Economic Disruptions in Long-Term Energy Scenarios – Implications for Designing Energy Policy

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Abstract

The main drivers of the transformation processes affecting electricity markets stem from climate policies and changing economic environments. In order to analyse the respective developments, modelling approaches regularly rely on multiple structural and parametric simplifications. For example, discontinuities in economic development (e.g., business cycles) are frequently disregarded. The distorting effects caused by such simplifications tend to scale up as the time horizons of such analyses increase, and can significantly affect the accuracy of long-term projections. In this study, we include information on economic discontinuities and elaborate on their influences. Based on historical data, we identify the impact of changes in economic parameters and examine their cumulative effect on the German electricity market by applying a techno-economic electricity market model for the period from 2005 to 2014. Similar changes may occur repeatedly in the future, and we expect that a more comprehensive understanding of their effects will increase the validity of long-term scenario assessments. Although dynamic developments have taken place in the past, their effects on such scenarios are regularly ignored. Results indicate that policy decision-making based on modelling frameworks can benefit from a comprehensive understanding of the underlying simplifications made in most scenario studies.

Keywords:

Scenario analysis, electricity markets, economic development, energy market modelling, uncertainty, macroeconomic cycles, electricity production

1 Introduction

Mathematical models are tailored to address specific research questions and aim to describe the links between the main determinants of the system under investigation. In the field of energy and climate policy assessment, market modelling approaches provide valuable insights and often form the basis for political decision-making processes.

However, the underlying assumptions made with respect to exogenous input parameters – such as GDP growth or energy-carrier prices – and their interdependencies can affect the validity of model-based scenario studies. As a result, the requirements for the scenario quality are high, calling into question their consistency [1,2] and their ability to encompass a wide range of contextual uncertainties when combining environmental, economic, and energy perspectives [3,4]. For simplicity, the modelling frameworks applied to long-term energy-system studies tend to assume continuous (or persistent) and/or linear growth trends for key factors like economic growth, energy carrier prices, or technological improvements (efficiency, learning rates, etc.). Fig. 1 illustrates both past dynamics and forecasts of the main factors that influence the electricity markets, and are crucial for the assessment of future policies. Changes in energy carrier prices traded at the global markets may be a source of productivity shocks. The volatility of GDP and electricity consumption may have only national level effects, but in case of global crises, many countries or regions with integrated single markets (as the EU) follow a common path, with similar trends for energy carrier prices, GPD development, energy consumption and environmental policies.

The further into the future the time horizon of the modelling framework lies, the more uncertainty arises regarding the adequacy of assuming linear trends, as comparison of the projected developments with historical data casts doubt on the propriety of such assumptions and, ultimately, on the reliability of the derived scenarios. The use of simplified linear trends has been replaced with an extensive variety of statistical techniques that significantly improve the quality of long-term forecasts [5]. They result in the trends shown in Fig. 1, which do not reproduce short-term dynamics.

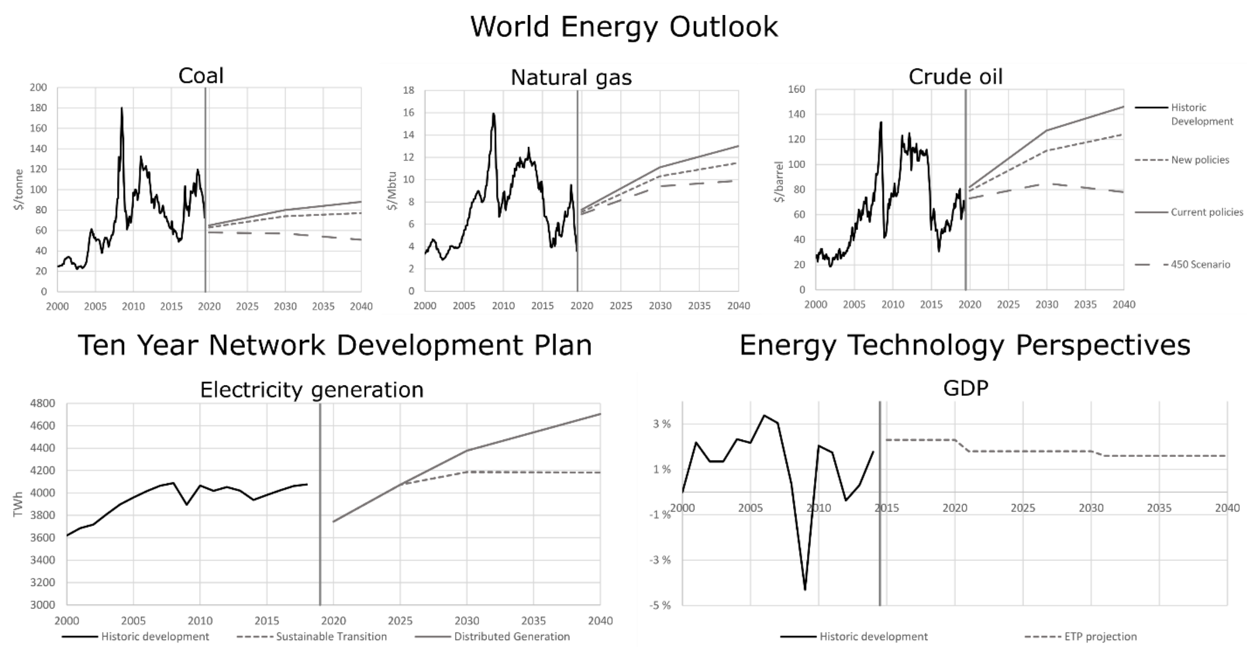


Fig. 1. Comparison of historical developments and projected development trends of various scenario studies.

Source: Author’s compilation based on historical data from [6–8] and projections from [9–11].

Although there is a close link between macroeconomic developments and the electricity market (e.g., due to an increasing or decreasing demand for power), business cycles and their relations to other key factors in the electricity market are generally overlooked in model-based scenarios.

This article aims to evaluate the inaccuracies that arise from neglecting nonlinear developments and the cyclical behaviour of key parameters in modelling frameworks. By analysing disruptions in economic growth, electricity demand, commodity prices and the expansion of generation capacities within the periods under consideration, we identified the implications for scenario analyses and modelling approaches. The German electricity market is the object of the study. By revealing the uncertainty caused by fluctuating patterns, the presented research will contribute to improving the informative value of energy-market modelling results and, ultimately, the effectiveness of the political decision-making process in selecting future energy transition pathways. Furthermore, it will expand the extensive scientific discussion on parametric uncertainty in the field of energy market modelling.

The presented research will assess the reference period from 2005 until 2014. With the financial crisis in 2007/08 bringing significant economic disruption, this period provides a conclusive overview of different growth and price patterns. This paper is organized as follows: Section 2 provides a brief overview of business cycles and links them to the concept of uncertainty and non-linearity in energy-market models. Section 3 introduces the applied modelling framework, scenarios and data sets. In Section 4, the results are presented and policy implications are discussed.

2 Background and motivation

Due to the financial crises of 2007-09 economic research of uncertainty again gained momentum in recent years (see e.g., Svetlova & Van Elst [12] and Jurado, Ludvigson & Ng [13]). The most prominent economic theories of uncertainty date back to the first half of the 20th century [14] – namely, the theoretical frameworks of Keynes (1921) [15], Hayek (1945) [16], Knight (1921) [17] and Shackle (1955) [18]. Based on those theories Svetlova and van Elst [12] differentiate the problem of decision-making under uncertainty in three categories: (i) risk in the exogenous world events that can be measured and represented in known probabilities, (ii) uncertainty arising from ambiguity when probabilities of the known events are not known, and (iii) uncertainty arising from unawareness when economic agents do not have a complete information about the events themselves. In this sense, macroeconomic uncertainty (iii) as time varying conditional volatility in economic and financial indicators proves to be strongly countercyclical to the real activity, with 2007-09 recession being the most representative episode of uncertainty increase since 1960 [13]. In the effort to develop methodological frameworks that are able to assess economic uncertainty in the context of energy markets, there exists an extensive amount of research (see e.g., Fuss et al. 2012 [19], Kang & Ratti 2013 [20], Conejo 2010 [21]). The presented categorisation of economic uncertainty is not explicitly transferable to most modelling frameworks applied. Thus, in the field of energy models, uncertainty can be attributed to three major categories: (i) parametric, (ii) structural [22], and (iii) context uncertainty [23]. The first category describes uncertainty stemming from the initial input parameter data sets [24] and structural uncertainty refers to model-specific assumptions and simplifications [25], while context uncertainty specifies the nexus of possible developments in social, economic and technological environments, as well as policy uncertainties. Different approaches have been implemented to address structural uncertainty in the climate and energy scenarios [3,26], as well as in the scenarios for energy-intensive industries [27].

Cyclical behaviour and the non-linearity of key input parameters can be interpreted as parametric uncertainty, and there are already several studies investigating cycles of certain elements within energy market models. Pesch et al. [23] analyse wind and solar time series with regard to their cyclical behaviour. Ford [24] and Arango & Larsen [25] explore the occurrence of capacity cycles within deregulated markets, which exhibit a continual fluctuation of over- and underinvestment. Along with investment, inventory and business expenditures exhibit clearly procyclical behaviour within business cycles. Cuddington & Jerrett [28] model asymmetric mineral price cycles with ‘super-cycle amplitude’ in relation to the growth rate of the global economy and respective structural developments. Joëts, Mignon & Razafindrabe [29] in their analysis of energy, agricultural and industrial markets stress that commodity prices are highly affected by macroeconomic uncertainty related to global business cycle.

The existing literature tends to avoid the issue of nonlinear patterns of energy commodity prices and prefers to assume linear time series – especially in the field of bottom-up perfect-foresight modelling. The application of real business-cycle theory to the analysis of environmental policies, changes in the energy sector and technological change has gained attention [30]. Applying the general equilibrium real business-cycle model, Heutel [31] proves that the chqanges of CO_2 emissions as a result of supply (and/or productivity) shocks is significantly procyclical, and argues that optimal environmental policy would “dampen the procyclicality of emissions”. In the context of business cycles, the relationship between energy (or, specifically, electricity) consumption and economic growth has been of considerable interest [32], as well as the direction of the causality between them [33,34]. The results conclude a stronger association between these factors for countries with higher wealth, in some cases diverging in the estimations of the strength of the causual direction. In that respect, the influence of commodity prices also has to be taken into account. A broad variety of research examines the link between energy commodity prices (e.g., oil prices) and economic activity [35,36]. In particular, there is a high degree of consensus in the literature that medium-term business cycles (i.e., 'conventional' business cycles of up to 8 years) are caused by energy price shocks [37], among other factors. In this paper, we do not focus on the impact of long-term commodity cycles (up to 50 years) that are also relevant for energy scenarios. Instead, we analyze the distorting 'noise' produced by medium-frequency dynamics within the conventional business cycle.

This study takes up the discussion of the connection between business cycles and electricity markets, and examines the impacts of economic discontinuities. The approach introduced therein focuses on changes in electricity consumption as a result of changes in GDP growth, as well as on the volatility of major energy commodity prices and emission allowances.

Many optimization models are constrained by the conditions of perfect foresight based on complete knowledge of future technological deployment [38], production costs, fuel prices and economic growth – and not least because scenarios extrapolate the historical experience and tend to inadequately anticipate long-term developments [39,40]. Van Vuuren & O'Neill [41] find deviations from current trends in population and the economic growth of IPCC scenarios when they verify them with the historical data. Since then, new methods of scenario development for large modelling exercises have been elaborated [4,26,42], and have improved researchers' interpretation of the scenarios as well as their understanding of the limitations of cost-optimization modelling [25]. These studies focus on the long-term developments (i.e., with horizons of 50 or 100 years) in energy or electricity markets. In this framework, systemic structural biases can occur due to underestimation of the pace of growth. In the short-term, however, bias also arises from the linearized assumptions of the input data.

Fig. 2 (a) depicts changes in energy carrier prices and emission allowances for the period under consideration (2005 to 2014), which shows volatility that was caused not only by the financial crisis of 2008 and the productivity crisis of 2009, but also by the introduction of the EU's emission trading system (ETS) in 2005. Controversial regulations pertaining to the two phases of ETS between 2005 and 2012 and uncertain CO_2 certificate prices led to the distortion of investment incentives for fossil fuel generators [43].

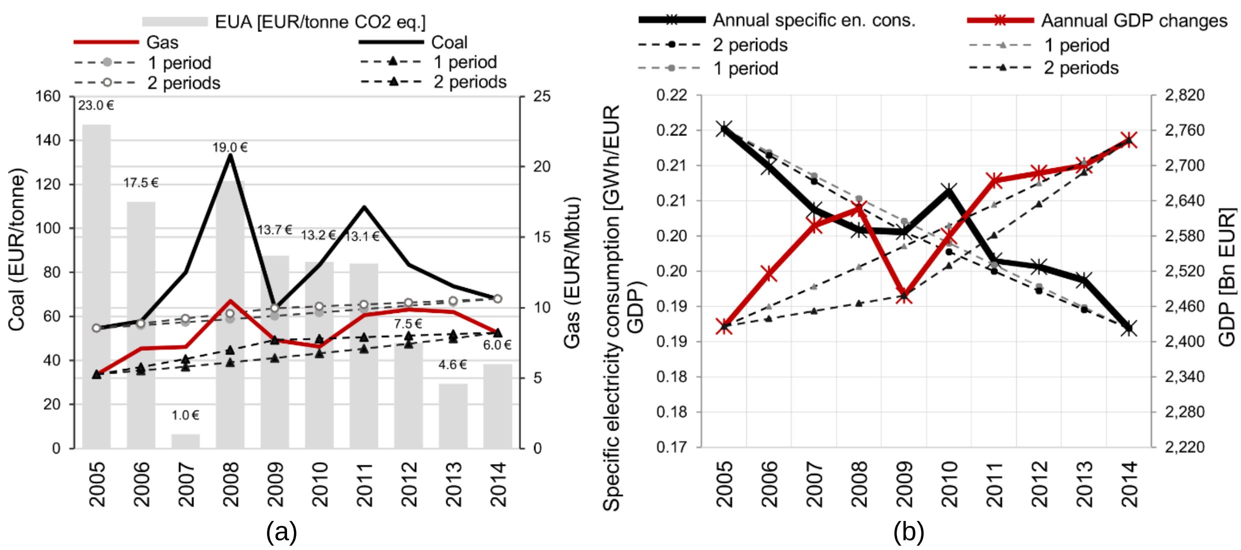


Fig. 2. (a) Changes in main input factors: gas and hard coal prices [2014 EUR], CO_2 certificate prices. (b) Changes in GDP and specific electricity consumption (final electricity consumption per EUR GDP).

Sources: EUA price 2005-2008: Trends and projections in the EU ETS: [44]; EUA price 2009-2014: [45]; [2014 EUR] coal and gas: BP Statistical Review of World Energy [6].

Fig. 2 (b) describes the development of the final electricity consumption per unit of GDP, characterising changes in the electricity demand for the production of goods and services. The dashed lines on both graphs (a, b) represent linearized developments within either one 10-year or two 5-year periods. These periods are analogous to the assumptions of cost-optimization models that rely on perfect foresight, where values of GDP and electricity demand for the end of the periods are assumed to be known and are given exogenously.

The main question examined by this paper is how much information can be expected to be lost through the application of linear and/or persistent growth trends in energy prices, economic growth and electricity demand. Furthermore, the effects of business cycles on effective energy and climate-policy design are explored. Electricity demand and economic factors as fuel prices or economic growth are the key drivers of uncertainty in the long-term modelling of liberalised electricity markets, see e.g. Möst & Keles [46]. By applying a decomposition analysis, we assess the intrinsic causes of changes in CO_2 emissions between the scenarios. We assess how the selection of the length of periods and information on existing dynamics can improve the interpretation of the results. We measure precision by comparing the differences between the historical development and model simulations.

3 Methodology

3.1 Model specifications

A 'learning-from-the-past' approach contributes to the assessment of scenario generation through the use of partial equilibrium bottom-up techno-economic models. This study applies the Electricity Market Model for Europe (EMME) [47], which is a linear optimization model featuring twenty-eight individual states of the EU plus Switzerland and Norway. It models both dispatch and investment by minimising total system costs (overall variable generation costs and investment costs) subject to electricity demand and a set of technical constraints. Equation (1) is an objective function typical for bottom-up partial equilibrium models of the wholesale electricity market:

$$\min Cost = \sum_{h,i,d} \left[Pr_{h,i,d} \cdot Cst_{i,d}^{var} \right] + \sum_{i,d} \left[\left(G_{i,d}^{inv} \cdot Cst_{i,d}^{inv} \right) + \left(G_{i,d} \cdot Cst_{i,d}^{fix} \right) \right] \qquad \forall\, h, i, d \tag{1}$$

Equation (2) describes the energy balance constraint, where exogenously given demand $D_{h,i,d}$ must be satisfied at each hour and in each region, with the left side of the equation equal to the supply in each region d for each hour h. The demand is price-inelastic, and is given as hourly time series. The supply is the sum of production $Pr_{h,i,d}$ from all power-plant technologies, plus the sum of imports $I_{h,k,d}$ from k to d, minus the sum of exports $I_{h,d,k}$ from d to k. In Equation (5), the amount of imports and exports is constrained by the interconnector net transfer capacities ($NTC_{k,d}$ and $NTC_{d,k}$), which are published by ENTSO-E [9] for each historical year. Note that interconnector line capacities are not equal for import and export flows between countries, reflecting the expected maximum volume of the flow under the existing network and technical constraints in both systems. Fig. 3depicts the states considered in the model and offers a schematized representation of cross-border interconnection lines.

In every hour, the production $Pr_{h,i,d}$ is constrained by the available generation capacity – see Equation (3). $G_{h,i,d}$ involves production from both installed $G_{h,i,d}^{inst}$ and endogenously determined invested capacity $G_{h,i,d}^{inv}$, which is constrained by the technical availability $\alpha_{h,r,d}$ of the respective dispatchable power plant technologies in Equation (4.1). The amount of CO_2 emissions is derived from endogenous production per technology, technology-specific technical parameters and a fuel-type specific emission coefficient. Equation (4.2) is the constraint for variable renewable generation defined by exogenous generation profiles $\varphi_{h,v,d}$ for wind and solar technologies. The hourly electricity price is the shadow price of the demand constraint given in Equation (2), and has a unit measure of EUR/MWh.

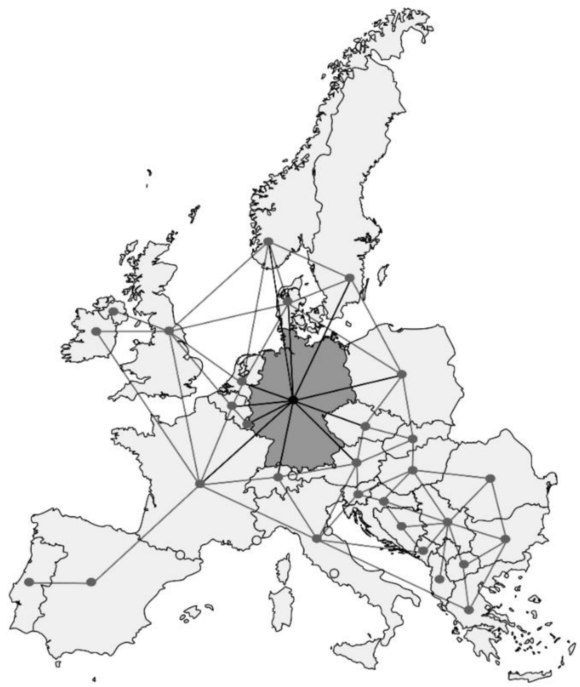


Fig. 3. Schematic representation of the countries considered and cross-border interconnections in the model.

The model represents the energy-only market, where the hourly electricity price can be interpreted as the market-clearing spot price in the respective region under a deregulated wholesale electricity market. Dynamic aspects such as electricity storage, technical ramping constraints and the operation of the reserve market are omitted for simplicity. This allows the model results to be traced, and facilitates their investigation in relation to the effect of stylized input data.

$$\sum_{i} Pr_{h,i,d} + \sum_{k} I_{h,k,d} - \sum_{k} I_{h,d,k} = D_{h,d} \qquad \forall\, h,i,d,k \quad (2)$$

$$Pr_{h,i,d} \leq G_{h,i,d} \qquad \forall\, h,i,d \quad (3)$$

$$G_{h,r,d} \leq \left(G_{h,r,d}^{inst} + G_{h,r,d}^{inv}\right) \cdot \alpha_{h,r,d} \qquad \forall\, h,r,d \quad (4.1)$$

$$G_{h,v,d} = G_{h,v,d}^{inst} \cdot \varphi_{h,v,d} \qquad \forall\, h, v, d \quad (4.2)$$

$$I_{h,k,d} \leq NTC_{k,d}\ ;\ \ I_{h,d,k} \leq NTC_{d,k} \qquad \forall\, h, i, d, k \quad (5)$$

where:

h	Specific hour of the year [-]
i, v, r	Technology index for all technologies i and for dispatchable r and variable v technologies [-]
d and k	Country indexes, denoting imports $I_{h,k,d}$ from k to d, and exports $I_{h,d,k}$ from d to k [-]
$Cst_{i,d}^{var}$	Variable generation costs [EUR/MWh]
$Cst_{i,d}^{fix}$	Quasi-fixed annual costs (e.g., labour costs) [EUR/MW]
$Cst_{i,d}^{inv}$	Investment costs (annuity recalculated from overnight costs) [EUR/MWe]
$Pr_{h,i,d}$	Electricity production [MWh]
$G_{h,i,d}$	Total generation capacity [MW]
$G_{h,i,d}^{inst}$	Installed generation capacity at the beginning of the period [MW]
$G_{h,i,d}^{inv}$	Invested generation capacity of gas, lignite and coal [MW]
$\alpha_{h,i,d}$	Technical availability factors for dispatchable technologies i [-]
$\varphi_{h,v,d}$	Exogenous generation profiles for variable technologies r [-]
$I_{h,i,k}$	Electricity imports from country k and $I_{h,i,d}$ electricity exports from country d [MWh]
$D_{h,d}$	Electricity demand [MWh]

$NTC_{d,k}$ Net transfer capacity between two countries from d to k, and $NTC_{k,d}$ in the opposite direction [MW]

In the 'dispatch' mode, the model was calibrated for the period 2005-2014 so that yearly runs delivered results close to reality with regard to the overall dispatch structure (~6 % of deviation between the statistic and the output data for each technology type), CO_2 emissions and wholesale electricity prices. In the 'investment' mode, the model extracted decreases in the installed capacities (divestment) exogenously from statistical data that take the vintage structure of power plant stocks into consideration [7,9,48]. The vintage structure deployed in the model allowed for an accurate account of respective technical factors. In order to exclude disruptions of policy-driven changes in renewable energy source (RES) capacities (PV and wind), they were accounted for exogenously. Hence, the investment model focused primarily on the capacity additions in gas- and coal-fired power plants [43]. Although the expansion of these capacities is, to some extent, also driven by energy policies, the authors excluded this association in the study.

3.2 Scenario specification and key drivers of the analysis

In order to assess the implications of assuming linear trends for selected key factors instead of considering their fluctuations, we analysed the period from 2005-2014. This period provided a conclusive overview of business cycles, with economic growth (January 2005 until May 2008), recession (May 2008 until April 2009), and a stage of timid growth/recovery (April 2009 until July 2010) [49]. In our analysis, we focused on the case of the German power system. In its efforts towards market liberalization – which target the integration of electricity markets – Germany fosters the creation of a single electricity market with the strong pursuance of low-carbon environmental policies, e.g. [50,51].

In the ‘dispatch’ mode, we aimed to investigate and quantify the effects of high-amplitude changes in macroeconomic input parameters within the defined modelling framework. We tested the sensitivity of the model for one 10-year (2005-2014) and two 5-year (2005-2009 and 2010-2014) intervals, assuming a linear growth pattern of the main economic input parameters within the respective intervals (see Tab.1). The scenarios applied in this framework can be distinguished by their temporal resolution. In a first *annual* scenario, we calculated CO_2 emissions as well as wholesale electricity prices in hourly resolution and producer surpluses, using historical statistical values for key input factors [6,52]. In a second step, we compared this scenario with two scenarios based on averaged data for a *1-period* scenario (II) and a *2-period* scenario (Ia, Ib).

Tab.1. Key assumptions behind the scenarios

Scenario	**Annual changes**										**Scenarios with linear growth [% p.a.]**		
											Ia	**Ib**	**II**
Designation:	*annual*										*2-period*		*1-period*
Time/Period	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2005-2009	2010-2014	2005-2014
Gas price [EUR/mil Btu]	4.1	5.6	5.7	8.2	6.2	6.1	7.6	8.6	8.0	7.0	5.6	-0.7	2.1
Oil price [EUR/BBL]	53.9	61.8	61.2	74.2	49.7	63.9	85.4	90.8	84.3	75.5	-2.0	8.7	3.8
Coal price [EUR/t]	43.0	45.6	63.1	104.9	51.3	70.2	88.3	72.6	61.3	57.9	0.02	-5.3	7.1
Growth rate GDP [%]	0.71	3.7	3.2	1.08	-5.62	4.08	3.66	0.49	0.49	1.60	0.53	2.0	1.37
Change in installed capacity* [Δ %, 2005=1]	HC 0 LI 0 G 0	HC-2.5 LI -0.6 GS 2.8	HC-0.5 LI 2.5 GS 3.3	HC 0.8 LI 1.8 G 10.3	HC-1.3 LI 2.2 G 12.2	HC 2.6 LI 3.3 G 15.2	HC 2.7 LI 13.3 G 15.6	HC 1.4 LI 10.3 G 27.9	HC-0.8 LI 5.2 G 29.6	HC-0.8 LI 6.2 G 30.4	HC -0.32 LI 0.54 G 2.9	HC 0.1 LI 0.77 G 3.0	HC -0.08 LI 0.67 G 2.9

*: HC – hard coal; LI – lignite; G – gas.

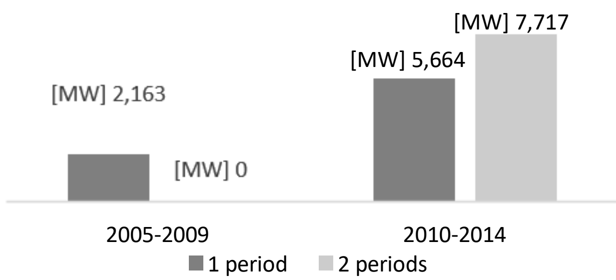
In the investment mode, we tested how these underlying assumptions affected the results of the introduced investment model. The investment decision regarding the expansion of the generation capacities of gas, coal and lignite power plants was determined on a yearly basis. We modelled short-term market equilibrium by following the approach presented by Hirth & Ueckerdt [53] and based on the analytical model provided by Stoft [54]. We took the 2005 generation fleet as a long-term capacity mix for the *1-period* scenario and the 2009 fleet for the *2-period* scenario. We adopted the decommissioning plan as described in Tab. 1 for each scenario. In the short-term, investment costs of the existing capacities were sunk. New investments were added annually and passed on to the next year within the period. The evaluation of the short-term profits of generators allowed us to discuss the effects of parametric uncertainty on the producer surplus in the Results section (see Fig. 9).

4 Results

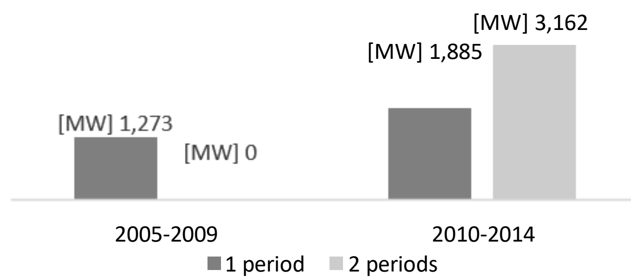
4.1 Results for the German electricity market

The main model outputs for each scenario differed with respect to the timing and magnitude of investments, prices and CO_2 emissions (see Tab.1). We experienced differences in the distribution of investments within the periods, as shown in Fig. 4 below. A detailed overview of annual investment patterns is provided in

Appendix A. Under the given assumptions, no investment occurred from 2005 to 2009 for the *2-period* scenario that takes into account the developments in fuel prices and demand in 2009, and takes this year as a reference point for future projections. The *1-period* scenario showed comparatively lower investments between 2010 and 2014. To trace back the underlying reasons, it would be necessary to analyse the data provided by the dispatch model more precisely.



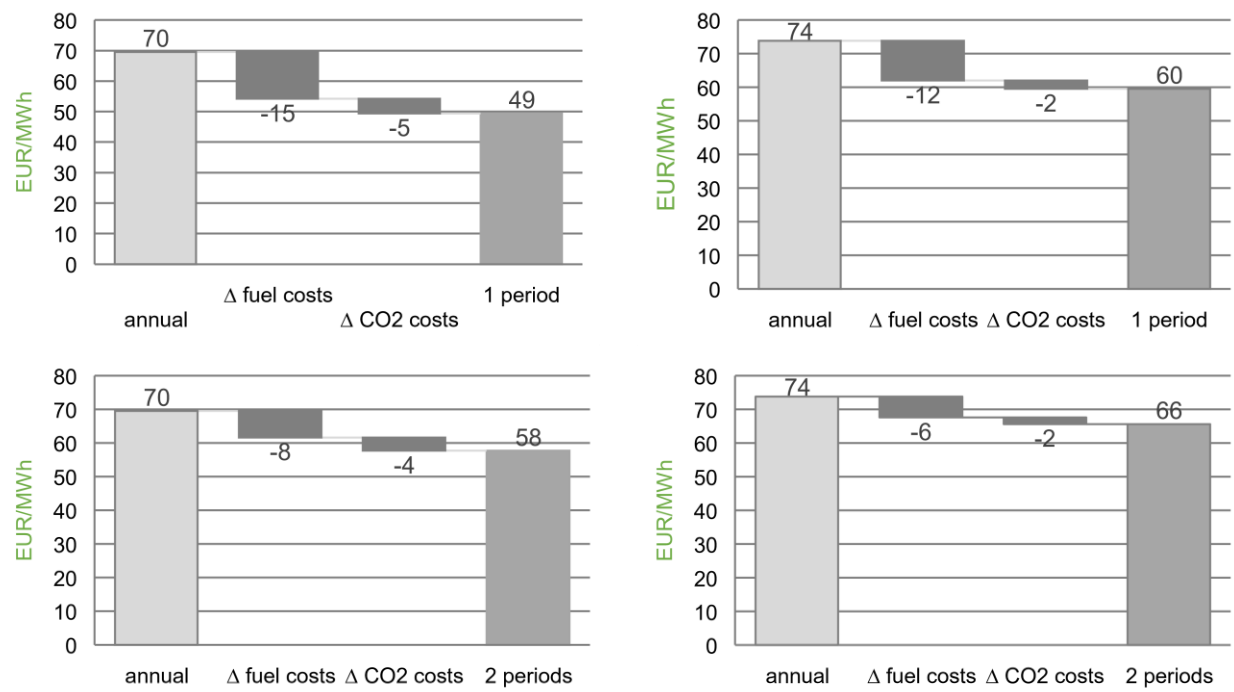
(a) Investment in coal-fired capacities in two periods (model results).



(b) Investment in gas-fired capacities in two periods (model results).

Fig. 4. Changes in coal and gas capacity investment patterns.

A simplification of the main input parameters describing the evolution of fuel prices and prices for emission allowances directly affected the composition of generation costs for the different power plant types. Consequently, their position in the merit-order changed significantly, resulting in a shift in the corresponding full-load hours. This can be illustrated by investigating generators´ typical mid- and peak-load variable costs for the year 2008, as depicted in Fig. 5. A decrease of 11 % and 21 % in generation costs (in the *1-period* and *2-period* scenarios, respectively) for a typical mid-load generator (a) resulted from a change in fuel prices (see Fig. 2). These averaged values did not capture the high spike in coal and gas prices, which was accompanied by high prices for allowances at the beginning of the second ETS period. For base-load coal-fired power plants, this difference varied more strongly than for gas-fired power plants (b), since the relative share of emission costs (in the form of ETS certificates) within the overall generation costs was higher. By considering two time periods, the resulting generation cost assumptions for mid- and peak-load power plants converged substantially closer to the annual data than the 10-year averages. On the one hand, the divergences of actual and modelled generation costs could lead to a major overestimation of profit opportunities for generators or, on the other hand, an underestimation of future wholesale electricity prices. This relationship might lead to false assessments of investment incentives for certain generation technologies.



(a) Average variable costs (EUR/MWh) for typical mid-load power plants (hard coal).

(b) Average variable costs (EUR/MWh) for typical peak-load power plants (CCGT).

Fig. 5. Decomposition analysis of changes in the variable generation costs for the three scenarios in 2008.

The structure of the generation mix and technology-specific investment costs in combination with variable costs were the major drivers for investment decisions – given the assumption of perfectly competitive electricity markets. The illustrated changes in the variable generation costs due to different assumptions on fuel and environmental costs determined the combined effect on the electricity price. To emphasize the difference between the three scenarios, we considered average wholesale prices for each year of the time-period in question (see Fig. 6). The *annual* scenario delivered prices that were close to statistical spot market data. The spot market price was at the highest point in the time period in 2008, reflecting the combined impact of changes in fuel prices and emission allowances. The *1-period* and *2-period* scenarios were not able to capture these dynamics. (For annual average wholesale electricity prices, refer to

Appendix A.) Changes in the cumulative CO_2 emissions inside the defined time-periods were another source of misinterpretation in the long-term scenarios. Fig. 7 presents the CO_2 emissions for the three scenarios. While the *1-period* scenario largely exceeded the *annual* scenario's emissions, the *2-period* scenario underestimated the amount of CO_2 emissions. The illustrated discrepancy was a result of diverse assumptions on the main input parameters that smoothed developments in commodity prices, demand, changes in the expansion of the generation mix, economic growth, and trade between the regions.

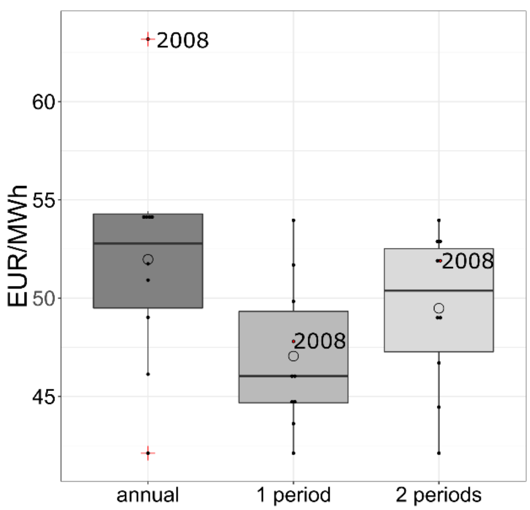


Fig. 6. Distribution of annual average electricity prices in three scenarios for each year between 2005-2014, where the 'o' and a horizontal band inside the box denote the average and the median, respectively.

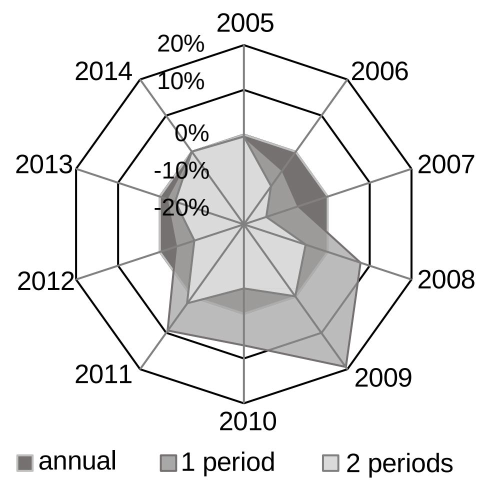


Fig. 7. CO_2 emissions from fuel combustion for electricity generation in three scenarios, where *1-period* and *2-period* scenarios are given as ratios to the *annual* scenario, which is set to 1.

In order to investigate the reasons behind the changes in the CO_2 emissions presented in Fig. 7, we applied a decomposition analysis. Our analysis was based on the Logarithmic Mean Divisia Index (LDMI) approach described by Ang [55], while the additive decomposition analysis model implemented in the current study related to the approach introduced by Karmellos et al. [56]. The combined effect of all factors on the total change in CO_2 emissions C_t defined in Equation (6) provided a perfect decomposition analysis without leaving residual terms in Equation **Fehler! Verweisquelle konnte nicht**

gefunden werden.. It accounted for the activity effect A_t that reflects changes in electricity consumption due to changes in economic growth. The electricity intensity effect I_t, explained as the ratio of electricity consumption to GDP, describes the increasing or decreasing share of electricity used for domestic production. The electricity trade effect T_t categorizes a country as a net exporter if $T_t > 1$, and as a net importer if $T_t < 1$. The energy efficiency effect $e_{i,t}$ shows how technology-specific changes in the energy efficiency of the generation sector benefit from a decrease in CO_2 emissions. This effect is highly sensitive to the technological data of each power plant type featured in the model and to the assumed vintage structure.

$$C_t = A_t \frac{EC_t}{A_t} \frac{EP_t}{EC_t} \sum_i \frac{F_{i,t}}{EP_{i,t}} = A_t I_t T_t \sum_i e_{i,t} \tag{6}$$

where:

t	Index for the time period [-]
i	Index for the generation technology [-]
C_t	Total change in CO_2 emissions [Mt]
A_t	Gross domestic product (GDP) for year t [billion 2014 EUR]
I_t	Electricity intensity effect [GWh/ billion 2014 EUR]
T_t	Electricity trade effect for year t [-]
EC_t	Electricity consumption [GWh]
EP_t	Total electricity production in the country from all sources [GWh]
$EP_{i,t}$	Electricity generated from fuel i
$F_{i,t}$	Amount of fuel input i for a respective generation type [GJ]

The derivation of these individual effects can be calculated with the use of logarithmic mean weight functions (see Appendix C). The change in CO_2 emissions between the base year (here 2014) and year t was broken down into the four drivers described above, as given in Equation **Fehler! Verweisquelle konnte nicht gefunden werden.**:

$$\Delta C_{0-t} = C_0 - C_t = \Delta A_{0-t} + \Delta I_{0-t} + \Delta T_{0-t} + \Delta e_{0-t} \qquad (7)$$

The results of the decomposition analyses for the three scenarios for each year relative to the base year 2014 are presented in Appendix C. Considering the pattern of CO_2 emissions given in Fig. 7, the year 2009 revealed a dramatic difference between the *1-period* and the *annual* scenario. However, since 2009 represented a benchmark year for the calculation of the average growth rates for the *2-period* scenario, it was unsuitable for the decomposition analysis (see Tab.1). Thus, the year 2008 was used for the illustration of the decomposition effects (see Fig. 8).

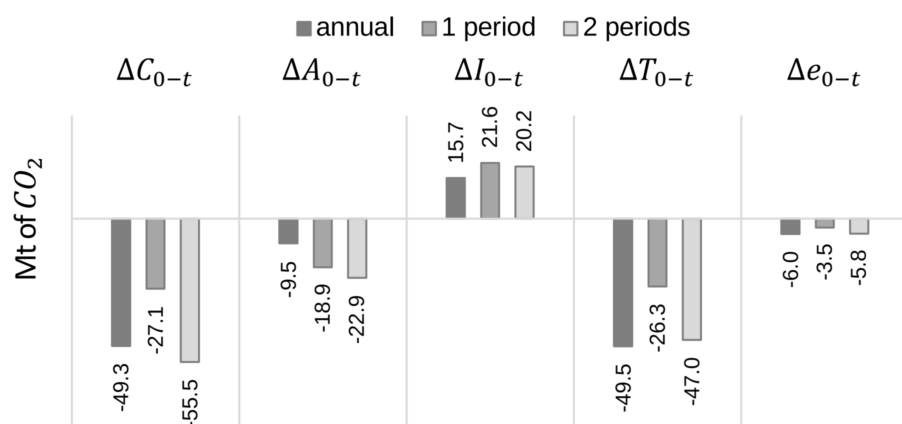


Fig. 8. Decomposition of changes in CO_2 emissions from fuel combustion in the electricity sector, comparing 2014 (0) to 2008 (t).

The change in the activity effect ΔA_{0-t} in *1-period* and 2-*period* scenarios had a higher impact on the increase in CO_2 emissions in 2008 relative to 2014 than the *annual* scenario. This was an effect of averaging the GDP growth from 2005 to 2009 (0.53 % p.a.), and from 2005 to 2014 (2 % p.a.). At the same time, the nominal GDP grew steadily from 2005 (2.4 billion 2014 EUR) to 2008 (2.6 billion 2014 EUR), and dropped by 6.7 % in 2009, almost returning to the level of 2005 [7]. The exclusion of this discontinuity in the measurement of economic growth had a significant effect on the estimation of the cumulative emissions in the period 2005-2014. Another substantial aspect was highlighted by the change in the electricity trade effect, ΔT_{0-t}. In the period 2005 to 2014, Germany's electricity exports to neighbouring countries increased constantly: thus ΔT_{0-t} was negative when comparing the base year 2014 with 2008. Considering the average price developments shown in Fig. 6 for the *1-period* scenario, the trade effect was nearly 47 % less than for the *annual* scenario. Model results indicated that the price effect stimulated domestic electricity production. As a result, exports increased and CO_2 emissions in the exporting country increased significantly.

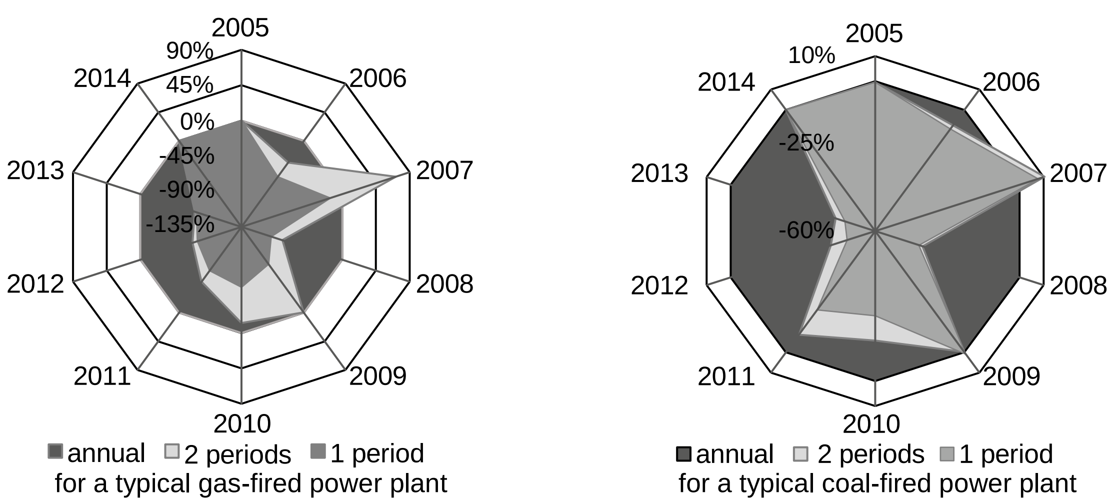


Fig. 9. Producer surplus.

Fig. 9 illustrates producer surpluses for the period from 2005 to 2014 (indexed to the *annual* scenario). The results suggest that surpluses for gas- and coal-fired power plants have not been captured sufficiently by the presented model setting. The misinterpretation of model results that reveal potential losses or gains for producers – but which do not reflect the actual market conditions – may lead to inaccurate projections of future capacity expansions, to altering the attractiveness of certain technology types, or to the rejection of possible windows of opportunities for niche technologies.

4.2 General policy remarks

An inaccurate estimation of producer surpluses (as shown in Fig. 8) for specific generation technologies might lead to false conclusions with regard to the future need for policy intervention. The timing and implementation of environmental regulations significantly affect investment decisions as well. The combined effects of policies and market design shape the investment decisions of electricity generators. Therefore, if disruptions in macroeconomic factors are not taken into consideration, policy measures aimed at energy transition may not be conceived in time, or may be insufficient.

Economic shocks as a source of changes in key macroeconomic variables like economic growth and interest rates, impact both the supply and the demand side of energy systems. This study focused its analysis on Germany as an example case. However, the identified implications are valid for a wider range of countries. In the period under consideration GDP development showed a similar trend. Additionally, European energy markets are highly integrated, where prices for energy carriers in different countries move comparably. Convergence of oil and gas prices at the European market has a long-term evidence [57,58]. An exception are lignite markets that are stronger regionalized than the markets of energy carriers (see [59]). Lignite prices are more dependent on regional and national developments, than natural gas, coal and oil. On the contrary, hard coal prices at the European borders follow the changes in oil prices [60]. However, the strength of specific impacts may vary across different countries, due to the structural differences of the respective markets. Fig. 9 presents absolute percentage changes in CO_2 emissions of electricity generation for the *1-period* and *2-period* scenario in relation to the annual scenario for several European member states.

1-period relative to the annual scenario [%] *2-period* relative to the annual scenario [%]

Fig. 10. Absolute changes in the CO_2 emissions between the annual refenrence scenario and 1 and 2-period scenarios for 2009-2014. See the data behind the graphs in the Appendix D.

Taking into account this aspect may be important in the assessment of carbon budgets on the EU level. Fig. 10 shows, that the *1-period* scenario results in a larger deviation of total CO_2 emissions, than the *2-period* scenario.

Considering the pattern of CO_2 emissions for the period studied, our results suggest that carbon budgets will not be described sufficiently by analogous modelling frameworks. In the presented period, the divergence of the overall CO_2 emissions of the *1-period* and *2-period* scenarios from the annual scenario amounts to approx. +114 Mt and -82 Mt, respectively. The divergence between the scenarios can be gasped by estimating the root mean square error (RMSE) – the results are presented in the Table D.2 of the Appendix D. The approach of assuming linear growth rates for key parameters promotes a misleading picture of the techno-economic background, overlooking the need for emerging technologies in order to achieve certain environmental goals (e.g., meeting CO_2 budgets).

The inaccuracies experienced might result in ineffective policy measures based on the gaps between the expected and actual generation costs, fuel prices, electricity demand and economic growth. As a consequence, if dynamic economic developments are not taken into consideration during the policy planning process, the need for further policy intervention in order to shape the design of the future electricity sector can be drastically misjudged. Consequently, the design of energy policy measures based on modelling frameworks may prove inefficient or ineffective if economic disturbances are not considered within the scenario analysis. While we are not able to precisely predict forthcoming economic disruptions, we do know that they will occur. Thus, for future policies it is necessary to have a better understanding of how to interpret long-term scenarios for power markets to take into account abrupt changes in the pace of economic growth.

5 Concluding remarks

Long-term projections for energy markets in general – and for the electricity market in particular – can be improved by incorporating the effects of major economic disruptions. Thus, a better understanding of the interpretation of modelling results can be formed by considering those disruptions in scenario studies. By investigating the response of the German power market to the to the last significant economic downturn, this work contributes to a comprehensive understanding of long-term risks, their possible sources and the magnitude of their impacts.

As we highlighted in the motivation section, the question of how uncertainty affects energy systems or commodity markets, is highly discussed in the literature. Jurado et al. [13] define uncertainty as the aggregate conditional volatility of many economic parameters against unforecastable event – uncertainty (iii) in the classification cited above. Joëts, Mignon & Razafindrabe [29] conclude with estimating a transmission of this uncertainty to commodity markets. Energy scenarios usually take into account uncertainty that can be estimated via probabilities – risk and uncertainty (ii) [21,46]. This paper focuses on electricity system with an emphasis on the German power market, evaluating the effect of volatility from an already known uncertainty and can bring in an argument for an assessment of scenarios in the future. Modelers should pay more attention to an appropriate time resolution and assessment of short-term non-linear behavior of input parameters if there is a positive tradeoff between workload and pragmatic research objectives.

By implementing statistical data from the economic crisis in 2008 and by assessing its implications for the German power sector, this study provides novel insights into the impacts of economy-wide disruptions on energy systems. We conclude that the validity of policy assessments based on scenario studies for energy systems can be improved if the occurrence of such events is taken into consideration.

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Declarations of interest: none

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Appendix A

Investment patterns

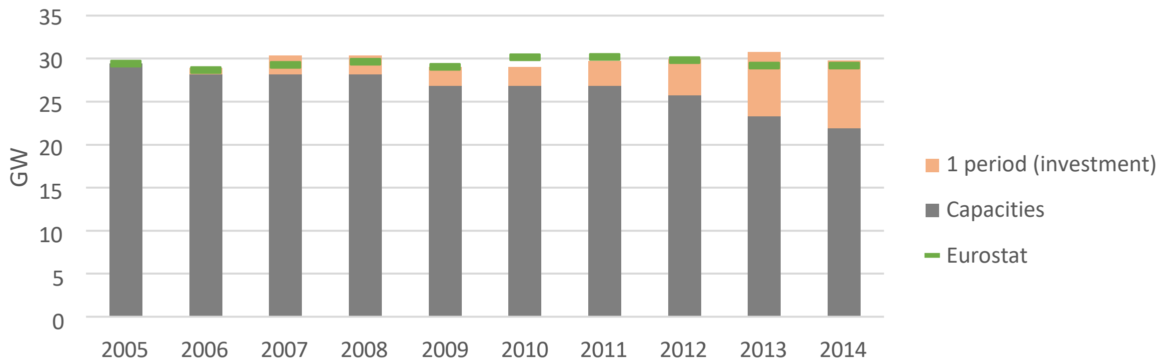

Fig. A.1. Investment in coal-fired capacities in the period 2005-2014 (model results).

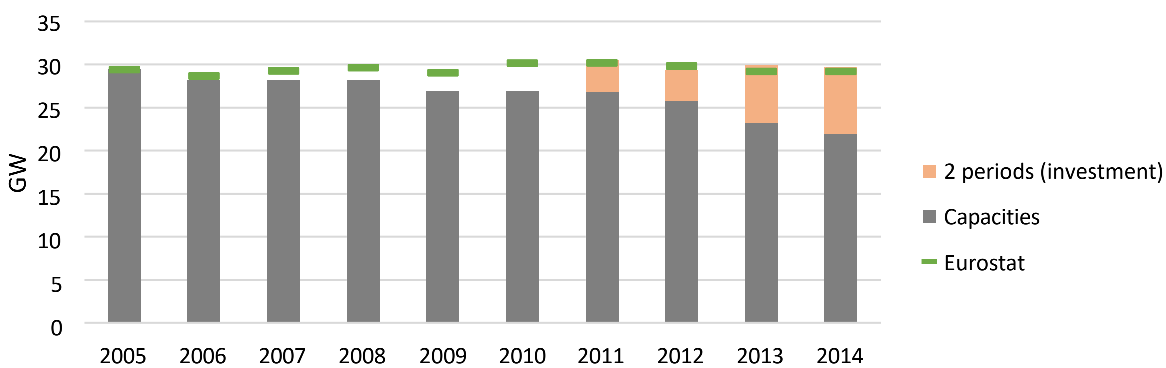

Fig. A.2. Investment in coal-fired capacities in the period 2005-2014 (model results).

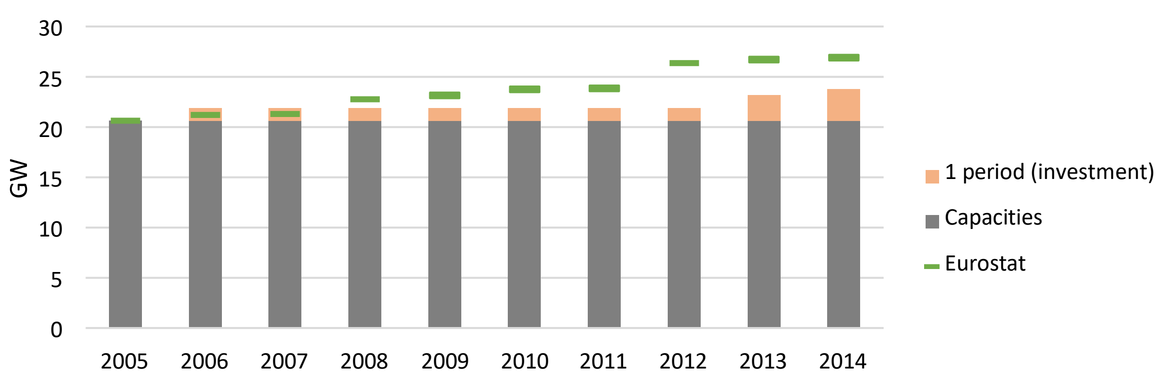

Fig. A.3. Investment in gas-fired capacities in the period 2005-2014 (model results).

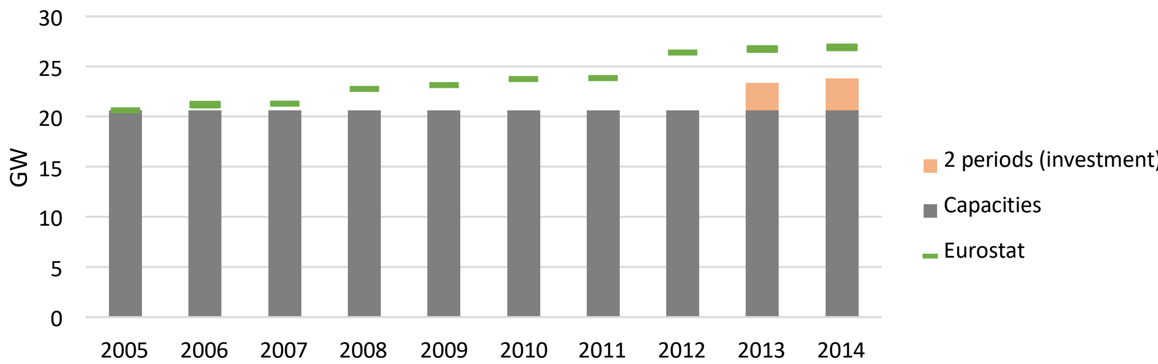

Fig. A.4. Investment in gas-fired capacities in the period 2005-2014 (model results).

Appendix B

Average electricity prices

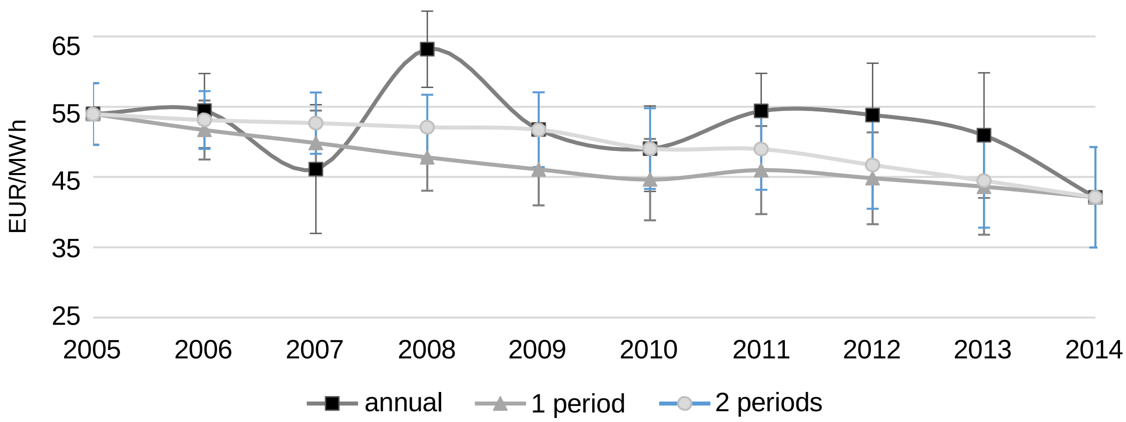

Fig. B.1. Average electricity prices (model results).

Appendix C

Decomposition analysis

LDMI formulae for decomposing changes in the power sector given in the Equation (7) calculated according to the LDMI method described in Karmellos et al. [56] applies logarithmic mean weight functions to estimate separate effects on the change in CO_2 emissions:

$$\Delta A_{0-t} = \sum \frac{C_t - C_0}{lnC_t \cdot lnC_0} \cdot \ln\left(\frac{A_t}{A_0}\right) \tag{8}$$

$$\Delta I_{0-t} = \sum \frac{C_t - C_0}{lnC_t \cdot lnC_0} \cdot \ln\left(\frac{I_t}{I_0}\right) \tag{9}$$

$$\Delta T_{0-t} = \sum \frac{C_t - C_0}{lnC_t \cdot lnC_0} \cdot \ln\left(\frac{T_t}{T_0}\right) \tag{10}$$

$$\Delta e_{0-t} = \sum \frac{C_t - C_0}{lnC_t \cdot lnC_0} \cdot \ln\left(\frac{e_t}{e_0}\right) \tag{11}$$

These Equations (8-11) have a unit value [Mt of CO_2] and give representation of the magnitude of each effect caused by parametric changes in the described scenarios. The tables bellow shows the individual effects (C.1-3)

Tab. C.1 Results of the decomposition analyses of changes for the *annual* scenario.

	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
$\Delta \boldsymbol{C_{0-t}}$	-91.8	-46.5	-13.3	-49.3	-57.3	-27.6	-18	19.3	9.84	0
$\Delta \boldsymbol{A_{0-t}}$	-23.8	-19	-12.9	-9.54	-21.6	-14.2	-6	-5.26	-3.95	0
$\Delta \boldsymbol{I_{0-t}}$	27.4	25.4	20.4	15.7	15.1	22.8	11.7	11.6	8.93	0
$\Delta \boldsymbol{T_{0-t}}$	-71.8	-50.6	-23.2	-49.5	-48	-35.4	-23.2	9.36	3.07	0
$\Delta \boldsymbol{e_{0-t}}$	-23.6	-2.28	2.42	-5.96	-2.72	-0.79	-0.58	3.55	1.79	0
Σ	-91.8	-46.5	-13.3	-49.3	-57.3	-27.6	-18	19.3	9.84	0

Tab. C.2 Results of the decomposition analyses of changes for the *1 period* scenario.

	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
$\Delta \boldsymbol{C_{0-t}}$	-92.6	-63.7	-37.4	-27.1	-16.8	-11.3	8.3	8.1	5.4	0
$\Delta \boldsymbol{A_{0-t}}$	-23.8	-23.0	-21.5	-18.9	-16.1	-13.0	-10.2	-6.8	-3.4	0
$\Delta \boldsymbol{I_{0-t}}$	27.2	26.5	24.7	21.6	18.5	15.0	11.7	7.8	3.8	0
$\Delta \boldsymbol{T_{0-t}}$	-72.2	-53.8	-34.5	-26.3	-18.9	-15.5	4.7	5.4	4.0	0
$\Delta \boldsymbol{e_{0-t}}$	-23.8	-13.4	-6.1	-3.5	-0.2	2.3	2.1	1.6	1.0	0
Σ	-92.6	-63.7	-37.4	-27.1	-16.8	-11.3	8.3	8.1	5.4	0

Tab. C.3 Results of the decomposition analyses of changes for the *2 periods* scenario.

	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
$\Delta \boldsymbol{C_{0-t}}$	-92.6	-72.6	-55.4	-55.5	-57.4	-40.6	-7.69	-2.58	0.51	0
$\Delta \boldsymbol{A_{0-t}}$	-23.8	-24.1	-24.1	-22.9	-21.6	-18.1	-14.7	-9.88	-4.97	0
$\Delta \boldsymbol{I_{0-t}}$	27.2	25.7	23.6	20.2	16.6	14	11.3	7.58	3.86	0
$\Delta \boldsymbol{T_{0-t}}$	-72.2	-59.4	-47.1	-47	-49.7	-36.6	-6.9	-2.13	0.63	0
$\Delta \boldsymbol{e_{0-t}}$	-23.8	-14.8	-7.88	-5.85	-2.74	0.16	2.52	1.85	0.99	0
Σ	-92.6	-72.6	-55.4	-55.5	-57.4	-40.6	-7.69	-2.58	0.51	0

Appendix D

Tab. D.1 CO_2 emissions range in scenarios for the selected EU member states

	Sum of CO_2 emissions 2009-2014			Difference to annual		Relative change	
	annual	**1-period**	**2-period**	**1-period**	**2-period**	**1-period**	**2-period**
state	[Mt CO_2]	[Mt CO_2]	[Mt CO_2]	[Mt CO_2]	[Mt CO_2]	%	%
AT	38.6	45.5	38.7	6.91	0.08	17.90	0.21
DE	1,774.5	1,890.3	1,758.5	115.83	-16.00	6.53	-0.90
DK	69.9	75.6	69.4	5.67	-0.56	8.11	-0.80
ES	223.2	256.7	215.6	33.55	-7.59	15.03	-3.40
GB	804.8	852.4	765.2	47.55	-39.66	5.91	-4.93
IT	521.8	555.1	511.2	33.28	-10.64	6.38	-2.04
NL	253.6	266.5	257.2	12.95	3.65	5.11	1.44
PL	663.2	686.5	661.8	23.24	-1.41	3.50	-0.21
FR	148.4	147.4	143.9	-0.96	-4.49	-0.64	-3.02
CZ	438.4	439.0	439.7	0.62	1.33	0.14	0.30
IE	55.5	59.2	56.4	3.68	0.83	6.63	1.49

Tab. D.2 Root mean square error (RMSE) estimated for *1-period* and *2-period* scenarios relative to *annual* scenario

	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**RMSE**
CO_2 emissions, [Mt]											
annual	225.4	262.1	298.1	256.7	244.8	282.0	282.8	327.2	321.9	315.8	
1-period	231.3	250.0	272.9	284.5	294.4	301.9	328.3	327.9	323.3	315.9	25.5
2-period	231.3	239.2	253.9	250.3	247.6	264.2	303.9	312.1	316.5	315.9	**18.9**
Wholesale electricity price, [EUR/MWh]											
annual	54.28	54.44	46.95	62.99	52.13	49.71	55.05	54.14	50.70	42.61	
1-period	54.68	52.09	50.05	48.21	46.59	45.34	46.30	45.20	44.07	42.61	7.0
2-period	54.68	53.55	52.95	52.53	52.39	49.86	49.33	47.09	44.92	42.61	**5.1**
Electricity generation: coal power plants [TWh]											
annual	100.3	93.4	117.8	82.2	68.8	106.6	89.6	133.6	132.2	127.6	
1-period	102.7	103.3	106.9	110.5	116.8	118.2	137.9	137.8	134.3	127.7	15.2
2-period	102.7	96.0	91.4	81.1	70.9	84.8	118.2	124.9	128.9	127.7	**0.7**
Electricity generation: lignite power plants [TWh]											
annual	113.4	149.3	166.1	153.9	160.5	163.4	172.1	173.3	171.4	172.5	
1-period	115.2	132.5	150.3	157.8	163.0	167.8	170.0	171.0	171.9	172.5	7.7
2-period	115.2	130.6	148.4	154.7	160.8	165.2	169.2	170.4	171.6	172.5	8.3
Electricity generation: nuclear power plants [TWh]											
annual	151.7	150.4	150.4	152.5	152.4	152.4	152.4	89.8	89.8	89.9	
1-period	151.7	143.1	135.1	127.4	120.2	113.4	107.0	101.0	95.2	89.9	23.7
2-period	151.7	151.9	152.0	152.3	152.5	137.1	123.4	111.0	99.9	89.9	**12.8**
Electricity generation: gas power plants [TWh]											
annual	37.8	30.1	10.9	34.1	14.0	11.0	28.1	27.2	22.4	17.0	

1-period	39.8	34.4	27.1	24.3	17.2	16.3	26.3	23.6	19.5	17.0	6.6
2-period	39.8	31.7	23.7	19.3	15.2	12.0	18.5	18.9	17.4	17.0	**7.6**
Electricity generation: wind power plants [TWh]											
annual	25.5	28.6	30.8	33.1	35.7	37.8	40.4	43.5	48.2	54.5	
1-period	25.5	27.8	30.2	32.9	35.8	38.9	42.3	46.0	50.1	54.5	1.5
2-period	25.5	27.8	30.2	32.8	35.7	38.8	42.3	46.0	50.1	54.5	**1.2**
Electricity generation: pv power plants [TWh]											
annual	1.9	2.6	3.8	5.5	9.5	15.8	22.6	29.5	32.8	34.5	
1-period	1.9	2.6	3.6	4.9	6.8	9.4	13.0	18.0	24.9	34.5	5.3
2-period	1.9	2.8	4.2	6.3	9.5	12.3	15.9	20.6	26.7	34.5	**4.0**