Comparing two different approaches for modelling risk aversion in power plant investment decisions

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Abstract

In the currently liberalised markets with volatile prices and changing government policies electricity producers are exposed to severe risks. This has increased the role of risk considerations in their power plant investment decisions. However, many simulation studies that look into policy effects on electricity markets still assume investment decisions to be solely based on profitability expectations derived from regression-based market forecasts. A plausible reason for not including risk considerations in the investment logic could be that a commonly accepted approach does not yet exist. In this article we present a methodology that helps to make and communicate necessary modelling choices for including risk considerations in power plant investment logic. Subsequently we apply this methodology in a case study that looks into the extent in which it matters to use a constant absolute risk aversion and a conditional value-at-risk approach. Results show that the development of technology specific risk premiums over time is much more volatile for the CARA compared to the CVAR approach, which affects the level and timing of technology switches caused by risk considerations. This difference in effect could have implications for research into the interaction between a carbon market and risk averse investment behaviour, which is an interesting focus for further research.

Keywords: conditional value-at-risk, CVAR, constant absolute risk aversion, CARA, electricity market, generation mix, agent-based modelling, power plant investment

1. Introduction

The role of risk considerations in power plant investment decisions has become more important during the last decades in the Central West European market. The liberalisation of electricity markets has made the profitability of power plants dependent on volatile prices, because in the liberalised system electricity companies are not able anymore to pass on the extra costs from price increases to the end consumer. Since power plant investments require a high financial commitment and are inherent to long lead- and depreciation times, this has forced electricity producers to rely in their investment decisions on the forecasts of variables of which the development is uncertain to them. Here we can think of highly volatile prices for commodities, electricity and carbon (read e.g. IEA et al. (2011)). On top of that electricity producers also have to deal with inconsistency in government interventions. Take for example the current debate in Germany and The Netherlands regarding the closure of coal-fired power plants.

The increased role of risk considerations could lead to different investment choices compared to risk neutral investment evaluations. As Groot Groot (2013) describes electricity companies currently spent time and effort on the identification and assessment of the most crucial investment risks and internalise the costs of these risks in the form of risk management costs and by increasing the hurdle rate. This internalisation of the costs of risk could lead to different technology choices due to technology specific risks and in some case companies even decide to postpone or abandon an investment option when the perceived risk is too high. This could have an impact on electricity markets on a system level. For example the IEA (2003, 2005) discusses how technology specific risks might make companies move away from more capital intensive generating technologies, which could lead to higher shares of gas-fired plants in the generation mix. Further the postponement of investment options could lead to more extreme bust and booms in power plant investment when we follow the line of reasoning by Ford (2001) and Olsina et al. (2006) that delays in power plant investments in combination with imperfect foresight of electricity producers can lead to busts and booms in investment.

Despite the currently more important role of risk considerations and the potential long-term effects on the electricity market, the field of research that uses simulation models to look into the long-term effects of different policy designs on the performance of electricity markets mainly assumes risk neutrality in investment decisions. As we look for example at de Vries and Heijnen (2007) and Assili et al. (2008) who look into capacity mechanisms or at Ford (2006) and Richstein et al. (2012) who look into carbon reduction policies or at Vogstad (2004) and Franco et al. (2015) who look into renewables support mechanisms, all studies choose to rely on the assumption of risk neutral investment behaviour. This entails that the investment rate in the market is defined by the expected profitability for investment options that is solely based on (imperfect) forecasts of

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future market conditions. Given the currently more important role of risk considerations in power plant investment decisions it is interesting to see that all these simulation studies do not correct the expected profitability for technology specific risks. A reason might be that a commonly accepted approach to include adjustment for risks in the investment logic of electricity market models does not yet exist.

It would be interesting to perform simulation studies that look into the interaction between risk averse investment behaviour and different policy designs. Namely, some government interventions like the introduction of carbon markets can expose electricity producers to new risks. Therefore this article proposes a methodology that aims to facilitate modellers in making the necessary model choices for including risk aversion in power plant investment logic. Because electricity companies often follow the steps of the enterprise risk management process (see e.g. Groot (2013)), the methodology is structured by these steps focusing firstly on the identification of risks, secondly on the assessment of risks and lastly on the inclusion of risks in the final investment decisions. The idea behind the methodology is not to force researchers towards using one approach for modelling risk considerations in power plant investment decisions, but to enable a structured debate regarding the implications of different modelling choices for the conclusions of simulation studies regarding the effect of different energy policy designs and regarding the credibility of different modelling choices.

The structure of this article is as follows: the second section elaborates on modelling choices with respect to the identification of risks for power plant investments, the third section elaborates on modelling choices with respect to the assessment of these risks by electricity producing companies and the fourth section elaborates on modelling choices with respect to the inclusion of investment risks in the final investment decision. Subsequently the fifth section presents a case study in which the methodology is applied on an existing agent-based electricity market model after which the last section concludes both on the potential use of the methodology for future research and its limitations.

2. Modelling choices with respect to the identification of risks

When including risk considerations in the investment logic of an electricity market model it is firstly important to consider the types of risks that should be included in the model given its research purpose and secondly in what way these risks should be mathematically represented in the model. Table 1 shows an overview of commonly identified risks in the risk management process for power plant investments based on a review of the publications of Groot (2013) and de Joode and Boots (2005), and a report of the IEA (2014). These entail risks regarding changes in government policy, changes in economic conditions, the occurrence of technological setbacks and the occurrence of regulatory setbacks.

For the choice of what types of risks to include in an electricity market model, this methodology proposes to keep the purposes of the simulation study in mind. When the purpose is to analyse the long-term effects of specific energy policies with an electricity market model, the first two risk categories seem the most relevant to be included. Namely, these are the type of risks with which most energy policies interact. For example changes in renewable support schemes can one the one hand expose high merit order plants to the risk of getting a lower amount of full-load hours of operation per year through changing the merit order by inducing investment in renewables; and can on the other hand expose investors in renewables plants to the risk of not receiving or receiving a lower amount of subsidy than expected. Or for example changes towards stricter carbon policies could worsen the business case for carbon intensive power plants, but could also influence the merit order by an increase in marginal costs for carbon emitting plants.

Category	**Risks regarding**
Government policy	Carbon reduction policies
	Renewables subsidy schemes
Economic conditions	Electricity price
	Fuel price
	Carbon costs
	Merit order
Technological setbacks	Construction delays
	Failure of assets
Regulatory setbacks	Delays in permit acquisition
	Agreements with partners

Table 1: Commonly identified risks in risk management process for power plant investment decisions

After choosing the types of risks to be included in the model, this methodology proposes to elaborate on the way in which these risks can be mathematically represented in the model. Considering that risk entails randomness to which we can assign a mathematical probability in contrast to uncertainty, risks should be included in the model with variables that show some form of random behaviour. When looking at including uncertainty[1] in government policies one could for example look at a discrete event representation (see e.g. Zhou (2015)). When looking at uncertainty in market conditions one could for example look at continuous probability distributions. For instance Fagiani et al. (2014) model fuel price uncertainty by means of a Weibull distribution. Because continuous distributions require Monte Carlo type simulations their usage requires more computational power. Therefore the choice between a discrete- or continuous distribution is also about the trade-off between the level of detail in the representation of uncertainty and the computational efficiency of the model.

[1] Often researchers refer to the including uncertainty instead of risk. One could argue that before agents have assigned a probability distribution to the randomness they observe, the randomness still entails uncertainty to them.

3. Modelling choices with respect to the assessment of risks

After choices have been made regarding the types of risks to include in the model, the next step is to set assumptions regarding how power plant investors assess these risks. Following the description of Gielis (2016) the quantitative risk assessment process that companies follow for power plant investment decisions can be summarised as shown in figure 1. For each specific risk to be assessed companies firstly look at what relevant data is available regarding the development of the respective variable(s) after which they fit these empirical data to a theoretical distribution that represents a range of possible impacts with corresponding probabilities of occurrence. Subsequently, when all individual risks have been assessed companies provide them as input to a computational model that calculates their combined impact on relevant project goals. For power plant investment decisions this often concerns the impact on the profitability of the project expressed in terms of net present values. When including risk considerations in the investment logic of an electricity market model, it is important to make modelling choices regarding each of these steps.

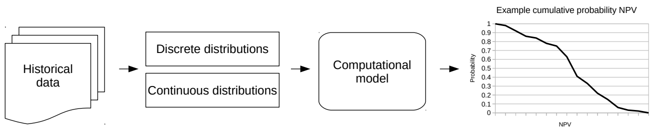

Figure 1: Quantitative risk assessment process. Copied from Gielis (2016).

Firstly it is important to specify what data is available to investors in the model. When the focus is for example on past economical performance of specific generating technologies a choice should be made whether companies only have access to data of their own power plants or also to data of power plants owned by competitors in the market. A related question could be to what extent investors know about the investment and decommissioning plans of their competitors (see e.g. Ford (2001)). Another interesting related question is whether to include information asymmetry among investors in the market or not. It could be for example interesting to look at the effect information asymmetry in the model when the electricity market is open to new entrants.

The next step is to make assumptions about how investors in the model derive probability distributions from their empirical data relevant for the assessment of their risks. As Groot (2013) describes in the quantitative assessment of risks companies often fit their empirical data to simple theoretic distributions like the triangular- or the normal distribution, but that some companies seem to make use of more sophisticated tools for their price projections. An example study that assumes the latter for all companies in the market is the dissertation of Chappin (2011) who models agents that use brownian motions to forecast fuel- and carbon prices.

When modelling choices have been made regarding the availability of data to investors and the type of distributions used, it is important to specify the time horizons that investors use in the model. One could make the assumption that investors base their risk assessment solely on historical data from a pre-defined past period of time or assume that investors also make use of projections of variables based on historical data over a future period of time.

Lastly it is important to specify the end product of risk assessments in the model. As Groot (2013) describes, the outcome of the quantitative risk assessment process often entails a distribution that represents the monetised impact with corresponding probabilities of occurrence derived from all the assessed risk combined. A commonly used measure for monetised impact is the net present value (see e.g. Altran (2011). Here also the way of standardisation can matter for the outcome of the risk assessment. Where for example Chappin (2011) expresses the NPV in Euro per MWh, Richstein (2015) expresses the NPV in Euro per MW nominal capacity. There exist reasons for both measures of standardisation, but it matters which one is chosen since the MW nominal capacity often entails a fixed variable while the amount of MWh production of power plants is variable.

4. Modelling choices with respect to the adjustment for risk

When all necessary modelling choices are made to clarify the way in which investors in the model derive the end product of each of their risk assessments, the next step is to make assumptions on how they incorporate the assessed investment risk in their investment decisions. This concerns modelling choices regarding the inclusion of risk mitigation strategies and regarding on what aspect of the by investors derived cash-flow distributions to focus: the dispersion of the distribution or on the worst-case scenarios?

This methodology proposes to firstly look into whether to include the option for investors in the model to use risk mitigation strategies given the purpose of the simulation study. Namely, these types of strategies can change the level of investment risk for investment options. The most commonly used risk mitigation strategies by electricity producers in liberalised electricity markets focus on the mitigation of price risks and entail the search for counter parties to agree on fixed price contracts or to agree on contracts on forward markets. An example simulation study that includes a forward market can be found in the dissertation of Dominguez (2008). Since the availability of options to hedge risks play an important role in real-life power plant investment decisions it is an interesting option to include forward markets in electricity market models. Especially for studies that look into the necessity of capacity mechanisms to ensure security of supply. However, as the dissertation of Dominguez (2008) shows, it requires the modeller to make assumptions that are difficult to make because there is currently limited empirical data available on forward markets.

Lastly, in order to model the actual effect of risk considerations on investment decisions it is necessary to specify how investors adjust their expectations regarding investment options for risk. Here we can make a distinction between approaches that focus on the dispersion of cash-flow distributions and approaches that focus on worst-case scenarios. Lemming and Meibom (2003) describe most of the commonly used approaches of which utility based approaches often focus on the dispersion of distributions like the theory of **?** and Pratt (1964) on absolute- and relative risk aversion and of which value-of-risk approaches often focus on worst-case scenarios[2]. Examples of studies that use the latter often use the conditional value-at-risk (CVAR) (see Rockafellar and Uryasev (2000)) like Fagiani et al. (2014) or Rocha et al. (2015). An often used argument for choosing a CVAR approach is that it is a measure for risk exposure that is commonly used in the industry. On the other hand an argument for a focus on the dispersion of distributions is that it says more about the unpredictability of the future profits of an investment option.

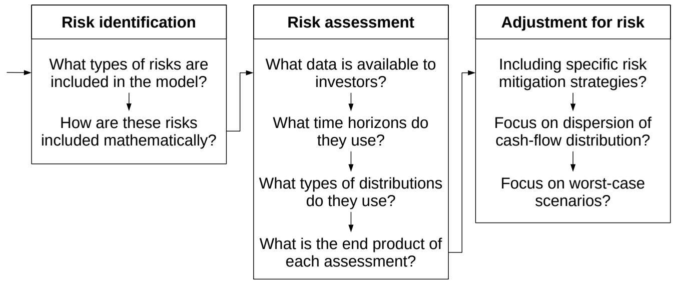

Figure 2: Overview of proposed methodology

Figure 2 provides an overview of all discussed modelling choices per main step of the risk management process that together form the proposed methodology for including risk considerations in the investment logic of an electricity market model.

5. Case study

This case study applies the previously discussed methodology on including risk considerations in the investment logic of an electricity market model in order to give an example on how it can be used and in order to reflect on its limitations. The case study looks into the extent in which it matters for the investment choices made in a model if we use theory of Arrow and Pratt on constant absolute risk aversion or the conditional value-at-risk to make investors adjust their investment expectations. In this section we elaborate on the case study in the following structure; the first subsection describes the agent-based model that is used for the case study, the second elaborates on how risk considerations are included in the investment logic of this model by following the methodology proposed in this article, and the last presents a discussion of the results of the case study.

5.1. Model description

For the case study we make use of an (open source) agent-based electricity market model that has been developed by Chappin et al. (2013a) with the purpose "to explore the long-term effects of interacting energy and climate policies by means of a simulation model of power companies investing in generation capacity" - Chappin et al. (2013b). The model simulates the development of one or two electricity wholesale markets over a period of 40 to 50 years by following yearly cycles in which spot markets clear on different demand segments, and in which agents make market forecasts and decide on the investment in new power plants and the decommissioning of old power plants of which the sequence is shown in figure 3.

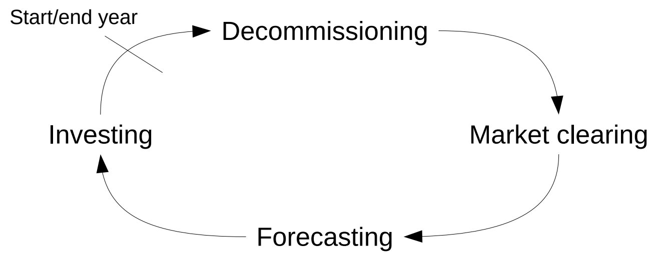

Figure 3: Simulation process

Table 2 gives a summary of the model parameters used. For a more elaborate description please have a look at Gielis (2016). To start, decommissioning decisions in the model are purely age based. Because the purpose of this research is to look into the effect of risk on technology choices, the decision has been made to model decommissioning as a simple and consistent pattern and not include economic considerations in the decommissioning algorithm. Demand for electricity in the model is considered to be inelastic and the market clears each year on 20 demand segments at the system marginal costs. In case there is not enough operational capacity to meet the peak demand the market clears on a value of lost load (VOLL) equal to €1,000 per MWh electricity. Because the focus of this case study is not on the interaction between energy policies and risk averse investment behaviour the model simulates an energy only policy scenario.

Investment decisions are made in the model based on NPV calculations. Firstly agents make forecast of the future demand, supply and fuel prices with which they estimate the market clearances on each segment of the demand curve in the year $t + 7$. Subsequently they estimate for each of their power plants the operational profits that they can earn from these market clearances. With the forecast of supply the agents take into account the decommissioning plans of their competitor. Since decommissioning in the model is age-based, these forecasts are 100% accurate. For the forecasts of demand and commodity prices the agents make use of simple regression analysis. Therefore their knowledge about future prices for electricity and commodities is not 100% accurate in case these prices are modelled with volatility. In their NPV calculations all agents assume a WACC of 9.9 %, which is based on 9% costs of equity and a loan interest rate of 12%. The ratio of debt in power plant investments is assumed to be 70%. The initial settings on operational capacity and demand are loosely based on the Cen-

[2]Some variants on value-at-risk focus on the dispersion of distributions like the max-loss deviation and conditional value-at-risk deviation (see Sarykalin et al. (2008))

Parameter	value	Unit
Forecasting/investment		
Forecast year	t+7	[year]
Back looking period	[t-5:t]	[year]
Debt ratio in investment	70%	[%]
WACC	9.9%	[%]
Market clearance		
Demand elasticity	inelastic	[-]
Clearing rule	System marginal costs	[-]
VOLL	1000	[€/MWh]
Decommissioning		
Decision logic	Age based	[-]
Government intervention		
Policy environment	Energy only	[-]
Initial settings		
Peak demand	200942.4	[MW]
Operational capacity	217758	[MW]

Table 2: Model parameters

tral West European (CWE) region[3] as also used by Richstein (2015).

Parameter	Unit	OCGT	CCGT	CoalPSC	HydroPower	Lignite	Nuclear
Performance							
Nominal capacity k_g	[MW]	150	776	758	1000	1000	1000
Thermal efficiency	[%]	38%	59%	44%	100%	45%	33%
Growth rate	[%/y]	0.21%	0.21%	0.33%	0%	0.5%	0.001%
Lifetime	[y]	30	40	50	100	50	40
Lead-time t^b	[y]	1	2	4	5	5	5
Permit time	[y]	0	1	1	2	1	2
Minimum running hours	[h/y]	0	0	5000	0	5000	5000
Fuel type	[-]	Natural gas	Natural gas	Coal, biomass	-	Lignite	Uranium
Capacity limit in market	[MW]	Inf	Inf	Inf	35000	62000	60563
Initial share	[%]	3.0%	13.1%	14.1%	15.1%	25.0%	29.8%
Financial							
Investment costs I_g	[€/MW]	359,350	646,830	1,365,530	1,602,700	1,700,000	2,874,800
Growth rate	[%/y]	0%	-0.77%	0%	1%	0%	0%
O&M costs	[€/(y*MW)]	14,370	29,470	40,970	38,480	41,454	71,870
Growth rate	[%/y]	0%	0.21%	0%	1.2%	0%	0%
Depreciation time t^D	[y]	15	15	20	30	20	25

Table 3: Technology specifications

The used technology specifications are shown in table 3. Most of these specifications are copied from copied from Richstein (2015), except for the specifications on the capacity limits of technologies and on the initial shares per technology in the market. Richstein (2015) has based the specifications on investment costs, operation and maintenance costs, thermal efficiencies and technology improvement on the IEA World Energy Outlook 2011 New Policies Scenario IEA (2011). Further the initial shares per generating technology in the market are based on the Eurelectric Power Statistics and Trends 2013 Eurelectric (2013). The capacity limit for hydropower is based on geographical limitations in the CWE region to build new hydropower capacity, the limit for lignite is based on the expectation that because of environmental reasons no new lignite capacity will be added to the current mix, and the limit for nuclear is included because of the nuclear phase out in Germany.

Lastly the input for demand growth and fuel price development are also copied from Richstein (2015). The parameters shown in table 4 are the input parameters used for the triangular distributions used for demand growth and the price development of lignite, biomass and uranium that determine the year-on-year growth rate. As discussed by Richstein (2015) the price development for coal and natural gas are modelled by correlated Ornstein-Uhlenbeck processes. To deal with the stochastic input we have generated 120 sequences with all the input parameters combined following a Monte Carlo approach. These 120 sequences are provided as input to each scenario that is run with the model in order to be able to compare their model output.

Type	Unit	Demand growth	Lignite	Biomass	Uranium
Start	€/GJ	n.a.	1.428	4.5	1.286
Average	[%]	1.3	1	1	0
Upper	[%]	5.4	4	7	1
Lower	[%]	-3.9	-2	-5	-1

Table 4: Input parameters for growth rates demand and prices for lignite, biomass and uranium. Copied from Richstein (2015)

5.2. *Application of methodology*

For including risk considerations in the investment logic of the model we follow the methodology described in sections 2 to 4. To start with the types of risks included in the model, for this research we include risks regarding fuel price development, demand growth and electricity price development as shown in table 5. This means that these variables show some type of random behaviour over time which causes unpredictability of the future profitability of investment options for agents in the model. For the price development of coal and natural gas this randomness is modelled by means of correlated Ornstein-Uhlenbeck processes. For the price development of biomass, lignite and uranium, and for demand growth this randomness is modelled by means of triangular distributions for the year-on-year growth rates. Subsequently the volatility in both fuel prices and demand growth cause volatility in electricity price development, which exposes investors in the model also to electricity price risk. The purpose of this study is to look into what it matters to make agents adjust their expectations for risk based on the dispersion of a cash-flow distribution or based on its worst-cases. We assume that including only risks regarding the future market conditions in the model is sufficient for this purpose.

Table 6 shows what relevant data for investment decisions is available to all agents and what data only to individual agents. The data that is available to all agents in the model concerns historical data regarding the development of prices for fuels and electricity, and regarding the year-on-year demand growth.

[3]Includes Belgium, France, Germany, Luxembourg and The Netherlands

Types of risks	Implementation
Fuel price	Gas, coal: Ornstein-Uhlenbeck
	Biomass, lignite, uranium: triangular distribution
Demand growth	Triangular distribution
Electricity price	Results from fuel price and demand growth

Table 5: Implementation methodology regarding risk identification

On top of that it concerns data regarding announced construction plans and decommissioning plans. The model assumes that all investment decisions taken by agents are announced directly known to all competitors. Since the model works with fixed periods of time for permit acquisition and construction this means that investors in the model are able to perfectly predict when new power plants come online. The same counts for decommissioning plans, since the lifetimes of power plants are fixed and decommissioning decisions are completely age-based. Data that is only available to individual agents concerns historical data of the performance of their own power plants and data from their own fuel price and demand forecasts. In this model we make agents base their risk considerations on the historical financial performance of their own power plants.

Accessible to	Data
All agents	Historical: prices for fuels and electricity, demand growth
	Future: Construction and decommissioning plans
Individual agents	**Historical: performance of own plants**
	Future: own fuel price and demand forecasts

Table 6: Availability of data to investors in the model

Table 7 gives an overview of the remaining modelling choices regarding the risk assessment. Agents in the model work with time horizons equal to $[t-5:t]$ to create empirical distributions for their risk assessments, which means that they only look back in time and not make use of any forecasts. These empirical distributions consisted of cases that each entail:

- The operational profits generated by one power plant during one year;
- Owned by the evaluating agent;
- Of the same generating technology as the investment option;
- Within the period of $[t-5:t]$.

This means that if an agent owns six power plants of the generating technology it is evaluating, the distribution would consist of 36 cases[4].

Subsequently, when an agent in the model has derived an empirical distribution with operational profits, it calculates a corresponding NPV distribution, which is the end product of the risk assessment. This distribution consists of cases that each entail an NPV value that corresponds to one of the operational profit

Modelling choice	Implementation
What time horizons?	[t-5:t] and t+7
Type of distributions?	Empirical
What end product?	NPV distribution

Table 7: Implementation for modelling choices regarding risk assesment

cases in the empirical distribution. These NPV values are derived based on the market forecast that the agent has performed to the estimate of fuel and electricity prices in the year t+7 and take into account the lead times and depreciation times of the power plant.

Modelling choice	Implementation
Inclusion of risk mitigation strategies?	Not within research purpose
Focus on dispersion of cash-flow distribution?	Yes, CARA approach
Focus on worst-cases in cash-flow distribution?	Yes, CVAR approach

Table 8: Modelling choices with respect to the adjustment of profitability expectations for risk

Lastly, table 8 presents the modelling choices made for this case study with respect to the way in which agents adjust their profitability expectations for risk. Firstly the option for agents to execute risk mitigation strategies is not included in the model. The purpose of this study is to look into the extent in which it matters for investment choices if we make use of an approach that focuses on the dispersion of a cash-flow distribution or on its worst cases. Therefore the we have included modelling logic in the model based on Arrow (1965) and Pratt (1964) CARA theory and modelling logic based on the CVAR approach (Rockafellar and Uryasev (2000)). With both approaches agents derive a risk premium RP that they add[5] to the expected NPV of an investment option as shown in the equation below with t in years and $\hat{OP}_{g,t+7}$ as expected operational profits in the year t+7 (see also table 3). The NPVs are standardised per MW capacity.

$$NPV_{g,t}^{adjusted} = \left(\sum_{t=0}^{t_b} \frac{-I_g/t_b}{(1+WACC)^t} + \sum_{t=t_b+1}^{t_b+t_D} \frac{\hat{OP}_{g,t+7}}{(1+WACC)^t} - RP \right) / k_g \quad (1)$$

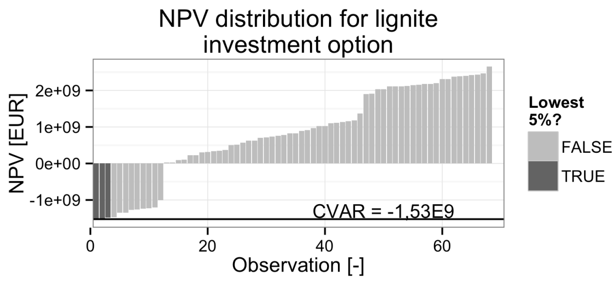

Figure 4: CVAR applied on lignite NPV distribution picked from a run in time step 22 which entails 68 cases, $\alpha = 5\%$

[4] Assuming that none of these plants is decommissioned and also the operational profits during the year t are included.

[5] Costs, like risk premiums entail negative values in the model

When agents use the CVAR approach they derive a CVAR from an NPV distribution $NPV_{0...n}$ by taking the average of the 5% (=α) worst-case NPVs from as shown in figure 4. Subsequently they derive the risk premium by multiplying the CVAR with a calibration parameter β which is in this study equal to 7%. The equation for the CVAR risk premium is shown below. Please note that in cases where the CVAR is positive, this study assumes a risk premium equal to zero.

$$RP_{CVAR}(NPV_{0...n}) = MIN(0, \beta * \frac{\sum_{i=0}^{\alpha\cdot(n+1)} NPV_i}{\alpha \cdot (n+1)}) \quad (2)$$

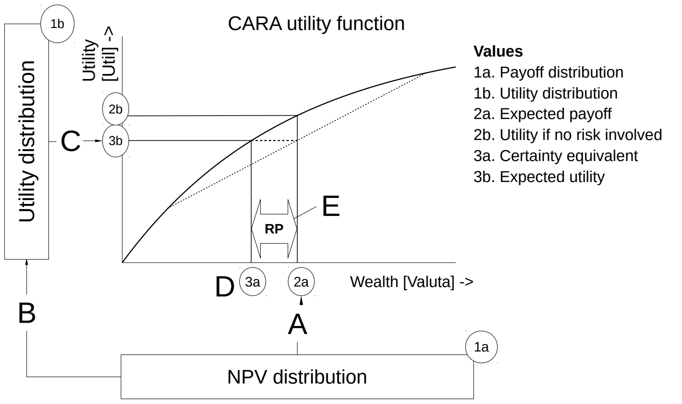

Figure 5: Implementation CARA theory

The way CARA theory is implemented in the model can be explained by means of figure 5. Here, the risk premium entails the difference between the certainty equivalent (3a) and the mean ($\overline{NPV}$) of the NPV distribution (2a). The certainty equivalent is derived by firstly calculating the corresponding utilities $U^{CARA}_{0...n}(NPV_{0...n})$ to the values in the NPV distribution with the CARA function shown below with γ as calibration parameter representing the level of risk aversion, which is in this study equal to $1e-9$.

$$U^{CARA}_{0...n}(NPV_{0...n}) = -\frac{1}{\gamma} \cdot e^{-\gamma \cdot NPV_{0...n}} \quad (3)$$

Subsequently the certainty equivalent CE can be derived by calculating the corresponding monetary value to the average utility (3b) of the utility distribution (1b). Lastly, the risk premium can then be derived as shown in the equation below.

$$RP(U^{CARA}_{0...n}, NPV_{0...n}) = \underbrace{-\frac{1}{\gamma} \cdot \ln\left(\frac{-\gamma \cdot \sum_{i=0}^{n} U^{CARA}_i}{n+1} + 1\right)}_{CE} - \underbrace{\frac{\sum_{i=0}^{n}(NPV_i)}{n+1}}_{\overline{NPV}} \quad (4)$$

5.3. Discussion of results

To analyse to what extent it matters for the investment decisions made in the model if agents use a CARA or a CVAR approach to adjust their profitability expectations for risk, we have performed three scenario runs:

- A CVAR scenario in which all agents use the CVAR approach;
- A CARA scenario in which all agents use the CARA approach;
- A risk neutral scenario in which all agents do not deduct a risk premium.

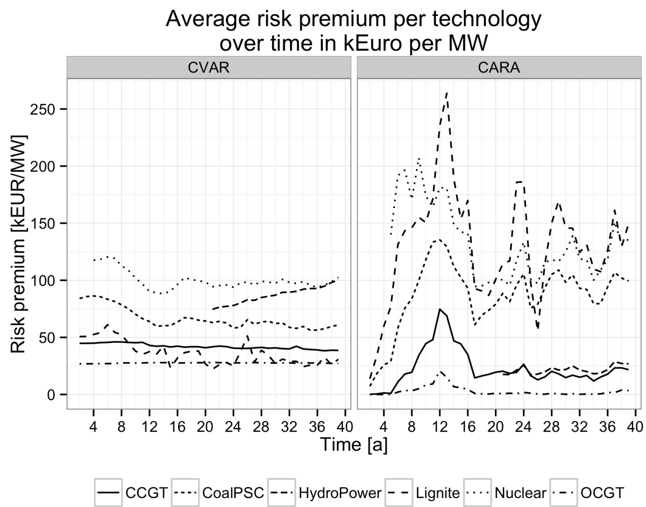

Figure 6: Average risk premium per generating technology over time in kEuro per MW over time for CVAR and CARA scenarios.

When we look at the average results on the risk premium development per technology in figure 6 it is interesting to see how the CVAR risk premiums remain rather stable over time while the CARA risk premiums show quite extreme volatile behaviour. The reason that the CARA premiums show such volatile patterns is that their height depends on volatility in past made operational profits. Because the model includes volatility in prices for fuel and electricity the volatility in operational profits changes over time. The reason that the CVAR premiums show on average more stable patterns over time is that despite the volatility in operational profits, the worst-case losses in the NPV distribution remain rather stable over time. This can be explained by the fact that these losses exist for a large part of the O&M and investment costs of the generating technologies, which are in the model rather stable over time. Here we can see how the choice for the CVAR or CARA approach can matter for the development of risk premiums over time in a model.

The interest of this case study lies in how does this difference in risk premium development between the CVAR and CARA scenarios influences investment decisions over time. A changed investment decision either entails that an agent expects a different technology to be the most profitable or that an agent expects that none of the technology options is profitable anymore after deducting the risk premium. In figure 8 we can see that with respect to changes in investment choices because of the risk premium, there is especially a visible difference in development over time in the average MW capacity that entails a switch in technology choice. Namely, that agents in the CARA scenario switch more MW capacity in technology choice compared to the CVAR scenario.

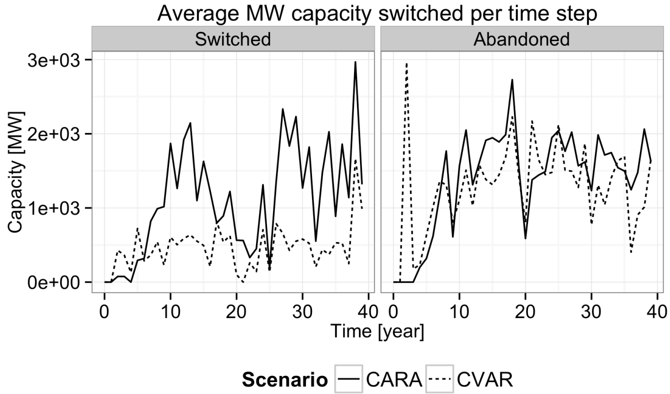

Figure 7: Average amount of MW capacity per time step that entail a change in investment choice because of the risk premium. Left: switches in technology choice. Right: capacity not invested in.

The reason for this difference is that the absolute difference in the height of risk premiums between different technologies is higher in the CARA compared to the CVAR scenario. This can be explained by the fact that the height of CARA risk premiums depends on the volatility in operational profits. Namely, because the price for natural gas often sets the market price, the operational profits of generating technologies lower in the merit order are more vulnerable to fuel price volatilities. This leads to the fact that in the CARA scenario risk premiums for coalPSC, lignite and nuclear plants are on average significantly higher compared to gas-fired power plants. Because the CVAR risk premiums depend on economic losses and not on the volatility in operational profits the differences in risk premiums per technology are on average lower, hence less switches in technology preference occur. Based on these results we can conclude that the choice between a CARA or a CVAR approach does make some difference for the (timing of) technology choices made by agents.

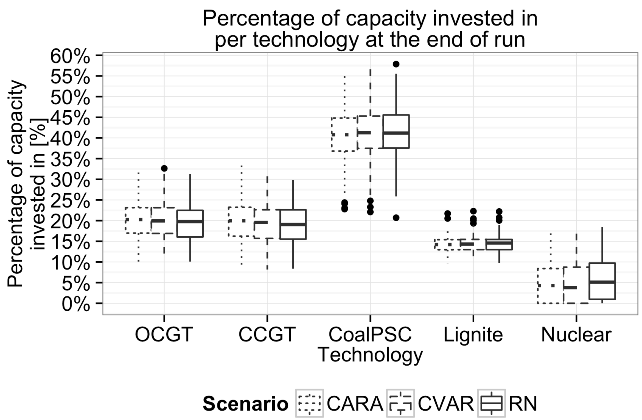

Figure 8: Percentage per technology of total capacity invested in at the end of run. Box plots cover all 120 runs.

Finally, if we look at how the risk premiums have influenced investment choices compared to the risk neutral scenario in figure 8, we can see that they lead to a slightly higher preference for gas-fired power plants in both the CVAR and the CARA scenario. This can be explained by the fact that in both scenarios the risk premiums have been higher for the more capital intensive generating technologies. The movement towards gas-fired power plants is slightly stronger in the CARA scenario, because of the merit order effect on the CARA risk premiums as explained above. However, for both scenarios counts that the impact of risk considerations on technology choices is in the end rather small. The reason is that the amount of MW capacity that entails a technology switch only entails a small 5% of all capacity invested in in the CARA scenario and only 2% in the CVAR scenario. This means that the difference in risk premiums among the different technology types have not lead to a switch in technology choice in the majority of the investment evaluations performed by agents in the model.

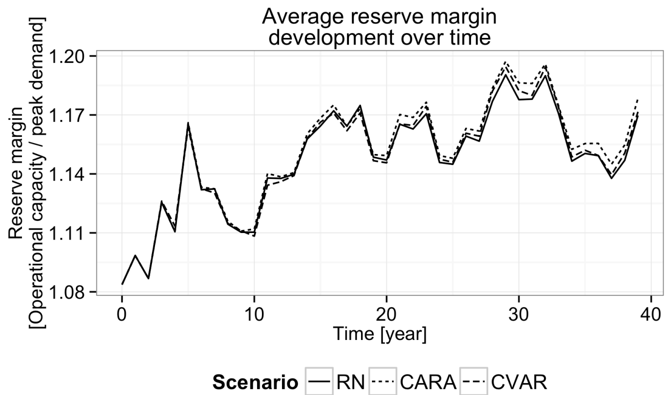

Figure 9: Average reserve margin development of all 120 runs per scenario.

When we look at the average reserve margin development in figure 9 we can see that despite that fact the risk considerations have not lead to a visible change in the magnitude or length of investment cycles. This can be explained by the fact that the amount of investment options that agents abandoned due to the risk premium entailed for both scenarios only 8% of the total amount of investments made. Moreover, in some of these cases it occurred that during the same time step one agent was still able to invest in a power plant because another agent abandoned an investment option earlier due to the risk premium. Based on these results we can conclude that the choice between a CARA or a CVAR approach does not make a visible difference for the timing of investments.

5.4. Limitations of methodology

The case study shows how the methodology can be used to structure relevant modelling choices for including risk considerations in the investment logic of an electricity market model. However, the methodology also has some limitations. Firstly the methodology focuses on choices made from the level of individual agents. This can be useful for agent-based modelling studies, but might be less useful for studies using the system dynamics approach. Namely, for the latter one is most likely searching for a way to mathematically express the effect of risk considerations on investment choices on a system level by means of differential equations. This does not take away that the modelling choices addressed by the methodology are still relevant for the underlying assumptions. A second limitation is that the methodology does not take into account modelling choices regarding the presence of phenomena like herding behaviour and the level of portfolio diversification of investors. These forms of risk averse behaviour could also have a impact on investment choices. For herding behaviour we can look for example at the run on coal-fired power plants in Germany the last decade. Despite the possible impact of both phenomena, we made the choice to follow the majority of the state-of-the-art simulation studies into the long-term development of electricity markets in which investment decisions are solely based on expected profitability.

6. Conclusions and policy implications

To conclude, in this article we presented a methodology for structuring the necessary modelling choices for including risk considerations in the investment logic of electricity market models. The methodology is follows three main steps of the risk management process that is often used in the power plant investment process to address investment risks: the identification of risks, the assessment of risks and the adjustment of expectations for risks. The idea behind the methodology is to enable researchers to make and present their modelling choices in a structured way by keeping the purpose of their research in mind. This makes it possible to open up debate regarding the best way to include risk considerations in power plant investment logic which can help us finding a more commonly accepted approach. To show an application example of the methodology we applied the methodology in a case study in which we looked into the extent in which it matters for the resulting investment choices if we use a CARA or a CVAR approach to make investors adjust their expectations for risk. For this study we made use of an agent-based model in which investors are exposed to risks regarding fuel price and electricity price development, and regarding year-on-year demand growth.

The results of the case study show the choice between CARA and CVAR matters visibly for the development of technology specific risk premiums over time. Because the CVAR risk premiums are based on economic losses they remain more stable in case of changing market conditions, while CARA risk premiums show highly volatile behaviour over time because they depend on the volatility in operational profits. On top of that both CVAR and CARA risk premiums made agents switch more often to gas-fired power plants, because for both the risk premiums are on average the highest for more capital intensive generating technologies. This effect is the strongest for CARA risk premiums because the operational profits of technologies lower in the merit order are more sensitive to fuel price volatilities. However looking at all investments made during the model both the effects of CVAR and CARA risk premiums are rather small. For both approaches only a small percentage of the investments entails a changed investment choice due to the risk premium and therefore they only have a minor effect on the total amount of technology choices made and on the occurrence of investment cycles.

The fact that the CVAR and CARA approach show especially differences in their effect on the level and timing of switches in technology choice, suggests that the choice of approach matters for research into the interaction between energy policy designs and risk averse investment behaviour. When we would for example simulate a scenario with a carbon market and with investment logic using a CARA approach, the expectation would be that the CARA risk premiums hence technology choices are influenced by carbon price volatility. This could be especially interesting when renewables are included which have high capital costs and zero marginal costs and that means that their operational profits due to the merit order are vulnerable to price volatilities. However, when we would model the same scenario but with a CVAR approach, the expectation would be that the effect of carbon price volatility on technology choices would be less present. Namely, because the CVAR approach is based on economic losses it is expected that the carbon price would mostly affect investment in carbon intensive technologies. To really look into this scenario further research is necessary.

Lastly, the proposed methodology in this article can be useful for making and communicating the modelling choices regarding the inclusion of risk considerations in a structured way, but has also some limitations. Firstly the methodology focuses on choices made from the perspective of individual agents. This can be useful for when using an agent-based modelling approach, but a system dynamics approach could require more focus on a system level. Secondly the methodology does not include phenomena like herding behaviour and portfolio diversification, while these forms of risk averse behaviour can also play an important part in the power plant investment process. Because the majority of the state-of-the-art models investment decisions rationally, i.e. purely based on monetary values, we have chosen to follow the same line with the methodology. For further research it could be interesting to look into the inclusion of these types of phenomena in power plant investment logic.

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