2007**	Global	Global
Photovoltaic	**20% *(5.3 - 47%)***	**1975-2006**	Global	Global
Biomass to electricity CHP	**5% *(2.5 - 9%)***	**1990-2002**	Sweden	Sweden
Small-scale hydropower *	**5% (0.5 - 20.6%)**	**1975-2001**	Global	Global
Coal power plants *	**5% (1 – 7.6%)**	**1960-1993**	Global	Global

** indicated data refers to learning rates of levelized cost, no data available for investment cost learning rates*

Generally, Table 1 depicts a range from -13 to 47 percent for learning rates across technologies. In order to correctly interpret the results a detailed look on the assumptions is required. A negative learning rate is a strong indication that other parameters, neglected in the study, strongly impact the investment costs. Similar arguments explain learning rates of 47 percent[5].

First, wind onshore learning rates have been assessed in-depth within many studies (Neij, 1999; Junginger 2000; Ibenholt, 2002). Especially, Lindmann et al. (2011) gives a detailed overview of wind onshore learning rates with an average of about seven percent. Second, with respect to wind offshore learning rates less research has been conducted so far, also caused by the very site-specific investment costs. Junginger et al. (2004) and Isles (2006) conducted research on component learning of wind offshore investment costs. Third, detailed analyses are derived for Photovoltaic learning rates in literature (van der Zwaan et al, 2004; Nemet, 2006 or Yu et al, 2010). The big range of learning rates represents learning rates of module or system investment costs. Fourth, biomass-to-electricity learning rates are poorly addressed in literature. Apart from

[5] A detailed discussion of the impact parameters on the selected energy technologies is done in chapter 6.

brief assessments of the International Energy Agency (IEA) most work has been done by Junginger et al. (2006). However, with respect to technological learning in the biomass to electricity sector the higher potential lies at the fuel preparation process rather than at the initial investment costs (de Witt, 2011). Fifth, investment costs of small-scale hydro power plants vary strongly depending on site-specific (technological) requirements. Consequently learning rates are derived for the levelized generation costs (Jamasb, 2006). Finally, learning rates of coal-fired power plants[6] are only reported with respect to their levelized generation costs (Jaskow, et al, 1985 and Jamasb, 2006).

2.5 Critical review of the historical investment cost impacts

The current electricity supply portfolio is still dominated by conventional power plants. The trend towards a more sustainable future portfolio requires an increased share of renewable energy sources as well as Carbon Capture and Sequestration (CCS) technologies. In general, non-fossil power plants demand a relatively higher share of raw material inputs. Especially wind energy, Photovoltaic and biomass energy plants increase the metal input substantially. Hydropower and nuclear plants show a lower metal intensity. Consequently, the scaling up of these energy plants requires an increasing production in the mining of the raw materials. Future material substitutions from steel to concrete could reduce the metal requirements[7] (Kleijn et al, 2011).

First, the shares of the single components of a wind onshore plant on its total investment costs are discussed in detail. According to Figure 6 about 76 percent of the total investment costs refer to the turbine, whereas only little impacts are identified for foundation, grid connection, engineering, ground area and financing (Krohn et al, 2009).

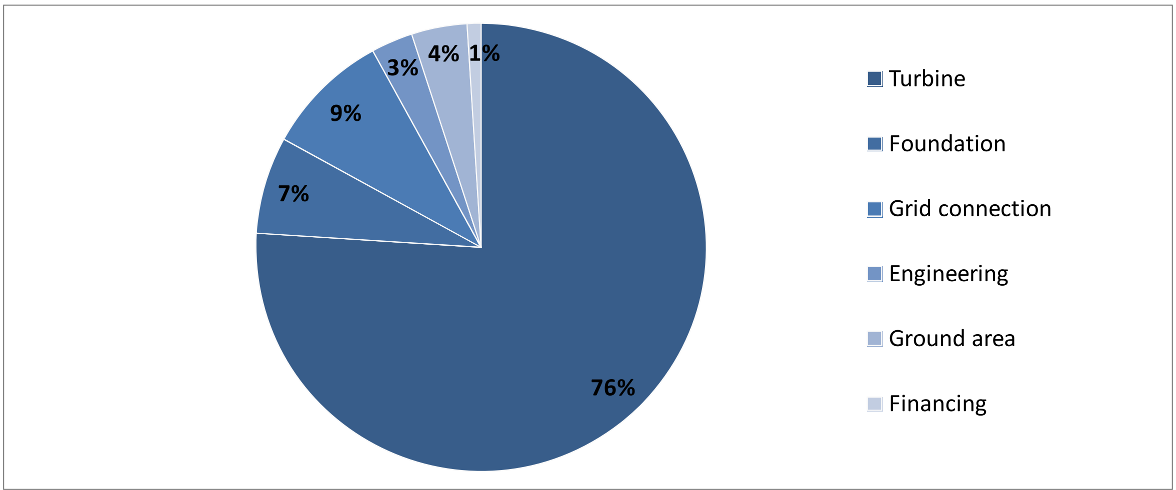

Figure 6 Breakdown by component of total investment costs of a wind onshore turbine in monetary terms. Source: Krohn et al, 2009

[6] However, due the technological similarity to biomass electricity plants same assumptions on learning rates are taken into account in this thesis.

[7] Nevertheless, concrete is very energy intense in production as well (see chapter 5.3.1).

Principally, the turbine mainly consists of the frame, the rotor, the generator and the gearbox. Consequently, a strong input of different types of steel is required. Depending on the capacity of the turbine, the rotor and the gearbox are produced by up to 100 percent of steel. Nevertheless, the generator and the frame demand up to 85 percent of the total material inputs in terms of steel (Ancona et al, 2003). Thus, the steel intensive production of the turbine and its significant share on the total investment costs indicate that steel price hold an impact of 42 percent up to 58 percent on total wind onshore investment costs. A similar impact of steel prices on specific wind investment costs is presented in Chupka et al. (2007).

Second, wind offshore investment costs are taken into account with respect to their major contributors. In contrast to wind onshore investment costs, the turbine contributes to half of the total investment costs only. Significant shares are allocated to the foundation as well as the grid connection expenditures. An overview is given in Figure 7 below. With respect to the turbine similar input material are used and, therefore, identical impacts of the material prices are identified (Smit et al, 2007).

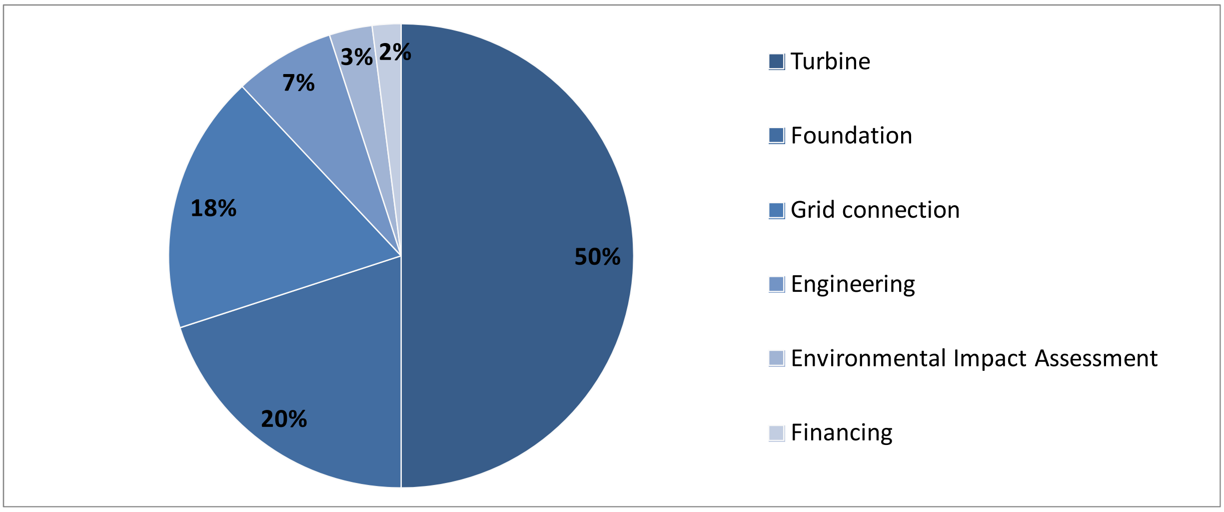

Figure 7 Breakdown by component of total investment costs of a wind offshore turbine in monetary terms. Source: Krohn et al, 2009

Regarding the additional equipment of wind offshore plants, the foundation and the grid connection are very material intensive, too. Thus, steel prices are responsible for about 45 to 50 percent of the foundation investment costs (Junginger et al, 2004). Depending on the type of foundation, concrete price can have strong impacts as well. Consequently, material price have a significant influence on the total wind offshore investment costs.

Third, Photovoltaic and in particular Photovoltaic module investment costs are analyzed. Module prices hold a share of 70 percent on the total investment costs. Out of this, module assembling is responsible for 40 percent, call processing for 27 percent, feedstock for 14 percent, wafering for 11 and ingot growth for eight percent (Sinke et al, 2004). An overview depicts Figure 8.

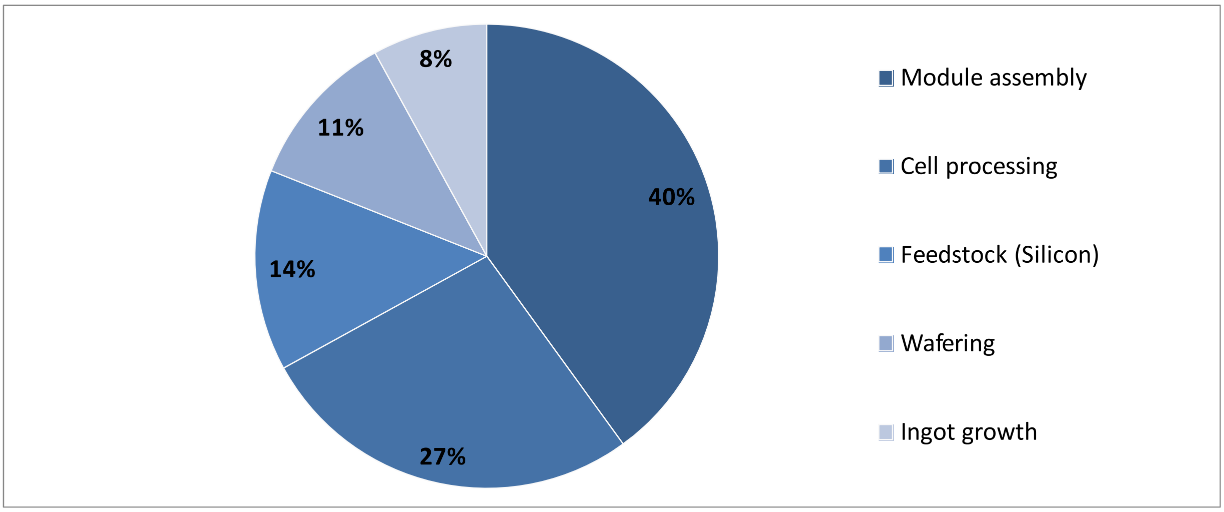

Figure 8 Breakdown by component of total investment costs of a Photovoltaic module in monetary terms. Source: Sinke et al, 2009

With respect to the material input, a major contribution is allocated to silicon. Although silicon is produced form quartz, which is almost unlimited available, its production requires additional manufacturing plants and this production is a very energy intensive process. Thus, silicon is a crucial input parameter to Photovoltaic module productions. Apart from silicon, another 30 percent of the module prices are driven by material prices. Solar glass as well as copper and aluminum dominate the costs of module assembling and cell processing (Sinke et al, 2004).

Fourth, investment costs of solid biomass combustion in Combined Heat and power plants are addressed. Generally, significant analogy exists for biomass and fossil-fired combustion plants (Kleijn et al, 2011). The boiler is responsible for more than half of the total investment costs whereas additionally the turbine and fuel handling hold relevant shares too; see Figure 9.

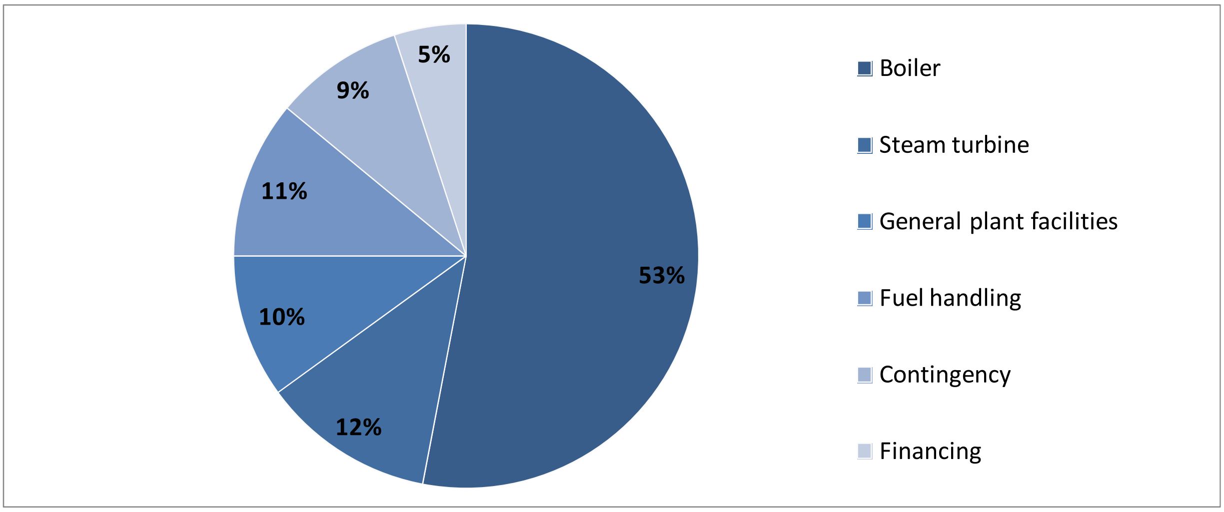

Figure 9 Breakdown by component of total investment costs of a biomass-fired Combined Heat and Power (CHP) plant in monetary terms. Source: Koornneef et al, 2007

In terms of raw material price inputs, about 80.000 tons of steel are demanded in a ten Megawatt biomass CHP plant. Moreover, this amounts to an impact of about 20 percent in terms of investment costs (Polytechnik, 2011). Nevertheless, CHP plants are generally customized and, may use different technological conversion processes. Therefore the material inputs vary significantly among the different plants. Thus, only average material inputs and price impacts are discussed in scientific literature.

Fifth, small-scale hydropower investment costs are taken into account. In principle, similar arguments, as in the case of solid-fuel combustion plants, are relevant for small-scale hydropower plants since 75 percent of their investment costs are depending on site specific conditions. However, on average up to 50 percent of the total investment costs is caused by the Environmental Impact Assessment. Furthermore, the hydro-technical construction accounts to about 30 percent, turbines to 12 percent and little shares are caused by electrical equipment, building and financing (EREC, 2010). Figure 10 provides an overview of average investment cost shares of small-scale hydro power plants.

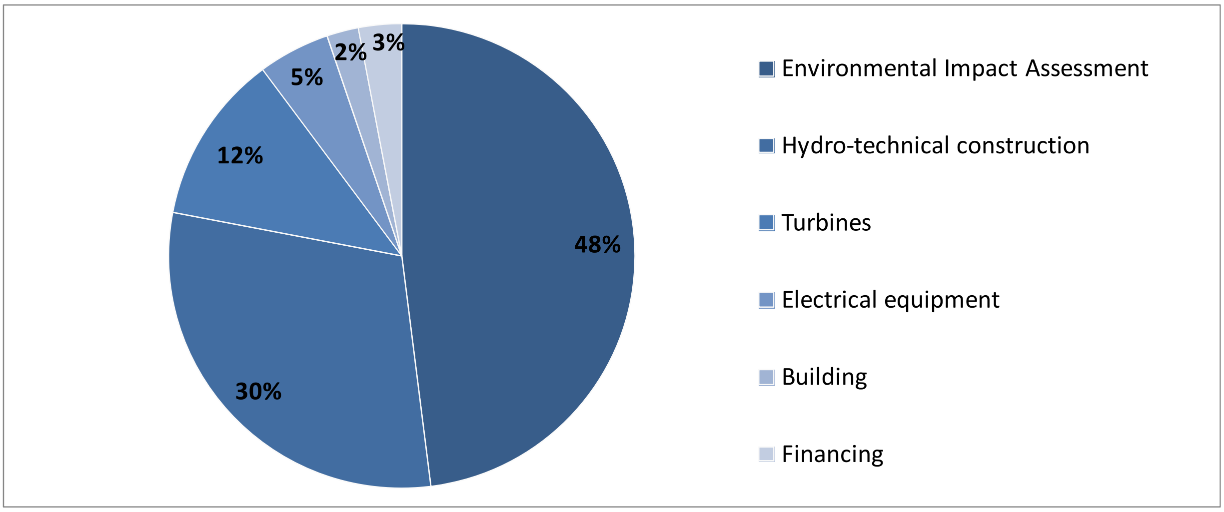

Figure 10 Breakdown by component of total investment costs of a small-scale hydropower plant in monetary terms. Source: EREC, 2010

Regarding the monetary share of material price on the investment cost, generally, minor effects are reported for small scale hydropower plants only (Kleijn et al, 2011). Bard (2006) points out a five percent impact on total investment costs of steel as well as concrete inputs.

In general steel, concrete and silicon prices are identified as main drivers in terms of raw material prices of renewable energy technology investment costs. However, major differences are apparent between wind, Photovoltaic, biomass energy and hydropower plants.

3 Methodology of this thesis

This section discusses and justifies the methodological approach of this thesis. In a first step, the principal interaction between energy prices, commodity prices and renewable energy technology investment costs is addressed. In particular, the multi-factor modeling approach of this dynamic interaction is highlighted. A theoretical discourse of econometric analysis is given in the following subchapter, depicting elementary rules of linear regression models as well as statistical background information. Finally, the boundary of this research is discussed, highlighting methodological challenges and exogenous assumptions.

3.1 Multi factor impact assessment of investment costs

This thesis considers the impact of steel, concrete and silicon prices on investment costs of wind energy on- and offshore, Photovoltaic, small-scale biomass Combined Heat and Power (CHP) as well as small-scale run-through hydro power plants. In last consequence, the impact on investment costs of conventional power plants is discussed, too. Depending on the technology, either only steel, concrete or silicon prices showed significant influence in the recent past or a combination of these material prices. Since these input materials are all very energy intensive, the relationship between energy prices and raw material prices is taken into account here. Therefore, an endogenous feedback from energy prices – forming the market where renewable energy technologies must compete – to the investment cost of renewable energy technologies is modeled within this thesis.

In a first step, the steel, concrete and silicon production processes are analyzed in order to indentify the components holding major shares in terms of production costs. Obviously this differs strongly depending on the production type. However, in common all three raw materials are very energy intense in production and, consequently, impacting their prices.

$$CP = \delta + \vec{\varepsilon} * EP + u_t \qquad \text{Eq. 3}$$

CP	Commodity price
δ	Constant
$\vec{\varepsilon}$	Vector of weighting factors of considered primary energy prices
EP	Vector of considered primary energy prices
u_t	Statistical disturbance term

According to formula Eq. 3 the different commodity prices are derived by a linear regression model, considering their main energy input prices, certain time lags and the standard disturbance term. In order to derive future forecasts of commodity costs, exogenous energy price assumptions (Capros et al, 2011) are taken into account. Thus, derived commodity prices refer more to commodity costs, since others[8] than the energy related costs are neglected when estimating the commodity prices. Historically, prices for coal, coking coal, natural gas and electricity as well as their associated consumption time series are forming the basis of this linear regression model.

In a next step, the impact of the mentioned raw material prices on investment costs of the selected energy technologies is dynamically taken into account. Amongst others, Nordhaus (2008) discussed that the problem of modeling technological learning appears in trying to separate learning by doing effects from technological change and, consequently, overestimating learning by doing effects. According to literature the most suitable approach is identified to be the multi factor impact modeling. Existing studies (Miketa et al, 2004; Yu et al, 2010 & Söderholm et al, 2007) have successfully applied this approach in order to consider effects like scale, R&D or partially raw material prices.

The ordinary learning by doing formula considers the dynamic investment cost development of renewable energy technologies depending on the cumulative capacity as already described in section 2.3 (see Neij, 1997 and Junginger, 2000). Consequently, a certain learning progress in terms of reduced investment costs is achieved in every incremental point in time from t to t+1, whereby usually taking into account annual steps. Building on learning rates defined in literature (see chapter 2.4), this learning progress is determined according to the difference in investment costs of year t to the initial investment costs. Therefore, replacing the initial investment costs $c(x_0)$ in formula Eq. 1 by an extended term allows considering multi factor impacts as R&D expenditures, scale effects as well as raw material impacts on top of learning by doing. However, this thesis solely focuses in much detail on the impact of different raw material prices, either solely or as a combination of various raw materials, depending on the relevant share of these commodities on the total investment costs. In this context, formula Eq. 1 is extended to:

$$INV(t) = \left(\alpha + \vec{\beta}\ \mathrm{CP} + u_t\right) * \left(\frac{x_t}{x_0}\right)^m \qquad \text{Eq. 4}$$

INV(t)	Investment cost in the year t
α	Constant
$\vec{\beta}$	Vector of weighting factors of considered commodity prices
CP	Matrix of considered commodity prices
u_t	Statistical disturbance term
x_t	Cumulative installed capacity in time t

[8] World demand of raw materials, production capacities and local characteristics of different raw materials hold an additional impact on their prices.

x_0 Initial cumulative installed capacity

m Learning by doing impact

The initial investment cost of the technology in formula Eq. 1 is replaced by the linear regression model in formula Eq. 4. As addressed at the linear regression model of commodity costs, the model in formula Eq. 4 only considers raw material impacts and learning by doing effects[9]. Additionally, adding parameters of time lagged commodity costs as well as first derivations to the commodity price vector $\overrightarrow{CP}$ increase the quality of the regression model significantly. At the process of calculating the regressors in Eq. 4, real historic observation data is used. In comparison to the traditional multi factor learning curve approach (i.e. see Miketa et al, 2004), this research follows a separate identification approach of learning by doing effects and raw material impacts. Moreover, considering a broad set of selected energy technologies, the limited data availability demands an independent calculation of these two impacts. The following chapter 3.2 supports the approach of a separate quantification of learning by doing effects and raw material price impacts.

Finally, future scenarios of renewable energy investment costs are derived based on the developed model in Eq. 4. In contrast to the identification of the regressors, where the real historical observed commodity price information is used, the scenario calculation builds on derived commodity costs of Eq. 3. This allows for an endogenous feedback from energy prices to future investment costs of (renewable) energy technologies, serving as a basis for simulation models of investment decisions as well as policy recommendations.

3.2 Empirical justification of the applied methodology

In contrast to recent other studies (see Yu et al, 2010), the quantification of multi factor learning curve impacts have been separated in this thesis. In order to illustrate the real energy price related impact and, consequently, depict the robustness of the investment cost development of selected energy technologies, the same methodology is applied to all selected energy technologies. Due to limited data availability, a simultaneous analysis of technological learning effect and raw material price impacts[10] is not conducted in this thesis.

Hence, historical information of technology investment costs is divided into two parts. On the one hand, a time period when apart from the annual inflation no additional raw material price increase as well as no additional energy technology investment cost increases have happened.

[9] Research and Development expenditures, strategic pricing, opportunity costs of investors, market power of suppliers are not taken into account in this research. Economies of scale are only considered indirectly, since input data of renewable energy investments has been filtered according to the scale of the plant.

[10] Learning by doing effects require all time series of cumulative capacity from the first unit of installation. Additionally, complete time series of investment costs are not available for all technologies, starting at early units.

On the other hand, into a time period when raw material prices and energy technology investment cost increased much stronger than the annual inflation.

Chupka et al. (2007) showed strong increases of wind and conventional energy generation construction costs beyond 2003, on average fifteen to thirty percent above the GDP deflator whereas in the years before 2003 technology investment cost developed in the same range as the GDP deflator. The same development within this time period is depicted in the CERA index (IHS, 2010). The CERA index, especially the PCCI (Power Capital Cost Index) indicates the impact of labor, engineering rates as well as steel prices, bulk materials and engineering equipment on power technology investment costs. The PCCI index is only available for the time period beyond 2000. In order to prove the development of technology investment cost before 2000, the CEPCI index (Chemical Engineering Plant Cost Index) (Vatavuk, 2002) is taken into account in this thesis. Generally, the CEPCI index demonstrates the investment cost development of chemical engineering plants, containing contributions of equipment, construction labor, buildings, engineering and supervision. Although chemical engineering plants are slightly different to power plants, the impact of raw material prices, selected in this research[11], on the plant investment costs is developing according to the same trend with a slightly steeper increase between 2005 and 2008. This is especially the case for wind onshore investment costs, corrected for the technological learning effect.

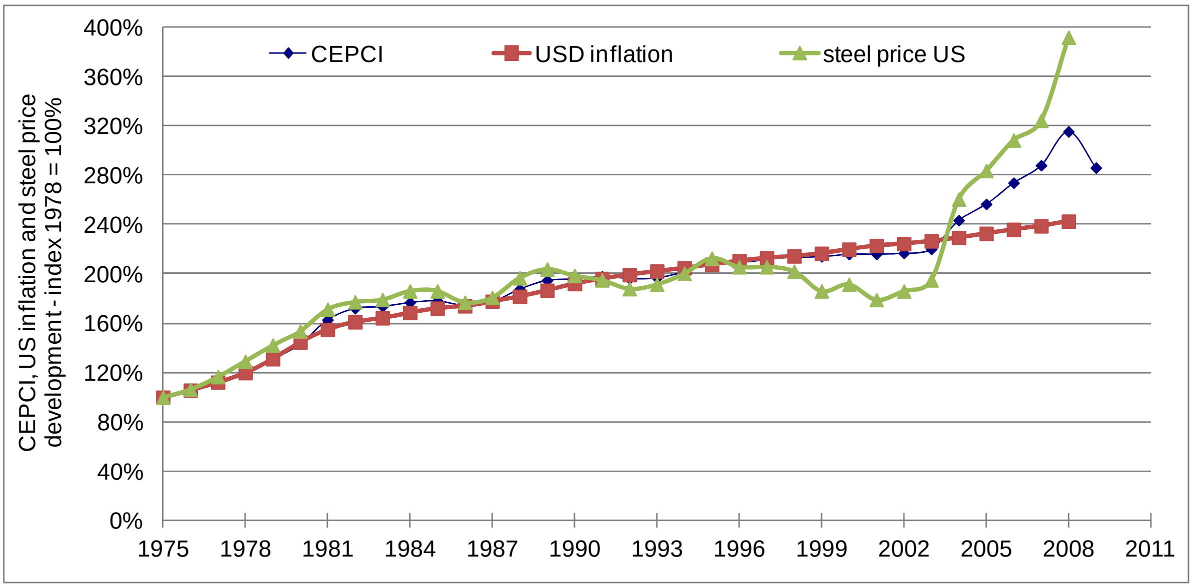

Figure 11 Historical development of the CEPCI index (Vatavuk, 2002), the US inflation (Worldbank, 2010) and the steel price development (DiFrancesco et al, 2009). Values of 1978 represent 100%.

Figure 11 illustrates the fact that until the year 2002 hardly any additional impact except the annual inflation has occurred on investment costs of energy technologies. Very limited

[11] Especially steel prices and concrete prices are relevant in this context.

deviations can be found from 1981 to 1985 as well as in 1988. Certainly, in both periods the steel price increased, too. However this deviation is negligible compared to the time period of 2002 and beyond. Therefore, taking the time period until 2002 and adjusting nominal investment costs of selected energy technologies for the inflation allows deriving technological learning rates being solely caused by experience due to increased cumulative capacity.

Building on the theory of technological learning effects (see chapter 2.3), the learning rate itself does not change over time[12]. Several learning rate studies (see Mc Donald et al, 2001) explore on the sensitivity of determining technological learning rates. Principally, learning rates are very sensitive to the consideration of the first unit taken into account. Furthermore, at least a period of three orders of magnitude in cumulative capacity installation should be considered. Otherwise, a distortion of the learning effect could be implemented, overestimating technological learning by doing. According to Junginger (2011) and Nordhaus (2008) no evidence of any energy technology exists where learning rates changed over time. But other factors than learning by doing influenced investment costs additionally and, therefore, they developed different than estimated by pure technological learning models.

As a consequence, this research builds on exogenously derived learning rates (see chapter 2.4) which are defined in the period before 2002, in a time period when in real currency units no raw material impact is noticed. Hence, the technological learning rate for each selected energy technology is considered constant throughout the complete observation period. In order to quantify the impact of raw material prices on energy technology investment costs, first their historical observations are corrected for technological learning effect identified above. Furthermore, running a linear regression model according to Eq. 5 identifies the impact of different raw material prices, respectively their time lagged impacts.

$$INV_{learn-corr}(t) = \alpha + \sum_{\mathrm{i}} \beta_{\mathrm{i}}\, \mathrm{CP_i} + \mathrm{u_t} \qquad \text{Eq. 5}$$

$INV_{learn-corr}$	Investment cost corrected for technological learning effect
α	Constant
β_ι	Weighting factors of considered commodity prices
CP_i	Considered commodity prices
u_t	Statistical disturbance term

Finally, combining both effects depicts the development of energy technology developments by considering technological learning by doing and the impact of raw material prices. In conclusion, the applied approach results in similar investment cost developments, as when considering both

[12] A limited learning by doing effect is only caused by a decreasing growth rate of the technology development. However, the learning rate is constant over time.

impacts within one common regression model (see Yu et al, 2010). However, a common regression analysis requires much more detailed data availability for a long time period in order to fulfill the theoretical preconditions for deriving learning curves. However, both approaches hypothesize that no major substitution processes in energy technologies will be ongoing throughout the observation period and consequently change the impact of raw material prices.

3.3 Econometric analyses – a theoretical discourse

In order to analyze the relation of energy prices and commodity prices, on the one hand, and commodity prices and investment costs of energy technologies, on the other hand, econometric analyses are conducted. Therefore, empirical time series of relevant price and investment cost developments are studied with statistical tools. This thesis builds on linear regression models, applying the ordinary least square (OLS) method (see Böhm, 2010 & Greene, 2012). The ordinary least square method preconditions the fulfillment of the Gauss-Markov Theorem in order to achieve significant results. The simplest, linear model is defined by Eq. 6:

$$Y_t = a + \vec{b}X_t + u_t \qquad \text{Eq. 6}$$

Y_t	Dependent variable
a	Constant – to be determined
b	Constant regressor – to be determined
X_t	Independent variable
u_t	Statistical disturbance term

In order to achieve the best fit of Y_t by applying the ordinary least square approach, the statistical disturbance term of Eq. 6 needs to be minimized under the side conditions Eq. 8 and Eq. 9 according to Eq. 7.

$$min \sum_{t=0}^{T} u_t^2 = min \sum_{t=0}^{T} (Y_t - (a + bX_t))^2 = f(a,b) \qquad \text{Eq. 7}$$

$$\frac{\partial f}{\partial a} = \sum_{t=0}^{T} (2a - 2Y_t + 2bX_t) = 0 \qquad \text{Eq. 8}$$

$$\frac{\partial f}{\partial b} = \sum_{t=0}^{T} (-2Y_tX_t + 2aX_t + 2bX_t^2) = 0 \qquad \text{Eq. 9}$$

Finally, b is the quotient of the covariance of X_tY_t to the variance from X_t. On the one hand, this states that if the dependent and independent variable are completely uncorrelated b equals zero. On the other hand, if the deviation of the independent variable to its expected value is large, this reduces its impact on the dependent variable. Furthermore, a is the difference of the mean of the dependent variable and the mean of the independent variable weighted with the factor b.

The ordinary least square method requires certain assumptions on the statistical disturbance term, respectively on the independent variable. These assumptions are known under the Gauss-Markov Theorem (see Greene, 2012), see formula Eq. 10 to Eq. 14.

$$E(u_t) = 0 \quad \forall \ t = 1, \dots T \qquad \text{Eq. 10}$$

$$Var(u) = \sigma^2 I \qquad \text{Eq. 11}$$

$$E(X'u) = 0 \qquad \text{Eq. 12}$$

$$r(X) = K \qquad \text{Eq. 13}$$

$$K < T \qquad \text{Eq. 14}$$

X_t	Independent variable
u_t	Statistical disturbance term
$\sigma^2 I$	Matrix of variance of the disturbance term
K	Rank of independent variable
T	Total number of observations

On the one hand, with respect to the requirement of independent time series, this theorem states the necessity of their stationarity. Non-stationary time series violating the Gauss-Markov Theorem lead to an underestimation of their variance and, consequently, an overestimation of the significance of the regressor. Moreover, the independent variables must not be related in order to estimate the regressors of the model.

On the other hand, concerning the disturbance term, the Gauss-Markov Theorem requires that the expected value of the product of the independent variable and the disturbance term is zero, see formula Eq. 12. Otherwise, the disturbance term would contain useful information for the model and hence result in a biased regressor. Additionally, the disturbance terms must not be serial correlated among themselves[13], since otherwise they distort the variance of the regressor which is therefore not efficient. Consequently, statistical test results are not acceptable anymore. The same effect appears in case of the violation of homoscedasticity of the disturbance term. Homoscedasticity asks for a constant variance of the disturbance term over all observations, see formula Eq. 11. Finally, the disturbance term must be normally distributed over all observations in order to allow significant confidence intervals of statistical tests and, consequently, their right interpretation.

However, autocorrelation of the disturbance is a wide spread phenomenon in econometric studies. Therefore, Cochrane and Orcutt (Cochrane, 1949 & Schulze et al, 2006) introduced an

[13] Note that different observations of the dependent variable might still be correlated amongst them, but the deviations from their expected values are not correlated.

estimator for serial correlated regression models, the so called Cochrane-Orcutt estimator. If u_t in model Eq. 6 is first order autocorrelated, the disturbance term is defined by

$$u_t = \rho u_{t-1} + e_t. \qquad \text{Eq. 15}$$

ρ   Dependence parameter of lagged disturbance term

Multiplying formula Eq. 6 by ρ and then reducing it by the same formula lagged by one observation results in

$$Y_t - \rho Y_{t-1} = (1-\rho)b_0 + \sum_{i=1}^{K} b_K \left(X_{k,t} - \rho X_{K,t-1}\right) + (u_t - \rho u_{t-1}). \qquad \text{Eq. 16}$$

Considering formula Eq. 15 in formula Eq. 16 eliminates the first order serial correlation of the disturbance term according to Eq. 17 and, therefore, meets the requirements of the Gauss-Markov Theorem described above.

$$Y_t - \rho Y_{t-1} = (1-\rho)b_0 + \sum_{i=1}^{K} b_K \left(X_{k,t} - \rho X_{K,t-1}\right) + e_t \qquad \text{Eq. 17}$$

In econometric analyses, the coefficient of determination, R^2, is often considered as the quality of the regression model (Eviews, 2009). Principally R^2 represents the percentage of the variance of the dependent variable, see formula Eq. 18.

$$R^2 = 1 - \frac{e\prime e}{y\prime y} \qquad \text{Eq. 18}$$

However, since the coefficient of determination increases with each additional variable, regardless its significance, the adjusted coefficient of determination is the more appropriate measurement of the quality of the regression. Hereby R^2 is adjusted by its degrees of freedom according to Eq. 19.

$$R^2_{adj} = 1 - (1 - R^2)\frac{T-1}{T-K} \qquad \text{Eq. 19}$$

Therefore, adding an additional parameter[14], first weaknesses the R^2_{adj}, but the R^2_{adj} increases only if the additional parameter increases the overall quality of the regression model significantly.

With respect to the quality of a regression model, principally several parameters are of key importance. Besides the adjusted coefficient of determination, the model parameter specification plays an important role. Consequently, the data availability as well as its quality is often a limiting factor for simplifying econometric models. Finally, the number[15] of data points is a crucial parameter in order to achieve a significant result.

3.3.1 Applied statistical test methods

In order to meet the Gauss-Markov Theorem discussed above in formula Eq. 10 to Eq. 14 several statistical tests exist to verify these assumptions. Within this thesis all relevant

[14] Adding an additional parameter increase the rank K of the independent variable by one.
[15] Also several statistical tests exist for a limited number of observations (White test for Homoscedasticity)

regressions are estimated with the computer model EViews 7 (Eviews 2009). It also provides different statistical test methods being applied in this research. Generally, a null-hypothesis is defined and tested against the opposite hypothesis. Tests indicate the probability of the null-hypothesis being either accepted or need to be rejected within a certain confidential interval[16].

As discussed in chapter 3.3 above, the ordinary least square method requires the stationarity of the dependent and independent time series. Therefore, different unit root test exists, to prove this characteristic within the specified confidential interval. The most common unit root tests are the Dickey-Fuller (DF) and the Augmented Dickey-Fuller (ADF) tests, whereas both are based on similar approaches. The dependent time series of formula Eq. 6 is non-stationary if ρ in formula Eq. 20 equals one, forming the null-hypothesis of the DF and ADF test.

$$Y_t = \rho Y_{t-1} + u_t \qquad \text{Eq. 20}$$

Consequently, the DF and ADF test compare the value of the t-statistic according to formula Eq. 21 to a critical value defined by Dickey and Fuller (Fuller, 1996). If the $\mathrm{DF_t}$ value is lower than the critical value of the corresponding significance interval, the null-hypothesis of a unit root can be rejected.

$$DF_t = \frac{\rho - 1}{\sigma_\rho} \qquad \text{Eq. 21}$$

With respect to serial correlation of the disturbance term mostly the Breusch-Godfrey (Breusch, 1978) test, a Lagrange Multiplier (LM) test, or the Durbin-Watson test (Durbin, 1971) is examined. Both tests assume the null-hypothesis of no autocorrelation. The LM test considers the number of observation times the coefficient of determination[17] to the critical value, which is chi² distributed. In contrast, the Durbin-Watson test looks only at first order autocorrelation. Hereby, the one-sided test compares values of d, depending on the disturbances only, to a lower and an upper threshold, taken from tables in literature (Greene, 2012). In case the regression model contains time lagged dependent time series, the Durbin-Watson test does not result in a significant interpretation and the LM test needs to be examined.

Regarding homoscedasticity, mainly two different tests are conducted in praxis. On the one hand, the White test (White, 1980) – a very general test – is applied in the case of fewer observation points. The null-hypothesis of the White test assumes homoscedasticity. This test conducts a regression, considering all independent variables of the original model plus their cross-products. The product of the number of observation and the coefficient of determination of the latter regression is compared to a chi² distributed critical value. On the other hand, Breusch-Pagan/Godfrey (Breusch, 1979) introduced a Lagrange multiplier test. As in the case of the

[16] As default a confidential interval of 5% is considered in econometric analyses.
[17] Referring to the regression of the original model extended by the lagged disturbances (as many as considered).

White test, the null-hypothesis is assumed to be homoscedasticity. Furthermore, a help-regression with the original independent variables explaining the square sum of the residuals is conducted. Again the product of the number of observation and the coefficient of determination of this regression is compared to a critical value that is chi² distributed[18].

Finally, the normality of the disturbance term is tested by considering the Jarque-Bera test (Bera et al, 1981). The Jarque-Bera test takes a null-hypothesis of normal distribution into account. Based on the skewness S, the kurtosis K and the number of observations T of the disturbance term series the Jarque-Bera value is calculated according to formula Eq. 22.

$$Jarque - Bera = \frac{T}{6} * (S^2 + \frac{(K-3)^2}{4}) \qquad \text{Eq. 22}$$

Again the Jarque-Bera statistic is chi² distributed[19] and if it exceeds the reported value the null-hypothesis needs to be rejected. Hence, a big probability value of the Jarque-Bera test indicates the normal distribution of the disturbance term.

3.4 Boundary of this research

The focus of this thesis is to quantify the endogenous feedback from energy prices to the investment costs of energy technologies. Frequently used raw materials in energy technology construction are very energy intense in production. Therefore, a strong linkage between raw material prices and energy prices is observed.

However, it is not the objective to model neither raw material price developments nor energy technology investment costs in full detail. Obviously, several other impacts influence the price of steel, silicon and concrete in addition to primary energy prices. Amongst others, these are supply and demand, profit margins, economic development, regional markets, transport capacities, toll and many more. Nevertheless, these issues are all exogenous parameters to most energy models and, therefore, cannot contribute to raw material price developments in dependence on endogenous parameter developments[20]. The same issue is relevant for the development of energy technology investment costs. Beside the above mentioned impacts, also the financial support mechanisms of renewable energy sources have an impact on the investment cost development. On the one hand, they can stimulate the market and, therefore, increase the demand of energy technologies and consequently their prices. On the other hand, high support levels will also increase the opportunity costs for energy technology producers and, therefore, also increase the price of their technologies. In contrast, in a well stimulated market

[18] The test is only powerful at a high number of observations, for fewer observations often the F-statistic is taken into account to proof the significance of the indicated help-regression.
[19] With two degrees of freedom
[20] In most energy models, only primary energy price and energy demand are endogenous parameters (see chapter 2.2)

growth rates of these energy technologies will increase and, subsequently, reduce costs due to learning by doing.

Technological learning by doing of energy technologies is taken into account in this thesis beside the impact of energy and raw material prices. However, due to the broad variety of selected energy technologies in this study and the limited data availability of some technologies, technological learning rates are not endogenously determined. Based on expert knowledge (Mc Donald et al, 2001; Junginger, 2011 and Nordhaus, 2008) an approach has been defined how to link exogenous learning rates to the endogenous raw material price impacts. Learning rates are taken into account based on a literature review (see chapter 2.4).

Finally, this thesis studies the impact of historical and recent impacts of energy and raw material prices on energy technology investment costs. Based on the derived relation some conclusions of future scenarios are drawn. However, conducting scenarios based on historical interactions implies that no fundamental technological change occurs. On the one hand, the coking coal input of the steel production strongly depends on the steel production process. Constantly increasing coking coal prices could additionally enforce the invention of less coking coal controlled steel production processes. On the other hand, high steel price could lead to material substitutions in several energy technologies, reducing the impact of steel price on their investment costs. However, regardless of a slighting or a rapid transition in material inputs the modeling approach of this thesis only considers technological change interactions as far as they have been observed in the recent past time period.

4 Model inputs – assumptions and substantiations

In the following part, an overview of the dataset for modeling the impact of primary energy and raw material prices on investment costs[21] of energy technologies is given. Therefore, on the one hand historical price developments are discussed in detail, focusing on their main drivers. Additional emphasis is given on the impact of economic growth on the development of raw material prices. On the other hand, historical renewable energy technology investment costs are depicted and discussed. An in-depth analysis on the impact of prices versus costs of renewable energy technologies is carried out, enabling correct interpretations of the following research.

4.1 Commodity price development – impact and dependences

This thesis concentrates on silicon, concrete and steel price impacts[22]. Consequently, only materials holding a high share on renewable energy investment costs are taken into account. Silicon, concrete and steel are in common very energy intense in production. In this context, the energy price development plays a crucial role for the future development of the selected commodity prices. Therefore, first the historic and future primary energy prices are taken into account here.

4.1.1 Historical energy price development and future projections

In terms of selected commodities, historical coal and natural gas prices are the main drivers of their production costs (Astier, 2010 and Pardo et al, 2011). However, electricity prices are of key relevance, especially in the silicon production (de Wild Sholten et al, 2005). Nevertheless, the energy dependency of the different commodity production technologies is very site-specific.

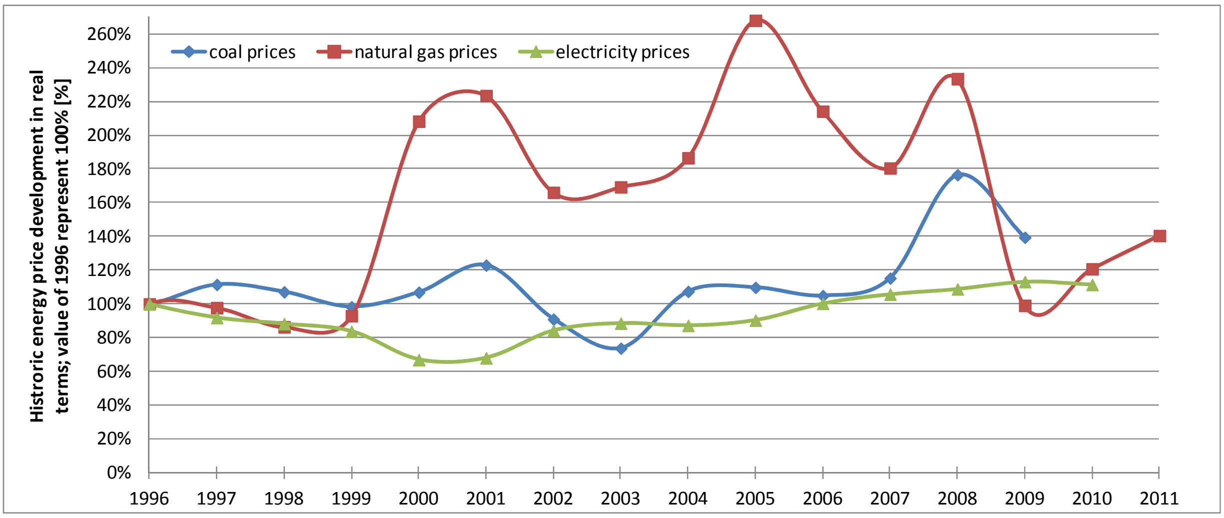

Figure 12 Historical development of relative coal (European Commission, 2009b), natural gas (Trading economics, 2011) and electricity prices – industry prices – (Eurostat 2011) from 1996 onwards in real units (Euro 2006).

[21] All commodity prices and investment costs within this thesis are expressed in real values of EUR2006.
[22] However, there are many other raw materials influencing the investments of energy technologies.

Figure 12 depicts an overview of the historical development on the one hand of primary energy prices, in particular coal (European Commission, 2009b) and natural gas (Trading economics, 2011). On the other hand, the relative electricity price development[23] (Eurostat, 2011) is illustrated since the year 1996. With respect to the reported coal price in the selected period a constantly fluctuating development is notices within a range of plus minus 20 percent. However, strong fluctuations are observed in the period beyond 2006, firstly with a rapid increase followed by a significant decline in 2009. This strong increase in 2008 by more than 180 percent of the value form 2006 was a consequence of the strong economic growth and the related energy demand increase worldwide. Furthermore, the following economic and financial crunch reduced the energy demand and, consequently, its price significantly again (Rademacher et al, 2011). In contrast, natural gas prices showed a strong fluctuation already starting in the year 2000. In general, natural gas prices are linked to crude oil prices (see Villar et al, 2006) with a certain time delay. The terrorist attack on September 11th, 2001 in the US was responsible for the strong decline of the natural gas price in the year 2002. With respect to the recent development, again, the economic boom followed by the regression was responsible for the natural gas price fluctuation. Finally, the historical electricity price within the industry sector only showed moderate fluctuations with relatively longer time period. An initial decrease in prices, caused by the liberalization of the electricity market, followed a constant increase of electricity prices above 1996 values. Due to the fact, that electricity prices are still driven by conventional energy carriers like coal and natural gas, their price increase had a significant impact on the electricity price, too.

Additionally, coking coal prices hold a significant impact on the development of steel and concrete prices. However, coking coal prices showed a similar historical trend in the time period until 2007. Production shortages in the year 2007 and beyond led to a significant increase of coking coal prices compared to coal prices. Consequently, econometric analyses within this thesis build on the coal price development, whereas different time lags of the coal price implicitly considering the coking process from coal to coking coal[24].

With respect to future energy prices this thesis refers to the PRIMES (Capros et al, 2011) energy model. Based on the results of coal, natural gas and oil prices a reference electricity wholesale price is derived within the Green-X model (Huber et al, 2004). In addition to the primary energy prices, the Green-X model also takes into account CO2 prices from the PRIMES model, having an additional impact on the wholesale electricity price. Figure 13 provides an overview of the future development of the coal and natural gas price as well as the electricity wholesale price according to the reference scenarios of PRIMES and Green-X.

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[23] The electricity price development refers to a mix within the European Union 15 Member States until 2004 and the EU 25 Member States beyond.

[24] The input for coking coal production is mainly coal whereas earlier coal prices are relevant for current (in the time of observation) coking coal prices.

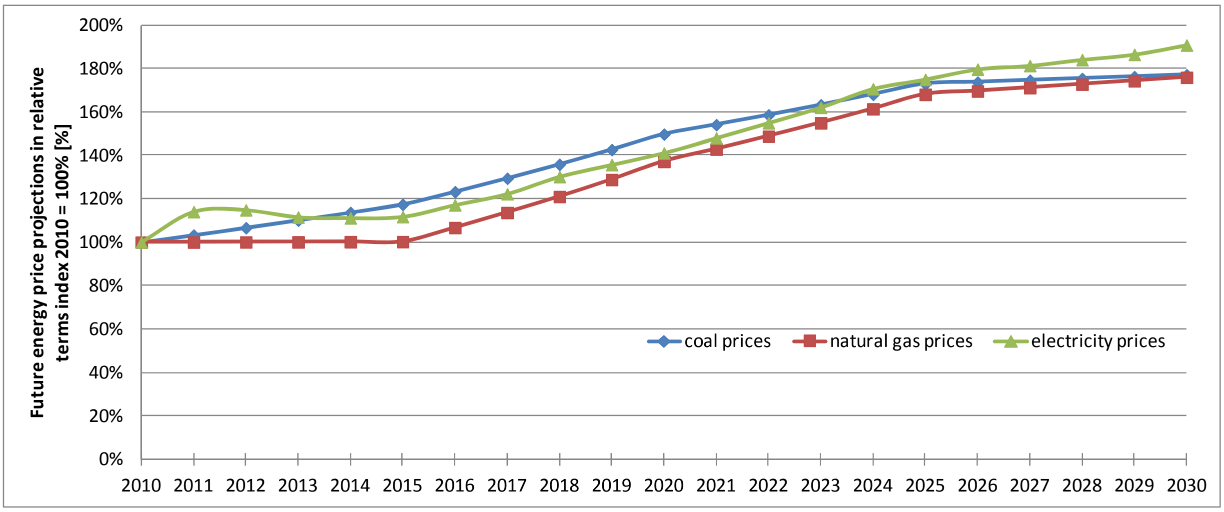

Figure 13 Future projections of coal and natural gas prices (Capros et al, 2011) and the electricity wholesale price (Huber et al, 2004) in real terms of Euro 2010, indexed to the year 2010.

In contrast to the historical observations of the energy prices shown in Figure 12, the future projections in Figure 13 only show a slight but constant increase[25]. However, especially the natural gas price is expected to remain constant until 2015 with a stronger increase beyond. Generally, the coal and natural gas price are expected to level off in 2025 at a level of about 165 to 175 percent of the current (2010) price levels. Regarding the wholesale electricity price, an initial solid increase is expected due to the direct influence of coal power plants. Hereby, the coal price itself and in addition also the CO2 price raise the power generation costs significantly. In the time period beyond 2020, when the higher share of coal plants is partly substituted by natural gas plants emitting less CO2, the overall reducing power generation cost effect is compensated by an expected electricity demand increase due to additional electric appliances.

4.1.2 Steel price development and its historical impacts

In existing literature, several different studies on the historical steel price development are published (Wooders et al, 2009; Worldsteel Association, 2008, Steel Business Briefing, 2011). Generally, it needs to be distinguished between different types and forms of steel items. On the one hand, it is differentiated between ordinary steel product, stainless steel product and steel scrap prices. On the other hand, steel products are again containing several types of steel items as flat, long or tube products sold in hot rolled coil or cold rolled coil production. However, the different steel items showed different prices developments in absolute terms over the last decades but having the same trend over time. Therefore, this thesis refers to flat, cold rolled coil

[25] Both reference models, PRIMES and Green-X, are focusing on the energy sector only where the economic development is an exogenous parameter. Consequently, no shocks or other rapid changes in energy demand and prices can be considered in annual averages of the different energy price developments.

steel products at the European market (see Steel Business Briefing, 2011). Their historical development is depicted in Figure 14 below.

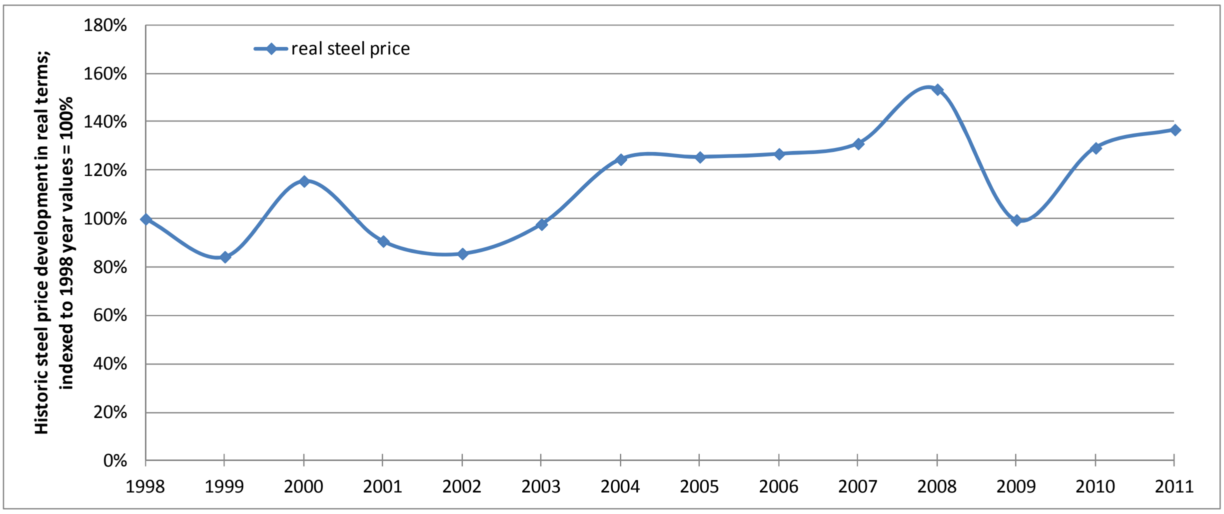

Figure 14 Historical, relative steel price development (Steel Business Briefing, 2011) in real units of Euro 2006/t from the year 1998 to 2011. Values of the year 1998 represent 100 percent.

As shown in Figure 14, historical fluctuations of the steel price become apparent. Although the depicted development of the steel price refers to the European market, the same picture can be drawn from other markets. Generally, the steel market is global a market where influences and trends of one market directly influence other regional markets, too. In this context, the decrease in 2001 is attributed to a rapid demand decrease after the terrorist attacks[26] in the United States of America on September 11th, 2001. In the time period from 2006 to 2008 a strong demand increase of steel products in China and India has been observed. Since both, China and India are large exporters of steel products, but have even exported more in the time period before 2006 (Wooders et al, 2009), their domestic steel demand increase had significant impacts on European and world steel market prices, see Figure 14. Furthermore, the decreasing steel prices in the year 2009 are explained by the global economic and financial crunch[26] end of the year 2008, followed by a recovery in the year 2010.

4.1.3 Silicon price development and its historical impact

Silicon price levels depend very much on the degree of purity. On the one hand, metallurgical grade silicon with an impurity of 0.15 to 0.05 ppmw[27] exists and, on the other hand, electronic grade silicon with an impurity of 10^{-4} ppmw (Hesse et al, 2004). However, with respect to historical Photovoltaic modules mainly electronic grade silicon was used in order to increase the overall energy efficiency. The required silicon was actually a byproduct of the silicon production

[26] A similar trend has been noticed previously at the historical coal price development.
[27] ppmw (parts per million weight)

for the electronic industry[28] (Junginger, 2010). Caused by an increased demand of silicon in both industries, a specific type of silicon was developed for the Photovoltaic industry – the solar grade silicon. Solar grade silicon has an impurity of less than 0.01 ppmw and, consequently, requires less primary energy input in its production. Particularly, the electricity consumption in silicon production is strongly reduced in Photovoltaic modules based on solar grade silicon (Jungbluth et al, 2009).

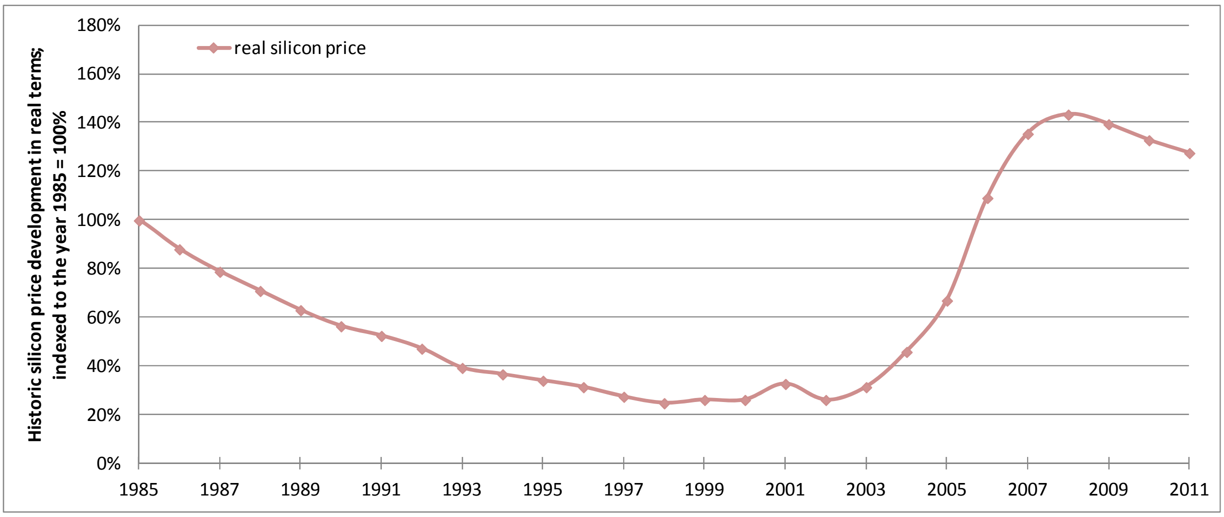

Figure 15 Historical, relative silicon price development (Yu et al, 2010) in real units of Euro 2006/kg from the year 1985 to 2011. Values of the year 1985 represent 100 percent.

An overview of relative silicon prices for the Photovoltaic industry over more than the last two decades is given in Figure 15 above (Yu et al, 2010). In contrast to steel prices a rather constant development of silicon prices is observed whereas in the period beyond 2004 price exceptional but significantly increased. First, the constant decrease from 1985 until 2003 was driven by the developments in the electronic industry and specific improvements in terms of energy and electricity intensity. Since electricity prices are dependent on the portfolio of the primary energy input, slight local differences occurred, still showing the same trend. However, in the year 2004 the demand of silicon for the Photovoltaic industry increased significantly, leading to a production shortage of silicon and, consequently, increasing its price. Hence, new capacities generating solar grade silicon were installed, requiring additional energy input into silicon production and further increasing its price[29]. After operating several new silicon production plants the market relaxed again in the year 2008, leading to decreasing silicon prices, supported by declining energy market prices.

[28] Due to the moderate Photovoltaic market growth no additional silicon was required.
[29] Additional supported by increasing energy and electricity prices in the period of strong global economic growth.

4.1.4 Concrete price development and its historical impact

In quantitative terms concrete holds a major share on construction materials of energy technology plants. However, due to the quantity of required concrete rather several regional markets than one global market exist. Concrete is not traded above a few hundred kilometers. Consequently, concrete prices vary among the different markets, but showed the same historical development in most relevant markets. In particular, concrete prices are dominated by cement prices, whereas cement production is a very energy intense process, too. This issue is supported by the comparison of the historical cement and concrete price trend, showing equal developments. Figure 16 gives an overview of the relative historical concrete price development in real units from the year 1985 to 2010 (Hourcade et al, 2007 and Bureau of Labor statistics, 2011).

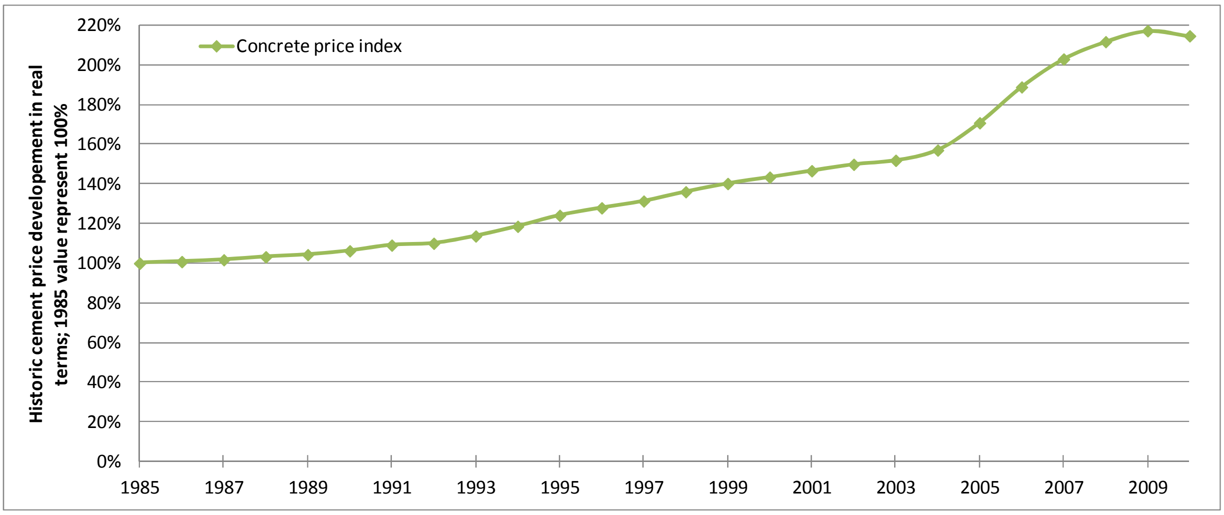

Figure 16 Historical, relative cement price development (Bureau of Labor statistics, 2011) in real units of Euro 2006/t from the year 1985 to 2010. Values of the year 1985 represent 100 percent.

In contrast to steel or silicon prices, concrete prices did not show any fluctuations within the last two decades but rather increased constantly. Although the growth rate of concrete prices increased slightly in the mid nineties, a significant increase is noticed beyond 2004. Additionally, a peak of concrete prices has been observed in the year 2008, whereas afterwards prices declined slightly. Likewise for other commodities, this strong price increase was impacted by raising primary energy costs and additionally stimulated by the global economic boom. Followed by a short delay in time[30], concrete prices decreased slightly from the last quarter of the year 2009 onwards.

[30] Due to their required preprocessing, cement input prices are dependent on earlier primary energy prices.

4.2 Assessment of selected historical energy technology investment costs

Allowing for an econometric assessment of the impact of energy and raw material prices on the investment costs of energy technologies requires studying their historical development. This thesis concentrates primarily on renewable energy technologies, in particular wind on- and offshore, Photovoltaics, small-scale biomass combined heat and power and hydropower plants. Besides renewable energy technologies some comments on conventional power technologies are discussed. Furthermore, a special focus is put on the issue of energy technology costs versus prices in order to avoid any distortion or overestimation of certain material price impacts.

4.2.1 Historical renewable energy technology investment cost – an in-depth analysis

First, wind energy investment costs are studied in detail. Generally, wind onshore energy technology has already been exploited since the early eighties. In contrast, the exploitation of wind offshore energy started in the early nineties. The historical development in terms of investment costs of both wind energy technologies was determined by technological learning effects (Neij, 1999; Isles, 2006 and Junginger et al, 2010b). In the beginning of the current century several additional aspects occurred, influencing the investment costs of wind energy plants too. Thus, Figure 17 depicts the development of wind on- and offshore energy plants of the last decade.

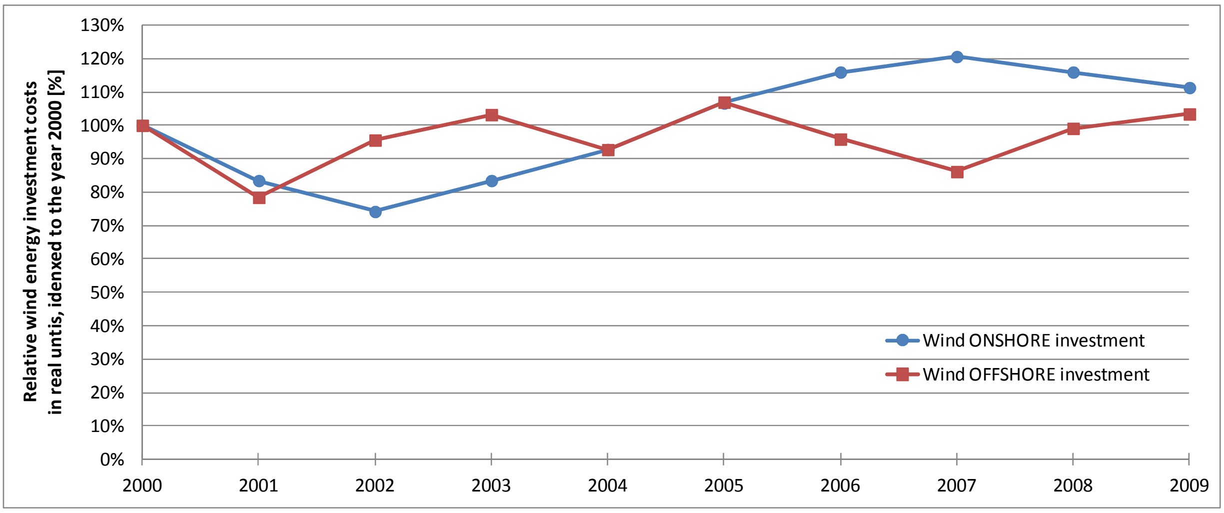

Figure 17 Relative development of historical wind energy investment costs in real units. Wind onshore development (circle line; Source: EWEA, 2010), wind offshore investment costs (square line; Source: Junginger et al, 2004).

In terms of wind onshore investment cost development, in Figure 17, a decline is observed until the year 2002, mainly caused by technological learning effects. In the following period investment costs increased due to increasing raw material prices[31], especially steel prices (Chupka et al, 2007). Moreover, strong financial support schemes in several European Member

[31] Regional aspects, scale effects and public R&D expenditures had slight impacts, too (Lindman et al, 2011).

States (Ragwitz et al, 2007) stimulated a strong demand on wind onshore technology, causing potential price increases. In times of decreasing primary energy and raw material prices, investment costs of wind onshore technologies decreased, too.

In contrast to wind onshore investment costs, fewer records are available on historical wind offshore investment costs. The development in Figure 17 indicates a rather stable development compared to the wind onshore technology. On the one hand, this is caused by the fact that investment costs of offshore wind energy in Figure 17 represent case studies according to Junginger et al. (2004) while onshore investment costs are annual averages. On the other hand, especially wind offshore investment costs are very sensitive to the distance to shore, the water depth and other technical circumstances. In addition, a significant contribution of increased raw material prices, in particular steel and concrete prices, to raising wind offshore investment costs is recognized beyond 2008.

Second, Photovoltaic (PV) energy technology investment costs are taken into account. In principle, investment costs are depending on the type of installation whereas it is distinguished between stand alone plants, roof-integrated plants or façade PV plants. However with respect to their module price a similar trend of the historical development is observed. Additionally, two major types of Photovoltaic technologies exist. Currently 95 percent of the installed PV plants are based on multicrystalline silicon modules whereas the other five percent are thin film modules using Cadmium telluride (van Sark et al, 2007). However, the Photovoltaic technology is characterized by a strong technological learning by doing rate. Ranges between 16 to 20 percent are reported in literature depending on the considered parameters (Junginger et al, 2010b or Nemet, 2006).

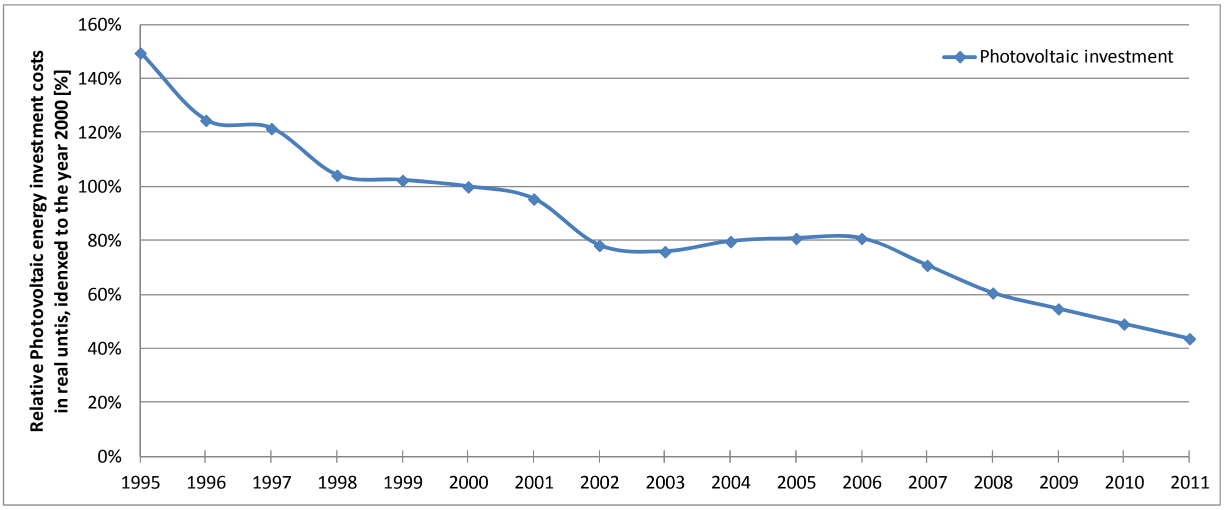

Figure 18 Relative development of historical Photovoltaic module investment costs in real units in the time period from 1995 to 2011 (Source: Yu et al, 2010).

Figure 18 above depicts the historical development of Photovoltaic module investment costs in real units in comparison to the year 2000. As mentioned previously, the early development of PV investment costs was dominated by technological learning by doing[32]. However, this trend continued, but in the period around 2004 the increasing silicon prices raised the PV investment costs significantly. Favorable financial promotion schemes for Photovoltaics (Teckenburg et al, 2011) have led to a high market growth rate, especially in Germany, Spain and also China. Therefore, strong technological learning effects have been achieved, reducing the investment costs of Photovoltaic significantly beyond the year 2007, see Figure 18.

Next, hydro power investment costs are analyzed with respect to their historical development. This thesis focuses on run-of-river plants only, whereas several slightly different applications exist (Giesecke et al, 2003). However, no direct relation to pump hydro power plants can be drawn in this respect. Investment costs of run-of-river power plants are, in general, very sensitive to their scale. Nevertheless, investment costs of small-scale plants even vary significantly between different regions. Therefore, variations up to more than hundred percent appear in historical observations depending on region (EREC, 2010), caused by topographical differences.

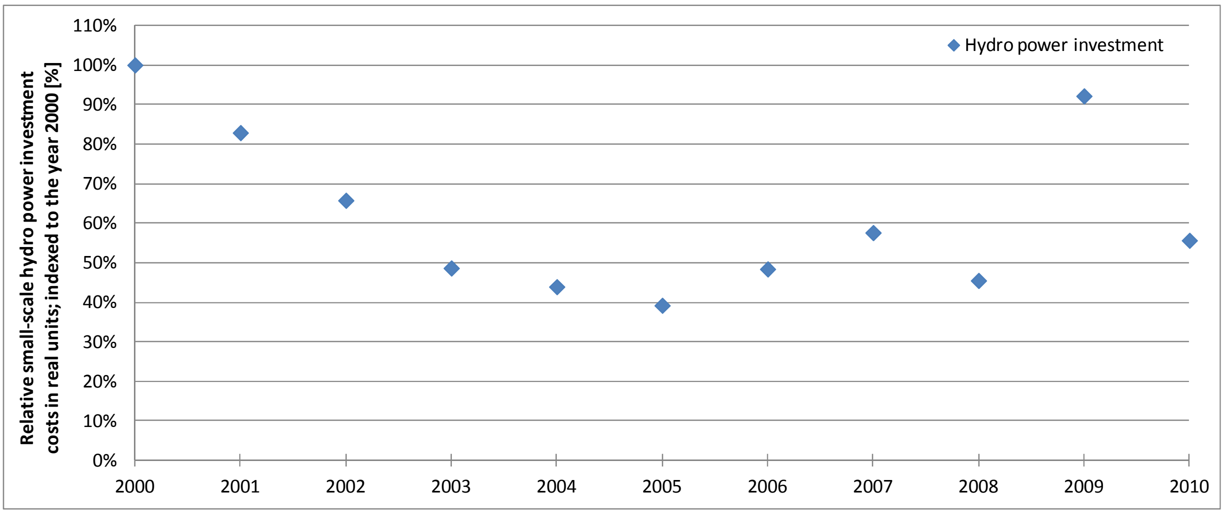

Figure 19 Relative development of historical small-scale hydro power investment costs in real units in the time period from 2000 to 2011 (Source: New Energy Finance, 2011).

Figure 19 shows the relative historical development of small-scale hydro power plant investment costs. Attention has to be drawn at its interpretation. The illustration rather reflects time-independent, site-specific investment costs than a historical development. Although significant investment cost reductions are illustrated, rather little technological learning rates are identified,

[32] Due to the comparatively high investment costs of PV modules, different studies of learning rates in the context of national versus global learning effects have been published (Junginger et al, 2010) in order to depict national advantages of intensive support schemes.

due to the maturity of the technology. Additionally, moderate growth rates of run-of-river plants limit the overall effect of technological learning by doing. Important impact of the depicted investment cost is allocated to the partly obligatory expenditures for the environmental impact assessment, amounting up to a share of fifty percent of the total investment costs (EREC, 2010). Generally, not only the national implementation of the environmental impact assessment varies among different countries, but also the terrain specification as the height of water differences impacts the overall investment costs significantly. Since Figure 19 illustrates investment costs of certain case studies across Europe[33], annual investment costs vary strongly according to the location of the case study plant.

Finally, solid biomass Combined Heat and Power (CHP) investment costs are selected in this thesis. Principally, biomass energy plants are categorized into solid, liquid and gas fired plants, each of them having specific technology requirements. Moreover, different preconditions on the fuel preparation are demanded in this respect. However, investment costs of biomass energy plants vary strongly depending on the final outcome of the energy plant, whereas this thesis only focuses on biomass CHP plants. Finally, the scale of the CHP plant impacts their investment costs significantly, too. Different technological approaches are applied for different scales of solid biomass CHP plants (Overend, 2006), having different levels of maturity and consequently costs. Figure 20 indicates the relative, historical development of small scale biomass CHP plants.

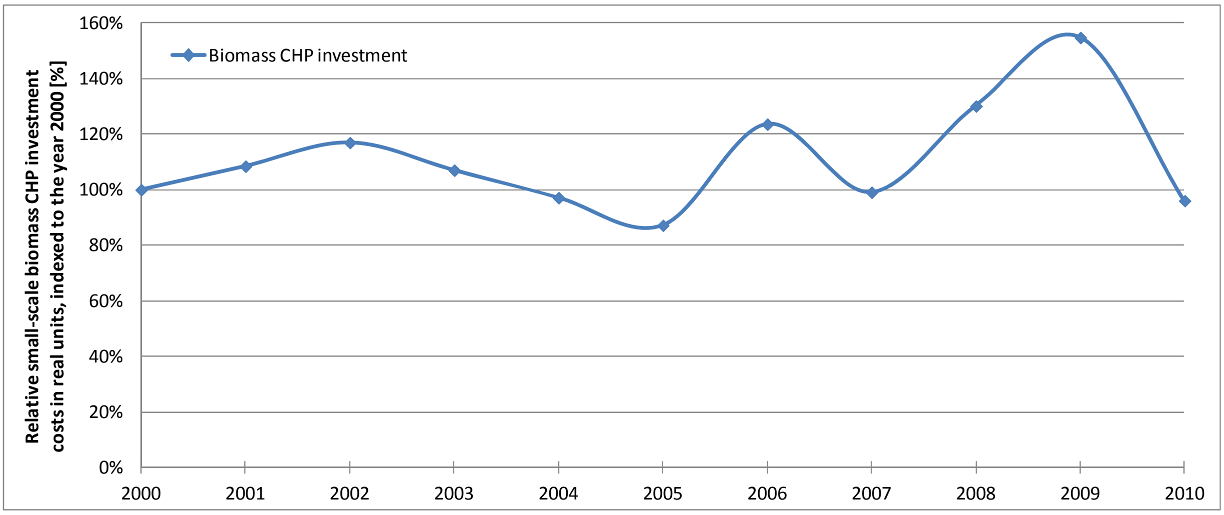

Figure 20 Relative development of historical small-scale biomass Combined Heat and Power (CHP) plant investment costs in real units in the time period from 2000 to 2010 (Source: New Energy Finance, 2011).

Given that investment costs of biomass energy plants are very sensitive to the implemented technological approach, data availability is very limited. Figure 20 indicates case study investment costs of small-scale biomass CHP plants. Generally, technological learning effects

[33] Due to limited data availability caused by a moderate market growth.

are rather low in the solid biomass energy sector[34] due to the similarity to the combustion process of conventional plants and their high degree of technological maturity. However, a fluctuating trend of the investment cost development is noticed in Figure 20. On the one hand, this trend results from the very site specific requirements and their associated costs of each single case study plant. On the other hand, some impact of energy and raw material prices, especially in the period of high prices, is observed as well.

4.2.2 The implication of prices versus costs

Reports of the historical development from selected renewable energy technology investment costs, depicted above, rather refer to prices of the technology than to their costs. However, technological improvements influence the production costs of the energy technologies. Consequently technological learning effects are only directly recognized in the costs of energy technologies.

According to the Boston Consulting Group (BCG, 1968), Junginger et al. (2010b) and Söderholm et al. (2007) prices and costs of energy technologies are developing, under certain circumstances, in line. These circumstances, however, have been distorted in the recent past. Therefore, the following points were taken into account when selecting historical investment costs of energy technologies.

First, a general theory divides the price setting mechanism of each item into four different stages (BCG, 1968 and Junginger et al, 2010b). In the *development phase* prices are even below costs, during the *price umbrella phase* prices stagnate while costs decrease, followed by the *shakeout phase* when price fall even faster than costs. The final phase is the *stability phase* where price and costs develop according to the same trend. The *price umbrella* and the *shakeout phase* are both relevant for selected renewable energy technologies. On the one hand, constant prices have been observed although technological learning decreased prices and, on the other hand, prices have been falling rapidly although production costs did not decrease in the same order of magnitude[35].

Second, strong demand increases of energy technologies caused by favorable support mechanisms, respectively only the future expectations of such demand increases, lead to increasing investment costs (Reynolds, 1999).

Third, financial support mechanisms, on the one hand, stimulate renewable energy deployment. On the other hand, higher financial support options encourage investors rather to invest in less suited wind sites rather than it supports competition and, consequently, boosts future research and development in order to decrease their costs (Berglund et al, 2006). Therefore, inefficient

[34] Technological learning in the biomass sector is rather identified in the preparation of fuel than at the turnkey investments themselves.
[35] Wind onshore and photovoltaic investments discussed in the previous chapter support this theory.

support measures (Ragwitz et al, 2007), offering too high financial support options, provide higher opportunity costs for investors than in an efficient market with adequate support levels. Consequently, the increased opportunity costs increase investment costs into renewable energy technologies significantly (Huber, 2011). Amongst other technologies, this effect has been reported in the case of onshore wind energy plants. Comparing investment costs of wind onshore plants in the United Kingdom to those in Spain, indicates the higher investment costs in the United Kingdom[36], see Figure 21.

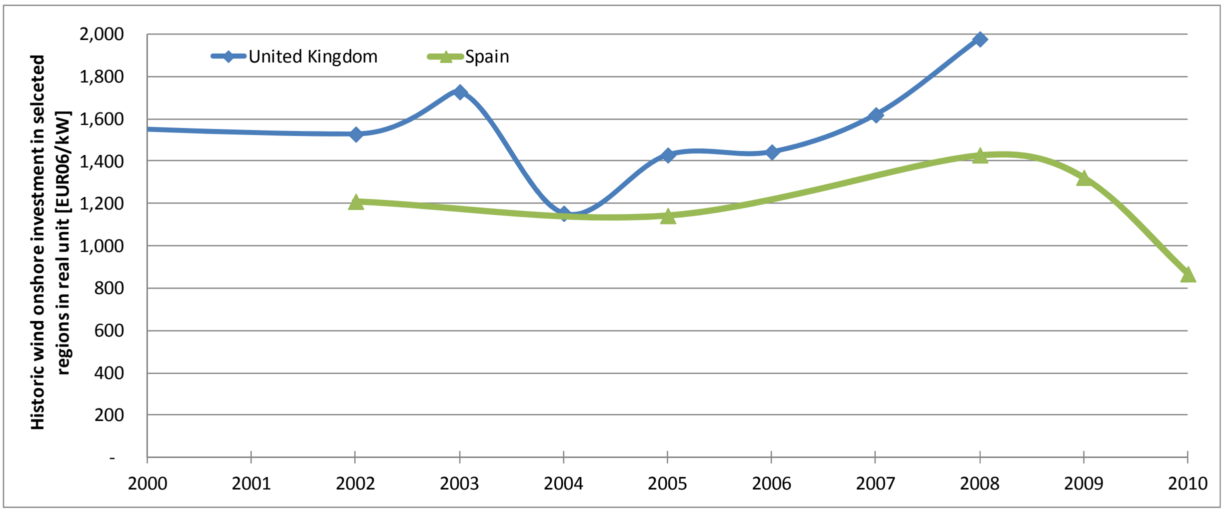

Figure 21 Comparison of historical wind onshore investment costs of the United Kingdom and Spain in real units [Euro2006/kW]. Source: New Energy Finance, 2011.

Figure 21 shows a rather constant development of onshore wind investment costs in Spain whereas stronger fluctuations are noticed in the United Kingdom. However, investment costs in both countries increased significantly beyond the year 2006. Nevertheless, investment costs in the United Kingdom are on average 30 percent higher supporting the discussion of higher opportunity costs in countries with general high financial support schemes.

In consequence this thesis takes into account investment costs of energy technologies in a mature market where prices and cost follow the same trend (see point one above). Additionally, emphasis is put on the implemented support scheme of selected countries since an effective and efficient support scheme reduces opportunity costs for investors and consequently the difference between costs and prices. As a result, considered energy technology investment costs meet the requirements to, on the one hand model technological learning and on the other hand model the impact of raw material prices, since investment costs do not contain significant additional market impacts.

[36] The United Kingdom had installed a tradable green certificate (TGC) scheme whereas Spain applied an efficient (premium) feed-in tariff. The TGC scheme offered by far higher total revenues for investors.

5 Raw material prices: The primary energy price impact

Raw material prices recently showed a significant fluctuating development. A major contribution supporting these strong fluctuations is allocated to primary energy prices. Consequently, on the one hand this chapter elaborates on different raw material production processes and their major energy inputs. On the other hand, the impact of primary energy prices on raw material prices is quantified according econometric models. In this respect, the results are discussed and interpreted in the mathematical context whereas the focus is put on the energy context. Finally, future scenarios on raw material price developments are derived and debated. However, supporting argumentation for the importance of the isolated consideration of energy price impacts on raw material price developments is presented. This thesis focuses on the steel price, concrete price and silicon price development until the year 2030.

5.1 Steel price development – impacts and drivers

Generally, the steel making industry is very energy intensive. Therefore, first the main differences of the various process types are analyzed with respect to their energy inputs. However, a major share of primary energy comes from hard coal products. Consequently, in a second step econometric analyses are conducted quantifying its impact. Based on this result, future forecast scenarios of the steel price are derived. Sensitivities of the coal price impact illustrated the range of potential future steel price developments. Finally, the often argued additional impact of economic growth on the steel price development is taken into account.

5.1.1 Technical processes and related primary energy consumption

In the focus of primary energy consumption of steel production it needs to be distinguished between the different technical production processes. In principal, three major technologies are in operation nowadays. On the one hand, the Basic Oxygen Furnace (BOF) technology mainly builds on iron ore and coking coal inputs. Hereby, the coking coal plays an important role in the context of energy input as well as for forming the physical structure of the steel product. However, the BOF system causes about 1.5 to 2.5 tons of CO_2 per ton of produced steel. On the other hand, the Electric Arc Furnace process produces steel only from steel scrap inputs. Therefore, the required energy input and, consequently, CO_2 emissions are significantly reduced to a level of about 0.4 tons of CO_2 per ton of steel. Finally, the Direct Reduced Iron (DRI) process has been developed in recent years. The DRI process starts from natural gas or coal which is then passed over the iron ore to produce sponge iron. The sponge iron needs then to be fed into an EAF process in order to produce steel (Wooders et al, 2009). In total, steel production by the DRI process followed by EAF system causes about the half of the CO_2 emissions than the BOF system and neither depends on steel scrap.

Current steel production is dominated by the Basic Oxygen Furnace. About two third of the global production is produced by BOF technologies. Although steel is produced globally, major shares, especially BOF systems are located in China and India. In contrast, only a quarter of the global steel production is based on Electric Arc Furnaces. The rest, about six percent are related to Direct Reduced Iron systems combined with EAF systems (World Steel Association, 2008). According to literature, this trend of a BOF system dominated steel production will continue in the near to mid-term future (Michaelis et al, 2000). A fast penetration of the DRI process is not expected within the considered time frame. In consequence, the market share of EAF process is limited too. On the one hand, the major input for EAF systems is steel scrap, whereas most steel products stay in operation for a long time period. Therefore, the input material for EAF systems is limited and additional required steel on the market must be provided by BOF systems from iron ore and coking coal. On the other hand, since DRI systems do not face high future expectations the need for EAF system is limited as well.

With respect to the energy consumption of the different steel making process a broad range is found in literature. Generally developing countries are rather on the upper end whereas industrial countries have already installed several energy efficiency measures. The most efficient BOF system is reported with a specific energy consumption of 19 Gigajoule primary energy per ton of produced steel (WEC, 1995) but also up to 40 GJ/t steel are reported in literature (de Beer et al, 1998). In contrast, the range of the energy consumption of an average EAF system is indicated with 4 to 6.7 GJ per ton of steel. Consequently, Figure 22 depicts the contribution of the different energy sources to overall final energy consumption of a BOF system.

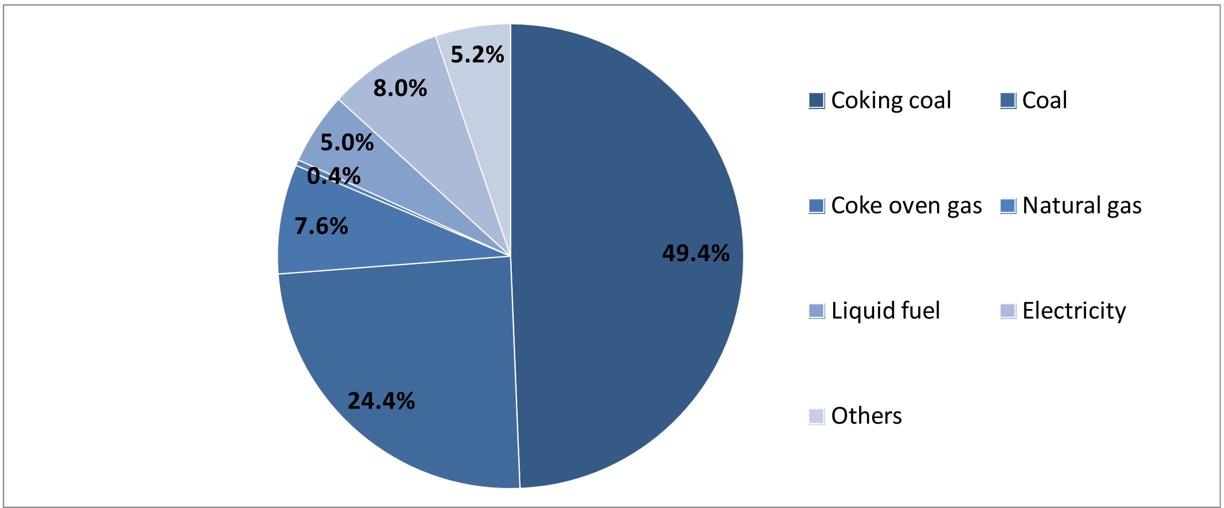

Figure 22 Final energy consumption of a Basic Oxygen Furnace steel making process. Source: Price et al, 2002

According to Figure 22 almost three quarters of the total final energy demand of a BOF system is provided by solid energy sources. Only eight percent are from gas sources, whereas a major share comes from coke oven gas again. Liquid fuels are only amounting to five percent and are mainly used for onsite transport. Finally, electricity demand is about eight percent, although about 80 percent of the electricity is produced onsite. With respect to solid fuels about two thirds are demand in coking coal[37], the rest is direct coal use. In monetary terms the overall energy input amounts to about 25 to 30 percent of steel production costs (de Beer et al, 1998).

Astier (2010) argues that the coal price will continue to dominate the input prices into steel making processes. On the one hand, only BOF systems – relying on coking coal and consequently coal – are able to produce additional steel without the use of existing steel scrap. On the other hand, India as second largest steel producing country worldwide does not have sufficient domestic coking coal reserves but is rich in iron ore and hard coal. Therefore, coal gasification is an increasing future option for India to produce steel which prolongs the input of coal prices on steel prices (Astier, 2010). Additionally, iron ore prices are expected to continue on actual level for at least the next ten years and will even increase beyond, indicating the importance of BOF systems in future steel making (Price et al, 2010).

5.1.2 The impact of coal prices – an econometric model

As discussed in chapter 5.1.1 above, coal prices are identified as a major driver of steel prices in the historical as well as future context. On the one hand, coal prices are responsible for coke prices required in BOF systems and, on the other hand, coal gasification will be important for future steel making processes. Therefore, an in-depth modeling assessment is carried out in order to quantify the impact of coal prices on steel prices. Formula Eq. 23 depicts the derived model specifications[38].

$$\frac{\Delta \mathrm{p_{steel}}}{\Delta \mathrm{t}} = c + DIFFCOAL * \frac{\Delta p_{coal}}{\Delta \mathrm{t}} + DIFFCOAL\_LAG * \frac{\Delta \mathrm{p_{coal}}}{\Delta(\mathrm{t}-1)} + u(t) \qquad \text{Eq. 23}$$

$\frac{\Delta \mathrm{p_{steel}}}{\Delta \mathrm{t}}$	Annual steel price growth rate
c	Constant parameter
$\frac{\Delta \mathrm{p_{coal}}}{\Delta \mathrm{t}}$	Annual coal price growth rate
$\frac{\Delta \mathrm{p_{coal}}}{\Delta(\mathrm{t}-1)}$	Annual coal price growth rate of previous year
u(t)	Statistical disturbance term
DIFFCOAL DIFFCOAL_LAG	Constant parameter of regression of the impact of annual coal price growth rates

[37] The above mentioned 19 GJ/t of steel already consider the energy input for coking coal production from ordinary hard coal.
[38] The model considers growth rates on an annual basis.

The model in Eq. 23 describes the annual change rate of the steel price development in dependence on a constant term, the annual change rate of the coal price, the annual change rate of the coal price of the previous year and the statistical disturbance term. In general, the constant term represents a floor price. Moreover, the impact of the coal price growth rate indicates the high share of coal products in steel production. In contrast, the coal price growth rate of the previous year represents the coal price impact on coke production used in steel-making processes. However, major impacts of delayed coal prices occur due to the fact that high volumes of coal are traded on long term contracts (Adams, 2006). Table 2 depicts the result of the econometric analysis of the model in formula Eq. 23.

Table 2 Parameter of the econometric analysis of the impact of coal price growth rates on steel price growth rates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.46943	20.44624	0.903317	0.3964
DIFFCOAL	2.493618	0.815295	3.058548	0.0184
DIFFCOAL_LAG	-4.475420	1.130665	-3.958219	0.0055

In the first column of Table 2 the constant coefficients of the econometric model are depicted. With respect to the third column, the t-statistic values indicate the significance level of the constant coefficients whereas a high absolute value represents a high significance. Additionally, the indicated probability in the fourth column shows that all coefficients are significant within the five percent confidential interval. Moreover, Table 2 highlights the strong, direct impact of coal price growth rate on steel price growth rates. In contrast, an indirect impact of the coal price growth rate of the previous year has been identified[39]. Thus, strong decreasing coal price growth rates potentially stimulate the steel production which creates a certain steel surplus. Consequently, this lowers the steel demand in the following period and, therefore, reduces the steel production too, finally increasing the steel price growth rate in the next year.

In general the discussed regression model results in well acceptable quality. The coefficient of determination value of R^2=0.7 indicates a good fit of the steel price growth rate explained by coal price growth rates only. However, the coefficient of determination adjusted for the degrees of freedom still indicates an acceptable value of R^2_{adj}=0.62.

Figure 23 indicates the historical annual steel price growth rates as well as the model result based on annual coal price growth rates. Additionally, the residual is plotted. In accordance to the coefficient of determination a general well fitted approximation results for the steel price growth rates. However, remarkable residuals occur only in the year 2000 and 2001 when steel price dropped and coal price raised. As mentioned earlier, steel prices dropped as a

[39] In a mathematical context the limited data set additionally restricts a more detailed investigation on the relationship between the two time series.

consequence of the terroristic attacks in 2001 whereas this did not have a similar strong impact on the coal price. Thus, since the model considers the energy price impact only this exogenous market impact leads to remarkable residuals in the year 2000 and 2001.

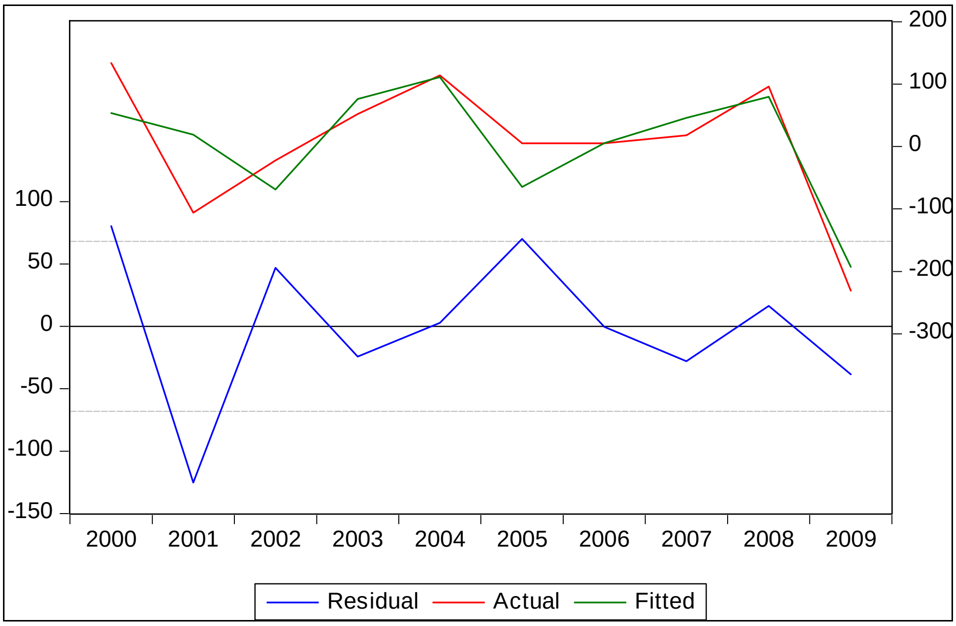

Figure 23 Comparison of the real historical development of the steel price growth rate to the result of the econometric analysis and its residual in real units, EUR2006/t steel. Source: own calculations.

In order to fulfill the statistical requirements, the analysis focuses on the annual growth rates, showing a stationary trend and, therefore, meets the preconditions for conducting an econometric analysis based on the OLS method (see chapter 3.3).

Table 3 Statistical evaluation of the econometric analysis of the steel price growth rate. Source: own calculations

Statistic overview	
Unit root:	Augmented Dickey-Fuller Test **H0...time series has a unit root** DIFFCOAL rejects H0 with 97% probability within 5% significance intervall DIFFSTEEL rejects H0 with 98.15% probability within 5% significance intervall
Normality:	Jarque-Bera Test **H0...regression is normal distributed** JB=0.585 Accept H0 with 74.6% probability
Serial Correlation:	Durbin Watson (1st order) - DW:2.87 -> undefined Breusch-Godfrey serial correlation test **H0...no serial correlation** $N*R^2$=6.885 $chi^2(5,0.95)$=11.070 => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test **H0...homoskedastic** $N*R^2$=0.215 $chi^2(2,0.95)$=5.991 => H0 accepted

Table 3 above depicts the result of the relevant statistical tests of the steel price model of formula Eq. 23. Apart from the stationary of the time series, the model is tested against normality distribution, serial correlation up to the fifth order and heteroscedasticity. All tests are positive in the sense of meeting the requirements of the Gauss-Markov Theorem discussed above. Therefore, the different test types are marked in green in Table 3.

Finally, in Figure 24 the steel price development is compared to historical observations as well as a future scenario is derived based on the future coal price development depicted in Figure 13. Besides the deviations of the model based steel price from real observations around the year 2000, generally, a slightly lower steel price is calculated based on coal price growth rates. Thus, neglecting market implications[40] and focusing on energy price impacts only rather results in steel production costs than in market steel prices.

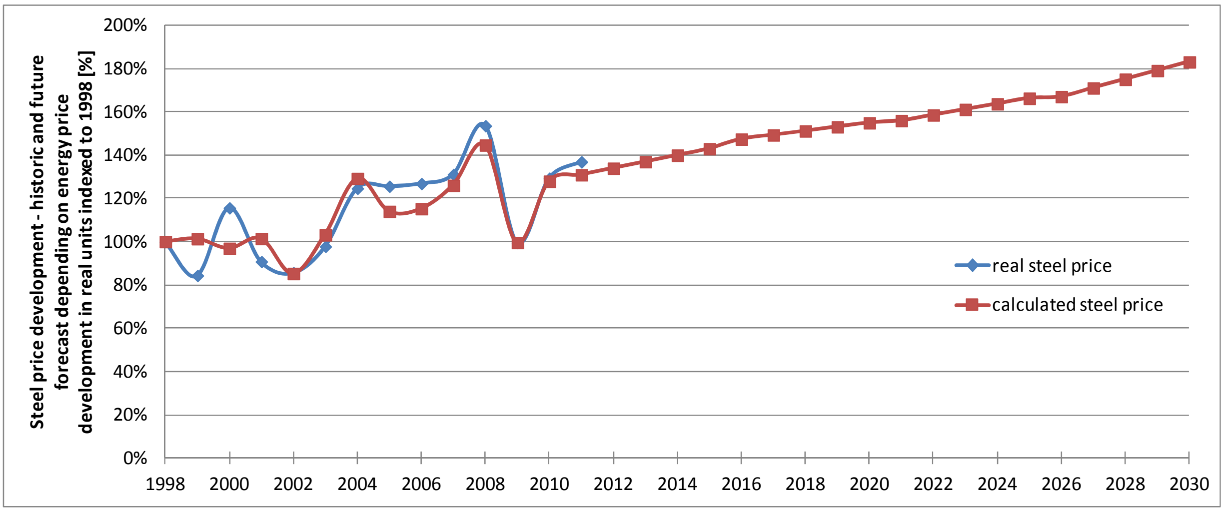

Figure 24 Future scenario of the steel price development according to coal price assumptions (Capros et al, 2011) in real units indexed to the year 1998 and comparison to historical observations. Source: own calculations

De Beer et al (1998) concluded that energy prices have an impact on steel prices of about 25 to 30 percent. Figure 24 illustrates a steel price increase of 35 percent between the year 2000 and 2005, whereas the coal price increases by 139 percent in the same time period – having an impact of about 25 percent on the steel price development. Nevertheless, future forecast scenarios based on econometric analyses have to be interpreted carefully, especially in the long term horizon to 2030 (see chapter 3.4).

5.1.3 Impact of economic growth – an extended steel price model

Apart from the energy price impact on steel prices it is often argued that the demand of steel drives its market price, too. Additionally, as for most raw materials, future steel demand is often modeled as a function of economic growth (Ericsson et al, 2009). Hence, although this thesis

[40] Supply and demand of steel products, strategic pricing of manufactures, policy instruments, etc.

focuses on the impact of energy prices on raw material prices only further research indicates the implications of an additional consideration of economic growth parameter in the steel price model. Therefore, the model of formula Eq. 23 has been extended to the model in Eq. 24.

$$\frac{\Delta p_{steel}}{\Delta t} = c + DIFFCOAL * \frac{\Delta p_{coal}}{\Delta t} + DIFFCOAL\_LAG * \frac{\Delta p_{coal}}{\Delta(t-1)} + DIFFGDP * \frac{\Delta GDP}{\Delta t} + u(t) \quad \text{Eq. 24}$$

The model in Eq. 24 takes into account the same parameter as before and additionally the economic growth rate per capita, $\frac{\Delta GDP}{\Delta t}$. In this context, Table 4 depicts the result of the model based on an OLS regression analysis. Apart from an insignificant value of the constant term hardly any difference exists to the original model. However, on the one hand, the coefficient of the economic growth rate indicates a rather insignificant value of the overall model specification. On the other hand, the absolute value of the GDP parameter is close to zero, implying only a marginal direct impact on the dependent variable, the steel price growth rate.

Table 4 Parameter of the econometric analysis of the impact of coal price growth rates and economic growth rates on steel price growth rates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.958103	32.26069	-0.060696	0.9536
DIFFCOAL	2.173729	1.472442	1.476275	0.1903
DIFFCOAL_LAG	-3.141444	2.168599	-1.448606	0.1976
DIFFGDP	0.060131	0.065836	0.913342	0.3963

Moreover, an in-depth analysis of the time series of the economic growth rate and the coal price growth rate indicates a correlation of about 50 percent. Thus, the additional parameter, economic growth rate, does not contain additional information for the model. This indicates the existence of multicollinearity of the model specification and, therefore, does not meet the Gauss-Markov Theorem.

Furthermore, the adjusted coefficient of determination declines in comparison to the original model. Therefore, the model extension does not add additional information to the steel price development. The high correlation between the energy price growth rate and the economic growth rate indicates that GDP impacts the coal price development. Thus, the pure reflection of energy prices allows a precise modeling of raw material price trends.

Finally, the outcome of the extended model[41] is presented in Figure 25. Additionally, a future scenario is based on the primary energy price and economic growth forecasts presented earlier.

[41] Attention has to be drawn that due to the fact of the high correlation factor between the dependent variables, coal price and economic growth rate, the result is less significant than in the original model presented in Figure 24.

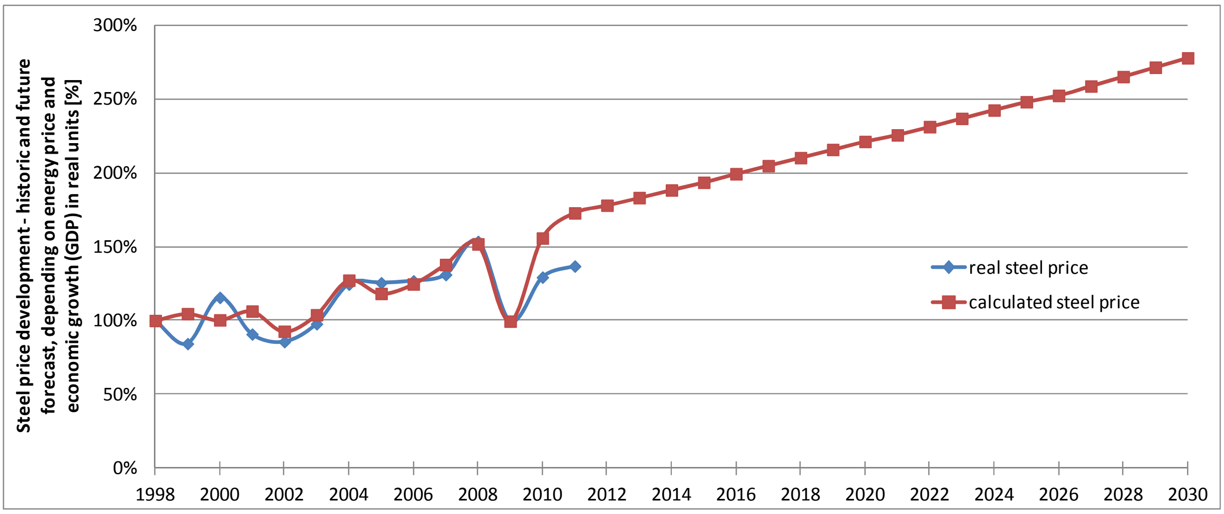

Figure 25 Future scenario of the steel price development according to coal price and economic growth assumptions (Capros et al, 2011) in real units indexed to the year 1998 and comparison to historical observations. Source: own calculations

In terms of the historical observation according to the extended model result in Figure 25, hardly any difference in steel price calculation is depicted. A slightly higher steel price compared to original model is identified due to the minimal direct feedback of economic growth rate on the steel price growth rate. In contrast with respect to the future scenario a discontinuity in the year 2011 appears, caused by the assumptions (Capros et al, 2011) taken into account. Additionally, stronger economic growth rates are expected at these exogenous assumptions. Consequently, steel price would be expected to triple within the 30 years time frame whereas in the original model an increase by 83 percent is expected only.

5.1.4 Sensitivity on energy price assumption

Generally, long term future scenarios bear uncertainty. In order to cope with the uncertainty of the exogenous future energy price assumptions, sensitivities of their impact on the steel price development are conducted. Therefore, a variation of plus minus 20 percent of the original coal price (see Figure 13) development is taken into account in the time period from 2010 to 2030.

Figure 26 depicts the future development of steel prices in dependence of a 20 percent reduced (calculated steel price – low) or a 20 percent increased coal price development (calculated steel price – high). At a first glance, a significant gap of about ten to twelve percent is noticed within the first ten years. This five to six percent sensitivity in steel price at a 20 percent coal price variation is again in line with reported values in literature (de Beer et al, 1998). Nevertheless, the impact of higher coal price decreases with increasing coal price assumptions whereby hardly any difference between the two sensitivity cases is seen beyond 2020. On the one hand, increasing coal price increase the energy efficiency and stimulate the steel production in other processes, i.e. Electric Arc Furnace. On the other hand, the steel price model reacts on changes in the coal price growth rate, which is rather low beyond 2025 compared to the previous time period. Consequently, the overall impact decreases additionally.

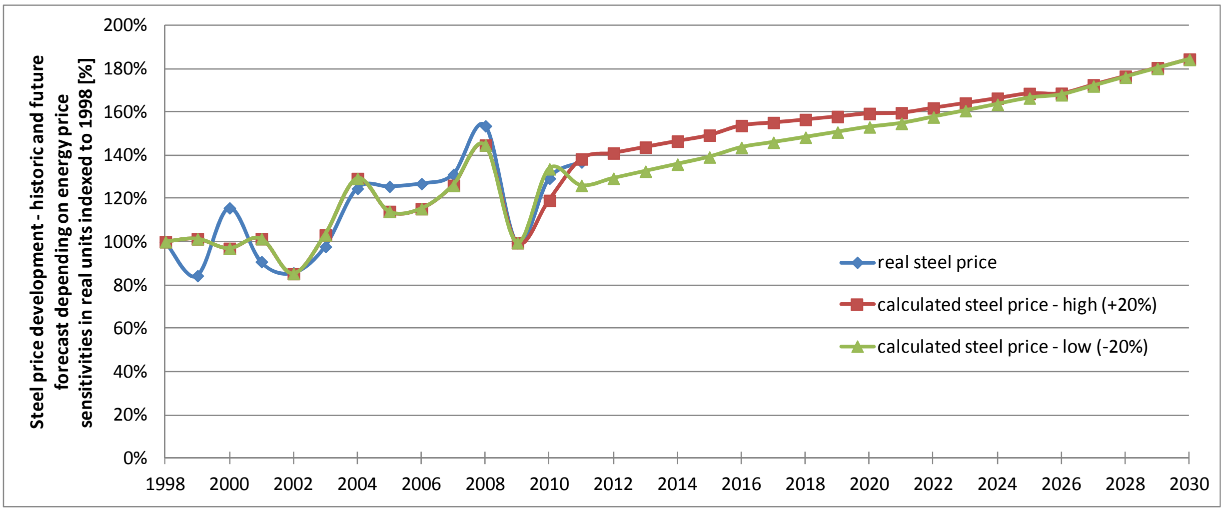

Figure 26 Sensitivity of future scenarios of the steel price development depending on assumed coal prices (Capros et al, 2011) variations in real units indexed to the year 1998 and comparison to historical observations. Source: own calculations

5.2 Silicon prices – impacts and drivers

Silicon holds the major share of raw material inputs in the Photovoltaic industry. However, the production of silicon experienced significant technological changes throughout the last decades. Nevertheless, it is a very energy intensive process with high shares of electricity consumption. Consequently, this chapter focuses on the interaction between electricity price and consumption development in the silicon industry to the silicon price development. Therefore, an econometric model is developed depicting the impact of monetary expenditures of electricity consumption on the silicon price development. Based on this model, future scenarios are derived in order to illustrate potential pathways of silicon prices. Additionally, sensitivity analyses discuss the robustness of the established econometric model.

5.2.1 Technical processes and related energy consumption

Generally, a major input material to silicon production is quartz sand followed by little amounts of coal. In order to produce one ton of metallurgical grade silicon about 2.81 tons of quartz sand are required and about 0.26 tons of coal as well as some charcoal (Jungbluth et al, 2009). In contrast to the limited primary energy input, the production of silicon from these raw materials is a more energy intense process. It is distinguished between the different types of silicon respectively their degree of purity (see chapter 4.1.3).

Starting from raw materials, in a first step metallurgical silicon is produced in a carbonthermic reduction. Hereby, Electric Arc Furnaces are applied in order to reduce the quartz sand with coal. Due to the high electricity consumption of this process, the economic behavior is strongly influenced by the electricity price of the region. Therefore, countries with high shares of hydro power generation are large producers of metallurgical silicon (Jungbluth et al, 2008). Furthermore, based on the metallurgical silicon, electronic grade silicon respectively nowadays also solar grade silicon is produced. In particular, the metallurgical silicon is first converted into gas and, subsequently, this gas is purified by means of distillation. Finally, by adding hydrogen in a deposition reactor, the Siemens reactor, the gas is decomposed onto a surface of electrically heated silicon rods (Jungbluth et al, 2009). According to these steps, electronic grade silicon is produced in the so called Standard Siemens route. Due to silicon production shortages around the year 2004 several other production processes have been introduced, like the modified Siemens route or a Fluidized Bed Reactor. The latter two processes are producing solar grade silicon. On the one hand, they have a slightly lower degree of purity but they fulfill the requirements of the Photovoltaic industry. On the other hand, energy consumption, especially electricity consumption is significantly reduced at the processes and, therefore, the silicon production costs too (Gürzenich et al, 2004).

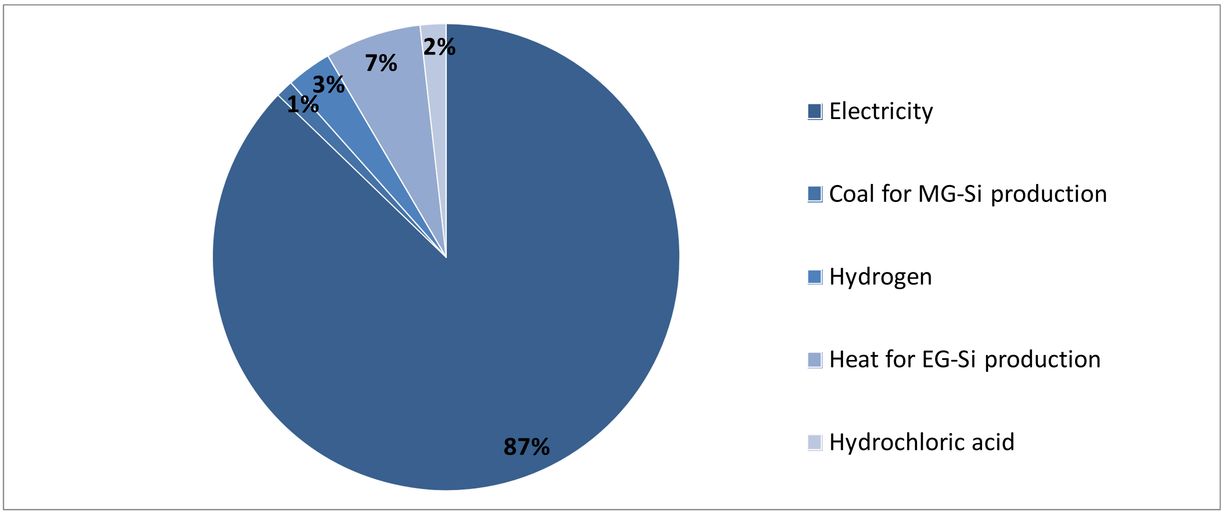

Figure 27 Final energy consumption of electronic grade silicon production in a Siemens route process. Source: Alsema, 2000.

Figure 27 indicates the final energy consumption in a Siemens route process for the production of electronic grade silicon (Alsema, 2000). The total silicon production is strongly dominated by electricity consumption, both in the production of required metallurgical silicon as well as in the final stage of deriving electronic grade silicon. With respect to solar grade silicon production based on the modified Siemens route, electricity consumption can be reduced to a share of 52 percent of the total energy input[42]. Nevertheless, electricity continues dominating the total energy consumption of silicon production within the Photovoltaic industry (Braga et al, 2008).

[42] Additionally, the Fluidized Bed Reactor is expected to decrease electricity consumption even stronger.

5.2.2 The impact of electricity expenditures – an econometric model

According to the identification of major input materials in silicon production (see chapter 5.2.1) an econometric model is established allowing for modeling future pathways of silicon prices depending on electricity expenditures. In contrast to other raw materials, in the case of silicon price not only the electricity price development but also the related electricity consumption had strong impacts on its historical development. Therefore, the electricity expenditures, the product of electricity price and consumption, in monetary terms is considered in the following model. This specific argumentation enables modeling both electronic grade and solar grade silicon price developments. In order to quantify the impact of electricity expenditures on silicon price developments the econometric model in formula Eq. 25 is derived.

$$\ln p^*_{silicon}(t) = \mathrm{c} * \mathrm{k}^* + SI\_ECL * \ln c^*_{ele}(t) + SI\_ECL\_LAG * \ln c^*_{ele}(t-1) + u(t) \qquad \text{Eq. 25}$$

$$p^*_{silicon}(t) = p_{silicon}(t) - \rho * p_{silicon}(t-1) \qquad \text{Eq. 26}$$

$$c^*_{ele}(t) = c_{ele}(t) - \rho * c_{ele}(t-1) \qquad \text{Eq. 27}$$

$$k^* = 1 - \rho \qquad \text{Eq. 28}$$

$p_{silicon}(t)$	Silicon price in the year t
$c_{ele}(t)$	Electricity expenditures for silicon production in year t
c	Constant parameter
ρ	Cochrane-Orcutt parameter
u(t)	Statistical disturbance term
SI_ECL SI_ECL_LAG	Constant parameter of regression of the impact of electricity expenditures for silicon production

The model in Eq. 25 indicates that the silicon price is a function of a constant term, the electricity expenditures and the one year time lagged electricity expenditures plus a statistical error term. In order to linearize the relation, the natural logarithmic has been introduced to the model. Moreover, all parameters of the regression have been transformed by the Cochrane-Orcutt factor (ρ=0.968) according to formulas Eq. 26 to Eq. 28. Hence, the overall regression estimation is corrected for first order serial correlation of the error term and thus fulfills the Gauss-Markov Theorem (see chapter 3.3). Generally, the silicon price is depending on the electricity expenditures of the same year as well as of the previous year[43]. The feedback of the previous year implies that technology development is a discrete development and consequently different silicon production facilities with different energy consumption characteristics have an impact on silicon prices.

[43] However, the model does not consider other parameters impacting silicon prices than energy prices.

Table 5 Parameter of the econometric analysis of the impact of electricity expenditures on silicon prices

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.093514	0.024009	3.895021	0.0006
LOG(SI_ECL)	0.229355	0.051594	4.445348	0.0001
LOG(SI_ECL_LAG)	0.261101	0.063125	4.136265	0.0003

Table 5 depicts the derived coefficients of the regression model in formula Eq. 25. The first column indicates almost similar impacts of the current and the preceding electricity expenditures and a significant lower impact of the constant term. However, according to the t-statistic all three parameters provide a significant contribution to the econometric model. Finally, the last column highlights the probability of the parameters significance which is within the one percent confidential interval. Generally, both parameters have a direct impact on the silicon price. Thus, different silicon production technologies, having different energy characteristics, influence the silicon price directly. Similar for different silicon production locations with varying electricity supply portfolios and consequently electricity prices.

Regarding the quality of the econometric model for the silicon price in formula Eq. 25 the coefficient of determination achieves $R^2=0.51$ and an adjusted coefficient of determination for the degree of freedom with $R^2_{adj}=0.48$[44]. This indicates that the model allows for an estimation of a future trend of the silicon price development based on pure energy expenditures but implies moderate deviations from real price developments.

Furthermore, Figure 28 compares the historical observation of the silicon price to the result of the discussed model in logarithmic units. Additionally, the residual term is plotted in the figure as well. Generally, a well acceptable approximation of the silicon price trend is depicted. However, significant residuals appear in the year 2001 and 2002. Real historical observation increased in 2001 whereas electricity prices declined in the same year due to falling coal prices. A second significant deviation appears for the year 2007 when silicon prices decrease again. The peak of previous years was additionally pushed to a higher level by market effects and, therefore, the model reacts slower on decreasing electricity expenditures as silicon price decreased in reality. Both deviations, caused by additional, exogenous effects to the model parameters, are mainly responsible for the reduced coefficient of determination of the derived model.

[44] The adjusted coefficient of determination of the econometric model is reduced by adding the Cochrane-Orcutt parameter from originally 0.74 to 0.48. However, the original model contained a serial correlation of the error term, holding useful information in it and, therefore, an overestimation of the impact parameters.

Figure 28 Comparison of the real historic development of silicon prices in logarithmic function to the result of the econometric analysis and its residual in real units, EUR2006/kg silicon. Source: own calculations.

In order to linearize the relation between electricity expenditures and silicon prices, the logarithmic function has been considered in this analysis. Additionally, the Cochrane-Orcutt method is applied, correcting for the serial correlation of first order. Table 6 gives an overview of all conducted statistical tests of the regression model of formula Eq. 25. Generally all tests are positive and, therefore, fulfill the requirement for econometric analysis based on the OLS method.

Table 6 Statistical evaluation of the econometric analysis of the silicon price development. Source: own calculations

Statistic overview	
Unit root:	Augmented Dickey-Fuller Test H0...time series has a unit root SI_ENERGY_COST rejects H0 with 99.7% probability within 1% significance intervall SI_COST Dickey_Fuller rejects H0 within 1% significance intervall
Normality:	Jarque-Bera Test H0...regression is normal distributed JB=3.395 Accept H0 with 18.3% probability
Serial Correlation:	Durbin Watson (1st order) - DW:1.141 -> autocorrelation 1st order Breusch-Godfrey serial correlation test H0...no serial correlation $N*R^2$=7.703 chi²(5,0.95)=11.070 => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test H0...homoskedastic $N*R^2$=0.869 chi²(2,0.95)=5.991 => H0 accepted

First, the Augmented Dickey-Fuller test rejects the null hypothesis within the one percent confidential interval and consequently indicates a stationary time series for all relevant price developments. Second, the normality test and the homoskedastic test accept the null hypothesis and, therefore, fulfill the Gauss-Markov Theorem. Finally, the Breusch-Godfrey serial correlation test is conducted[45], in order to test for serial correlation up to the fifth order, highlighting that the model does not result in serial correlated disturbance terms.

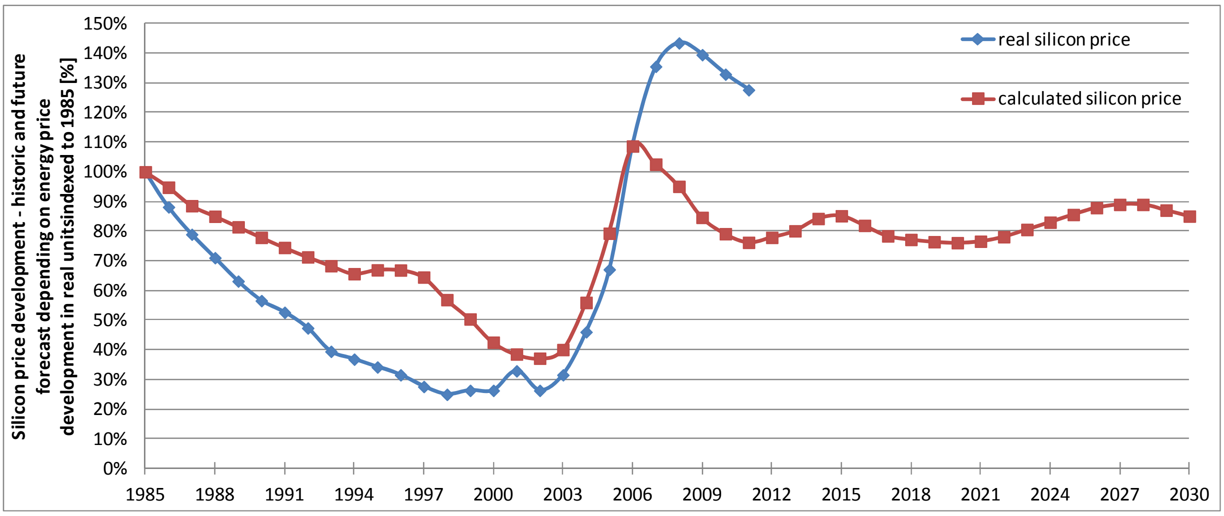

Figure 29 Future forecast scenario of the silicon price development according to electricity expenditures (Huber et al, 2004) in real units indexed to the year 1985 and comparison to historical observations. Source: own calculations

Finally, Figure 29 presents the historical and future development of the silicon price in dependence on electricity expenditures[46]. Obviously moderate deviations occur in comparison to historical observations in some years, whereas the trend of the development can be acceptable explained by only taking into account energy prices. The lack of silicon production in 2004 and, therefore, associated additional energy demand in silicon production in these years led to an increase in silicon prices. Regarding the long term future forecasts, attention has to be drawn to the model which cannot consider other than historical observed, technological changes in silicon production and, therefore, the long term silicon price forecast is uncertain. Additionally, the model only considers energy price impacts, and consequently the silicon price development in Figure 29 rather refers to silicon costs than prices, since market impacts are neglected.

5.2.3 Sensitivity on energy price assumptions

Generally, the future forecast of the silicon price in Figure 29 is derived from electricity expenditures of silicon production according to the discussed model. However, long term electricity price forecasts until the year 2030 are uncertain and, therefore, sensitivities of the

[45] The Durbin Watson test itself does not indicate a significant test result due to the time lagged parameters of the regression model for the silicon price.

[46] Future electricity prices are taken from the Green-X database (Huber et al, 2004).

electricity price are taken into account. Based on the original assumption of the electricity price (Huber et al, 2004) a variation of plus minus 20 percent is considered. In contrast, the electricity consumption of silicon production is considered in its original forecast. Figure 30 depicts the two sensitivity cases of increased and decreased electricity prices beyond 2010.

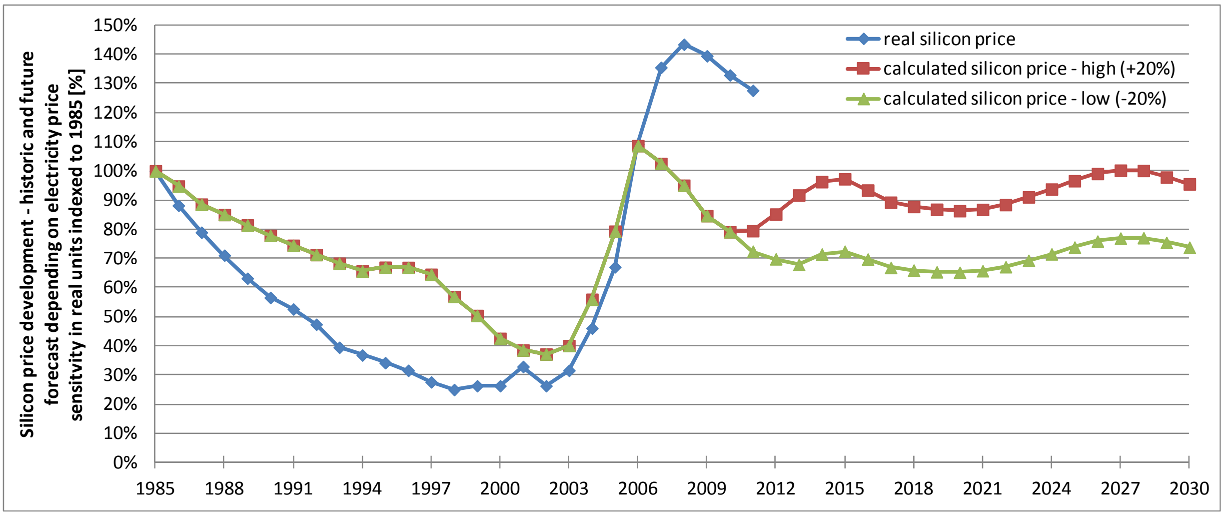

Figure 30 Sensitivity of future forecast scenarios of the silicon price development depending on assumed electricity prices (Huber et al, 2004) variations in real units indexed to the year 1985 and comparison to historical observations. Source: own calculations

In comparison to the original future scenario of the silicon price, the sensitivity cases of the electricity price show a deviation between four and twelve percent. In first years a smaller reaction of the reduced/increased electricity price is noticed due to the impact of previous, time lagged electricity prices. Latter a rather constant deviation is noticed. Generally, a strong sensitivity of the electricity price change on the silicon price change up to 14 percent is observed.

5.3 Concrete prices – impacts and drivers

A major share of input materials to all energy technologies holds concrete. With respect to energy prices, the most relevant component of concrete is cement. Although different approaches are applied in the cement producing industry it is a general energy intense process. Therefore, an econometric model is developed, quantifying the impact of coal and natural gas prices on the concrete prices. Consequently, a future pathway scenario of concrete prices is derived according to the econometric model. In order to cope with the uncertainty of the underlying energy price assumptions, sensitivity analyses are conducted and discussed.

5.3.1 Technical process and related energy consumption

In consequence of the comparatively energy intensive production of cement in contrast to the concrete production, the energy inputs and associated prices in the cement industry are considered as the relevant drivers of the concrete price. Generally, three production steps are distinguished: The mining and preparation of raw materials, the clinker burning and the finish grinding. As the first step is a rather electricity intensive process[47] the clinker burning is the overall most energy intensive production step, accounting for about 90 percent of the total energy use. However, the total energy consumption depends very much on the moisture content of the raw materials. In contrast, the last production step only requires about five percent of the total energy consumption (Worrell et al, 2000). According to the different moisture content of the raw materials different technologies are selected. Starting at wet rotary kilns using raw materials containing up to 38 percent water to dry kilns with pre-heater with much less energy consumption are installed nowadays. Additionally, semi-wet and semi-dry kilns are in operation with reduced moisture content and consequently energy consumption compared to the wet rotary kiln (Szabó et al, 2003). Although broad ranges of energy consumptions of the different technologies are published in literature, a rough difference of doubling thermal energy demand of a wet rotary kiln at 6,000 MJ/t clinker to a dry rotary kiln with pre-heater at 3,000 MJ/t clinker is observed (European Commission, 2009b).

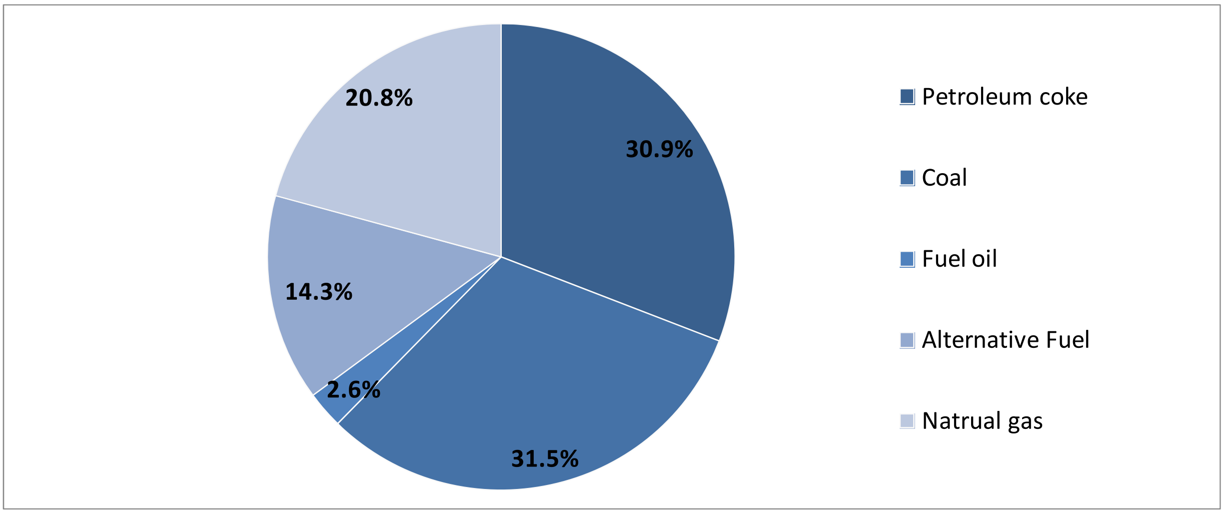

Figure 31 Final energy consumption of the cement production within the EU27 cement industry in the year 2006. Source: Pardo et al, 2011.

Figure 31 depicts the share of primary energy demand of the cement production of the European Union in the year 2006 (Pardo et al, 2011). Almost two thirds of the total energy consumption refers to coal and coke. Natural gas holds an increasing share due to its lower emissions but is currently mainly used in on-site electricity production. Moreover, alternative fuels as biomass energy are used in the cement industry. However, the biomass products used are dominated by rubber tires and sewage sludge. The small share of fuel oil is mainly used in on-site transport of raw materials. Finally, the dominance of high fossil energy demand continues until 2030 even in very high energy price scenarios due to little energy saving potentials (Pardo et al, 2011).

[47] The primary energy demand hereby depends on the regional electricity supply portfolio but is generally very much natural gas driven (due to some on-site gas power plants).

5.3.2 The impact of primary energy prices – an econometric model

Figure 31 identified coal, coking coal and natural gas as the main contributor of primary energy sources in the cement industry. Since coal prices are significantly influencing coking coal prices, an econometric model for concrete price estimations is derived from the historic coal and natural gas price. Although a slight shift towards some alternative fuel sources is observed in the recent past, in terms of costs, coal and natural gas energy will dominate the energy input in the future (Klee, 2009). The concrete price model is characterized through formula Eq. 29 below.

$$p_{concrete}(t) = c + COAL * p_{coal}(t) + COAL\_LAG * p_{coal}(t-1) + GAS\_LAG2 * p_{gas}(t-2) + u(t) \quad \text{Eq. 29}$$

$p_{concrete}(t)$	Concrete price in the year t
$p_{coal}(t)$	Coal price in year t
$p_{gas}(t)$	Natural gas price in the year t
C	Constant parameter
u(t)	Statistical disturbance term
COAL COAL_LAG	Constant parameter of regression of the impact of coal prices and the impact of the previous year coal price
GAS_LAG2	Constant parameter of regression of the impact of gas prices

Generally, the present concrete price is explained by a constant term, the present coal price, the previous year coal price and the natural gas price of two years ago. The model of formula Eq. 29 allows considering all prices in real units of EUR2006/ton since their prices show time stationarity within the investigated time period. In the model of Eq. 29, the impact of the present coal price reflects energy use for heat production in clinker burning. Additionally, the time lagged impact of the coal price results from the pre-preparation of coking coal where coal plays a determining role. With respect to the gas price, highest impacts are identified for two year time lagged prices. On the one hand, high volumes of gas are traded on long term contracts. On the other hand, small on-site storage facilities lag the impact of gas prices additionally. Moreover, the discrete representation of the continuous technology development in the model leads to additional time lagged influences of the primary energy prices.

Table 7 Parameter of the econometric analysis of the impact of coal and natural gas prices on concrete prices

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.051995	6.287213	1.121641	0.2910
COAL	0.437210	0.127989	3.415983	0.0077
COAL_LAG	0.244251	0.111543	2.189748	0.0563
GAS_LAG2	4.564659	0.635887	7.178416	0.0001

Table 7 highlights in the first column the different coefficients of the model of Eq. 29, its standard error in the second, the significance parameter in the third and the probability of the insignificance of the parameter in last column. Consequently, all energy prices hold a direct impact on the concrete price at a well proven significance value within the five percent confidential interval. The constant parameter in the model reflects the additional costs of concrete that are not influenced by primary energy prices, as the most significant impact of primary energy prices is on cement only. Moreover, due to the pre-preparation of coking coal from coal the time lagged coal price hold a direct impact as well. However, it is not as strong as the current coal price, since limited production capacities of coking coal distort the coking coal market price slightly.

Although, cement and concrete in particular are not traded on international markets only minor influences of regional market effects are noted. Therefore, the econometric model in Eq. 29 results in a high coefficient of determination adjusted for the degree of freedoms, $R^2_{adj}=0.84$. Hence, a pure consideration of the main energy input price allows for a precise forecast of concrete prices trends in the future.

With respect to the small trading markets of concrete, respectively cement and the related market effect, further research focused on the additional impact of economic growth (GDP). Chapter 5.1.3 concluded that the additional consideration of GDP does not contribute to the overall model since GDP impacts are implicitly considered in energy price assumptions. However, in the context of concrete, GDP holds a little impact since concrete/cement manufactures are able to strategically increase prices – higher than caused by the raising energy price – in times of economic growth due to the little markets, compared to steel markets. Nevertheless, the overall quality of the model is only marginally increased and, therefore, the model of formula Eq. 29 is applied in this thesis.

Figure 32 discusses the historical concrete price observation and compares it with the result of the concrete price model presented above as well as the residual between the two time series. A well fitted concrete price is observed during the time period of very volatile energy prices, whereas slight deviations occur in the period before. Nevertheless, as the coefficient of determination indicates an appropriate concrete price estimation results from the model in Eq. 29. The deviation in 2002 results from the strong increasing gas prices in the according year.

Furthermore, the residuals of the econometric model as well as the time series of the primary energy prices are statistically tested, allowing for estimations of future concrete prices based on the OLS methodology (see chapter 3.3). Generally, the null-hypothesis of non-stationarity of concrete, coal and natural gas prices can be rejected at high probability factors. Depending on the different tests the null-hypothesis is rejected even within the five percent confidential interval, see Table 8. Moreover, the residuals of the estimation are normal distributed with a probability of above 90 percent. With respect to serial correlation of the error term the Breusch-Godfrey test is applied, indicating no serial correlation[48] up to the order of five. Lastly, Table 8 depicts homoscedasticity of the econometric assessment of concrete prices according to the Breusch-Pagan-Godfrey test.

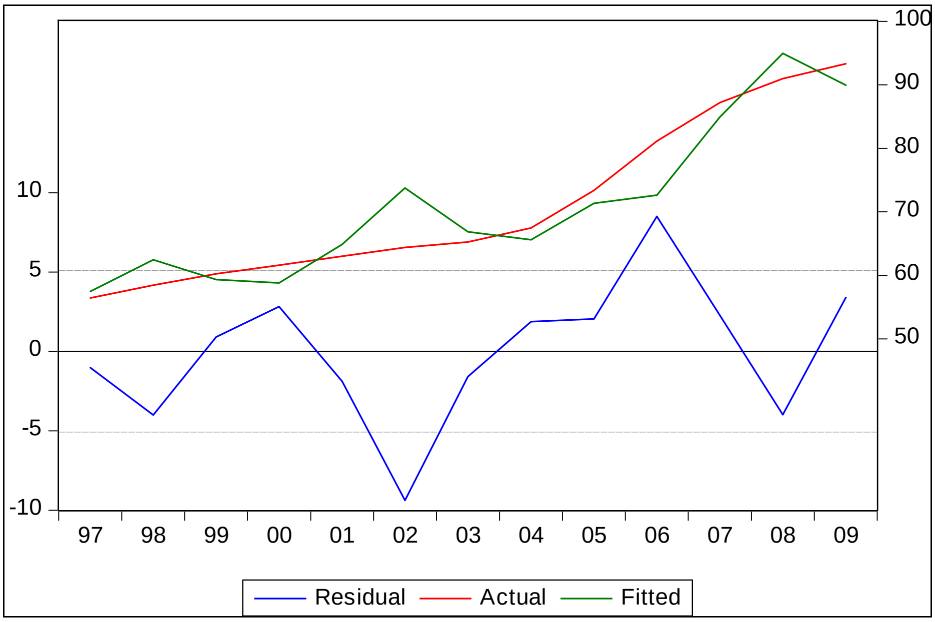

Figure 32 Comparison of the real historical development of concrete prices in absolute terms to the result of the econometric analysis and its residual in real units, EUR2006/t. Source: own calculations.

Table 8 Statistical evaluation of the econometric analysis of the concrete price development. Source: own calculations

Statistic overview	
Unit root:	Augmented Dickey-Fuller Test H0...time series has a unit root CONCRETE rejects H0 with 43% probability // Trend & Intercept COAL_PRICE rejects H0 with 72.3% probability // DF within 5% significance GAS_PRICE_TE rejects H0 with 78.7% probability // DF within 5% significance
Normality:	Jarque-Bera Test H0...regression is normal distributed JB=0.2 Accept H0 with 90.5% probability
Serial Correlation:	Durbin Watson (1st order) - DW:1.55 -> 1.816 undefined Breusch-Godfrey serial correlation test H0...no serial correlation $N*R^2=3.566$ $chi^2(5,0.95)=5.991$ => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test H0...homoskedastic $N*R^2=2.698$ $chi^2(3,0.95)=7.815$ => H0 accepted

[48] The Durbin Watson test delivers an undefined result for first order serial correlation. However, due to the time lagged parameters in the model the result is not significant and the Breusch-Godfrey test is applied.

Finally, future scenarios are calculated according to the econometric model. Figure 33 illustrates the concrete price development indexed to the year 1985 and compares it to real historical observations. Apart from the deviation in the year 2002, caused by strong increasing natural gas prices, a well acceptable approximation is explained through the primary energy price development. However, with respect to the future scenarios a significant decrease of concrete prices in the first year of simulation is recognized. Responsible is the switch from historical statistics of natural gas prices to the general energy price assumptions (Capros et al, 2011) in this thesis which are far below historical records. By trend leveling off concrete prices are expected beyond the year 2020 when energy prices are expected to grow moderately too. In this respect attention has to be drawn to chapter 3.4. The econometric model solely considers the impact of primary energy prices regardless any market effects. Moreover, with an extended time frame of the scenarios their uncertainty increases. On the one hand, input assumptions might be effected by unanticipated events and, on the other hand, technologies could develop faster or slower as expected distorting the identified relations.

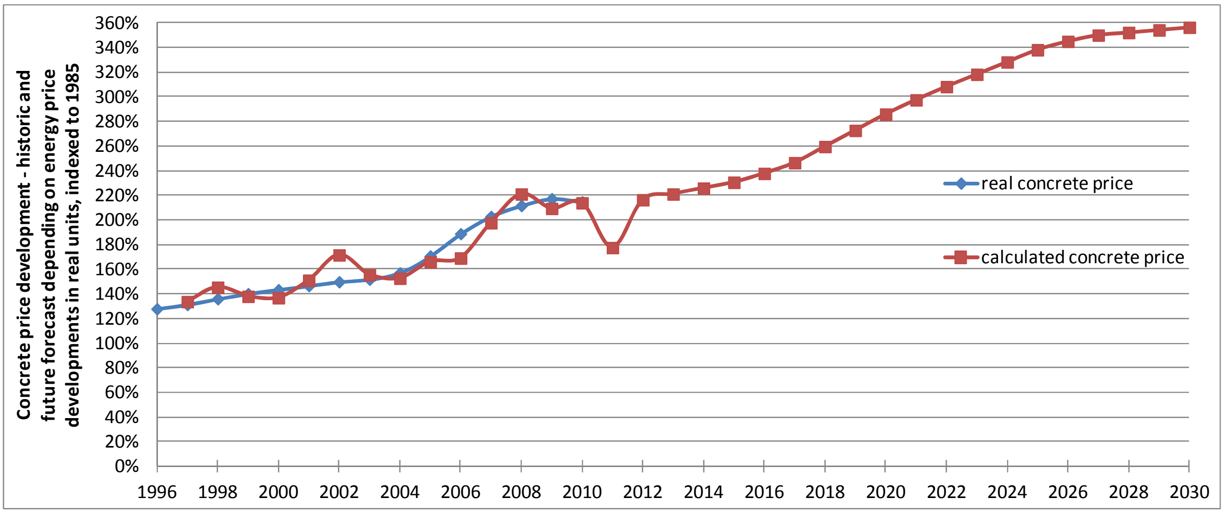

Figure 33 Future forecast scenario of the concrete price development according to coal and natural gas prices (Capros et al, 2011) in real units indexed to the year 1985 and comparison to historical observations. Source: own calculations.

5.3.3 Sensitivity on energy price assumptions

In general, the econometric model of formula Eq. 29 explains the relationship between coal and natural gas prices and the concrete prices based on historical time series. However, based on the assumptions that no fundamental change in the production process of concrete is expected until 2030 (Pardo et al, 2011), future scenarios are derived based on the historical relation. Nevertheless, sensitivities in energy price assumptions are carried out in order to discuss potential impacts in energy price changes on concrete prices. Consequently, Figure 34 indicates the future concrete price development at 20 percent increased and 20 percent lower coal and natural gas prices as currently assumed by the European Union (Capros et al, 2011).

Generally, the future scenario on coal and especially natural gas prices taken into account in this thesis are already very conservative. Therefore, and further decrease in the future of about 20 percent is quite unlikely. However, Figure 34 depicts a high impact of primary energy prices on concrete prices. The different primary energy prices are assumed from 2011 onwards, whereas in the first years, due to the time lagged impact of energy prices, only moderate changes in the concrete price are observed at around 17 to 27 percent from the original scenario. Nevertheless, beyond 2020 the concrete prices deviate by more than 50 percent from original scenarios reaching 68 percent in the year 2030. Consequently, concrete prices react very sensitive to energy price changes, as an energy price increase by 20 percent raises concrete prices by 8 to 18 percent according to Figure 34.

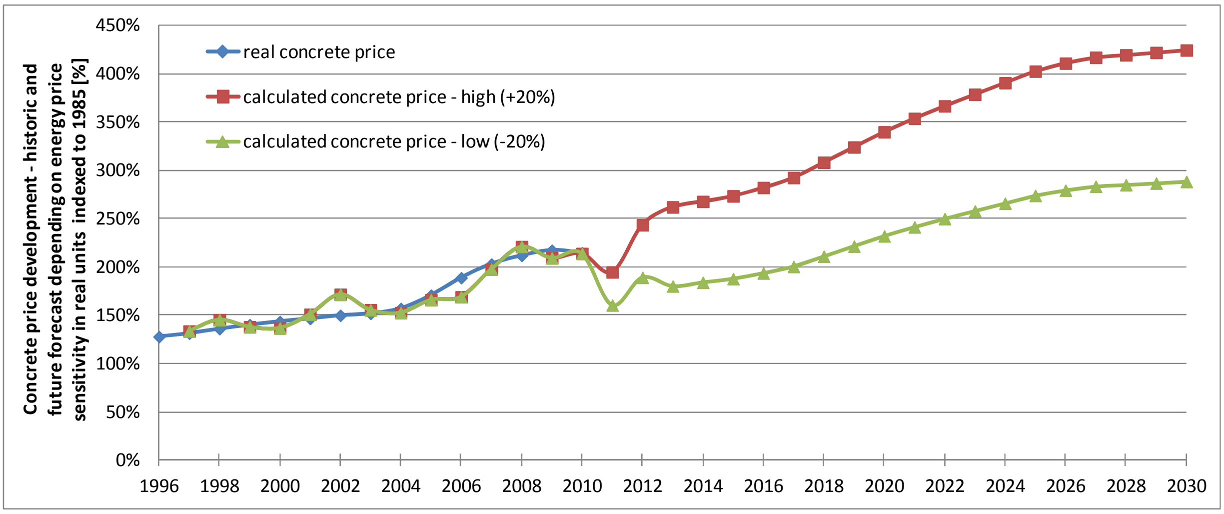

Figure 34 Sensitivity of future scenarios of the concrete price development depending on the assumed coal and natural gas price (Capros et al, 2011) variations in real units indexed to the year 1985 and comparison to historical observations. Source: own calculations.

6 Energy technology investment costs – drivers and pathways

This chapter focuses on a detailed assessment of energy technology investment costs highlighting their main impact parameters. Special emphasis is given to the quantification of raw material price influences as well as to the effect of learning by doing. Generally, renewable energy technologies are selected, whereas particularly wind onshore, wind offshore, Photovoltaic, Biomass Combined Heat and Power (CHP) as well as small-scale hydro power plant investment costs are considered. Hence, econometric models are developed explaining the historical development of the investment costs and are used accordingly in order to derive future scenarios. Additionally, sensitivity analyses of energy price assumptions allow for drawing conclusions on the robustness of the different technology investment costs. In this context, a direct feedback from energy prices to the relevant investment costs of energy technologies, which are responsible for future energy prices, is given.

6.1 Wind onshore investment costs – drivers and impacts

Among renewable energy sources, wind onshore energy is one of the largest technologies in terms of installed capacity (Eurostat, 2011b). Nevertheless, generation costs of wind onshore technologies are still above market prices. On the one hand, technological improvements steadily decreased the investment costs of onshore wind turbines. On the other hand, different exogenous effects rather have an increasing effect as discussed in chapter 2.5. Particularly, steel prices hold a significant impact on the investment costs of onshore wind turbines. In terms of wind onshore investment costs, about 42 percent up to 58 percent, depending on the scale of the wind energy turbine, are caused by steel inputs (Ancona et al, 2003 and Krohn et al, 2009).

Consequently, this section elaborates on the impact of steel prices on the investment costs of onshore wind energy technologies. Thus, an econometric model is developed in order to quantify the impact. Moreover, the simultaneous effect of technological learning by doing is taken into account. In a next step, a scenario of the future development of wind onshore investment costs is estimated under consideration of the above derived steel price development. Finally, sensitivity analyses indicate the robustness of wind onshore investment costs on changes of energy and raw material prices.

6.1.1 The impact of steel prices

First, in order to quantify the pure impact of steel prices on wind onshore investment costs their historical records have to be adjusted from other influences (see chapter 3.2). According to Figure 11 energy technology investment costs have not been influenced by others than technological learning effects until the year 2003. Therefore, a technological learning rate of seven percent is identified for onshore wind technologies in this time period, which is constant over time according to theory. Consequently, a pre-adjustment of historical wind onshore investment costs for the effect of learning by doing is carried out considering the technology penetration of the World Energy Outlook 2008 (IEA, 2008).

Following the discussion above, steel prices are the main drivers in terms of commodities of onshore wind investment costs. Subsequently, an econometric model is derived explaining the investment costs corrected for technological learning effects by the steel price development[49]. Thus, formula Eq. 30 describes the model for estimating the adjusted wind onshore investment costs.

$$\ln INV_{WI-ON}\,(t) = c + STEEL * \ln p_{steel}(t) + STEEL\_LAG * \ln p_{steel}(t-1) + u(t) \qquad \text{Eq. 30}$$

$INV_{WI-ON}(t)$	Investment cost of onshore wind in the year t corrected for technological learning effects
$p_{steel}(t)$	Steel price in the year t
$p_{steel}(t-1)$	Steel price of the previous year t-1
c	Constant parameter
u(t)	Statistical disturbance term
STEEL STEEL_LAG	Constant parameter of the regression of the direct and time lagged impact of steel prices

Generally, in order to meet the preconditions for estimating the wind onshore investment costs with the discussed OLS method, the Gauss Markov Theorem must be fulfilled. Therefore, the natural logarithmic is used in order to linearize the model in Eq. 30. Moreover, the disturbance term does not contain any information by definition. On the one hand, a direct impact of current steel prices is identified in the model. On the other hand, also a direct impact of the previous year's steel price is recognized. The time lagged impact occurs from long term contracts of steel supply for wind technology manufactures but also the long time period of admission procedures is responsible for the delayed impact[50]. Consequently, Table 9 indicates the regressors of the econometric model and its statistical assessment.

Table 9 Parameters of the econometric model, indicating the impact of steel prices on investment costs of onshore wind energy technologies. Source: Own calculation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.359379	0.966299	-0.371913	0.7227
STEEL	0.556760	0.155566	3.578923	0.0117
STEEL_LAG	0.642003	0.144951	4.429112	0.0044

[49] Since other commodities do have a slight impact on the wind onshore investment costs, too, this model might overestimate the impact of the steel price in case of same commodity price trends.

[50] When signing a contract for the installation of a wind turbine a certain steel price is assumed.

In the first column of Table 9 the regressors of the econometric model are depicted. Additionally, the second last and last column indicates the significance value of the regressor, respectively its probability. With respect to the constant term c a negative value is calculated but at a low significance level[51] and a relatively high probability of insignificance. Therefore, the constant does not contribute significantly to the estimation of wind onshore investment costs and only fulfills the mathematical structure of econometric models. In contrast, the regressor of the current steel price value shows a direct impact. Moreover, its standard error is comparatively small and, therefore, results in a high significance value, even within the standard five percent confidential interval. Furthermore, the regressor of the one year time delayed steel price even shows a stronger value in absolute terms. As mentioned above, high volumes of steel are traded on long term contracts and, therefore, the previous year prices are even more relevant in wind onshore manufactures. With respect to its significance value, a higher value is achieved indicating the importance of this parameter. The probability value is even within the one percent confidential interval.

Regarding the quality of the estimation, the pure consideration of steel prices represents a well acceptable approximation for wind onshore investment costs corrected for technological learning effects. The model of formula Eq. 30 results in a coefficient of determination of $R^2 = 0.90$ and corrected for the degree of freedom it still achieves a high value of $R^2_{adj}=0.87$.

Figure 35 depicts the historical wind onshore investment costs adjusted for the technological learning effect and the approximation of the econometric model in logarithmic scale on the right-hand side of the figure. Additionally, the residual of these two time series is plotted on the left scale. The coefficient of determination has already indicated a well explanation of the investment costs by the steel prices. Nevertheless, minor deviations appear in some years. These differences are caused by others than energy related impact parameters, such as support policies increasing the demand of the wind onshore technology or other market influences. However, fitted investment costs according to the econometric model are rather below the actual investment costs. Generally, growing steel prices increased the pure investment costs[52] of wind onshore technology significantly during the last decade and leveled off in the beginning of the economic credit crunch in 2009.

[51] The significance value is calculated as the quotient of the regressor to its standard error of each variable.
[52] But technological learning by doing countered the increasing effect.

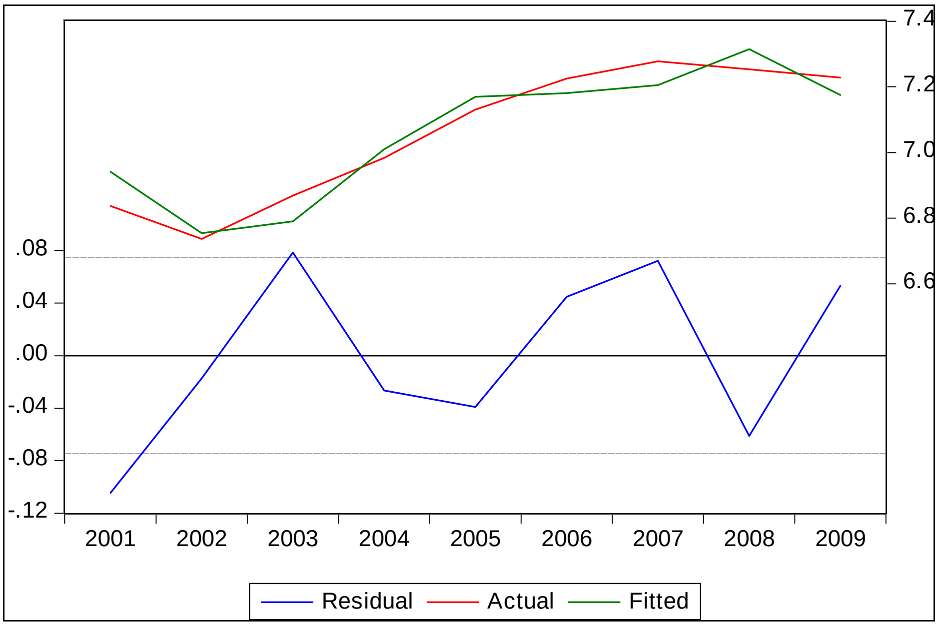

Figure 35 Comparison of historical observed wind onshore investment costs to estimated investment costs according to the model without consideration of technological learning by doing effect. Additionally, the residual of the estimation is plotted at the left scale. Source: Own calculations

Furthermore, the econometric model of formula Eq. 30 is statistically tested on normal distribution, serial correlation and homoscedasticity of the error terms as well as of unit roots in the integrated time series. An overview of the statistic test result is given in Table 10 below.

Table 10 Statistical test results of the econometric model for wind onshore investment costs. Source: Own calculations.

Statistic overview			
Unit root:	Dickey-Fuller Test		
	H0...time series has a unit root		
	LOG_STEEL	rejects H0 within 10% significance intervall	
	LOG_INV_EWEA	rejects H0 within 5% significance intervall	
Normality:	Jarque-Bera Test		
	H0...regression is normal distributed		
	JB=0.658	Accept H0 with 71.9% probability	
Serial Correlation:	Durbin Watson (1st order) - DW:1.99-> no autocorrelation of 1st order		
	Breusch-Godfrey serial correlation test		
	H0...no serial correlation		
	$N*R^2=8.13$	$chi^2(7,0.95)=14.067$	=> H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test		
	H0...homoskedastic		
	$N*R^2=0.833$	$chi^2(2,0.95)=5.991$	=> H0 accepted

Initially, the Dickey-Fuller test is applied testing for the stationarity of the steel price and the wind onshore investment cost development. In both cases the null-hypothesis of existing unit roots can significantly be rejected. Moreover, the normal distribution of the error terms of the econometric model is given with an acceptable probability of 72 percent according to the Jarque-Bera test. The Durbin Watson test points out that no first order autocorrelation is identified and additionally the Breusch-Godfrey test does not detect any serial correlation up to the seventh order. Finally, homoscedasticity is given with a well accepted probability of 66 percent. Consequently, the econometric model fulfills all requirements of the Gauss-Markov Theorem and, therefore, carries out efficient and unbiased impact parameters.

6.1.2 Wind onshore investment costs – results and pathways

In order to derive the effective wind onshore investment costs, in the result from Figure 35 the technological learning by doing effect has to be in considered addition. Therefore, the previously assumed learning rate of seven percent and the wind energy penetration according to IEA (2008) is taken into account. Figure 36 depicts a comparison of the historical observed wind onshore investment costs to the two model results.

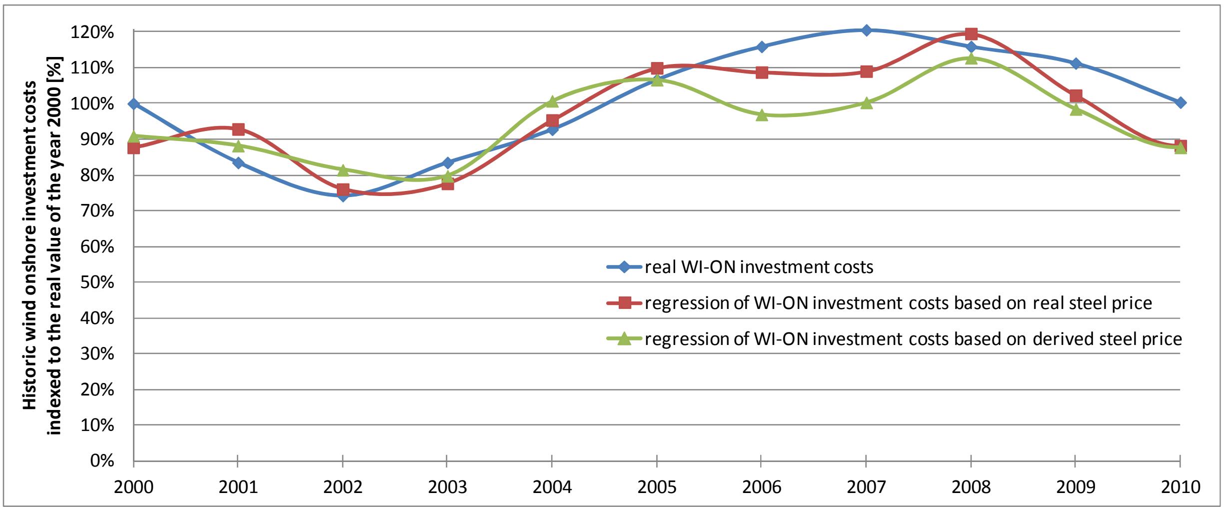

Figure 36 Comparison of real historical wind onshore investment costs to estimated investment costs considering technological learning and the impact of, on the on hand, real steel prices and derived steel prices in chapter 5.1.2, on the other hand,. Source: Own calculation.

On the one hand, the real historically observed steel price is taken into account for the calculations. On the other hand, the derived steel price based on the model of chapter 5.1.2 forms the basis of the calculation. Naturally, in both cases the same conditions of technological learning by doing are assumed. Generally, both estimations that are based on steel price assumptions are slightly below realized investment costs, apart the year 2008 when high market steel prices were noticed but wind investment costs stabilized. Thus, the approximation based on commodity prices rather indicates the production costs than the real market prices. Additionally, the consideration of the calculated steel price results in an even lower investment cost estimation, confirming the interpretation that solely considering energy price impacts indentifies only the minimal impact on investment costs.

Applying the same model for future forecast scenarios allows an estimation of the trend of onshore wind energy technologies until the year 2030. Hence, Figure 37 compares the two approaches of modeling future investment costs of wind onshore technology.

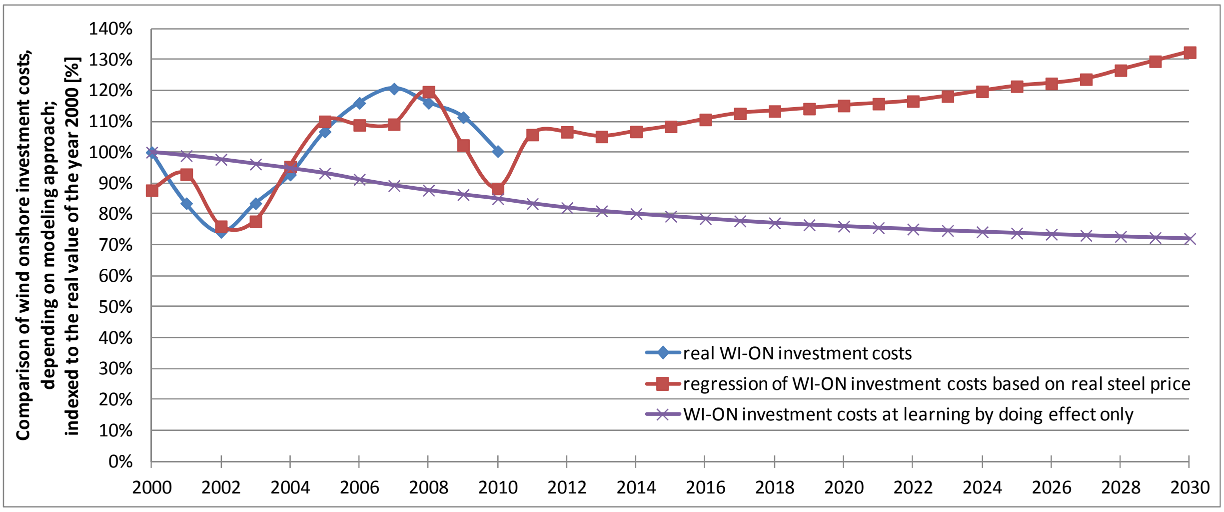

Figure 37 Future scenarios of onshore wind energy investment costs, on the one hand, based on technological learning effects (LR=7%) only and, on the other hand, additionally considering the steel price impact too. Source: Own calculations.

On the one hand, the impact of the steel price and technological learning are considered and, on the other hand, the ordinary one factor learning curve approach is realized. Although a future scenario based on historical evidence requires attention[53] in terms of interpretation a clearly more precise estimation is given compared to neglecting the impact of steel prices. Otherwise, in times of decreasing steel prices wind onshore investment costs would be overestimated at neglecting steel prices in investment cost estimations and vice versa. However, Figure 37 depicts, that the technological learning effect would be completely compensated by the impact of steel prices and consequently wind onshore investment costs would increase by about 25 percent until 2030 compared to nowadays (2011). Perceivable in both scenarios is the decreasing effect of technological learning beyond the year 2020 observable when a doubling of cumulative, global installation takes longer than nowadays.

6.1.3 Sensitivity analysis on energy price assumptions

According to chapter 5.1 and 6.1.1 wind onshore investment costs are in terms of commodity prices mainly impacted by steel prices as well as coal prices hold a significant impact on steel

[53] Technological relation and input parameters are assumed to be constant in the considered time period. Energy prices are exogenously assumed and, therefore, the scenario has a normative character, showing a potential future development in case of the assumed input parameters.

prices. These impacts have been quantified in econometric models based on historical evidence. Additionally, many studies have been published assuming no major technology changes, neither in steel production nor in wind onshore energy technologies. Consequently, future scenarios have been published based on the derived econometric models. In order to quantify the implications of different energy price assumption, sensitivity analyses are carried out in Figure 38.

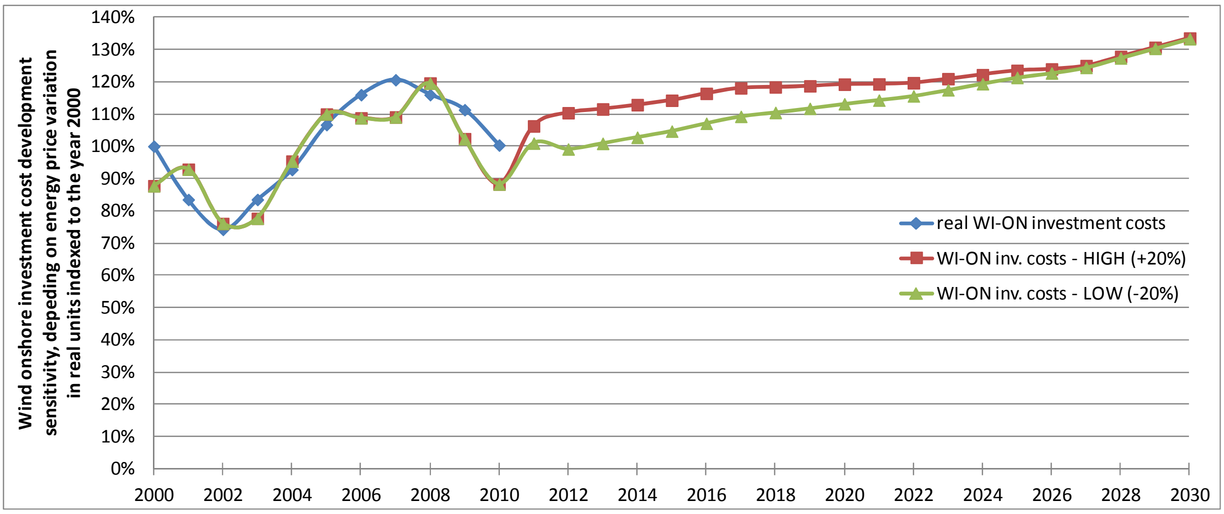

Figure 38 Sensitivity of future scenarios of wind onshore investment costs depending on the sensitivity of exogenous energy price (Capros et al, 2011) variations in real units indexed to the year 2000 and comparison to historical observations. Source: own calculations.

Figure 38 depicts the implication of 20 percent increased and reduced coal prices compared to the original assumption of the EU forecast (Capros et al, 2011). In a first step, the consequence of a changing coal price for the steel price has been discussed in Figure 26. The 20 percent coal price deviation changes steel prices about seven percent. In contrast, this change of a seven percent steel price deviation implies still a significant change in wind onshore investment costs, by about four to five percent. Similar results are published in literature by Ancona et al (2003) and Krohn et al (2009). The decreasing effect of the sensitivity in wind onshore investment costs beyond 2020 is described the reduced impact of coal prices on steel price in this time period. Generally, the investment cost of onshore wind technologies react very sensitive on steel price changes, but less sensitive on pure energy price changes.

6.2 Wind offshore investment costs – drivers and impacts

With respect to wind energy technology a different characteristic of investment costs appear for offshore wind energy converters. A comparatively low penetration in terms of installed capacity is noticed on the electricity market until 2010 (Eurostat, 2011b). However, according to future scenarios (Resch et al, 2009) it is a promising renewable energy technology. A detailed specification of the wind offshore investment cost development is given in chapter 2.5. However, an overall stronger technological learning effect of wind offshore investment costs is identified than in the case of wind onshore investment costs (Junginger et al, 2010b).

From a technological point of view, moderate differences occur between on- and offshore wind energy converters. However, with respect to their input materials, similar commodities are used (Smit et al, 2007). In contrast, the foundation of offshore wind energy converters differs significantly from onshore technologies. Consequently, this chapter focuses on the dynamic development of investment costs of the additional equipment of offshore wind energy plants compared to onshore. Previous research (Junginger et al, 2004) highlighted an impact of commodity prices on foundations of wind offshore turbines of 45 to 55 percent in terms of investment costs. Thus, the impact of technological learning, steel and concrete prices on foundation, platform and grid connection of offshore wind plants is derived in this chapter. These impacts on the converter itself are assumed as identified in the chapter above (chapter 6.1).

An econometric model is developed in order to quantify the impact of commodity prices on the investment costs of additional wind offshore equipment. Moreover, the simultaneous effect of technological learning by doing is taken into account. Hence, a scenario of an overall future development of wind offshore investment costs is derived[54]. Finally, sensitivity analyses indicate the robustness of wind offshore investment costs on changes of energy and raw material prices.

6.2.1 The impact of steel and concrete prices

Likewise in the case of onshore wind technology, the effects of commodity prices and technological learning on the investment costs of the additional equipment of offshore wind energy technology is identified separately. Therefore, the learning by doing rate is derived in the time period when no impacts of commodity prices have been observed according to Figure 11 and assumed to be constant throughout the total observation period. This process allows for a pre-adjustment of the investment costs of the additional equipment of offshore wind technology by the learning by doing effect and, consequently, quantifying the pure impact of steel and concrete prices. The separate consideration of the turbine and the additional equipment of the offshore wind technology is based on two issues. On the one hand, the additional equipment shows a stronger technological learning effect and, on the other hand, besides the steel price the concrete price has a significant impact on this equipment, too. The model of the investment costs of the additional equipment of offshore wind turbines is discussed in formula Eq. 31 to Eq. 35.

$$\ln INV^{*}_{WI-OFF}(t) = c * k^{*} + STEEL * \ln p^{*}_{steel}(t) + CONCRETE * \ln p^{*}_{concrete}(t-1) + u(t) \quad \text{Eq. 31}$$

$$INV^{*}_{WI-OFF}(t) = INV_{WI-OFF}(t) - \rho * INV_{WI-OFF}(t-1) \quad \text{Eq. 32}$$

[54] This scenario considers the impact of commodity prices on the investment costs of wind turbines according to the onshore approach and on top the impact on the additional equipment of an offshore installation.

$$p^*_{steel}(t) = p_{steel}(t) - \rho * p_{steel}(t-1) \quad \text{Eq. 33}$$

$$p^*_{concrete}(t-1) = p_{concrete}(t-1) - \rho * p_{concrete}(t-2) \quad \text{Eq. 34}$$

$$k^* = 1 - \rho \quad \text{Eq. 35}$$

$INV_{WI-OFF}(t)$	Investment costs of the additional equipment of offshore wind installation, corrected for learning effects in the year t
$p_{steel}(t)$	Steel price in year t
$p_{concrete}(t-1)$	Concrete price in the previous year (t-1)
c	Constant parameter
ρ	Cochrane-Orcutt parameter
u(t)	Statistical disturbance term
STEEL CONCRETE	Constant parameter of regression of the impact of steel and concrete prices

The model in Eq. 31 indicates that the investment costs of the additional equipment of wind offshore installations are a function of a constant term, the steel price and the one year delayed concrete price plus a statistical error term. In order to linearize the relation the natural logarithmic has been introduced to the model. Moreover, all parameters of the regression have been transformed by the Cochrane-Orcutt factor (ρ=0.3348) according to formulas Eq. 32 to Eq. 35. Hence, the overall regression estimation is corrected for first order serial correlation of the error term and thus fulfills the Gauss-Markov Theorem (see chapter 3.3). Generally, a direct impact of the steel price is identified whereas the concrete price influences the investment costs one year delayed. Among others, this issue is caused by the fact that wind offshore installations usually require a longer planning and admission procedure. Therefore, one year delayed concrete prices are taken into account in actual installations but steel price are mostly considered in real times. Table 11 depicts the quantitative impact of the constant term as well as the steel and concrete price on investment costs of additional equipment of offshore wind energy in logarithmic values.

Table 11 Parameters of the econometric model, depicting the impact of steel and concrete prices on the investment costs of additional equipment of wind offshore technology (foundation, grid connection). Source: Own calculation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.926751	0.785796	2.451972	0.0321
STEEL	0.059409	0.159477	0.372524	0.7166
CONCRETE	0.864993	0.226285	3.822584	0.0028

The first raw in Table 11 explains the constant term of the model in Eq. 31, whereas the second raw addresses the steel price impact respectively the third raw the one year time delayed concrete price. However, all three components are adjusted by the Cochrane-Orcutt parameter as indicated above. The first column indicates the quantification of the regressors of the commodity price impacts. Generally, a direct impact of all parameters is observed. Regarding the significance coefficient (t-value) of the regressors the constant and especially the concrete price show high significance, both within the five percent confidential interval. In contrast, the steel price impact achieves only minor significance in the model specification at a high uncertainty level of significance. Nevertheless, it contributes importantly to the overall quality of the model.

With respect to the quality of the model, a well fitted estimation of the investment costs of the additional equipment of wind offshore installations, adjusted for technological learning effects is achieved. The coefficient of determination R^2=0.60 results in an acceptable range and even the coefficient of determination adjusted for the degree of freedoms is R^2_{adj}=0.53[55].

Figure 39 depicts the discussed results and compares it to the realized investment costs of the additional equipment of offshore wind installations corrected for the identified learning progress. The high volatility of the realized investment costs is mainly caused by little data availability and, therefore, considered investment costs of specific case studies. Consequently, the impact of exogenous circumstances like distance to shore and depth of water is reflected in the investment costs distorting the time series of these investment costs.

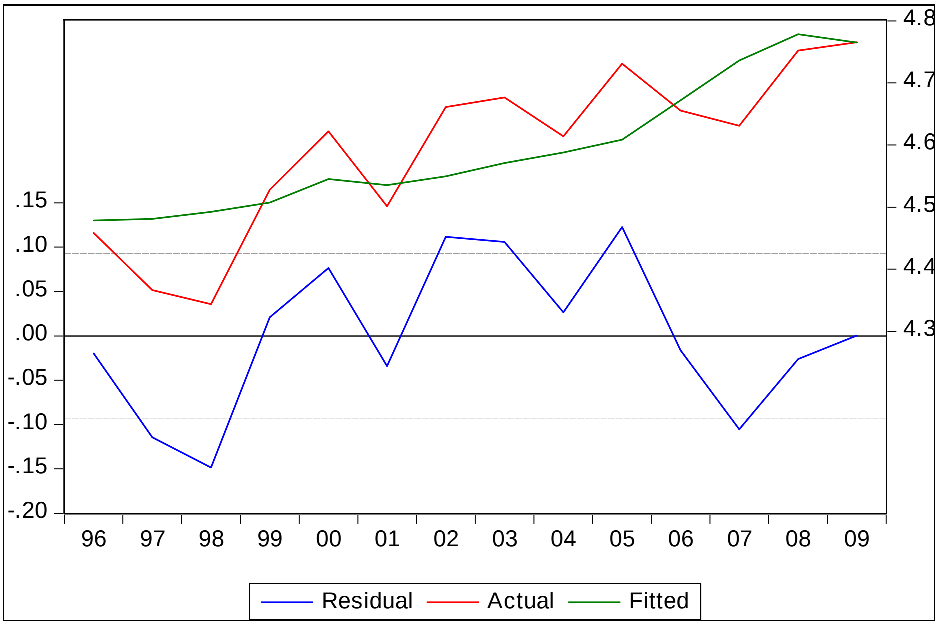

Figure 39 Investment costs of additional equipment of wind offshore technology: Realized and estimated investments costs according to the model without consideration of technological learning effects illustrated in natural logarithmic scale and residual of the two time series. Source: Own calculation.

55 A lower value of quality is achieved in contrast to wind onshore, caused by the major differences in the characteristics of investment costs depending on the type and distance to shore of offshore wind energy installations.

However, the model only considers the energy and commodity price impact and, thus, results in a more continues function, explaining the trend of the historical realized investment costs. In this context, the residual of the two time series does not contain any information but only depicts random exogenous effects of the realized investment costs. This issue is supported by the statistical tests that have been carried out according to the residuals of the econometric model.

An overview of the results of the normality, serial correlation and homoscedasticity test as well as the unit root test of the original time series is given in Table 12. The null hypothesis of non-stationarity of the investment costs, the steel price and the concrete price is rejected in all three cases at rational significance level. The Jarque-Bera test points out the normal distribution of the residual of the estimation with a probability of 76 percent. Furthermore, the application of the Cochrane-Orcutt procedure eliminates the serial correlation and thus, the model fulfills the requirements of the Gauss-Markov Theorem. Finally, the null-hypothesis of the homoscedasticity of the residuals is accepted by the Breusch-Pagan-Godfrey test.

Table 12 Statistical test results of the econometric model of investment costs for the additional equipment of wind offshore installations. Source: Own calculation

Statistic overview	
Unit root:	Augmented Dickey-Fuller Test H0...time series has a unit root wi_off_extra rejects H0 with 43% probability // Trend & Intercept steel rejects H0 with 82.3% probability // DF within 5% significance concrete rejects H0 with 71.8% probability
Normality:	Jarque-Bera Test H0...regression is normal distributed JB=0.542 Accept H0 with 76.26% probability
Serial Correlation:	Durbin Watson (1st order) - DW:1.55 -> 1.816 undefined Breusch-Godfrey serial correlation test H0...no serial correlation N*R²=1.967 chi²(2,0.95)=5.991 => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test H0...homoskedastic N*R²=1.276 chi²(2,0.95)=5.991 => H0 accepted

6.2.2 Wind offshore investment costs – results and pathways

Moreover, the investment costs of the additional equipment of offshore wind installations showed considerable learning by doing effects at a learning rate of LR=10% and penetration according to Fichaux, et al (2009). Combining the material price impact and the technological learning effects illustrates the dynamic development based on the model in formula Eq. 4. However, combing the investment costs of the turbine and of the additional equipment explains the total wind offshore investment costs.

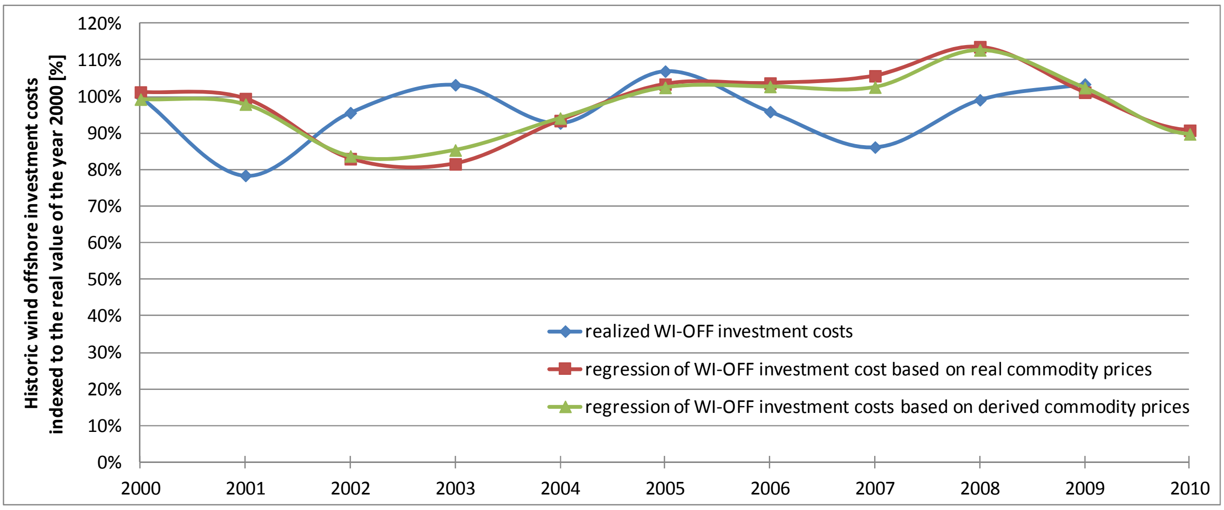

Figure 40 Comparison of realized historical wind offshore investment costs to estimated investment costs taking into account technological learning effects, steel and concrete price impacts. On the one hand, real historical commodity prices are considered and, on the other hand, calculated commodity prices. Source: Own calculations.

Figure 40 addresses the realized historical as well as the estimated wind offshore investment costs depending on the commodity price[56] and technological learning impact. As discussed earlier, the historical realized investment cost data refer to explicit case studies and, therefore, hold high volatility depending on the site specific circumstances[57]. Nevertheless a reasonable estimation of the trend of total wind offshore investment cost is derived in the model. However, the strong deviations from 2001 to 2003 are due to underestimated onshore wind investment costs which are partly considered as offshore turbine investment costs too. In this time period, decreasing steel prices significantly reduced onshore investment costs but offshore investment cost rather increased based on additional technical requirements compensating the decreasing input price impacts. A rough calculation of average offshore wind energy investment costs (EWEA, 2010) indicates a similar trend as the model result in Figure 40. This trend shows less volatility as the investment costs according to the case studies but a higher peak in the year 2007 and 2008.

Finally, future scenarios are discussed in Figure 41 considering the technological learning effect and in the other case the steel and concrete price impact in addition. The pure learning by doing expects a decrease in investment costs to about 60 percent of the year 2000 level in 2030. In contrast, additionally taking into account steel and concrete prices, drive future investment costs to about 114 percent of the year 2000 level in 2030. Therefore, increasing steel and concrete prices are expected to increase wind offshore investment costs significantly and totally compensate the learning effect. However, in contrast to expected future onshore investment

[56] On the one hand, real commodity prices are considered and, on the other hand, the derived commodity price based on the energy price assumptions (see chapter 5).
[57] No distinction between different depth of water respectively distance to shore could be made due to the limited data availability.

costs, offshore investment costs are only expected to increase by 14 percent compared to 25 percent at onshore installations. Based on the assumption of a rapid penetration of offshore wind energy, a decreasing effect of learning by doing is estimated in the later years. Generally, the model estimations build on the assumption that no major changes in terms of production and installation technology appear within the considered time period.

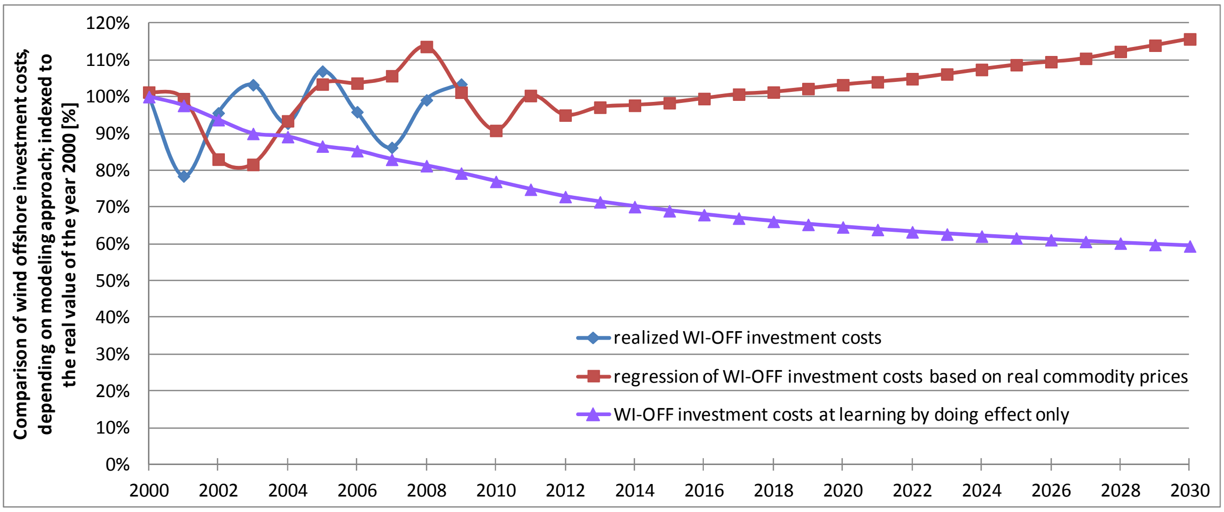

Figure 41 Future scenarios of offshore wind energy investment costs, on the one hand, based on technological learning effects (additional equipment: LR=10%) only and, on the other hand, considering the steel and concrete price impact, too. Source: Own calculation.

6.2.3 Sensitivity analysis on energy price assumptions

Since wind offshore investment costs hold major impacts by steel and concrete prices, which are again strongly influenced by primary energy prices, future scenarios largely depend on their scenarios. Additionally, the future scenarios are derived by the presented econometric models and, therefore, build on the historical relation between energy prices, raw material prices and the investment costs of energy technologies. Consequently, the scenarios are to be interpreted as normative scenarios, depicting how investment costs will look like if energy prices will develop as assumed. In order to broaden the range of potential future investment costs of offshore wind installations, sensitivity analyses are carried out based on the energy price variation of 20 percent increased and reduced prices compared to the original assumptions (Capros et al, 2011). Figure 42 compares the two sensitivities from the year 2010 until 2030.

Generally, a variation of coal and gas price by 20 percent, results in a comparatively low change of steel prices but stronger changes of concrete prices. Nevertheless, the impact on investment costs of offshore wind energy technology is quite moderate at about three to five percent. This slightly higher impact level compared to onshore wind investments costs is effected by the higher material input. The constantly and slightly growing deviation from original scenarios represents the dominating concrete price impact compared to the steel price impact, since steel prices are less sensitive to energy prices in the time period beyond 2020 compared to concrete prices. In conclusion it can be stated that based on the model analyses wind offshore investment costs react to energy price variations in a relation of a quarter.

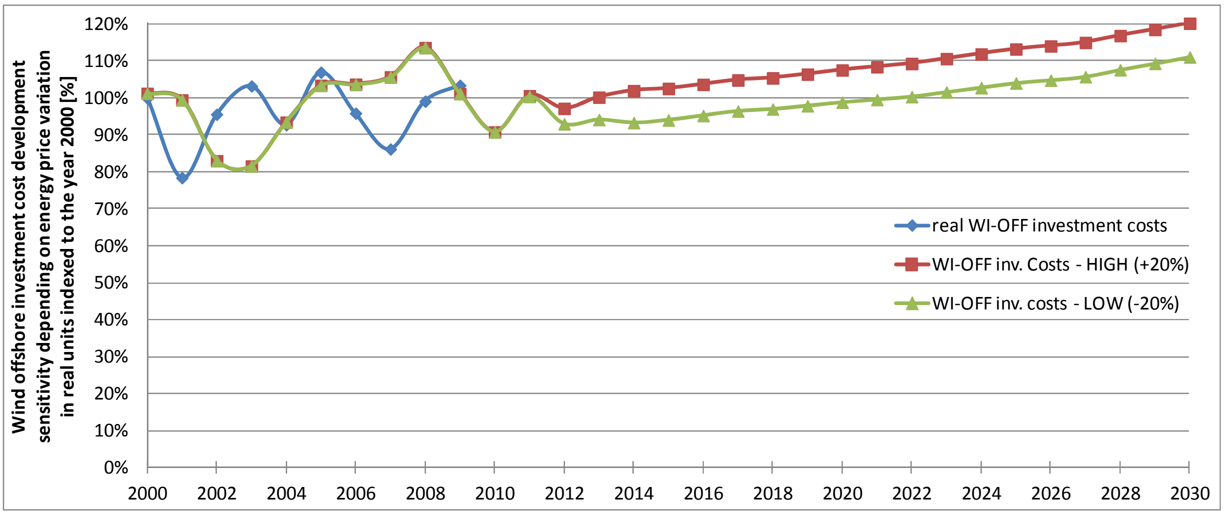

Figure 42 Sensitivity of future scenarios of wind offshore investment costs depending on the sensitivity of exogenous energy price (Capros et al, 2011) variations in real units indexed to the year 2000 and comparison to historical observations. Source: own calculations.

6.3 Photovoltaic investment costs – drivers and impacts

Photovoltaic energy currently shows a comparatively low market penetration in terms of electricity generation, but holds the strongest annual growth rates among all renewable energy sources (Eurostat, 2011b). With respect to its specific investment costs, Photovoltaic is still more expensive than most other renewable electricity generation technologies but shows significant cost decrease over time, especially in recent years (Resch et al, 2009). However, the high demand of energy and raw materials in the production of Photovoltaic modules keeps specific investment costs on the upper scale of energy technology investment costs.

Generally, it is distinguished between crystalline silicon and thinfilm Photovoltaic modules[58] whereas crystalline modules have a market share of about 87 percent (EPIA, 2008). Thinfilm Photovoltaic modules build on Cadmium-Telluride (Fthenakis, 2004) and, therefore, are independent from the energy intense silicon production. Thus, this thesis concentrates on investment costs of crystalline silicon installations. Therein, silicon prices are responsible for about 13 to 27 percent of the total investment costs of Photovoltaic installation (Sinke et al, 2009 and Nemet, 2006). Consequently, an econometric model is derived focusing on the impact of silicon prices and technological learning effects on investment costs of Photovoltaic installations. Additionally, future scenarios of crystalline silicon Photovoltaic investment costs are estimated based on the model. Finally, sensitivity analyses depict the range of future development pathways depending on the future energy price assumptions.

[58] In addition, amorphous and CIS Photovoltaic modules exist, but do not have significant market shares.

6.3.1 The impact of silicon prices

Principally, a similar methodological approach is applied for the quantification of the silicon price impact on Photovoltaic investment costs as in the case of wind energy investment costs. First, the technological learning by doing rate is identified in a time period when no impacts of energy and silicon price have been noticed at Photovoltaic investment costs in real terms. This time period is selected according to Figure 11. Thus, the technological learning rate is assumed to be constant over time. This approach allows for a pre-adjustment of Photovoltaic investment costs for the technological learning by doing effects and, therefore, quantifying the pure silicon price impact. The econometric model of estimating Photovoltaic investment costs is depicted in the formulas Eq. 36 to Eq. 40.

$$\ln INV_{PV}^{*}(t) = c * k^{*} + SIL * \ln p_{silicon}^{*}(t) + SIL\_LAG3 * \ln p_{silicon}^{*}(t-3) + u(t) \quad \text{Eq. 36}$$

$$INV_{PV}^{*}(t) = INV_{PV}(t) - \rho * INV_{PV}(t-1) \quad \text{Eq. 37}$$

$$p_{silicon}^{*}(t) = p_{silicon}(t) - \rho * p_{silicon}(t-1) \quad \text{Eq. 38}$$

$$p_{silicon}^{*}(t-3) = p_{silicon}(t-3) - \rho * p_{silicon}(t-4) \quad \text{Eq. 39}$$

$$k^{*} = 1 - \rho \quad \text{Eq. 40}$$

$INV_{PV}(t)$	Investment costs of Photovoltaic installation, corrected for learning effects in the year t
$p_{silicon}(t)$	Silicon price in year t
$p_{silicon}(t-1)$	Silicon price three years ago, year (t-3)
C	Constant parameter
ρ	Cochrane-Orcutt parameter
u(t)	Statistical disturbance term
SIL SIL_LAG3	Constant parameter of regression of the impact of silicon price and the three years delayed silicon price

The model in Eq. 36 indicates that the Photovoltaic investment costs, adjusted for technological learning effects, are a function of a constant term, the silicon price and the three years delayed silicon price plus a statistical error term. In order to linearize the relation, the natural logarithmic has been introduced to the model. Moreover, all parameters of the regression have been transformed by the Cochrane-Orcutt factor (ρ=0.2927) according to formulas Eq. 37 to Eq. 40. Hence, the overall regression estimation is corrected for first order serial correlation of the error term and thus fulfills the Gauss-Markov Theorem (see chapter 3.3).

Generally, a direct impact of silicon prices on the investment costs of Photovoltaic installations is identified, whereas in addition a delayed impact of the silicon price of three years ago has important influences too. Historically, silicon from the electronic industry has been used in the Photovoltaic industry and, therefore, no delay of the silicon supply for Photovoltaic production has occurred. In contrast, the production shortage of silicon in peak time of Photovoltaic demand reduced the actual silicon supply and enforced a delayed silicon price impact. However, the combination of the direct and the three years lagged impact also stabilizes the Photovoltaic investment costs in times of constantly growing silicon price[59]. Table 13 indicates the result of the quantification of the model parameters of formula Eq. 36.

Table 13 Parameters of the econometric model indicating the impact of silicon prices on the investment costs of Photovoltaic technology adjusted for technological learning effects. Source: Own calculation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.029428	0.003241	2477.367	0.0000
SIL	0.009922	0.002221	4.46703	0.0005
SIL_LAG3	-0.006526	0.002172	-3.005238	0.0095

The first column of Table 13 depicts the regressors of the model. With respect to the constant term, the positive value represents the theoretical minimum of the investment cost without the consideration of learning effects in case of zero silicon costs. The high value of the t-statistic and the zero probability value indicate the high significance of this parameter for the model. Furthermore, a direct impact of the actual silicon price is indicated. The well acceptable significance value and the related probability within the one percent confidential interval explain the importance of the parameter. In contrast, the three year time lagged silicon price holds an indirect impact. This indirect impact is rather mathematically interpretable, since due to its negative regressor it stabilizes the learning corrected Photovoltaic investment costs in times of rapid silicon price changes.

Regarding the quality of the model an acceptable coefficient of determination of R^2=0.58 is achieved. Basically, the model describes the investment costs very well but the coefficient of determination is reduced after the adjustment of the regressors by the Cochrane-Orcutt procedure. However, the coefficient of determination adjusted for the degree of freedom is still at R^2_{adj}=0.52. Additionally, Yu (2010) argues that Photovoltaic investment costs are influenced by other raw material price as silver prices, which are not energy price related and, therefore, are not considered in this study.

A comparison of the realized Photovoltaic investment costs, corrected for the identified technological learning effects, to the estimation of the model is discussed in Figure 43. Learning

[59] Due to different reference silicon prices of the two parameters a strong immediate growth rate of silicon prices does not impact the Photovoltaic investment cost in the same strong extent.

corrected Photovoltaic investment costs historically developed constant with some volatility at a very low scale. According to the model result, silicon costs are not responsible for this volatility. In contrast, stronger investment costs changes beyond the year 2000 are very well explained by the model purely considering silicon prices. Nevertheless, very minor deviations between the two time-series appear which are not explainable by energy related impacts but rather by exogenous market effects. Generally, a significant contribution of the silicon price on learning by doing corrected investment costs of Photovoltaic is noted in Figure 43.

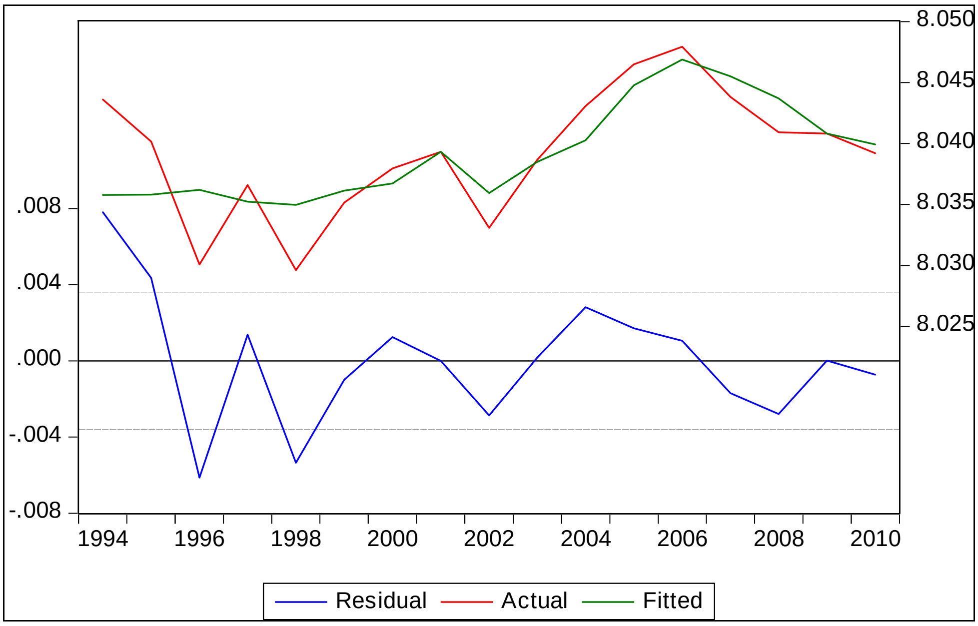

Figure 43 Comparison of historical observed Photovoltaic investment costs to estimated investment costs according to the model without consideration of technological learning by doing effect. Additional, the residual of the estimation is plotted at the left scale. Source: Own calculations

In order to justify the model approach based on the OLS method, the statistical preconditions of the Gauss-Markov Theorem have been tested. First, the stationarity of the for learning effect corrected investment costs of Photovoltaics and the silicon price have been tested by the Augmented Dickey-Fuller test and the ordinary Dickey-Fuller test. In all cases the null-hypothesis of instationarity, respectively holding a unit root, can be rejected. The Dickey-Fuller rejects the null hypothesis even within the ten and five percent confidential interval respectively. Moreover, the normal distribution of the residuals of the model estimation is tested by the Jarque-Bera test and accepted with a significance probability of 86.7 percent. With respect to serial correlation of the residual term, the originally occurred serial correlation of first order has been eliminated by the application of the Cochrane-Orcutt methodology. Therefore, the Durbin-Watson test as well as the Breusch-Godfrey test indicates no serial correlation at a high significance probability of 85 percent. Lastly, the Breusch-Pagan-Godfrey test accepts the null hypothesis of homoscedasticity of the regression residuals. An overview is given in Table 14.

Table 14 Statistical test results of the econometric model of investment costs of Photovoltaic technology. Source: Own calculation

Statistic overview		
Unit root:	Augmented Dickey-Fuller Test H0...time series has a unit root silicon PV	 rejects H0 with 72% // Dickey_Fuller test within 5% significance rejects H0 with 67.8% // Dickey_Fuller test within 10% significance
Normality:	Jarque-Bera Test H0...regression is normal distributed JB=0.286	 Accept H0 with 86.7% probability
Serial Correlation:	Durbin Watson (1st order) - DW:1.61 -> NO autocorrelation Breusch-Godfrey serial correlation test H0...no serial correlation N*R²=0.466	 chi²(2,0.95)=5.991 => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test H0...homoskedastic N*R²=3.373	 chi²(2,0.95)=5.991 => H0 accepted

6.3.2 Photovoltaic investment costs – results and pathways

With respect to the investment costs of Photovoltaic installations a remarkable learning by doing effect is realized at a learning rate of LR=20%. Considering their rapid market penetration according to IEA (2008) significantly impacts the Photovoltaic investment costs. Combining the material price impact and the technological learning effect illustrates the dynamic development based on the model in formula Eq. 4. Thus, Figure 44 addresses the total Photovoltaic investment costs within the last three decades.

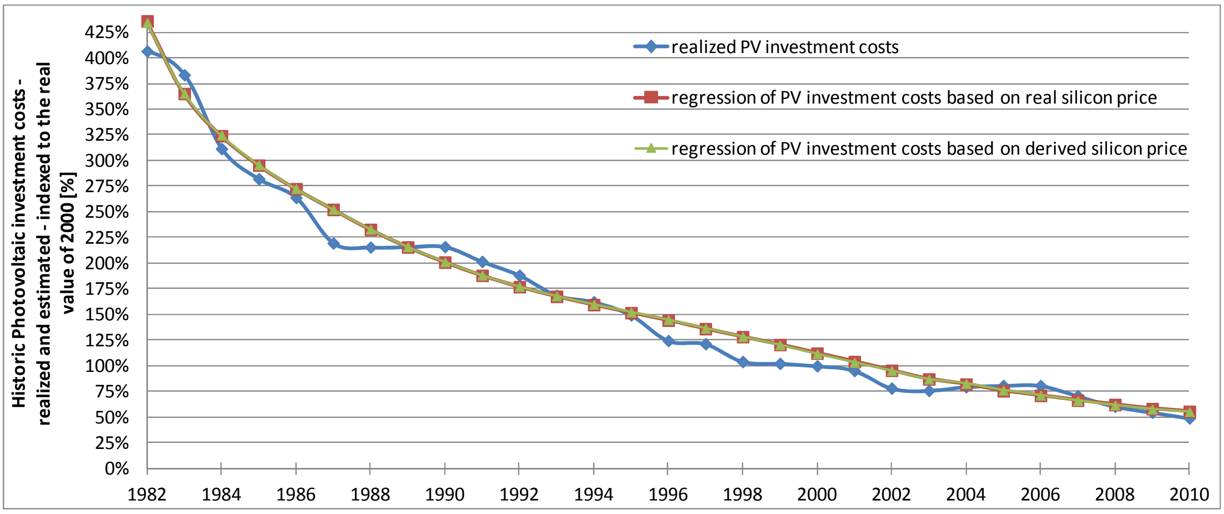

Figure 44 Comparison of realized historical Photovoltaic investment costs to the estimation according to the econometric model considering the impact of silicon price, once realized silicon price and once the derived silicon prices based on the energy price development. Source: Own calculation.

Generally, fast decreasing investment costs of Photovoltaic are observed since the early eighties. Additionally, only light fluctuations occurred in this time period. Taking into account the estimation of Photovoltaic investment costs based on the real silicon price and adding the technological learning effect results in a well acceptable approximation. However, as previously indicated in Figure 43, the significant impact of silicon prices around the year 2004 is compensated by technological learning effects. Hence, silicon prices have indeed an impact on Photovoltaic costs but with respect to their investment costs they are hardly recognizable. Moreover, taking into account the real observed silicon price or the calculated silicon price based on the electricity expenditures of silicon production does not influence the model estimations of Photovoltaic investment costs.

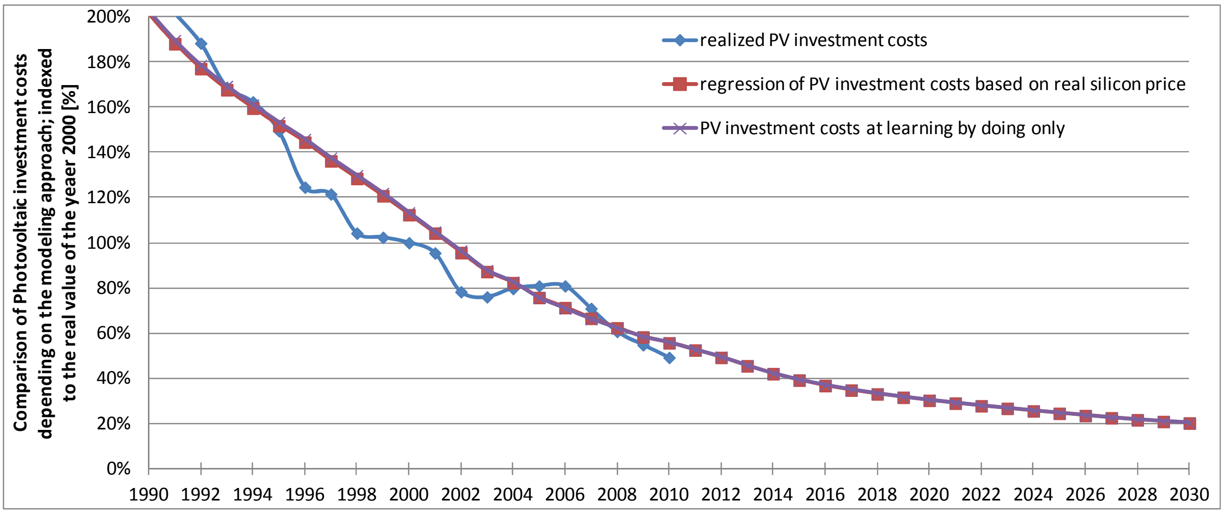

Figure 45 Future scenarios on Photovoltaic investment costs, on the one hand, based on technological learning effects (LR=20%) only and, on the other hand, additionally considering the silicon price impact. Source: Own calculations.

Finally, scenarios of Photovoltaic investment costs are derived according to two different approaches. On the one hand, a pure consideration of the learning by doing effect represents the ordinary dynamic modeling approach. On the other hand, technological learning effects and the impact of silicon prices are combined according to the model derived in chapter 6.3.1. The result of these two future scenarios until the year 2030 is again compared to historical observations and illustrated in Figure 45. Generally, Photovoltaic investment costs are expected to further decrease by about 35 percent within the next twenty years. However, this decrease is mainly driven by technological learning effects too, although a slower decrease is expected than historical observed due to the longer time it takes for doubling the installed capacity. Thus technological learning effects have a much stronger impact on Photovoltaic investment costs than silicon prices do. Therefore, hardly any difference between the two modeling approaches is recognized in Figure 45.

6.3.3 Sensitivity analysis on energy price assumptions

Finally, this research has addressed the impact of silicon prices on the investment costs of Photovoltaics, which are; however; largely compensated by technological learning effects. Nevertheless, silicon prices are very energy and especially electricity intensive in production. Therefore, a sensitivity analysis is carried out investigating the impact of 20 percent increased or reduced electricity prices on the investment costs of Photovoltaics. However, this analysis is based on the econometric model derived in this thesis and consequently assumes that no major changes in Photovoltaic production will occur in the timeframe until the year 2030. The result of the sensitivity analysis is depicted in Figure 46.

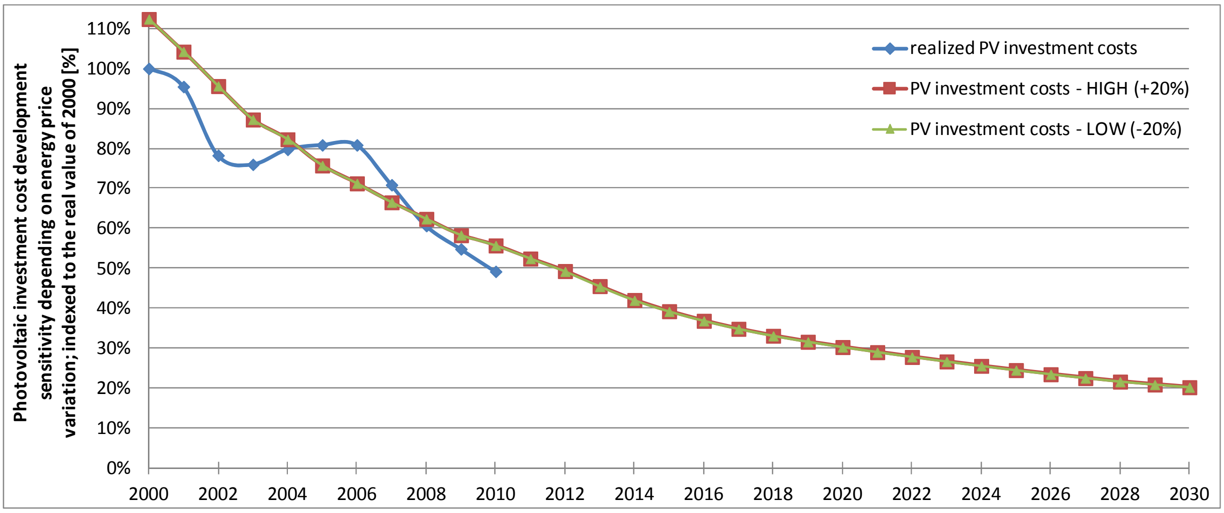

Figure 46 Sensitivity of scenarios of Photovoltaic investment costs depending on the sensitivity of exogenous energy price (Capros et al, 2011) variations in real units indexed to the year 2000 and compared to historical observations. Source: own calculations.

As chapter 5.2.3 discussed the quantitative impact of electricity expenditures on silicon prices; a variation of electricity prices by 20 percent changes the silicon price by up to 12 percent. In contrast; an almost negligible impact of this twelve percent silicon price variation is recognized in Photovoltaic investment costs. A maximal deviation of 0.14 percent in Photovoltaic investment costs scenarios is noted.

6.4 Small-scale biomass CHP investment costs – drivers and impacts

Generally, solid biomass energy is a key technology in the heating sector and in addition increasingly important in the electricity sector, contributing to about ten percent of the European renewable electricity generation nowadays (Eurostat, 2011). According to future scenarios (Resch et al, 2009) electricity produced by solid biomass will potential quadruple in absolute terms. However, several different technology types exist, depending on the output energy, the scale and the type of fuel. This thesis focuses solely on the small-scale biomass combined heat and power plants (CHP). Generally, in terms of the combustion process significant similarities of the technological equipment exist to the conventional energy sector with a slight adaption in case of biomass energy use (Kleijn et al, 2011). The largest components in terms of costs are the boiler section, up to 82 percent, the fuel handling, up to 23 percent and the steam turbine up to 15 percent (Koornneef et al, 2007). With respect to commodity prices, steel and concrete prices hold a relevant impact on the investment costs of small-scale biomass CHP plants. According to manufacturers (Polytechnik, 2011) the impact of steel prices on the overall investment costs is identified on average at about 20 percent[60].

Therefore, this chapter addresses the impact of steel and concrete prices on the investment costs of small-scale biomass CHP plants. An econometric model quantifies the impact of these commodity costs in a mathematical context. Moreover, the results are interpreted in an energy related context. Technological learning by doing effects, simultaneously influencing the investment costs, are considered, too. Based on these empirically identified relations between commodity price and technological learning effects, on the one hand, and small-scale biomass CHP investment costs, on the other hand, future scenarios of the investment costs are derived. Furthermore, sensitivity analyses of the investment costs at varying primary energy price assumptions are discussed.

6.4.1 The impact of steel and concrete prices

In line with the general methodology of this thesis the technological learning effect and the impact of steel and concrete prices on small-scale biomass CHP investment costs are identified separately. Based on a pre-assessment, the technological learning rate (see chapter 2.4) is identified in a time period when no other commodity price impacts than considered in the inflation are observed, see Figure 11. Considering the technological learning rate as constant throughout the total observation period allows a pre-adjustment of the investment costs in order to determine the pure impact of steel and concrete prices. The econometric model of small-scale biomass CHP investment costs is discussed in formula Eq. 41.

$$INV_{BM-CHP}(t) = c + CONCRETE\_LAG * p_{concrete}(t-1) + STEEL\_LAG * p_{steel}(t-1) + u(t) \quad \text{Eq. 41}$$

$INV_{BM-CHP}(t)$	Investment costs of small-scale biomass CHP plants, corrected for learning effects in the year t
$p_{concrete}(t-1)$	Concrete price of the previous year (t-1)
$p_{steel}(t-1)$	Steel price of the previous year (t-1)
c	Constant parameter
u(t)	Statistical disturbance term

[60] Additional material requirements in the biomass energy use are observed in the feedstock preparation.

CONCRETE_LAG	Constant parameter of regression of the impact of the
STEEL_LAG	one year delayed concrete and steel price

The model indicates that small-scale biomass CHP investment costs, corrected for technological learning effect, are explained by a constant term, the one year time lagged concrete and steel price as well as an error term. Due to the moderate volatility of the time series no linearization need to be taken into account. The one year delayed impact of both commodity prices is caused by the fact that the planning procedure mostly requires a longer time period. The constant term represents the part of the investment costs being independent of energy and raw material prices. Furthermore, the statistical error term does not contain any information on investment costs but solely indicates the random difference between the real and estimated investment costs. Consequently, Table 15 depicts the quantitative parameters of the regression analysis and its statistical significance values.

Table 15 Statistic parameters of the econometric model, indicating the impact of steel and concrete prices on the investment costs of small-scale biomass CHP plants. Source: Own calculation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1395.545	1613.881	0.864714	0.4158
CONCRETE_LAG	12.86543	20.73821	0.620373	0.5547
STEEL_LAG	4.367436	3.266496	1.337040	0.2230

The first column in Table 15 highlights the coefficient of the investment cost model described above. A direct impact of the constant term as well as the commodity prices is shown. Therefore, a high concrete or steel price level in the previous year increase biomass CHP investment costs considerably. However, as the third and fourth columns illustrate the related significance level respectively its probability, a relatively low significance is observed for all parameters, especially the steel price. Additionally, the probability value is clearly above the standard confidential interval of five percent but still in a well acceptable range.

In this context, various other econometric models are derived in order to explain the biomass CHP investment costs by solely commodity prices. However, mathematically well determined models result in a high quality of the approximation but do not explain the investment cost in the energy related context. Thus, negative impacts combined with direct effects of commodity prices as well as depending influences from one commodity price on the other are only explaining the mathematical structure of the time series of investment costs[61], but are not the consequence of the impact of volatile energy and raw material prices. Consequently, the model of formula Eq. 41 is taken into account investment cost estimations, resulting in a bigger residual term and, therefore, lower quality, but explains the commodity price impact in an energy related context.

[61] Biomass CHP investment costs refer to case study results which necessarily consider very site-specific applications and, therefore, distort the investment cost time series in addition.

With respect to the quality of the econometric model of formula Eq. 41 a coefficient of determination of R^2=0.38 and an adjusted coefficient of determination of R^2_{adj}=0.21 is achieved. These weak quality coefficients are the consequence of the bigger residual terms in this model. In a pure mathematically structured model, better coefficients of determination can be achieved (R^2=0.77 and R^2adj=0.64). Nevertheless, the discussed model approximations result in a well acceptable indication of the trend of investment costs caused by energy and raw material prices.

An illustration of the historically realized small-scale biomass CHP investment costs, corrected for technological learning effects, and the model approximation as well as its residuals are given in Figure 47. A rather stable but slightly raising development with some fluctuations of investment costs is depicted during the last decade apart from the peak between the years 2007 and 2009. Although the model estimation does not exactly follow the realized investment costs, the model result describes its trend, based on energy and raw material prices. However, especially in peak times of energy and raw material prices, an underestimation of biomass CHP investment costs is noticed since the pure consideration of energy and raw material price rather reflect the technology production cost than their total investment costs.

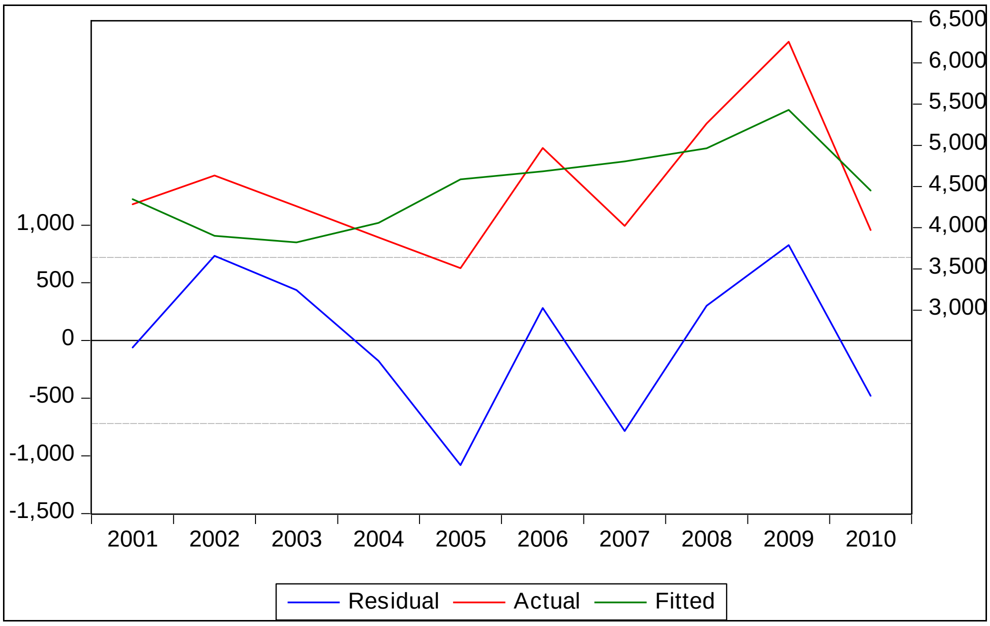

Figure 47 Comparison of historical realized small-scale biomass CHP investment costs corrected for technological learning effects and the model result on the right scale. In addition, the residual of the two time series is plotted on the left scale. Source: Own calculations

Finally, the presented biomass CHP investment cost model has been statistically tested in order to fulfill the Gauss-Markov Theorem (see chapter 3.3). First, the Augmented Dickey-Fuller test points out that no unit root has been identified, implying the stationarity of all relevant time series. Regarding the statistical behavior of the residual term the three main tests have been carried out. Therefore, the Jarque-Bera test indicates with a probability of 72.5 percent that the residual term is normal distributed. With respect to autocorrelation of the residuals, the Durbin-Watson test did not result in a significant result. Therefore, the Breusch-Godfrey serial correlation test accepts the null hypothesis of no serial correlation at a significant probability. Finally, the homoscedasticity of the residuals is accepted, too. An overview of the statistical test results is given in Table 16 below.

Table 16 Statistical test result of the econometric model for small-scale biomass CHP investment costs. Source: Own calculation

Statistic overview	
Unit root:	Augmented Dickey-Fuller Test H0...time series has a unit root BM_CHP rejects H0 with 90.1% probability // DF within 1% significance steel rejects H0 with 82.3% probability // Trend&Intercept // DF 5% concrete rejects H0 with 82% probability // DF within 1% significance
Normality:	Jarque-Bera Test H0...regression is normal distributed JB=0.642 Accept H0 with 72.53% probability
Serial Correlation:	Durbin Watson (1st order) - DW:1.55 -> 1.816 undefined Breusch-Godfrey serial correlation test H0...no serial correlation $N*R^2=1.047$ $chi^2(2,0.95)=5.991$ => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test H0...homoskedastic $N*R^2=1.243$ $chi^2(3,0.95)=7.815$ => H0 accepted

6.4.2 Biomass CHP investment costs – results and pathways

With respect to realized historical investment costs of small-scale biomass CHP plants the dynamic context by combining the impact of concrete and steel prices as well as technological learning effects is illustrated in Figure 48. Caused by the given maturity of the biomass CHP technology a moderate technological learning rate (LR=5%) is taken into account only. Additionally, the future doubling of cumulative installed capacity (IEA, 2008) is limited by the fact of maturity, resulting in moderate technological learning effects. Generally, technological learning in the biomass energy sector rather takes place in the feedstock preparation than in the technology investment costs[62] (de Wit, 2011).

Similar to the historical observation of offshore wind investment costs, small-scale biomass CHP investment costs refer to specific case studies rather than to annual averages and, therefore, show higher volatility. Moreover, approximations of the investment costs derived by the econometric model do not explain the exact development caused by reasons discussed earlier.

[62] Biomass feedstock preparation is a more novel technology with a larger technological learning potential than the energy plant which mostly only show little adoptions to mature conventional energy plants.

However, decreasing investment costs in the time period 2001 and 2004 are caused by the impact of concrete and steel price. Furthermore, an increasing effect on biomass CHP investment costs is noticed in the period from 2005 to 2009 when commodity prices peaked. The derived model estimations show an impact from steel and concrete price of about 20 to 28 percent which is confirmed by biomass CHP manufactures (Polytechnik, 2011). Taking into account the calculated commodity prices (chapter 5) based on the primary energy price development does not change the investment cost significantly than when considering realized commodity prices. However, the consideration of the energy related part of commodity prices only depicts the minimal impact on investment costs, see Figure 48.

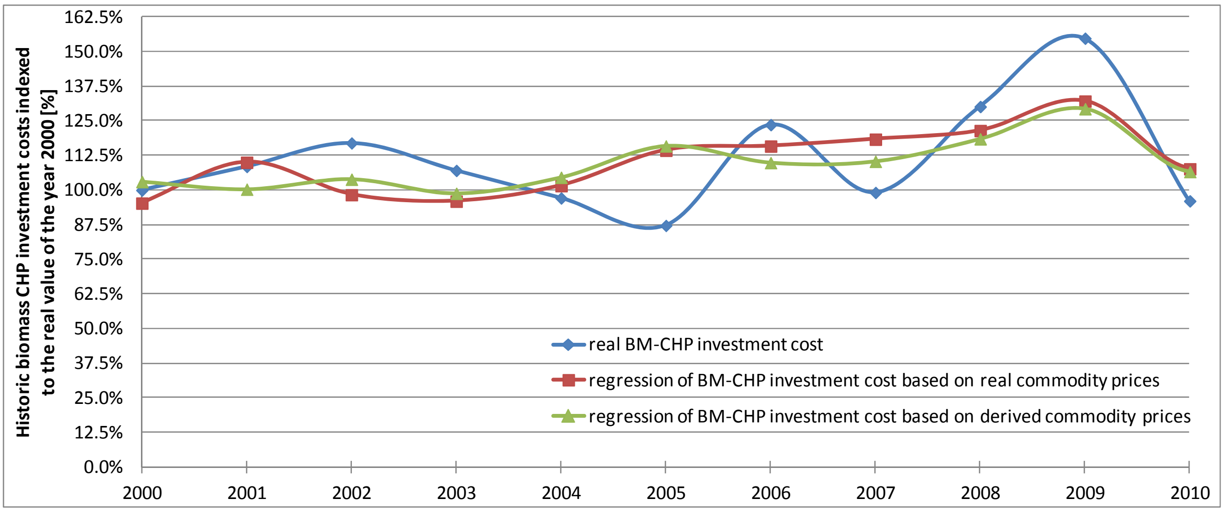

Figure 48 Comparison of small-scale biomass CHP investment costs. On the one hand, historical realized and, on the other hand, estimated investment costs first based on real steel and concrete prices, and second on derived steel and concrete prices. Source: Own calculations.

Finally, future scenarios of small scale biomass CHP investment costs are derived from the econometric model. Since the model is based on the historical relation between commodity prices and investment costs, the future scenarios assume no major technology change in the relevant time period. Figure 49 depict the comparison of the investment cost development depending on the modeling approach. On the one hand, only the standard learning by doing effect is considered and, on the other hand, the additional impact of concrete and steel prices is taken into account, too. With respect to the historical development a much more precise fit is achieved by the new modeling approach. In the context of future forecasts, the pure learning by doing effect expects an investment cost decrease by four percent up to 2030 compared to nowadays (2012). In contrast, the additional consideration of concrete and steel prices results in an investment cost increase of 38 percent in the same time period. Nevertheless, the future investment cost development strongly depends on the underlying assumptions on the primary energy price development.

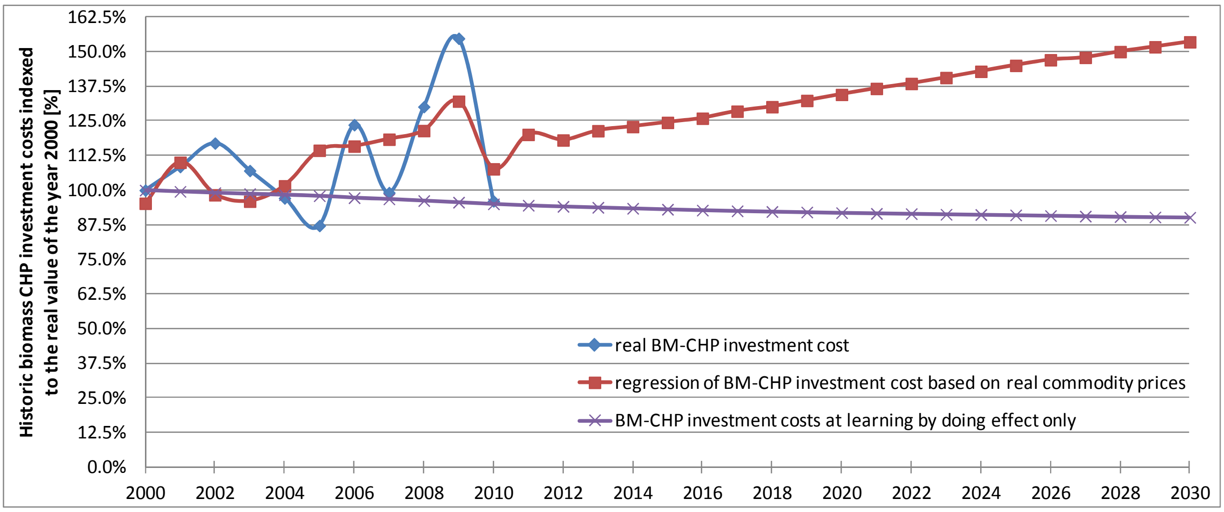

Figure 49 Future scenario of small-scale biomass CHP investment cost, on the one hand, based on technological learning effects (LR=5%) only and, on the other hand, additionally taking into account steel and concrete price impacts. Source: Own calculations.

6.4.3 Sensitivity analysis on energy price assumptions

Finally, sensitivity analyses of small-scale biomass CHP investment costs are carried out depicting their future development depending on the energy price scenarios. Therefore, an increase respectively decline of 20 percent to the originally assumed primary energy prices (Capros et al, 2011) is taken into account here. The consequence of different energy prices in terms of the steel and concrete price is discussed in chapter 5.1.4 and 5.3.3 respectively. Furthermore, based on these commodity prices Figure 50 highlights the sensitivity analyses with respect to biomass CHP investment costs. Hereby, the historical development is based on the realized commodity price whereas the sensitivity analyses are introduced in the year 2011.

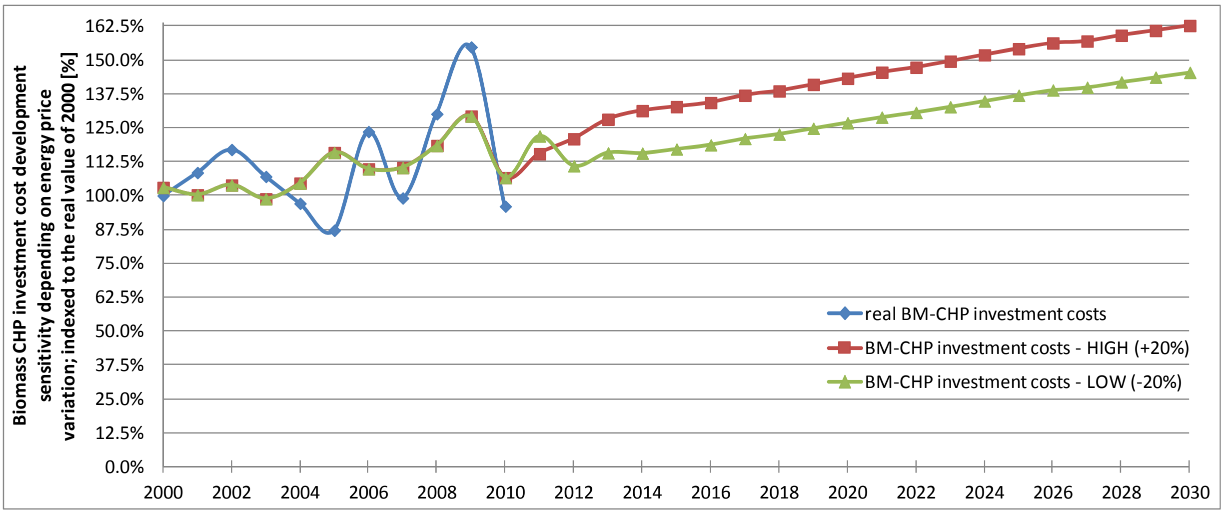

Figure 50 Sensitivity of scenarios of biomass CHP investment costs depending on the sensitivity of exogenous energy price (Capros et al, 2011) variations in real units indexed to the year 2000 and compared to historical observations. Source: own calculations.

Energy price variations by 20 percent result in about five percent steel price and about twelve percent concrete price changes. However, these commodity prices influence small-scale biomass CHP investment costs by four to six percent. Consequently, according to the approximation of biomass CHP investment costs they are robust in terms of short term energy price fluctuations but react strongly on long term energy price developments.

6.5 Small-scale hydro power investment costs – drivers and impacts

Small-scale hydro power installations are currently contributing to about ten percent of the total European renewable electricity generation (Eurostat, 2011b). Nevertheless, a significant future exploitation potential is identified, both in terms of new installations as well as refurbishments (Resch et al, 2009). Therefore, the potential future investment costs development of small-scale hydro power plants is of key importance. However, especially hydro power investment costs depend on many different technical and environmental aspects and, therefore, are difficult to compare. Generally, about half of the investment costs are used in the planning and admission procedure whereas the rest is divided into turbines, electrical equipment, construction and building (EREC, 2010). This share on investment cost supposes that concrete and steel prices are the major drivers in terms of commodity prices of small-scale hydropower investment costs. However, in literature only impacts of five percent each on steel as well as construction costs on the total investment costs are discussed (Bard, 2006).

Therefore, this chapter addresses the impact of steel and concrete prices on the investment costs of small-scale hydropower plants. In this context an econometric model is derived from historical observations, quantifying the impact parameters. Additionally, technological learning by doing effects are indentified at small-scale hydro power plants and are considered in the conducted investment cost estimations. Furthermore, scenarios of the dynamic development of the investment costs are derived from the model. In order to depict the robustness of the investment costs in terms of volatile energy prices, sensitivity cases are discussed.

6.5.1 The impact of steel and concrete prices

According to the principal methodological approach of this thesis, the impact of commodity prices and technological learning effects on small-scale hydro power investment costs are determined separately. In a first step, the technological learning effect is determined in a time period when no impact of commodity prices on engineering investment cost has been noticed according to Figure 11. The identified learning rate is supposed to be constant throughout the considered time period. This allows for a pre-preparation of the historically realized investment costs and thus the quantification of the pure impact of commodity prices. Generally, historical small-scale hydropower investment costs of this research build on case study results and, therefore, show a strong volatility, implicitly representing the site specific technical and environmental requirements. However, the model in formula Eq. 42 estimates the learning corrected investment costs by their main commodity prices.

$$\frac{\Delta \mathrm{INV_{Hydro}}}{\Delta t} = STEEL\_LAG * \frac{\Delta p_{steel}}{\Delta(\mathrm{t}-1)} + CONCRETE\_LAG * \frac{\Delta p_{concrete}}{\Delta(t-1)} + u_t \qquad \text{Eq. 42}$$

$\frac{\Delta \mathrm{INV_{Hydro}}}{\Delta \mathrm{t}}$	Annual small-scale hydro power investment cost (corrected for technological learning) growth rate
$\frac{\Delta \mathrm{c_{steel}}}{\Delta(\mathrm{t}-1)}$	Annual steel price growth rate of the previous year (t-1)
$\frac{\Delta \mathrm{c_{concrete}}}{\Delta(\mathrm{t}-1)}$	Annual concrete price growth rate of previous year (t-1)
u_t	Statistical disturbance term
STEEL_LAG CONCRETE_LAG	Constant parameter of regression of the impact of annual steel and concrete price growth rates

Principally, the model focuses on annual growth rates in order to increase the approximation quality. Hence, the annual growth rate of the investment costs depends on the previous year's annual growth rate of steel and concrete prices. In contrast to all other selected technologies no constant parameter is taken into account[63]. This is caused by a broad range of the investment costs due to their site specific requirements. The one year time delayed impact of steel and concrete price growth rates is affected by long planning and admission procedures. According to the theory of the Gauss-Markov Theorem the statistical disturbance term does not contain any information but only represents the difference between realized and estimated small-scale hydro power investment costs. A quantification of the impact parameters is given in Table 17.

Table 17 Parameters of the econometric model, indicating the impact of steel and concrete prices on the investment costs of small-scale hydro power technology. Source: Own calculation.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STEEL_LAG	3.805532	3.341348	1.138921	0.2841
CONCRETE_LAG	34.19096	61.46667	0.556252	0.5916

The first column of Table 17 indicates a direct impact of one year delayed annual steel and concrete price growth rates on hydropower investment costs. However with respect to the significant value a rather low value is indicated, especially at concrete price growth rates. Additionally the last column depicts the probability of the insignificance of the selected parameters. Although the t-statistic is still within an acceptable limit, the uncertainty that the steel

[63] Usually, the constant term represents the minimum value of the dependent variable whereas the independent variables react according to their elasticities.

and especially concrete price growth rate explain small-scale hydropower investment costs is rather high. Hence, according to the model parameters only a little impact of commodity prices on the total investment costs of small-scale hydropower plants is identified.

In contrast, an econometric model has been derived explaining the investment costs by commodity costs in a pure mathematical approach. Obviously, the time series of investment costs can be explained by the time series of commodity prices when considering their difference and combinations as well as longer time delays. Anyhow, this model results in significant indirect and direct impacts of the same commodity prices. Consequently, a mathematical relation is derived based on historical evidence but is not explainable in a rational energy related context. This interpretation of the additional model determination supports the supposition of only marginal impacts of selected commodity prices on small-scale hydro power investment costs.

Regarding the original model presented in formula Eq. 42, a quality in terms of the coefficient of determination of R^2=0.16 is achieved. On the one hand, the missing constant term in the model description and, on the other hand, the rather insignificant regressors increase the absolute value of the residual term and, therefore, reduce the quality of the regression analysis. The coefficient of determination adjusted for the degree of freedom only results in R^2_{adj}=0.07, indicating a pure approximation of the investment costs.

In this context, Figure 51 depicts a comparison of the historically realized to the estimated small-scale hydropower investment cost growth rates based on realized commodity prices. In addition, the residuals of these two time series are plotted on the left scale.

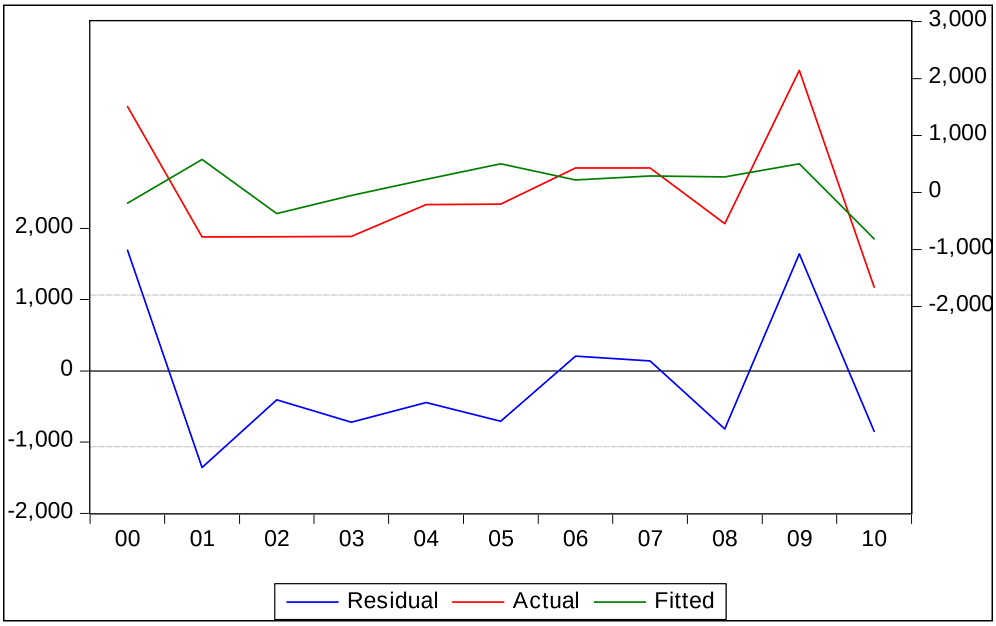

Figure 51 Historical realized small-scale investment cost growth rates and the approximation according to the derived model. Both time series are depicted without the consideration of technological learning effects. In addition, the residual is plotted. Source: Own calculation

Generally, Figure 51 depicts a rather constant, slightly negative growth rate of realized investment costs until the year 2006 and a higher volatility with a significant growth rate increase in 2009. In contrast, the approximation of the model in formula Eq. 42 shows a slight annual increase of investment costs in the same time period and an only marginal stronger increase in 2009. Therefore, on the one hand the peak in investment cost in the year 2009 is not attributed to peaking commodity prices but rather to increased expenditures of the specific case study for technical and environmental obligations. On the other hand, the model, especially the rather insignificant concrete price regressor, overestimates the commodity price impact continuously. However, the specific case study results distort the model additionally and, therefore, lower the quality of the investment cost approximations, too.

Nevertheless, the model is verified by statistical tests of the used time series and the residual term in order meet the requirements of the Gauss-Markov Theorem (see chapter 3.3). Due to the consideration of growth rates, the stationarity of the time series is given at a very high probability, all within the five percent confidential interval. With respect to the statistical disturbance term, the normal distribution is test by the Jarque-Bera test and identified with about 42 percent probability. Additionally, the residual are tested against autocorrelation. The Durbin Watson test result is undefined but the Breusch-Godfrey test accepts the null-hypothesis of no serial correlation at a high probability. Finally, homoscedasticity is positively tested by the Breusch-Pagan-Godfrey test. An overview of the statistic test results presents Table 18.

Table 18 Overview of statistical test results of the econometric assessment of small-scale hydropower investment costs. Source: Own calculations.

Statistic overview		
Unit root:	Augmented Dickey-Fuller Test H0…time series has a unit root hydro d(steel) d(concrete)	 rejects H0 with 86.7% probability // DF within 5% significance rejects H0 with 99.9% probability rejects H0 with 90.8% probability // None // DF 5% significance
Normality:	Jarque-Bera Test H0…regression is normal distributed JB=1.751	 Accept H0 with 41.67% probability
Serial Correlation:	Durbin Watson (1st order) - DW:1.55 -> 1.816 undefined Breusch-Godfrey serial correlation test H0…no serial correlation N*R²=1.49	 chi²(2,0.95)=5.991 => H0 accepted
Homoskedastic:	Breusch-Pagan-Godfrey test H0…homoskedastic N*R²=0.849	 chi²(2,0.95)=5.991 => H0 accepted

6.5.2 Small-scale hydropower investment costs – results and pathways

In order to address the dynamic development of small-scale hydropower investment costs in total terms, the technological learning effect is considered, too. Hereby a technological learning rate of LR=5% and a market penetration according to IEA (2008) is considered. A comparison of the historically realized investment costs to the approximation of the discussed model is presented in Figure 52. Additionally, the investment cost estimation based on the mathematical model is included for comparison only.

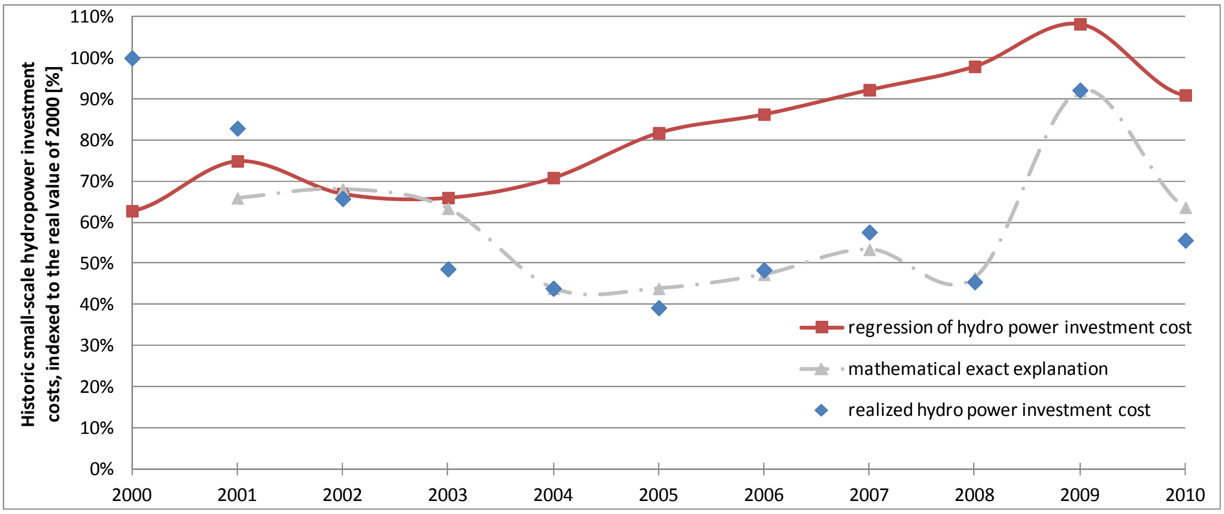

Figure 52 Comparison of historically realized small-scale hydro power investment costs and approximation by the econometric model based on commodity prices. Additionally, an approximation by a mathematical description is depicted. Source: Own calculation

At a first glance, a strong overestimation of the impact of concrete and steel prices is noted in the model approximation of the small-scale hydropower investment costs. The missing constant term[64] in the model attributes stronger impact to independent parameters and, therefore, results in an overestimation of their impacts. In contrast, the mathematical model explains the historical development very well. However, as discussed above no rational interpretation of the different impact parameters of the commodity prices can be derived in an energy related context. On the one hand, the model, focusing on a rational interpretation in terms of energy markets, does not explain the small-scale hydropower investment costs. On the other hand, the mathematical model does not follow any characteristics and relations of plausible energy market behaviors. Consequently, small-scale hydropower investment costs are only very weak or not impacted by steel and concrete prices at all.

However, future scenarios up to the year 2030 are derived. Therefore, Figure 53 discusses the difference in modeling approaches of solely considering technological learning effects. In contrast, the quantified steel and concrete price impacts are taken into account in addition. The

[64] Due to the strongly varying realized investment costs no significant constant term can be determined.

future scenario development is driven by increasing energy and raw material prices. Nevertheless, according to the above identified negligible impact of commodity prices this future assessment is not based on fundamental empirical relations. With respect to the two modeling approaches, neither the technological learning theory nor the multi factor impact approach result in a precise estimation of small-scale hydropower investment costs. Thus, only investment costs of similar site characteristics can be taken into account for estimating their future development. Furthermore, it is sufficient to apply the ordinary technological learning methodology since hydropower investment cost show a strong robustness against commodity price volatility and energy and raw material prices do not provide additional information to the model.

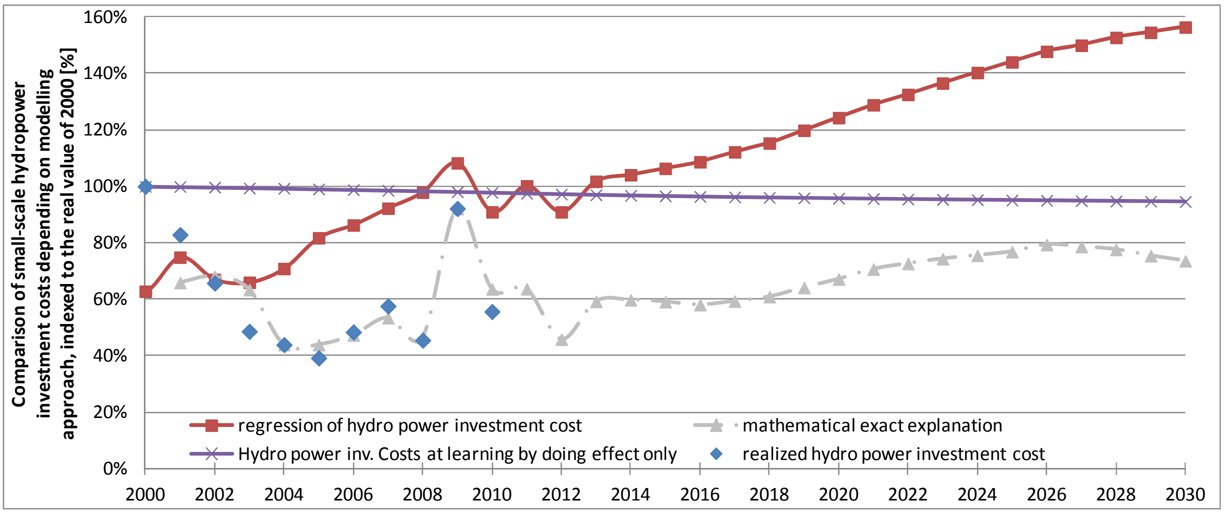

Figure 53 Scenarios of small-scale hydro power investment costs, on the one hand, solely considering learning by doing effects and, on the other hand, the impact of steel and concrete prices, too. Source: Own calculations.

6.5.3 Sensitivity analyses on energy price assumptions

Generally, sensitivity analyses of varying energy price assumptions are carried out in order to discuss the robustness of hydropower investment costs. However, chapter 6.5.2 identifies no significant contribution of energy and raw material prices to the explanation of the investment cost development. Consequently, a high robustness can be concluded from this research without additional sensitivity analyses.

7 Comparison and implications of dynamic investment cost models

The quantification of the impact of energy and raw material prices on energy technology investment costs above highlighted the technology specific characteristics. Thus, this chapter addresses the comparison of the main identified characteristics in the historical context as well as their estimations in the future context. Consequently, the investment cost development itself and in addition the quality of the applied modeling approach is discussed. Moreover, the robustness respectively the sensitivity of the selected energy technology investment costs against volatile energy and raw material prices are depicted.

Furthermore, the implications of the derived energy technology investment costs for the electricity market are taken into account. In this context, electricity generation costs of assessed technologies are derived based on standard economic assumptions. The technological similarity of biomass CHP plants and coal fired conventional CHP plants allows for a rough estimation of their future development. Consequently, in terms of economical feasibility a different electricity market portfolio might develop in the considered time period up to the year 2030.

7.1 Comparison of the energy technology investment cost development

Generally, investment costs of energy technologies, especially renewable technologies, declined with increased experience and technological improvements. However, during the last decade strong fluctuations of investment costs have been observed; see Figure 54. The volatile character of historically realized energy technology investment costs induced to focus research on the responsible impact parameters[65] such as energy and raw material prices.

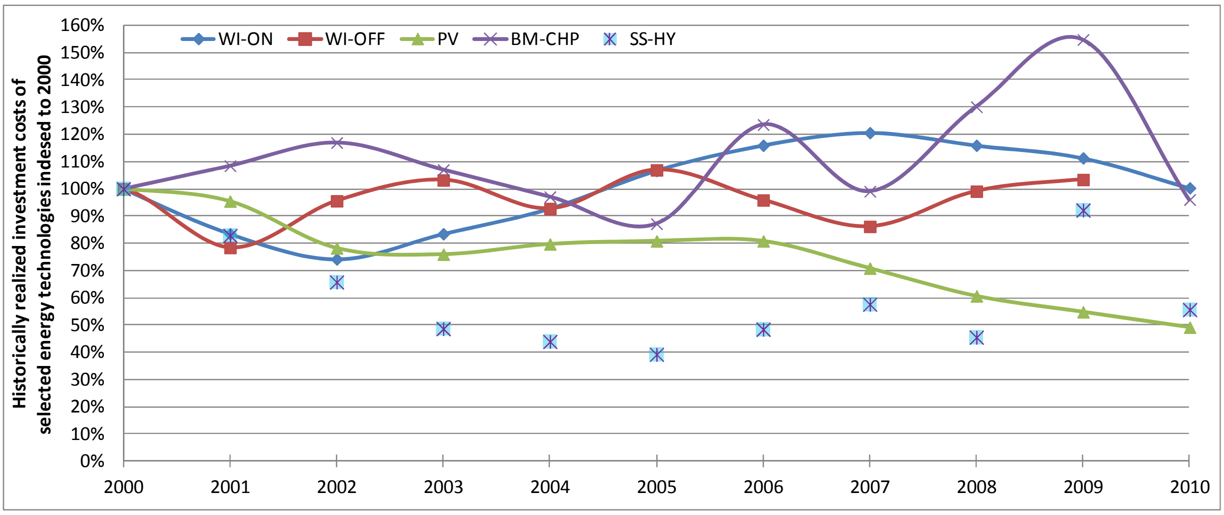

Figure 54 Historical development of realized investment costs of onshore and offshore wind turbines, Photovoltaic, small-scale biomass CHP and small-scale hydropower plants in the time period 2000 to 2010. Source: (EWEA, 2010; Junginger et al, 2004; Yu et al, 2010; New Energy Finance, 2011).

[65] Apparently, strong impacts are shown from other parameters like i.e. R&D expenditures, economies of scale and market price effects in addition.

Figure 54 compares the historical development of onshore and offshore wind, Photovoltaic, small-scale biomass CHP and small-scale hydropower investment costs. Whereas Photovoltaic investment costs showed an almost continuously cost decreasing effect, most other technology investment costs peaked in the second half of the last decade. However, biomass CHP and hydropower investment cost refer to specific case study results. Especially in the case of hydropower this implies that investment costs contain site specific requirements and, therefore, are not comparable among them. Therefore, in the later hydropower investment costs are not taken into account for further comparison. Nevertheless, chapter 6.5 concludes that energy and raw material prices do not have a significant impact on hydropower investment costs.

In-depth assessments are carried out in chapter 6, in order to model the investment cost development of the presented energy technologies. On the one hand, econometric models consider the impact of commodity prices and, on the other hand, technological learning effects are taken into account hereby. Thus, the model builds on empirical evidence and, therefore, explains the investment cost development based on energy and raw material prices. Consequently, Figure 55 compares the model based investment cost approximation to the historical realized investment costs.

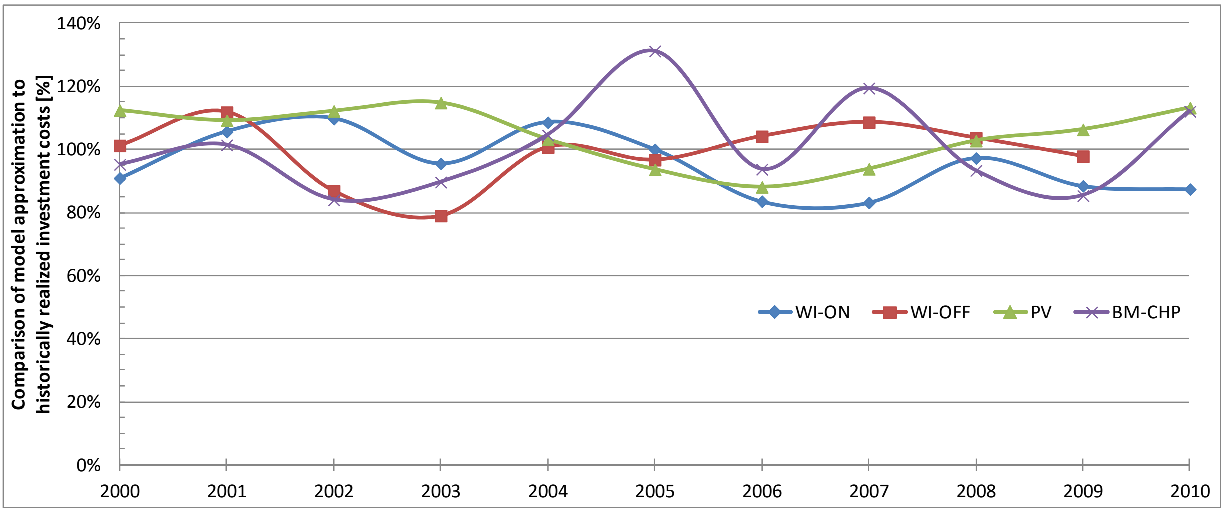

Figure 55 Comparison of the model based investment cost approximations to the historically realized investment costs of selected energy technologies in the time period 2000 to 2010. Source: Own calculations.

In general, the investment cost approximations deviate only slightly from the historical observed values. Figure 55 illustrates that the deviations vary strongly over time, depending on the effect of other exogenous impacts, not considered herein. Thus, in times of strong technology demand, investment costs increased additionally but the model does not react directly, leading to an underestimation of the depicted investment costs. Nevertheless, some significant deviations are applicable especially in the case of small-scale biomass CHP investment costs, mainly caused by the site specific historical data. Moreover, the deviations differ between technologies. With respect to onshore wind investment costs a slight overestimation in 2001 and 2002 is noticed when real investment costs decreased significantly. Beyond 2005 a slight underestimation is caused by investment cost drivers related to market characteristics besides the impact of energy and raw material prices. In case of Photovoltaic, the moderate stagnation of investment costs between 2002 and 2006 caused some deviations in investment cost estimations. Principally, the model allows for a precise approximation of investment costs and a dynamic reaction on energy and raw material price changes. Nevertheless, the model based investment cost approximations rather underestimate the realized investment costs since the energy and raw material price impacts consider more the technology production costs than the market prices.

Furthermore, scenarios of the selected energy technology investment costs are derived and compared based on the established models. Figure 56 depicts the development of investment costs in a historical and future context in relative units indexed to the year 2000.

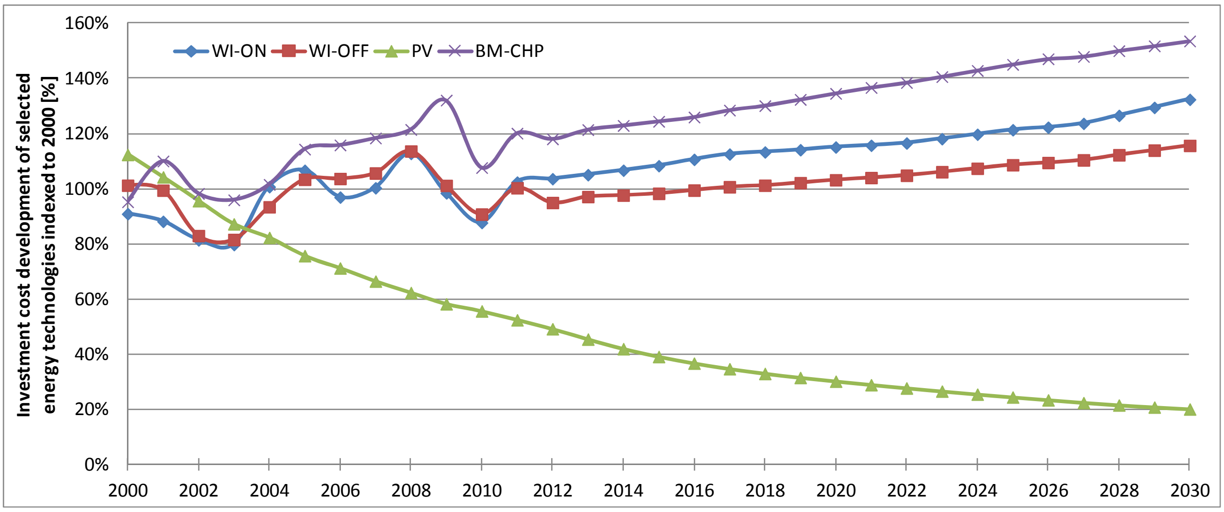

Figure 56 Illustration of selected energy technology investment costs based on modeling results in the time period up to 2030 in relative units indexed to the year 2000. Source: Own calculations.

With respect to the historical time period the dynamic development is characterized by the impact of energy and raw material prices. Apart from Photovoltaic investment costs an increasing trend is noted. In terms of future scenarios, a continuous increase of wind on- and offshore as well as biomass CHP investment costs is expected. Basically, the more mature a technology is, the more are technological learning effects compensated by energy and raw material price impacts. Consequently, wind offshore investment costs are expected to increase by 16 percent in year 2030 compared to year 2000 whereas wind onshore investment costs are about 32 percent higher than in year 2000 and biomass CHP investment costs even by 54 percent. In contrast, Photovoltaic investment costs show hardly any impact of energy and raw material prices but show strong technological learning effects. Thus, investment costs are expected to decrease continuously to about 20 percent in 2030 compared to the year 2000.

Regarding the impact of energy and raw material prices on investment costs a sensitivity analysis points out their robustness of the selected energy technologies. Figure 57 addresses the relative investment cost change at a relative primary energy price variation of up to plus minus 30 percent. Hereby, the primary energy prices influence the relevant raw material price according to the econometric models of chapter 5. Moreover, the commodity prices are taken into account in the sensitivity analysis according to the derived models of chapter 6. The sensitivity assessment is carried out on the basis of the technological power portfolio of 2010.

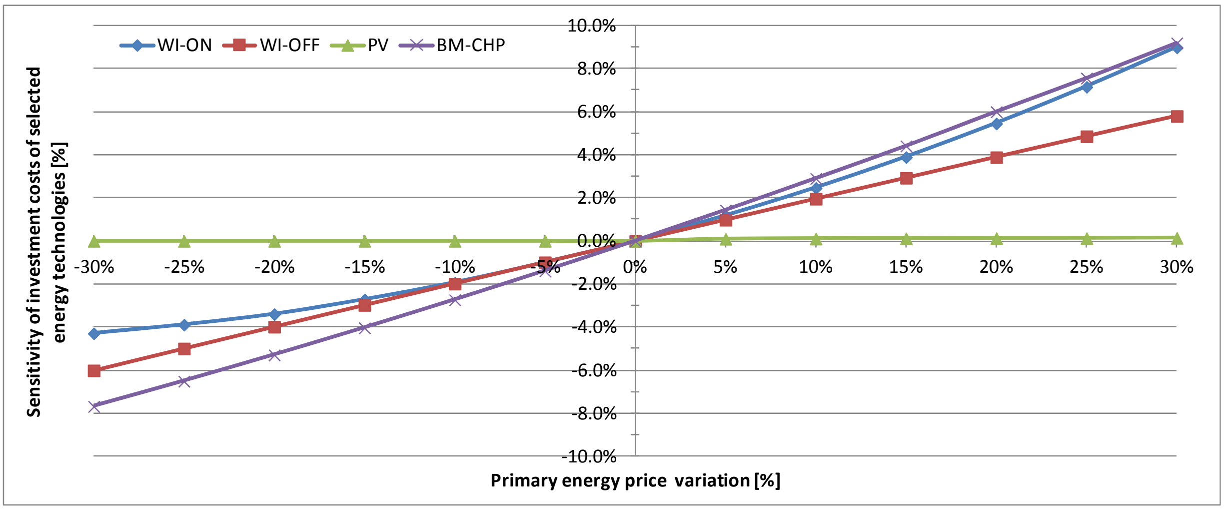

Figure 57 Sensitivity analysis of selected energy technology investment costs depending on primary energy price variations of plus minus 30 percent. Source: Own calculations.

Generally, only a marginal impact of increasing energy prices on Photovoltaic investment costs is determined whereas biomass CHP and onshore wind investment costs react with an investment cost increase of nine percent on a 30 percent energy price increase. Wind offshore investment costs are still sensitive but less than onshore, due to the stronger learning effects compensating the price increases partly. In contrast, declining energy prices do not reduce wind onshore investment costs in the same magnitude[66]. A similar but weaker effect is observed for small-scale biomass CHP investment costs. Generally, novel technologies are holding strong future market growth potentials and, therefore, show stronger learning effects. This learning effect partly compensates the impact of increasing energy and raw material prices and, therefore, these technologies are more robust against energy price impacts. Additionally, chapter 6.5 discussed the high robustness of small-scale hydropower investment cost against energy and raw material price due to their low share on total investment costs.

7.2 Implications on the energy market

This thesis considers renewable energy technologies for electricity production which in general show electricity generation costs above current market prices (Resch et al, 2009). On the one

[66] Declining energy prices are not directly represented in investment costs but only react time lagged.

hand, increasing energy prices might, therefore, lower the gap between market prices and renewable electricity generation costs. On the other hand, increasing energy prices impact the selected energy investment costs differently and might, therefore, distort the merit order of the energy technologies. In order to address the implications of the completed results on electricity market simple estimations of investment costs of conventional coal fired CHP plants are conducted.

In terms of the technological process a biomass fired CHP plant applies a very similar approach like a coal fired CHP plant (Overend, 2006). Both technologies burn the primary energy input in order to generate steam, powering a steam turbine and, therefore, producing electricity[67]. Moreover, many options exist of cofiring coal plants with biomass energy at only little additional installations of technical equipment. Cofiring CHP plants show slightly lower conversion efficiency and only need to be adopted with respect to the ash deposition (Baxter, 2005). Therefore, similar technological components are installed in coal and biomass fired CHP plants. Consequently, the raw material input of both technologies only differs to a minor extent. Kleijn et al (2011) identified similar relative iron inputs into coal and biomass fired CHP plants. However, in case of carbon capture and sequestration (CCS) appliances of coal plants, the relative metal requirement increases significantly. Moreover, in terms of technological learning effects similar results are published in literature for both technologies (Junginger et al, 2010b). Only very moderate learning by doing rates are identified for the investment costs[68]. Hence, the derived approximation of the assessed biomass energy CHP investment cost development allows an indication of the development of conventional coal fired CHP plants, too.

A pure consideration of the economics of the electricity market allows deriving some implications of the endogenous impact of volatile investment costs on the electricity market. However, important technical challenges in terms of grid stability, intermittency and market balancing are not considered within this assessment. Consequently, electricity generation costs of selected electricity technologies up to the year 2030 are discussed, representing the costs of new installations in the specific years, see Figure 58[69]. Therefore, the investment cost development is taken into account according to model approximation under consideration of technological learning effects and the impact of energy and raw material prices.

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[67] Many different technologies exist to generate electricity from solid primary fuels (Obernberger, 2008).
[68] With respect to biomass energy, a comparable higher learning rate appears in the fuel preparation.
[69] Thereby, standard assumptions are taken into account with respect to weighted average cost of capital (WACC=6.5%) and a depreciation time of 30 years for coal plant and 15 years for renewable plants. Moreover investment costs in 2005, operation and maintenance costs and full-load hours of coal plants refer to a 400 MW plant cited in literature (D'haeseleer et al, 2007). Additional CO2 emissions and CO2 prices are considered in the calculation. Hereby an average CO2 intensity of a current coal power plant is considered with 743gCO2/kWh (Schiffer, 2011) and CO2 price development according to Capros et al (2011). With respect to the selected renewable energy sources the corresponding data is taken from the updated Green-X database (Huber et al, 2004).

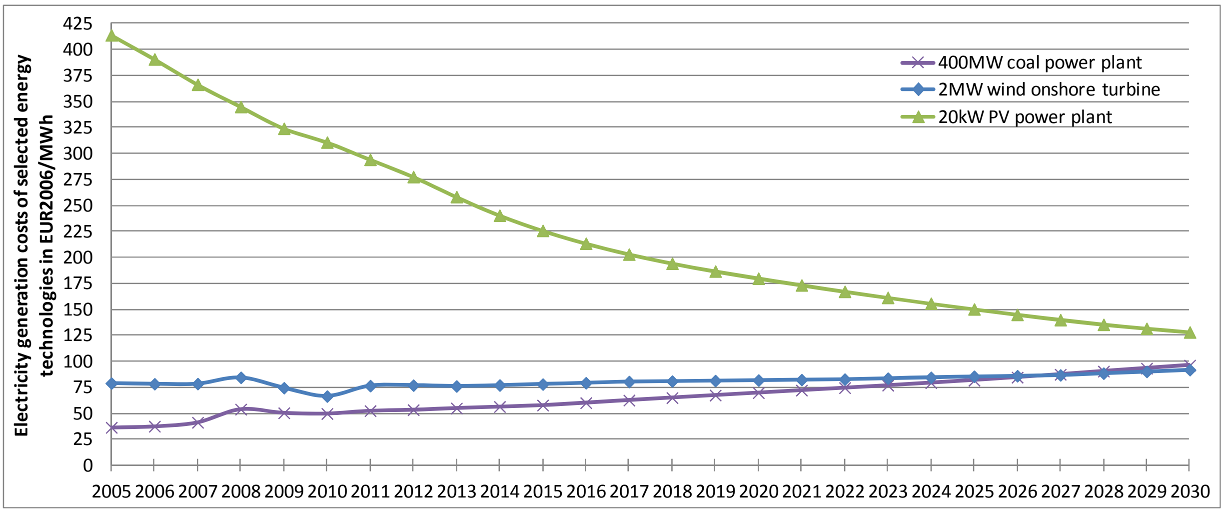

Figure 58 Levelized annual electricity generations costs in EUR2006/MWh, considering the impact of energy and raw material price on investment costs of selected energy technologies. Economic assumptions: (discount rate 6.5 percent, deprecation time 15 years (RES) respectively 30 years (coal) as well as CO2 prices (Capros et al, 2011). Source: Own calculation

On the one hand, Figure 56 and Figure 57 indicate the strongest impact of energy and raw material prices on biomass CHP investment costs among the selected technologies, whereas additionally a very sensitive character is identified, too. On the other hand, in terms of electricity generation costs the investment cost reflect only a certain share of the relevant costs, especially in the case of fuel based technologies like biomass or coal fired CHP plants (IEA, 2004).

Figure 58 indicates significantly increasing coal power electricity generation costs up to the year 2030. This increase is driven by 50 percent of raising fuel prices, 30 percent CO_2 price increases and the rest is caused by investment cost increases. With respect to the year 2008, the peak of the energy and raw material price impact is significantly noticed with a relaxing period beyond. Moreover, wind onshore electricity generation costs show an almost constant development until 2015 with slight fluctuations in the period 2008 to 2011. Beyond 2015 a moderate increase is expected. According to this scenario, in the year 2025 wind onshore generation costs reach the breakeven point to coal fired electricity generation costs. In contrast, Photovoltaic electricity generation costs are expected to decrease in the same magnitude as historically observed until 2020. The slower decline in generation costs beyond 2020 is caused by the strong market penetration in that time and the resulting slower doubling of cumulative installations. According to this scenario, grid parity[70] of Photovoltaics is achieved around the year 2017 but its generation costs will not decline to the level of conventional plants until 2030.

[70] Grid parity represents the point in time, when Photovoltaic electricity generation costs are in the range of household electricity prices (EPIA, 2011) – in Austria about 200 EUR/MWh.

8 Conclusions and outlook

Finally, conclusions are drawn from the key findings of the thesis. Consequently, an assessment of the methodological improvements as well as their limitations is discussed. Moreover, the implications of the developed modeling approach on renewable energy technology investment cost scenarios are addressed. Furthermore, a technical outlook focuses on the consequences for selected energy technologies caused by the derived scenarios. A political outlook opens a qualitative discussion on future support measures of energy technologies. Additionally, open questions are discussed in the context of political implications as well as methodological approaches.

8.1 Methodological conclusions

Dynamic investment cost modeling in energy models incorporates generally learning by doing effects. This approach builds on a constant decrease of investment costs with each doubling of cumulative output. A detailed assessment of this methodology is carried out in scientific literature (Wright, 1936; BCG, 1968, McDonald et al, 2001 or Neij et al, 1999 and Junginger et al, 2010b). However, amongst others, Nordhaus (2008) argued for improved modeling approaches in order to cope with the hidden perils of the ordinary one factor learning by doing approach. The allocation of exogenous effects like knowledge, economies of scale or material price impacts towards learning by doing leads to a bias of learning by doing effects and, consequently, misleading future scenarios.

Thus, this thesis discusses a modeling approach focusing on the impact of energy and raw material prices and learning by doing effects on energy technology investment costs. On the basis of a constant learning by doing rate, the pure impact of energy and raw material prices[71] is derived. Therefore, an endogenous feedback from energy to raw material prices and further to the investment costs is realized. The results of the modeling assessment have shown that a technology specific analysis is a key criterion for the identification of energy and raw material price impacts. With respect to some technologies, energy and raw material prices have a direct impact on their investment costs whereas other technology investment costs are additionally indirectly or time delayed affected. Moreover, the impact of energy and raw material prices on some energy technology investment costs rather refers to growth rates than to the direct costs.

Generally, the derived methodology results in a very supportive approach at the estimation of energy technology investment costs. However, specific technological characteristics control the quality of the analyses significantly. Nevertheless, on the one hand, estimations of selected energy technology investment costs have been derived for the recent historical development. In

[71] Principally, in this study renewable energy technologies are selected, showing already relevant market penetration whereby the effect of knowledge (R&D expenditures) and economies of scale is comparatively small to the impact of energy and raw material prices.

this context, the volatile character of recent historical investment costs is very precisely described by the derived models. In particular, good approximations are achieved in the case of wind power and Photovoltaic energy investment costs whereas for solid biomass CHP investment costs only moderately acceptable results are achieved. In the case of small-scale hydropower investment costs no significant impact of energy and raw material prices has been identified. On the other hand, scenarios on the future development are calculated by the model quantifying potential future pathways of the investment costs depending on energy price assumptions up to the year 2030.

A comparison of the new modeling methodology and the standard learning by doing approach is depicted in Figure 59 in terms of selected energy technology investment costs. Thus, the results according to the new approach considering energy and raw material prices as well as learning by doing effects are put into relation to the results solely derived by the standard learning by doing approach. Consequently, any indication above the zero percent threshold in Figure 59 represents a potential underestimation of the investment costs if energy and raw material price impacts are neglected in their estimations.

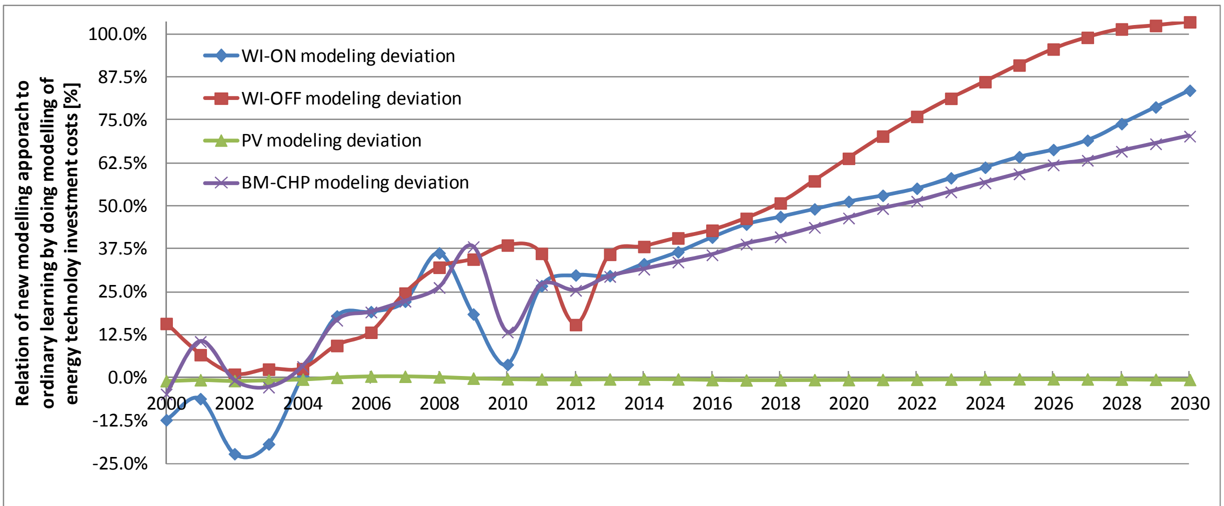

Figure 59 Comparison of the dynamic development of selected energy technology investment costs in terms of modeling approach. Depiction of the relation of the discussed multi factor impact approach to the ordinary learning by doing approach. Source: Own calculation

With respect to the past decade, Figure 59 indicates the underestimation of investment costs derived solely under consideration of learning by doing effects. Additionally, the volatility of the investment costs is only explained by energy and raw material price impacts. Moreover, apart from onshore wind energy investment costs in the early 2000 years, energy and raw material prices significantly compensated technological learning by doing effects. Regarding Photovoltaic investment costs, hardly any impact of energy and raw material prices is identified. In terms of future scenarios, increasing energy and raw material prices will continue to dominate learning by doing effects and, therefore, increase the energy technology investment costs.

Considering the energy and raw material price impact in the calculation of dynamic investment cost developments allows for an indication of the robustness against their price volatility. Hence, the lower the energy and raw material price impact is, the more stable the energy technology investment costs are.

In contrast, the methodological approach requires additional information on the underlying background data. In order to indentify the pure energy and raw material price impact, not only the technological learning effect must be taken into account. Additionally, the market effect in terms of prices versus costs must be considered in the input data selection. Moreover, other exogenous drivers such as R&D expenditures or the economic growth deflator are important parameters of energy technology investment costs which needs to be reflect in the input data selection.

However, it is not the aim of this approach to explain the selected energy technology investment costs by their different drivers but rather to quantify the endogenous feedback from energy prices to raw material prices on the investment costs. Therefore, the market effect as well as mentioned other effects are not directly considered in the analyses and only addressed in the data selection process. Furthermore, the impact of energy and raw material prices is derived by econometric models based on empirical evidence. Thus, future scenarios of investment costs build on a continued relation between the different parameters and, therefore, only depict the implications of the assumed energy price scenarios for investment costs. Consequently, the uncertainty of the scenarios increases by time due to the degrees of freedom[72] in the models.

8.2 Techno-economical outlook

Generally, the multi factor impact model allows for a precise approximation of the energy technology investment costs. This thesis investigated wind on- and offshore, Photovoltaic, small-scale biomass CHP and small-scale hydro power investment costs. Except from the latter, a well acceptable explanation of the investment costs is given by energy and raw material price impacts accompanied by the learning by doing effect. However, in the case of small-scale hydro power plants hardly any impact of energy and raw material prices is identified whereby the modeling approach does not result in a more precise estimation of the investment costs than the standard learning by doing approach. Therefore, investment costs of small-scale hydropower plants are highly robust against energy and raw material price volatilities, and can only be estimated for similar technical site characteristics.

According to Figure 59, wind on- and offshore as well as biomass CHP investment costs are very sensitive to energy and raw material price impacts. On the one hand, their historical volatility is explained by the impact of fluctuating material prices. On the other hand, future

[72] Material substitution might change the identified impact of energy and raw material prices.

scenarios based on the derived models expect a significant increase of the investment costs until 2030. Attention needs to be drawn to the underlying exogenous energy price assumptions (Capros et al, 2011). However, the multi factor impact modeling approach enables a discussion on the implications of raising primary energy prices in future. Therein it is often argued that increasing primary energy prices will increase the electricity wholesale market prices. Consequently, an accelerated market competiveness of renewable electricity technologies could be expected. In contrast, results of the thesis depict the significant technology specific impact of energy prices on raw material prices and, furthermore, on the investment costs of (renewable) energy technologies. Thus, the modeling approach quantifies the feedback from energy prices to the investment costs of energy technologies. However, additional results indicate that raising energy prices increase investment costs of (renewable) and, therefore, also their electricity generation costs. But, electricity generation costs of conventional power plants[73] are even more impacted by raising energy prices due to their increasing investment costs accompanied by the increasing fuel prices. Moreover, investment costs of more mature (renewable) energy technologies are stronger impacted by energy and raw material prices than technologies at a currently moderate market share in terms of capacity. Thus, technologies like Photovoltaic benefit from a more robust character against increasing energy prices. In addition, their investment cost development is highly driven by technological learning effects[74].

8.3 Political outlook

Nowadays, European Member States introduced different financial support schemes in order to promote the investments into renewable energy technologies. Various amendments are published in frequent time periods considering new market developments. In the context of increasing investment costs caused by raising energy and raw material prices no adjustments in support policies have been observed so far. Nevertheless, a general link of financial support schemes to the growth rates of energy and raw material prices appears inadequate. A potential overcompensation of generation costs would be the consequence for some technologies. However, considering the development of annual electricity generation cost changes, caused by energy and raw material prices, at adjustments of support levels is a key criterion for an efficient and sufficient support of renewable energy sources in the future.

Furthermore, especially in the early stage of a technology development a high support of R&D activities increases the learning effects. Moreover, based on the results of this thesis, strong learning effects dominate over energy and raw material price impacts. Consequently, technology investment costs become more robust against the energy price volatility. In order to quantify this effect further research focuses on the additional modeling consideration of R&D expenditures.

[73] The results are based on a modern 400 MW coal fired power plant.
[74] Additionally, the increasing energy price accelerates the market competiveness of Photovoltaic, too.

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