Investitionskosten erneuerbarer Energietechnologien unter dem Einfluss schwankender Rohstoffpreise – eine ökonometrische Analyse

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Introduction

Following the current trend of ambitious RES targets within the European Union as well as abroad, the design of applied promotion schemes becomes continuously more important. In order to improve design criteria towards more effectiveness and efficiency, in the recent past several studies have been published wherein conducted scenarios of future RES support have been discussed in detail. A key parameter for such estimations, and in particular for the *Green-X* model as applied here, is the future development of renewable energy technology investment costs. A standard approach in energy modeling for the determination of the future development of investment costs is to apply the concept of technological learning. The predicted future deployment in combination with identified technological progress (due to learning by doing) allow for an endogenous calculation of the investment cost development. Recent observations have shown that investment costs of most (energy) technologies have not strictly followed scientific expectations. Nevertheless, most deviations stand in context to other market price characteristics. Therefore, Panzer et al. (2011) discussed crucial parameter of dynamic investment cost developments, specifically for renewable energy technologies.

First, raw material prices recently showed a very fluctuating development. Major contribution supporting this strong fluctuation is allocated to primary energy prices. Consequently, on the one hand this chapter discusses the impact of primary energy prices on raw material prices and quantifies the impact under consideration of econometric models. In this respect, the results are interpreted in the mathematical context whereas discussions focus on the energy-related viewpoint. On the other hand, special emphases are given to the identification of the impact of raw material prices on renewable energy technology investment costs. Additionally, the dynamic effect of technological learning by doing on energy technology investment costs is considered, too. Finally, future scenarios on energy technology investment cost developments are derived and debated.

Default background assumptions

As this research focuses on the dynamic development of renewable energy technology costs in the light of both technological learning and impacts of energy and raw material prices a literature review is carried out to identify progress ratios of technological learning effects (Hoefnagels et al, 2011). An overview of selected energy technologies addressed in this report is given in Table 1.

Table 1 Overview of technological progress rate (LR=1-PR) assessment of different renewable energy technologies and the underlying learning rate of this study. Source: Hoefnagels et al, 2011.

Range found in literature	PR	Time frame	Price data region	Capacity
Wind onshore	**93%** *(81-101%)*	**1981-2004**	Global	Global
Wind offshore	**90%** *(81-113%)*	**1991-2007**	Global	Global
Photovoltaic	**80%** *(53-94.7%)*	**1975-2006**	Global	Global
Biomass to electricity CHP	**95%** *(91-92%)*	**1990-2002**	Sweden	Sweden

Generally, progress ratios appear sensitive to the market and the time frame of observation. Thus, a too short time period respectively a too small market might lead to an over- or underestimation of learning effects. A minimum of three times the power of ten in terms of cumulative installations should be considered in the quantification process of learning rates.

Methodology

Based on an in-depth technology analysis the major drivers, in terms of commodity prices, of renewable energy technology investment costs were identified. They include the steel, concrete and silicon price. As these commodities are all very energy intense in production, econometric models have been derived in order to quantify the impact of energy prices on commodity prices and furthermore on the investment cost development of RES technologies.

General concept:

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

- **Identification of the impact of primary energy prices on commodity prices:** The impact of energy prices on raw material prices is identified based on empiric evidence by deriving econometric models. Hereby, the Ordinary Least Square estimation is applied considering the statistical preconditions of the Gauss-Markov Theorem.[1] However, market price effects of raw material prices and other exogenous impacts are neglected.
- **Econometric assessment quantifying the impact on RES investment costs:** Defined econometric models estimate the quantitative impact of one or more commodity price impacts on RES technology investment costs. Hereby, time delayed impacts or relative impacts are considered too. Results are compared to historically realized investment costs and discussed in the energy related context.
- **Future scenarios of dynamic investment cost developments are discussed:** As a final step, a quantitative assessment of the impact of energy respectively raw material prices on the future development of investment costs for RES technologies is conducted. In order to depict different potential future investment cost pathways, sensitivity analyses are depicted based on varying primary energy price assumptions.

Thus, following the concept sketched above, the subsequent section starts with the discussion of the relation between energy prices and raw material prices. In order to allow a serious future raw material price forecast accompanied by the fact that a modeling of raw material

[1] Greene (2012) gives an overview of the mathematical details of the applied methodology

prices is beyond the scope of the applied model *Green-X*, only the energy price related drivers of raw material prices are considered. Therefore, other drivers such as market demand as well as political (fiscal) interests or transport issues are neglected. Thus, in the following section we rather talk about raw material production costs than market prices.

Generally, only the steel-, concrete- and silicon price are considered in this study. Consequently, the data gathering process of both, raw material prices and energy prices was of key importance for the overall project result. Furthermore, regression analyses are conducted depicting the relation between material and energy price as well as future expectation of different trends are considered. However, with respect to future energy price, as driver for the endogenously calculated raw material prices, exogenous assumptions are taken into account, see Capros et al. (2011). More precisely, the crude oil, natural gas and coal price is taken from PRIMES scenarios, whereas the corresponding electricity wholesale price represents an endogenous result of the *Green-X* model (linked to crude oil, natural gas and coal prices).

Therefore, formula Eq(1) below describes the principal structure of the mathematical relation between energy and commodity prices.

$$CP = \delta + \vec{\varepsilon} * \mathrm{EP} + u_t \qquad \text{Eq(1)}$$

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

In a next step, the impact of raw material prices on investment costs of the selected energy technologies is dynamically taken into account. Amongst others, Nordhaus (Nordhaus, 2008) discussed that the problem of technological learning modeling appears in trying to separate learning by doing effects from technological change. This might lead to overestimation of learning by doing effects. According to literature the most suitable approach to cope with that is to use 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 as scale, R&D or partially raw material prices.

This analysis focuses solely on the impact of different raw material prices, either for a single or as combination of various raw materials, depending on the relevant share of these commodities on the total investment costs. Additionally, adding parameters of time lagged commodity costs as well as first derivations to the commodity prices increase the quality of the regression model significantly. In this context, formula Eq(2) represents the mathematical structure of the investment cost model.

$$INV(t) = \left(\alpha + \vec{\beta}\,\mathrm{CP} + u_t\right) * \left(\frac{x_t}{x_0}\right)^m \qquad \text{Eq(2)}$$

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
x_0	Initial cumulative installed capacity
m	Learning by doing impact

Finally, future scenarios of renewable energy investment costs are derived based on the developed model in formula Eq(2). In contrast to the identification of the regressors, where the real historic observed commodity price information is used, the scenario calculation builds on derived commodity costs of Eq(1). This allows for an endogenous feedback from energy prices to future investment costs of (renewable) energy technologies, serving as basis for simulation models of investment decisions as well as subsequently deriving potential policy recommendations.

Results

With respect to the steel price, the model describes that the annual change rate of the steel price development is depending on a constant term, the annual change rate of the coal price in the assessed and the previous year as well as 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 growth rate of the coal price in 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 (Adams, 2006)[2].

Regarding silicon prices, the model 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. Hence, the overall regression estimation is corrected for first order serial correlation of the error term and thus fulfills the Gauss-Markov Theorem. Generally, the silicon price is depending on the electricity expenditures 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 silicon prices.

Finally, considering the concrete price, it 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 allows considering all prices in real units of EUR2006/ton since their price show time stationarity within the investigated time period. 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 and on the other hand

[2] Generally, apart from the energy price impact it is often argued that the demand of steel drives its market prices too. Future steel demand is often modeled as function of economic growth. An additional model tested the impact of GDP on steel prices and concluded that hardly any difference exists to the original model. Moreover, an in-depth analysis of the time series of 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.

small on-site storages facilities lag the impact of gas prices additionally. Moreover, the aggregated representation of the continuous technology development in the model, leads to additional time lagged influences of the primary energy prices.

An overview of the forecast scenarios of the calculated steel, concrete and silicon price based on the econometric models derived in this study is presented in Figure 1.

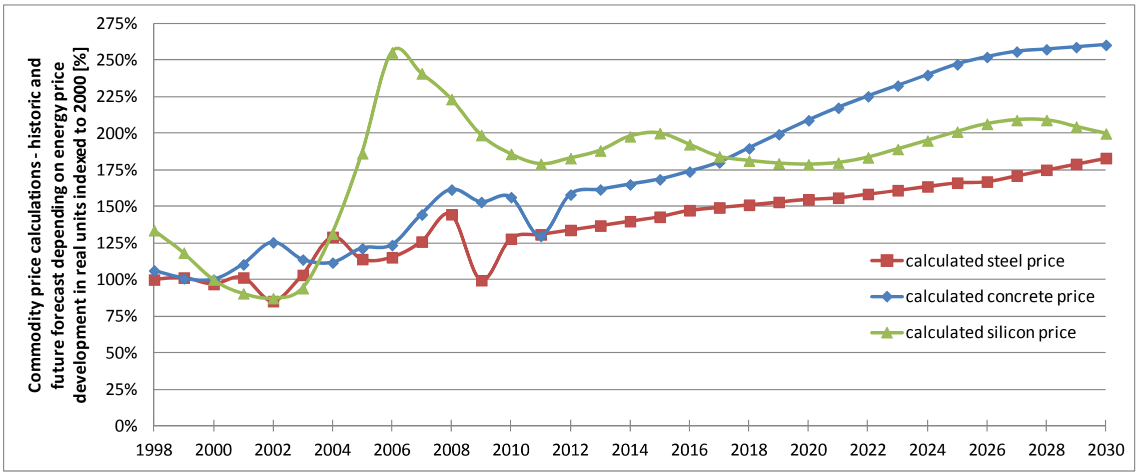

Figure 1 Historic development of forecast scenario of the steel, concrete and silicon price depending on the assumed energy input prices indexed to the year 2000. Source: Own calculation.

Next, the impact of the discussed commodity prices on the investment costs of wind onshore, wind offshore and Photovoltaic has been quantified. Additional results are derived for small scale Biomass CHP plants and small-scale hydro power plants. However, due to the very site specific technological requirements of these two renewable energy types less significant results are achieved and are not commented in this report (see therefore: Panzer, 2012).

In the context of onshore wind energy technology, following historic observations 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 by the steel price development. 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. 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 approval procedures is responsible for the delayed impact.

A slightly different approach is applied in the case of offshore wind. The separate consideration of the turbine and the additional equipment for 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 indicates that the investment costs of the additional equipment for 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[3] factor. Hence, the overall regression estimation is corrected for first order serial correlation of the error term and thus fulfills the Gauss-Markov Theorem. 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.

Principally a similar methodological approach is applied at the quantification of the silicon price impact on Photovoltaic investment costs as in the case of wind energy investment costs. The model indicates that the Photovoltaic investment costs 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. Generally, 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. The production shortage of silicon in peak time of Photovoltaic demand reduced the actual silicon supply and enforced a delayed silicon price impact[4]. 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[5].

Figure 2 depicts the historic development of investment costs derived from the discussed econometric models. Additionally, forecast scenarios until the year 2030, assuming that no major changes in the technology production occurs in the selected time period[6] are presented.

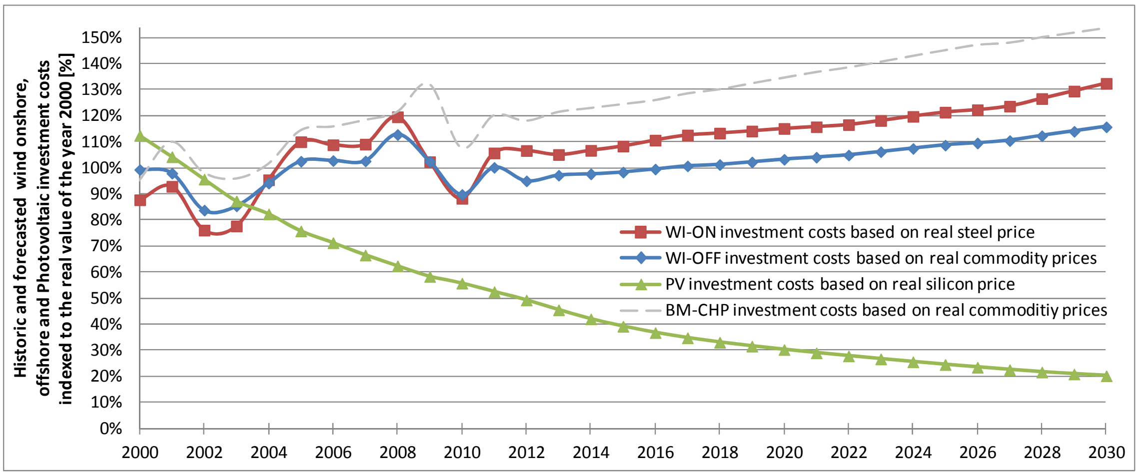

Figure 2 Scenarios of wind on-, offshore and Photovoltaic investment costs. Source: Own calculation

On the one hand, in the historic context, Figure 2 highlights the impact of volatile primary energy and raw material prices on energy technology investment costs. On the other hand, in

[3] The Cochrane-Orcutt procedure a statistical correction of first order serial correlated residuals of an econometric modeling result (Greene, 2012).

[4] 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.

[5] 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.

[6] According to literature this assumption is justified for discussed energy technologies (Panzer, 2012)

the future context, obviously the effect on technological learning by doing is completely compensated by the impact of energy and raw material prices, at least in the case of wind energy technologies. In contrast in the case of Photovoltaic, the strong technological learning effect is hardly compensated by volatile silicon prices.

Additionally, Figure 2 indicates the historic and potential future investment cost development of small-scale biomass CHP plants. Generally, the rare data availability of biomass CHP investment costs only allows for a rough estimation of their future development. However, the approximation meets the historical observations very well. In respect of future forecasts strong investment costs increases are expected due to the commodity price dependence and the relatively low technological learning effects. However, based on the technological similarity of biomass fired and conventional CHP plants (Baxter et al, 2005) similar implications can be drawn for future investment costs of coal fired plants.

Conclusions

Taking into account the primary energy and raw material price in addition to default technological learning for analysis of past and estimations of future (renewable) energy technology investment costs is identified as a successful criterion. On the one hand, historically volatile investment costs can be described by the new modeling approach. On the other hand, the pure consideration of the energy related share of input commodities in (renewable) energy technology investment cost addresses the minimum impact of commodity prices and therefore prevents from overestimating future investment costs. Figure 3 illustrates the improvement in modeling approaches of investment costs exemplarily for wind onshore energy.

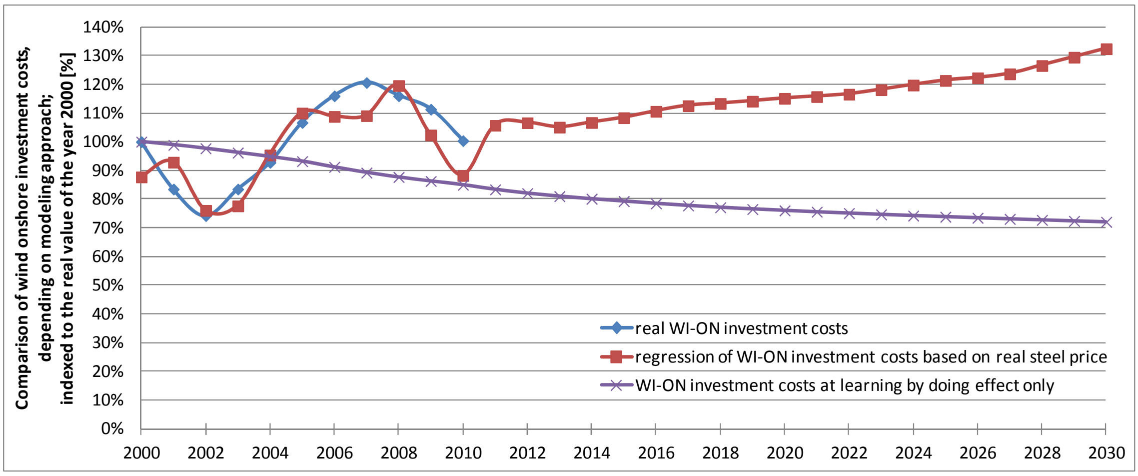

Figure 3 Comparison of different modeling approaches in terms of past and futuredevelopment of onshore wind energy investment costs. Note: The two scenarios are based, on the one hand, on technological learning effects (LR=7% and future market penetration according to IEA, 2008) only and, on the other hand, additionally considered the steel price impact. Source: Own calculations.

Generally, the multi factor impact approach allows a comparatively precise estimation of wind onshore investment costs. However, the estimation is rather below the historic realized investment costs, since it only reflects the energy related impact driver more than the total market prices. Nevertheless, according to Figure 3, previous scenarios, only considering learning by doing effects, lead to major deviations compared to actual price observations. According to new calculations done by use of the above presented methodology, wind onshore investment costs are expected to increase in forthcoming years, meaning that the technological learning effect[7] would be compensated by increasing steel prices.

However, the significance of the new modeling approach largely depends on the (renewable) energy technology. Therefore Figure 4 compares the results of wind on- and offshore as well as of photovoltaic investment costs estimations based on application of the new modeling approach. Consequently, the historic and future investment cost estimations based on learning by doing and commodity price impacts have been set into relation to the estimations based on learning by doing impacts only. Therefore Figure 4 highlights the significance of taking into account commodity prices in investment costs estimations per technology.

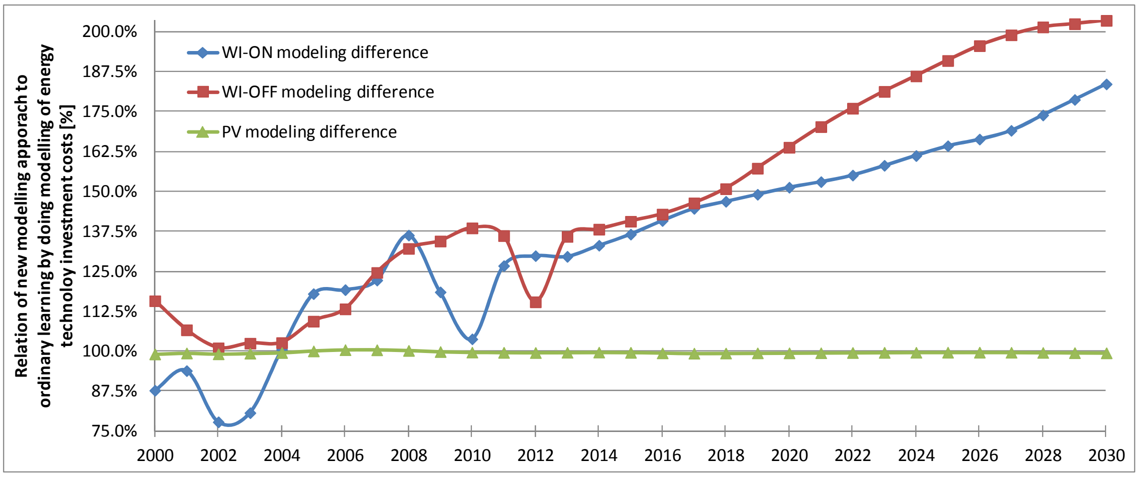

Figure 4 Comparison of the consequences in investment costs forecasts depending on the modelling approach. The figure illustrates the ratio of the results of the new approach to the results by the ordinary learning by doing approach. Source: Own calculations.

In the case of wind energy, especially the incorporation of the historical observed energy and raw material price volatility in investment costs estimations leads to a significant deviation from the ordinary technological learning estimations. With respect to future forecasts, the exogenously assumed primary energy prices (Capros et al, 2011) mainly drive the investment cost development. Comparatively minor differences occur between on- and offshore wind energy investment costs. Mostly, only site specific technical requirements influenced these differences. The stronger deviation of offshore wind investment costs in terms of modeling approaches beyond 2020 is driven by significantly increasing concrete price based on coal and gas price increases in this time period. In contrast, Photovoltaic investment cost estimations are hardly influenced by the modeling approach. Only very minor deviations of about one percent occur in the period around the year 2004 when silicon prices peaked strongly. Generally, the strong learning rate (LR=20%) accompanied by a rapid market penetration of the technology lead to important technological learning effects dominating the dynamic development of investment costs. However, based on the technological similarity of biomass fired and conventional CHP plants (Baxter et al, 2005) some implications might be drawn for coal fired plants as well. Consequently, increasing energy and raw material prices might not only increase renewable technology investment costs but also conventional investment costs, potentially even stronger.

[7] A technological learning rate of 7% is assumed and a future market penetration according to IEA (2008)

In conclusion, the discussed modeling approach allows to improve estimations of (past and) future investment costs. Moreover, the impact of silicon prices additionally highlights the robustness in case of input price variations. Consequently, photovoltaics show a more robust development in times of volatile energy prices than wind energy investments. Generally, novel technologies show higher learning rates and an additional faster market penetration, pushing the learning effect.

In general, this research builds on econometric models derived from historic observations of energy and commodity prices as well as investment costs. Long term future forecasts up to the year 2030 therefore assume that no technological changes will appear in the selected time period distorting the statistical relation between these prices. Consequently, long term investment cost forecast are increasingly uncertain but are a significant indication of the expected trend based on exogenous future energy price assumptions.

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