MASTER THESIS

Analyses of Risk Factors in Conventional and Renewable Energy Dominated Electricity Markets

Oliver Tietjen

Berlin, August 2014

Freie Universität Berlin (FU)

Potsdam Institute for Climate Impact Research (PIK)

Supervisiors: Prof. Dr. Ottmar Edenhofer (PIK)

C.Sc. Ph.D. Theocharis Grigoriadis (FU)

Student ID: 4541224

Triftstraße 1, 13353 Berlin

+49 162 214 65 40
o.tietjen@gmx.net

Table of Contents

List of Figures

List of Tables

Abstract

The large scale expansion of renewable energies challenges many prevailing electricity markets all over the world. There is an ongoing scientific debate if a market design solely based on marginal cost pricing is sufficient to integrate renewable energies. Of particular interest is the question if the investment risks of renewable plants, mostly due to their capital intensity, are prohibitive high in a pure market setting. Moreover, their fluctuating production nature might also increase the investment risks for conventional fossil plants. The objective of this paper is therefore to examine these questions.

For this purpose, a numerical electricity market model is conducted in a Monte Carlo simulation to compute the investment risks of different renewable and fossil plant types. The resulting risk values are then incorporated in the model to study the influence of the risk on the investment decisions. Furthermore, the risk is integrated on a stand-alone (per plant type) and on a portfolio basis. The later case accounts for hedging effects between different plant types to lower the overall investment risks. This procedure is done for a market dominated by renewable and a market dominated by fossil fuel plants to analyze the difference.

The results confirm that renewable energies have higher investment risks compared to fossil plants on a stand-alone basis. But renewables can be used as hedges for gas plants, which increase their investment attractiveness in the fossil fuel market. However, in the renewable dominated market there are not further hedging advantages and the renewable stand-alone risks remains high. If these high investment risks lead to suboptimal renewable investments, a de-risking market design extension might be a proper solution. Another finding is that the investment risks for gas plants rise with higher renewable shares, due to the impact of the fluctuating renewables availability on the electricity price and the production volumes of the gas plants. This also has policy implications: An increased risk of gas plants might hamper their construction which can cause blackouts. If this indeed becomes a problem, a capacity market as an additional market design element can be a solution since it leads to safer revenues.

1 Introduction

An important cornerstone to mitigate climate change is the worldwide expansion of renewable energies. Many countries introduced therefore support schemes to subsidy renewable energies in the electricity sector (IPCC 2014). A notably example is Germany, where a feed-in-tariff scheme is in place. Under this support instrument, renewable producers are protected from market forces, which is one reason why a rush increase of green electricity could be observed over the last years. However, it is widely accepted that also renewable energies must introduced to market signals in order to realize an efficient electricity market (e.g. Steggals et al. 2011). Clearly, this becomes more important with higher shares of renewables in a market. Nevertheless, there exists considerable uncertainty about the proper design of future electricity markets with high shares of renewable energies (IEA 2014).

A particular important difference to today´s mainly fossil fuel dominated markets is the potential change in the investment risks for electricity producers: The capital intensity of renewables makes them inherently risky, since their investment costs are sunk and their revenues depend on the volatile electricity price (IEA 2014). Additionally, their production volume depends on the weather and varies between the years. For these reasons, some observers see the need for “de-risking” low carbon technologies (e.g. Schmidt 2014). But not only might the investment risks of renewables themselves be problematic, since also the revenues of fossil plants are affected by the fluctuating nature of renewable production.

In this field of research the topic of this paper is located. The main research interests are to analyze the investment risks for renewables in a pure market setting and how the investment risks change for fossil plant types with increasing shares of renewable energies. Furthermore, the portfolio risk of a representative investor of a renewable market shall be compared to the portfolio risk of a conventional, fossil fuel dominated market. The results have certain implications for the future electricity market regarding de-risking market design elements.

For this purpose, a three sage approach is followed: In the first stage, optimal plant capacities for typical renewable and fossil plants are computed numerically with a stylized investment and a dispatch optimization model. The resulting capacities re-enter the same model as an exogenous input in the second stage. Then Monte Carlo simulations for three scenarios, each for different risk factors like fuel prices and renewable availabilities, are applied. With this Net Present Value (NPV) distributions and corresponding investment risks for each plant type are obtained. For the third stage, the model is extended to include these investment risks. Thus, the model computes again the optimal capacities like in the first stage, but now the technology specific investment risks are part of the investment decisions. This three stage procedure is done for a conventional market with high shares of fossil plants and for a market dominated by renewable energies to study the difference between both markets. They differ with respect to their input parameters only in the CO_2 price, which is higher in the renewable market. Moreover, the investor evaluates plant risks on a portfolio basis. This means she accounts for the correlation between the NPVs of the plant types in a portfolio optimization, which is part of the third stage. Hence, the investor can hedge some risk via investments in non-perfectly positive correlated plant types. This reflects the current state in electricity markets where typical hedging possibilities are flawed, since for example long-term contracts between producers and consumers are seldom observed (Rodilla & Batlle 2012). Thus, investors or firms often diversify their plant portfolios to lower their investment risks (e.g. Bolinger 2013).

The outline of this paper is as follows: In the next section an overview of the related literature and the contribution of this paper are presented. Thereafter the basics of idealized electricity wholesale markets are briefly explained. In section 4, long-term investments decisions from a finance perspective are introduced. Besides the investment decision criteria (4.1), it is in particular described how risks are evaluated in investment decisions and how portfolio optimization functions (4.2). On the basis of these theoretical considerations, the numerical model approach is conducted in section 5, where firstly the procedure is explained in detail (5.1). Then, in section 5.2, the results of the model are presented in sequence of their stage number. In section 6, the results are discussed and implications for the future market design are drawn. The paper ends with a short conclusion.

2 Literature Overview

Basically, there are different streams in the literature regarding high shares of renewable energies. A first stream focuses on the system integration of renewable energies (e.g. Cochran et al. 2012; IEA 2014). Besides other aspects, these studies analyze the impact of variable renewables on the security of supply, which means, for example, the increasing costs of ensuring a certain level of reliability.

Other studies show the short-run price depressing merit order effect caused by renewable energies with zero variable costs (e.g. Sensfuss et al. 2008) and additionally the long-run impact on the optimal capacity mix (Saenz de Miera et al. 2008; Bushnell 2011): Since the residual demand (total demand minus renewable production) becomes more dispersed and the capacity factors of the fossil plants decrease, more flexible plants with lower fixed and higher variable costs enter the market.

Kopp et al. (2012) explicitly model the profitability of renewables for the German market up to a renewable share of 80% in total consumption. They conclude that the prevailing on marginal cost pricing based energy-only market is not sufficient to refinance renewable energies and see the need for a market design extension. Another discussion of the market design for high renewable shares is given in Winkler & Altmann (2012), who also doubt that the current energy-only market is suitable to recover the costs of renewables.

However, these studies do not model or account in detail for the investment risks. In contrast, Redpoint (2009) and Poyry (2009) model the British electricity market up to 2030 with about 35% renewables in the production. They apply Monte Carlo simulations for the fluctuating renewable availability and find that the price volatility and hence the investment risks increase with the renewable share. Green & Vasilakos (2011) also observe a rise in the price volatility in a similar (but simpler) model framework. But they do not find a significant increase in the revenue volatility for the fossil plants due to the wind penetration compared to a case where only the demand is volatile.

Another large strand of literature focusses on the efficiency of different renewable support schemes, but only some model explicitly the risk. If investment risk is considered, a typical finding is that a feed-in-tariff leads to lower investment risks for renewable producers compared to a quota or a feed-in premium scheme (Fagiani et al. 2013; Kitzing & Ravn 2013; Kitzing 2014). The reason is that the producers receive a certain amount per output in the case of a feed-in-tariff and hence only the volume of the output is risky. Under the other instruments they additionally face the electricity (and quota) price risk. Opposed to these findings, Nagl (2013) shows that for weather uncertainty the height of the investment risk depends on the slope of the fossil plants´ supply curve. Thus, more market integration as in the case of a quota or a feed-in premium scheme might also be favorable for renewable producers.

The next body of literature is not only related to renewable energies but very relevant for this analysis. The Mean-Variance portfolio theory (MVP) was initially developed by Markowitz (1952) to determine efficient financial portfolios that do not include unnecessary risk. The MVP uses the correlation between returns of different assets to diversify the risk. However, Bar-Lev & Katz (1976) are the first who transfer it to the electricity sector, namely to determine efficient plant portfolios in the USA. Instead of financial assets, the MVP in the electricity sector includes plant assets. Awerbuch used the MVP to study the impact of renewable energies on the efficient plant portfolios (e.g. Awerbuch 2000). A typical outcome of these MVP applications is that capital intensive plants like renewables lower the portfolio risk and hence are more expanded as in a deterministic framework. The reason is that they have high fixed and thus less risky costs. In contrast, less capital intensive plants like gas plants have highly volatile fuel costs and are therefore less favorable in terms of risk (Awerbuch & Spencer 2007). However, these applications are made from a social planer perspective, where the returns of the plants are measured by the generation costs and the electricity price does not play any role.[1]

Roques et al. (2008) are the first who apply the MVP to the electricity sector from a private investor´s point of view. In this setting the electricity price becomes a very important risk factor, since the profits of electricity firms are strongly affected by it. This changes the results of the MVP dramatically: Instead of capital intensive plants, high variable cost plants become more favorable in terms of risk. In particular, they show that gas plants are to a certain degree "self-hedged". The reason is that they often set the price in the electricity market and therefore can transfer their volatile variable costs directly to the consumers. Moreover, the resulting volatile electricity prices affect the profits of the capital intensive plants and thus they are more risky. This risk advantage of price setting high variable costs plants in a market setting is also shown analytically by Meunier (2013).

A drawback of the approach of Roques et al. (2008) is that they simply assume fixed production volumes and normal distributed fuel, carbon and electricity prices and then apply a Monte Carlo simulation to compute the plant returns and their correlations. Instead, Lynch et al (2013) couple a Monte Carlo simulation with an electricity optimization model. Hence, their approach considers market interactions and allows for an endogenously electricity price and production volume computation. They also apply MVP for the resulting returns of the Monte Carlo simulation. Like Roques et al. (2008) they find that gas plants are most favorable in terms of (portfolio) risk. However, their approach has also a large disadvantage: Their model does not include scarcity prices such that all plants have negative expected returns. From this follows that the peaker plant has no risk, because the electricity price never exceeds the variable costs of the peaker. Thus, the peaker loses always its complete capital costs. Nevertheless, it is the only efficient investment in their portfolio, since all other plants make even higher losses.

Finally, another method to account for risk in investment decisions is given by the real option approach (cp. Dixit & Pindyck 1994). It is an often used method to account for the risk about uncertain developments, for example the CO_2 price path. Fortin et al. (2008) couple a real option approach with a Monte Carlo simulation to calculate profit distributions and apply a

[1] Beside the papers of Awerbuch there are some other MVP applications for the electricity sector from a social planner perspective, for example Delarue (2011), Arnesano et al. (2012) and Bhattacharya & Kojima (2012).

portfolio optimization. They are the first who use the Conditional Value at Risk instead of the variance in the portfolio optimization in the energy sector, which is also done in this paper. One main finding is that investors have an incentive to include wind in their portfolios even if the expected CO_2 price is not high enough to make wind profitable, which can be traced back to the diversification effect of wind.[2]

In this paper a similar approach like in Lynch et al. (2013) is followed. But the here used model computes the long-run equilibrium which means it also includes scarcity prices. Furthermore, instead of optimizing the portfolio of a single investor, like in Roques et al. (2008) and Lynch et al. (2013), the portfolio of a representative investor is optimized. More precisely, the portfolio optimization is integrated in the electricity market model. Therefore, the model considers also the feasibility of the portfolio in the electricity market. This procedure avoids extreme results like in Lynch et al. (2013) with a portfolio that consists only of peaker plants which is not realistic and in fact hard to interpret in their study. However, this method and the pre-coupled Monte Carlo simulations are conducted to analyze the investment risks in renewable energy compared to fossil fuel dominated markets. This is a significant contribution to the above described literature, since only some studies analyzed model based investment risks, especially for renewables, up to today. Moreover, no study, to the best of my knowledge, compared investment risk in one coherent framework between fossil fuel and renewable dominated markets.

3 Basics of the Electricity Wholesale Market

In this section, fundamental concepts of electricity markets are introduced. The focus is exclusively on investment and dispatch decisions of electricity producing plants that sell their output to the wholesale electricity market. For example, balancing markets, heat as a by-product or other specifics of the electricity market like net constraints or storage are not part of the model analysis in this paper. The advantage of a simple model is that the effects of certain risk factor inputs on the market outcome can be ascribed to basic market mechanisms. Hence, the risk effects are isolated from additional effects that might come into play if, for example, storages are introduced.

[2] Besides the here presented paper, there are some other real option applications for the electricity sector for example Fortin et al. (2008) and Fuss et al. (2012).

In the following, a simple deterministic (without risk) market model is outlined (see e.g. Bushnell 2011 for a similar model). This is done for two reasons: Firstly, it helps to clarify important economic notations and concepts used in this paper. Secondly, it leads to the same results as the numerical model used later on, but is modeled from a firm rather than a social planer perspective as the numerical model. The firm perspective is more convenient when analysing investment risks. Throughout the whole paper I assume perfect competition between firms in the electricity market and abstract from typical electricity market problems like insufficient demand elasticity. The underlying literature of this subsection is the standard economic text book of Varian (2010) and for the electricity economics related content Stoft (2002).

Suppose firm $i \in I$ can construct a plant type with variable costs vc_i per unit of produced electricity q_{it} in period $t \in T$. In order to produce electricity, each firm needs capacity cap_i, which can be used in all periods. The investment costs of one unit capacity are given by $invc_i$. In period t, the demand is $D_t(p_t) > 0$ for the corresponding electricity price p_t. In equilibrium, $\sum_i q_{it} = D_t(p_t)$ holds, which means total supply equals demand. Firm i´s total short-run profit is defined as the total revenues minus the total variable costs, denoted as $\pi_i^{sr} = R_i - V_i$, with $R_i = \sum_t p_t \, q_{it}$ and $V_i = \sum_t vc_i \, q_{it}$. Note that I abstract from discounting here for reasons of legibility, instead the discount rate is introduced to the model in the next section.

In the short-run perspective, the production is endogenous to the firms, but capacities are fixed, because the considered stretch of time is too short to adjust the capacities. This implies that in the short-run the investment costs of the existing capacities are sunk, assuming that the capacities cannot be sold. These sunk costs are a special case of fixed costs[3], which emerge independently of the production level. Opposed to variable costs that increase with the production and hence, can be adjusted in the short-run. Therefore, a rational profit-maximizing firm only considers its variable, but not its fixed costs, since the later emerge independently of the decision. Taking the long-run perspective, there are no fixed costs and thus, all costs are variable. In this case, investments in capacities are also endogenous to the firm. Here the long-run or total profits π_i are $\pi_i = \pi_i^{sr} - invc_i cap_i$. The firms maximize their long-run profits over q_{it} and cap_i by taking the capacity constraint $q_{it} \leq \ cap_i$ for each period into account:

[3] The fixed costs are not sunk if the respective production factor can be sold.

$$\max_{q_{it},cap_i} \pi_i = \sum_t (p_t - vc_i) q_{it} - invc_i cap_i + \sum_t \lambda_{it} [cap_i - q_{it}] \tag{1}$$

Taking the derivatives with respect to q_{it}, cap_i and λ_{it}, leads to the Karush-Kuhn-Tucker conditions:

$$p_t - vc_i - \lambda_{it} \leq 0 \quad \perp \quad q_{it} \geq 0 \quad \forall\, i,t \tag{2}$$

$$-invc_i + \sum_t \lambda_{it} \leq 0 \quad \perp \quad cap_i \geq 0 \quad \forall\, i \tag{3}$$

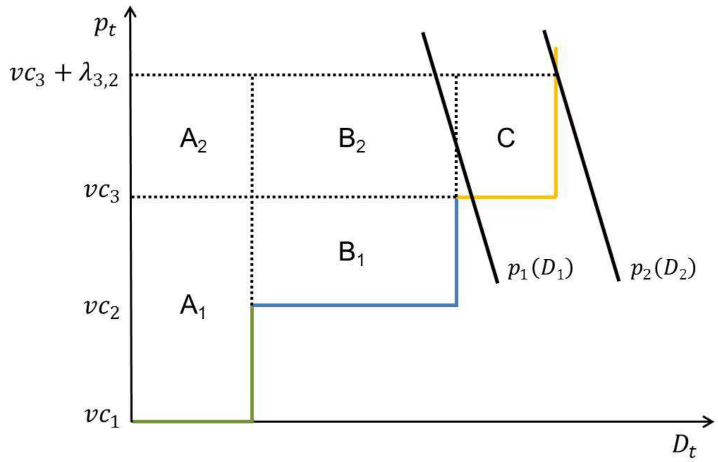
$$cap_i - q_{it} \leq 0 \quad \perp \quad \lambda_{it} \geq 0 \quad \forall\, i,t \tag{4}$$

From condition (2) follows that the price equals the marginal cost of all firms that produce in period t, which is $p_t = vc_i + \lambda_{it}$. The shadow price of the capacity λ_{it} is only positive if the capacity constraint (4) of the respective plant is binding, otherwise it is zero. Condition (3) shows that if the sum of the shadow prices over all periods of one plant type is equal to its investment costs $invc_i$, the firm invests in capacity ($cap_i > 0$). Note that in the short-run maximization, condition (3) is skipped because cap_i is exogenous. However, in the short- and long-run the shadow prices reflect the marginal value of the capacity evaluated by the willingness to pay given by the electricity price p_t. Since all electricity is produced and all capacity is constructed at the margin in the long-run equilibrium the market price is just as high to recover the costs of the firms. Thus, the profits of all firms are zero, $\pi_i(p_t^*, q_{it}^*, cap_i^*) = 0$. This implies that given the optimal amount of capacities, the short-run profits cover the fixed (investment) costs:

$$\pi_i^{sr}(p_t^*, q_{it}^*) = \sum_t (p_t^* - vc_i) q_{it}^* = invc_i cap_i^* \tag{5}$$

The short-run profits are also denoted as producer surplus, because in the short-run, when capacities are fixed, producers earn a surplus above their variable costs. Suppose there are $I = 3$ plant types with $vc_1 < vc_2 < vc_3$ and $invc_1 > invc_2 > invc_3$, two short-run static market situations are given in figure 1.

Figure 1 Merit-order



The colored step function is the aggregate supply curve, also called merit-order. The firms supply electricity if the price is at least as high as their variable costs[4], while for example the green horizontal part is as high as the variable costs and as broad as the amount of capacities installed of plant one. The same is valid for the blue and yellow horizontal parts of the supply function for the two other plant types. In period one, the demand is presented by the inverse demand function $p_1(D_1)$, intersecting the supply curve at the yellow horizontal part, which means that $p_1 = vc_3$. The capacities of firm one and two are fully utilized (their capacity constraints (4) are binding) and they earn a producer surplus: Firm one gains the area A_1 and plant two B_1, which is used to recover some part of the investment costs. In the second period, the demand is higher and all capacities are fully utilized which is termed as scarcity time. The price rises such that the inverse demand function intersects the supply curve and the market clearing condition $\sum_i q_{it} = D_t(p_t)$ is fulfilled. Those consumers with the highest willingness to pay get electricity while the others lower their consumption. Now all three firms receive a producer surplus: Firm one gets the areas A_1 + A_2, firm two B_1 + B_2, and firm three gains area C. In this paper, short-run profits that are earned with prices above the variable costs of the peaker plant (the one with the highest variable costs) are termed scarcity rents. [5] Which are the areas A_2, B_2 and C in the current example. Obviously there must be scarcity times in which some consumers pay more than the variable costs of the peaker plant otherwise the peaker cannot recover its investment costs. Furthermore, the scarcity rents are also necessary for the

[4] More precisely, they supply if the price is as least as high as their short-run marginal costs. However, in this simple idealized model, the short-run marginal costs consists only of variable costs and the shadow price of the capacity, while the later is only positive if the capacity is already fully utilized.

[5] Scarcity rent has no uniformly definition. For example, Stoft defines scarcity rents “as revenues minus variable costs” (Stoft 2002:70). This definition would include the whole producer surplus. However, the distinction between the rents earned in scarcity and non-scarcity times is convenient for the later analysis of the results.

other plants, because in the long-run equilibrium all plants earn zero profits which include gains from scarcity times.

Finally, it is important to consider what is meant by long-run zero profits. Due to the assumption of perfect competition, all firms have marginal revenues, which are equal to their long-run marginal costs and hence they earn zero economic profits. However, generally in economics the costs of the production factors are given by their market prices, which measure the opportunity costs of the factors. These costs refer to the foregone opportunity to use the factors in another profitable way. The cost of the money used to invest in capital – as a production factor – is given by the interest rate. Basically an investment is the transformation of today´s money into future money. For several reasons this money is not for free, or to put in other words, the transformation needs a positive interest rate. Main factors influencing the cost of money are the time preference of consumption, inflation and risk (Brigham & Houston 2009). The interest rate that incorporates these factors is called the normal rate of return. Thus, firms, or more precisely the investors of the firms, earn a normal rate of return in the long-run equilibrium that is as high as the opportunity costs of capital. Therefore, firms have zero-profits in the long-run equilibrium. Opposed to this economic definition, accounting profits neglect the implicit opportunity costs. Hence, in the long-run equilibrium accounting profits are positive and given by the normal rate of return.

4 Long-Term Investment Decisions

In finance "the process of evaluating a company's potential investments and deciding which ones to accept" (Brigham & Daves 2007:396) is called capital budgeting. The here involved capital are the different power plants, which can be seen as long-term assets. The term budget refers to a plan which contains the projected future capital expenditures. In the following subsections, the relevant basic concepts of long-term investment decisions are outlined, whereby the link to electricity market model is explained. The first subsection deals with the main criterion for investment decisions, while in 4.2 the focus is on investment risks and portfolio optimizations.

4.1 Investment Decision Criterion

This section briefly explains the Net Present Value as most important investment decision criterion, which is also used in the numerical model. Moreover, the link to the long-run profits is explained. The source for this section is Brigham & Houston (2009).

First of all, it has to be mentioned, that in finance the cost of capital is calculated as the weighted average cost of capital (WACC). The WACC takes into account the different sources of capital and weights their respective costs to calculate a single cost of capital. Roughly described, a firm chooses an optimal capital structure, i.e. an optimal share of equity and debt, as capital sources, to maximize the firm´s value. However, in this paper there is no distinction between capital sources. The here assumed perfect market environment without, for example, taxes or transaction costs, makes such a distinction irrelevant. For simplicity, one investor is assumed which represents many identical investors that face an interest rate r, which is in this case always equal to the WACC.

The theoretically superior criterion to evaluate investment decisions is the Net Present Value (NPV), because it shows how much a project adds to the investor´s wealth. The NPV is the sum of all discounted cash flows over the period of a project:

$$NPV = \sum_{t=1}^{T} \frac{CF_t}{(1+r)^{t-1}}, \text{with } CF_t \text{ as the cash flow in period } t. \tag{6}$$

The cash flows are discounted with the rate r, which is the interest rate (or WACC), that represents the opportunity costs of capital as described above. If a project has a positive NPV it should be realized, because it makes the investor wealthier. Applied to the basic market model of section 3, the NPV of firm i becomes

$$NPV_i = -invc_i cap_i + \sum_{t=1}^{T} \frac{(p_t - vc_i)q_{it}}{(1+r)^{t-1}}, \tag{7}$$

which is basically the long-run profit, but now the future short-run profits $(p_t - vc_i)q_{it}\ \forall\ t > 1$ are discounted to the present $(t = 1)$. The investment costs emerge in the first period and hence, are not discounted. Note that the capacities are used immediately from the beginning of the first period on.

A result of the basic electricity market model is the zero-profit condition in the long-run. Analogously the NPV of all firms are zero, $NPV_i = 0$, since they are exactly the long-run profits. Thus, each firm earns the normal rate of return r as an accounting profit, but no economic profit, which would only be the case if $NPV_i > 0$.

4.2 Investment Risks

In the previous sections, the impact of risk on the model and on the investment decision criterion was neglected. This subsection expands this deterministic framework through the incorporation of risks in the investment decision process. This and the following subsections relates to Brigham & Houston (2009) if no other reference is noted.

First of all, risk is defined more precisely: In general, risk arises due to a lack of information or the uncertainty of the future. Risk refers to the possibility of some unfavorable events in the future to occur (Brigham & Daves 2007:34). While there exist several definitions of risk in the literature (cp. Gross et al. 2007), I follow Knight (1921), who defines risk as the measurable part of the uncertainty. Therefore, the here analyzed investment risk is the potential loss of a certain value, which can be calculated by risk measures. Furthermore, I define risk factors as interdependent or independent parameters that influence the investment risk.

Since risk is related to potential negative events, it is typically negatively evaluated in finance and economics. Therefore, a standard assumption is that investors are risk-averse, which means they prefer a safe return compared to a risky return, when both have the same expected value. Hence, risk has a negative impact on the investor´s utility and consequently, she must be compensated for bearing risk. The typical way to incorporate risk in long-term investment decisions is to adjust the discount rate for risk. Thus, the discount rate of the NPV calculation as the investment criterion is the risk free rate plus a risk premium. Since the discount rate reflects the cost of capital (WACC), this means that a higher risk increases the investment costs. In this paper, investors are also risk averse. However, I do not explicitly calculate risk premia which are added to the discount rate. Instead a utility function of the investor is specified in section 4.2.2 which accounts for the negative impact of the risk.

4.2.1 Risk Evaluation Types

In capital budgeting, the risk of an investment project, which means here an asset or plant, can be evaluated with three types of risks: Stand-alone risk, corporate (or within-firm) risk and market risk:

Stand-alone risk relates to the investment risk involved in a single project, while ignoring the relationship to other projects of the firm or to the general market risk. Thus, it can be defined as the "risk an investor would face if he or she held only one asset" (Brigham & Houston 2009:233). A sophisticated way to analyze stand-alone risk is to run a Monte Carlo simulation:[6] A software picks randomly risk factor values (e.g. variable costs and sales prices) of predefined probability distributions and calculates the project´s profitability (NPV). This procedure is repeated several hundred or thousand times, each time with other randomly drawn values for the risk factors. Since each Monte Carlo run computes different NPV, the simulation results in a NPV probability distribution. While the mean of the distribution is the expected NPV, the risk can be measured in different ways, as explained in the following.

A typical risk measure is the standard deviation (or variance) of the NPV distribution: The smaller the standard deviation the tighter the probability distribution and thus, the lower the risk. However, using the standard deviation relies on the assumption of normally distributed NPVs otherwise it can lead to misleading results (Fortin et al. 2008). Another frequently used measure is the Value-at-Risk (VaR). The β-VaR is the loss γ that is with a predefined probability (the confidence level β) not exceeded (Conejo et al. 2010). Hence, the VaR is a downside risk measure which takes care of bad outcomes and neglects outcomes higher than the confidence level. The VaR has the disadvantage that it does not take account of greater losses than the threshold γ, while this negative tail might also contain relevant information (Fortin et al. 2008). Furthermore, following Artzner et al. (1999) the VaR is only a coherent measure for normal distributed profits. Since the later computed NPVs are not necessary normal distributed, I follow Fortin et al. (2008), Ehrenmann & Smeers (2011), Fuss et al. (2012) and Fagiani et al. (2013) who use the Conditional-Value-at-Risk (CVaR) for a risk analysis in the electricity sector. The CVaR does not rely on normal distributed profits and takes also account for fat tails in the distributions. The β-CVaR is defined as follows (Rockafellar & Uryasev 2000):

$$CVaR_\beta = (1-\beta)^{-1} \int_{f(x,y) \geq \gamma_\beta(x)} f(x,y)\, p(y) dy \,, \tag{8}$$

where $f(x,y)$ is the loss function depending on the investment decision vector x, which represents here the different assets (plants) or portfolio of assets that can be invested in and on the random vector y which stands for the risk that affects the losses (e.g. sales risk), while $p(y)$ is the probability distribution of y. The β-CVaR is the conditional expectation about the losses that exceed the threshold γ.[7] Therefore, the difference to the VaR is that the CVaR is the mean of all losses above the threshold (i.e. greater losses) instead of the threshold itself, which is the VaR (see figure 15 appendix 8.1 for a graphical illustration).

[6] Other important methods are, for example, sensitivity and scenario analysis (see Brigham & Houston 2009).
[7] In equation (8) the threshold has the confidence interval as subscript, which means γ_β, because the threshold depends on the confidence interval.

The next investment risk type is the corporate or within-firm risk. In this case the investment risk of a single project is related to risks of the other assets of a firm. The risk of each project depends on how much risk it adds to (or removes from) the overall risk of a firm. More precisely, if the NPV distribution of a single new project is not perfectly positive correlated with the portfolio NPV distribution of the existing assets of a firm, the new project might have a lower risk than under a stand-alone risk evaluation. The reason is that the new project and the existing portfolio do not make the same losses under the same market conditions and thus, some risk is diversified away. This is also the main insight of the Mean-Variance Portfolio theory described in the next section.

The within-firm risks takes account of within-firm diversification, but it does not consider that the stock of one firm is only one part of the whole portfolio of an investor. In contrast, the market or beta risk, as the third investment risk type, accounts also for the stockholder diversification. Basically, one can distinguish between diversifiable (also unsystematic) risk and market or beta (also systematic) risk (Brigham & Daves 2007). A perfectly diversified investor bears, by definition, no diversifiable risk and faces only market risk, which is the risk of a portfolio consisting of all stocks of the market. The market risk cannot be diversified, because it relates to events like war or recessions that affect most firms. If one assumes rational well-diversified investors and a perfect capital market[8] the risk of a project should be evaluated by the covariance of its return with the market risk, which is measured in the Capital Asset Pricing Model (CAPM) by the beta: The higher a project correlates with the market risk, the higher is the risk of the project and thus, the higher must be the discount rate. That includes a risk premium, at which the project is evaluated. In the CAPM, the diversifiable risk does not play any role in determination of the risk premium, because investors can completely diversify it away.

However, taking the general equilibrium perspective of the CAPM for the risk evaluation is out of scope of this paper. Instead I implicitly assume that capital markets are not perfect and take a partial equilibrium perspective by conducting portfolio optimizations solely for the electric market (Blyth 2008). More precisely, the perspective of an investor, representing many small investors who behave in the same manner, is taken, that can only invest in electricity producing firms. Hence, the investor can only diversify its plant portfolio, while the risk of a single plant is evaluated in this portfolio context. In this sense, the plant risk is evaluated in a within-firm context, because one large firm – that stands for many small firms – owns all plant capacities and maximizes its profit subject to its portfolio risk. This is done with

[8] For other assumptions of the CAPM see Brigham & Daves (2007:84)

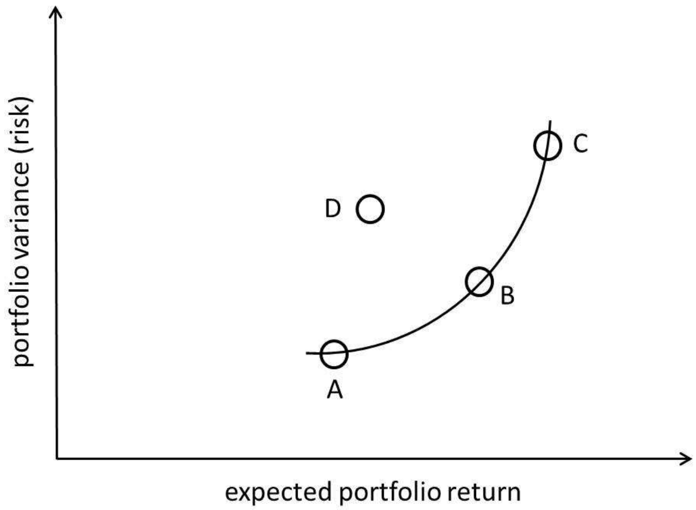
a portfolio optimization as explained in the next section. Moreover, the later conducted numerical portfolio optimization is confronted with profit maximizing investors that incorporates stand-alone risk to see the diversification incentives and gains.

4.2.2 Portfolio Optimization

With classical Mean-Variance Portfolio theory (MVP), developed by Markowitz (1952), optimal portfolios can be computed. The MVP results in efficient portfolios for which the expected returns cannot be increased without increasing the variance (as risk measure) of the portfolio returns. In order to optimize a portfolio, one needs the expected return and the variance of each potential asset of the portfolio. Moreover, the correlation between the expected returns of the assets is essential to determine the variance of the portfolio returns. From this follows one main insight of the MVP (cp. Roques et al. 2008): The value of an asset depends on the portfolio in which it is evaluated. If one asset has high returns at the same time whereas the other assets in the portfolio generate low returns, some risk is diversified away, such that the overall portfolio risk decreases. For such diversification effects correlation coefficients between the assets of lower than one are necessary. If, for example, two assets have the same expected return, but a correlation coefficient of minus one, the risk is completely diversified away, because they are perfect hedges. The other extreme case, a coefficient of plus one, implies that there are no diversification effects. Hence, a correlation matrix is an essential ingredient of the MVP.

The portfolio return is optimized via the weights of each asset in the portfolio subject to an accepted portfolio variance (or the variance is minimized subject to a minimum return). By varying the accepted risk in the optimization, one gets the efficient frontier that is a curve consisting of efficient portfolios as exemplified in the following figure.

Figure 2 Efficient frontier



Source: Based on Markowitz (1952)

The three portfolios A, B and C lie on the efficient frontier and thus do not imply any unnecessary risk to obtain the respective expected return. In contrast, portfolio D could have a higher expected return for the same risk if the composition of assets is changed such that the point is shifted to the right. Hence, portfolio D is not efficient. Portfolios to the right of the efficient frontier would be preferable, but are not feasible for the given assets.

The combination of risk and return, which means what composition of assets an investor chooses for the portfolio, depends on her preferences. A standard mean-variance utility function representing her preferences is given by (e.g. Roques et al. 2008, Meunier 2013):

$$U = E\left[r_{\mathrm{p}}\right] - \frac{1}{2}\alpha Var_{\mathrm{p}} \tag{9}$$

The utility U increases with the expected portfolio return $E\left[r_{\mathrm{p}}\right]$ and decreases with the portfolio risk, given by the variance of the portfolio returns Var_{p}. Thus, there is a trade-off between risk and return where the former is weighted by the coefficient of absolute risk aversion α. A risk neutral investor does not put any weight on the risk – the alpha is zero. Consequently, the higher the risk aversion of the investor, the higher is the alpha.

However, as explained in the previous section, the variance (or standard deviation) has drawbacks and is not the preferred risk measure in this paper. Instead the CVaR is chosen which needs a different specification of the portfolio optimization problem compared to the MVP. The CVaR portfolio optimization, introduced by Rockafellar & Uryasev (2000), is as follows:

$$\min_{\gamma, x_i, aux_k} \gamma + \frac{1}{s(1-\beta)} \sum_k aux_k$$
$$s.t. \quad E\left[r_p(x_i)\right] \geq R, \sum_i x_i = 1, \sum_i r_{ik} x_i + \gamma + aux_k \geq 0, \;\; aux_k \geq 0 \; \forall \, k, \;\; x_i \geq 0 \; \forall \, i \tag{10}$$

The solution of this problem is the minimal β-CVaR of a portfolio constrained by an expected portfolio return that must be as least as high as a minimum accepted return, which means $E\left[r_p(x_i)\right] \geq R$. The constraint $\sum_i x_i = 1$ restricts the sum of the asset shares x_i to one. The variable γ is the threshold of the CVaR, hence, it is the VaR (see previous section), aux_k is an auxiliary variable for $k \in s$ and s is the sample size of the distribution of the returns. Thus, r_{ik} is one return observation k of asset i of the sample. Finally, β is again the confidence level of the CVaR.

Since in this paper the return is given by the NPV and the risk by the CVaR, the utility function of the investor becomes:

$$U = E\left[NVP_p\right] - \alpha CVaR_p \tag{11}$$

This is the same specification as in Fagiani et al. (2013), but they do not account for portfolio effects. Instead they subtract the CVaR of single plants (stand-alone risk) from the expected NPV and call this the risk-adjusted NPV. Therefore, their risk-adjusted NPV is the same as the investor´s utility for stand-alone risks in this analysis. In the following, the term $\alpha CVaR$ is denoted as cost of risks, because it reflects the loss in utility (costs) due to the risk. The portfolio optimization in (10) and the utility function in (11) are integrated in the numerical model as explained later on.

Up to this point, the basics of the electricity market and long-term investment decisions under risk were explained. In summary, investors maximize their wealth via the NPV. In the long-run equilibrium this leads to NPVs of zero, which means zero economic profits for investors. Transferred to the electricity market model, this means that the sum short-run profits equal the fixed costs in the long-run. However, investors earn a normal rate of return r as accounting profits. This rate reflects the costs of capital (WACC) and is used as discount rate for the NPV calculation. Basically there are different ways of how the risk of an investment decision is evaluated and the risk is accounted for in the investment decision process. In this paper, the portfolio of a representative firm on the electricity market is optimized. Thus, the risks of investment projects (plants) are evaluated in a portfolio context within a (representative) firm. Instead of adjusting the discount rate for the risk premium, the costs of risk are included in a utility function of the investor, which is an often used method to account for risk. These theoretical considerations are implemented in a numerical electricity market model within a three-stage process, explained in the following sections.

5 Numerical Analyses of Investment Risks in Electricity Markets

Based on the earlier descripted theoretical considerations, in this section a numerical optimization model is developed to compute investment risks for different plant types in a market dominated by fossil plants and a market dominated by renewable energies. Moreover, the investment risks are integrated in the model to analyze the impact on the investment decisions. For the implementation a three-stage process is applied, which is described in the following subsection.

5.1 Modelling Approach

First of all note that this model exercise is not tailored to a specific electricity market in the real world, though German demand and renewable availability data are used. Instead the investment risks in two hypothetical markets are analyzed. One market is dominated by conventional fossil plants and is termed the CON market. This market represents many of today´s markets, which have high shares of coal electricity in total production. The other market is called the RES market because it is dominated by renewable energies, especially by wind power. This RES market stands for potential future electricity markets, where I assume that much effort is made to limit the damage of climate change. The assumed lever to achieve lower carbon emissions is an effective carbon market that internalizes the emission externalities. Hence, the assumed expected CO_2 price is with 100 €/t much higher in the RES market compared to the CON market with 30 €/t. I abstract from further subsidies for the renewables, because besides the emissions there are no market failures in this idealized markets. Apart from the CO_2 price all other model inputs are identical in both markets for the sake of comparing the investment risk. Furthermore, there are no existing capacities in both markets since I do not model a real electricity market. Thus, I follow a greenfield approach. Next a brief overview of the three stage procedure for analyzing the investment risk described.

In the first stage of the procedure, the optimal capacities of the CON and RES market are computed in a deterministic framework. The used model optimizes the capacity investments and the hourly plant dispatch over a period of 25 years, while each year consists of representative days. The model is described in detail in next section. For the reason that all capacities are built endogenously, all plant types make zero (economic) profits. The two runs (one for each market) undertaken in the first stage are denoted as the base runs.

In the second stage, the same model is adopted again, but now the capacities are fixed at the optimal capacities of the first stage. This means that the perspective is changed from the long- to the short-term. Hence, only the dispatch over the 25 years is optimized. Then for the given investment decision, Monte Carlo simulations are applied. This means that certain risk factors attain different values, generated by stochastic processes or taken from distributions, in each model year. Three scenarios for variable cost risk, demand risk and renewable availability risks are conducted. Each scenario consists of 1000 Monte Carlo runs and is applied to both, the CON and the RES market. Since a deviation of the input parameters leads to a deviation in the profits, the Monte Carlo simulation results in a NPV distribution for each plant type. Therefore, the CVaR of each plant type as a stand-alone risk measure can be calculated. The stochastic processes and the scenarios are explained in section 5.1.2.

Finally, the CVaRs of the plant types are integrated in the investment decisions in the third stage. Given the utility function of the representative investor, the CVaRs are evaluated in terms of costs of risk and emerge as an additional cost factor in the optimization model. Thus, in the third stage the capacities are endogenous like in the first stage, but additionally the investor faces the different costs of risks for each plant type, which are determined in the second stage. Moreover, this optimization is done for an evaluation of the costs of risk on a stand-alone basis and in a plant portfolio context to see the potential diversification effects of the later.

5.1.1 Model Description

In this section, the investment and dispatch optimization model is described. The model results in the long-run equilibrium. Hence, for the same input parameters it yields the same results as the market model of section 3.

The model has a time span of $Y = 25$ years, while each year consists of $S = 4$ seasons and each season has $H = 168$ hours (one week). Hence a typical week of each season is modeled on an hourly basis to represent a full year. The electricity production (in MWh) of technology i in year y, season s and hour h is given by q_{iysh}, while each unit has variable costs vc_{iy} of

$$vc_{\mathrm{iy}} = \frac{fp_{\mathrm{iy}} + cof_{\mathrm{i}} cop_{\mathrm{y}}}{\eta_{\mathrm{i}}} \quad \forall\, i, y\,, \tag{12}$$

where fp_{iy} is the fuel price, cof_{i} is the CO_2 emission factor, cop_{y} is the CO_2 price and η_{i} is the energy conversion efficiency. In order to produce electricity, capacities cap_{i} (MW) of the respective plant type must be built, while a unit of capacity has investment costs of $invc_{\mathrm{i}}$. Additionally, operation & maintenance (O&M) costs om_i arise per unit of installed capacity and year over the plants´ lifetime.

In every hour the electricity demand X_{ysh} is given by the linear demand function

$$X_{\mathrm{ysh}} = a_{\mathrm{ysh}} - b_{\mathrm{y}} p_{\mathrm{ysh}} \quad \forall\, y, s, h\,, \tag{13}$$

where the parameter a_{ysh}determines the maximum demand when the electricity price p_{ysh} is zero and the parameter b_{y} is the slope of the linear demand function. For the sake of deriving the wealth, the integral of the inverse demand function (13) is taken, which results in the gross consumer surplus $CS_{\mathrm{ysh}}^{gross}$:

$$CS_{\mathrm{ysh}}^{gross} = \frac{a_{\mathrm{ysh}} X_{\mathrm{ysh}} - \frac{1}{2} X_{\mathrm{ysh}}^2}{b} \quad \forall\, y, s, h \tag{14}$$

Since the model determines the long-run equilibrium with perfect competition, the producer surplus is completely used to cover the fixed costs (see section 3). Therefore, the wealth is solely defined as the total consumer surplus of all periods, termed as CS. The total consumer surplus is the total gross consumer surplus less the total costs of electricity production. Under the described conditions, the maximization problem is as follows:[9]

$$\begin{aligned} \max_{q_{iysh}, cap_i, X_{ysh}} CS = & \sum_{y \in Y} \sum_{s \in S} \sum_{h \in H} \left(CS_{\mathrm{ysh}}^{gross} - \sum_{i \in I} vc_{\mathrm{iy}} q_{\mathrm{iysh}} \right) (1+r)^{-y+1} \\ & - \sum_{i \in I} \sum_{y \in Y} om_{\mathrm{i}}\, cap_{\mathrm{i}} (1+r)^{-y+1} - \sum_{i \in I} invc_{\mathrm{i}}\, cap_i \end{aligned} \tag{15}$$

$s.t.$

$$\sum_{i \in I} q_{\mathrm{iysh}} = X_{\mathrm{ysh}} \quad \forall\, y, s, h, \tag{16}$$

$$cap_{\mathrm{i}} av_{\mathrm{iysh}} \geq q_{\mathrm{iysh}} \quad \forall\, i, y, s, h, \tag{17}$$

$$q_{\mathrm{iysh}} \geq 0 \quad \forall\, i, y, s, h, \quad cap_{\mathrm{i}} \geq 0\ \forall\, i \tag{18}$$

In equation (15) the gross consumer surplus, the variable costs, and the O&M costs are discounted on an annual basis with the factor r. The discount rate is assumed to be 7%, which is in line with the related literature (e.g. Roques et al. (2008) use 5% and 10%). The

[9] Note that the gross consumer surplus and the variable costs are adjusted such that the representative days represent a full year. The adjustment factor is skipped here to improve the legibility. The model is computed as a Quadratically Constrained Program (QCP) by the solver CPLEX with the software GAMS.

investment costs are not discounted, because investments only take place in the first year. The market clearing condition in (16) assures that the supply of all technologies equals the demand in every hour. The capacity constraint in (17) restricts the production to the installed capacities of each plant type multiplied with its availability factor $av_{\mathrm{iysh}} \in [0;1]$ of a specific hour.

The considered stylized technologies are coal plants, combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT) as fossil plants. For renewable technologies, wind onshore and photovoltaic plants (PV) are included. For simplicity, all plant types have a lifetime of 25 years, which may be too short for coal plants, but should not affect the results in a significant manner. The data inputs of the model are given in the appendix 8.2, where all data are in line with the literature. Note that the construction time is as in Lynch et al. (2013) only used to scale up the investment costs. The whole investment costs and the capacity expansion emerge in the first year.

The hourly demand and renewable energy availability parameters are calculated from real German data of the years 2011 to 2013. The wind and PV availabilities are scaled up such that the former has an expected annual average availability 25% and the later of 13.5%. The reason is that in the long-term, which is of interest here, one MW of wind and PV will produce more electricity due to technological progress than the existing and partly rather old, average capacities. The slope of the demand function b_{y} is assumed to have an expected value of 50. Compared, for example, to Green & Vasilakos (2011) who uses a slope of five, the value of this slope is rather high. However, the object of study is a future electricity market[10], where it can be assumed that the short-run price elasticity of demand increases significantly. The value leads to a maximum elasticity of -0.12 in the CON and -0.28 in the RES market (base runs), while the average elasticity is -0.05 for the former and -0.07 for the later.

Furthermore, I assume that all input parameters do not change over time in the first stage. Hence, all years are identical. This means there are no trends, for example for the demand or the fuel prices, which is not realistic. However, this simplifies the analysis as explained in the next section.

[10] Clearly, the CON market represents today´s electricity markets. But for reasons of comparability, the same parameter values are assumed for both markets.

Taking the investor´s perspective, the expected NPV before the investment decision for each plant type is given by

$$E[NPV_i] = -invc_i cap_i + \sum_y \frac{om_i cap_i + E\left[\sum_s \sum_h \left(p_{ysh} - vc_{iy}\right) q_{iysh}\right]}{(1+r)^{y-1}} \quad \forall\, i\,, \tag{19}$$

where the price is the inverse demand function $p_{ysh} = \left(a_{ysh} - X_{ysh}\right)/b_y$. There are only expectations about the short-run profits. Hence, the investment and O&M costs are known with certainty. This follows from the risk factor definition in the next section. Clearly, the long-run equilibrium condition is $E[NPV_i] = 0$. In the first stage, all risk factors are as expected, therefore the condition is fulfilled.

In this version, the model from (15) to (18) is only used in the first stage to compute the optimal base capacities of the CON and RES market, which is the risk neutral case or alternatively the deterministic case. In the second stage, the capacities are fixed at these base capacities and the risk factors attain in every year and Monte Carlo run different values as described in the next section. For the third stage, the model is extended for the risk incorporation and risk averse investors are assumed. This is explained in section 5.1.3.

5.1.2 Scenarios and Risk Factors

In order to obtain for each plant type NPV distributions and related CVaRs, Monte Carlo simulations are adopted in the second stage. In the following, the varying risk factors of the Monte Carlo simulations and their underlying stochastic processes, respectively distributions, are defined.

The considered risk factors are the coal, gas and CO_2 price, the demand and the availability of wind and PV. All risk factors can vary between years and are then fixed for a whole year. In the case of the fuel and the CO_2 costs, explicit prices are modelled. In reality these prices fluctuate also within a year. However, I assume that electricity producers fix the prices via contracts for one year, which eliminates the within year volatility. Contracts with longer duration are ignored, because they are seldom in the electricity market (Roques et al. 2008).[11] The hourly demand and renewable availabilities parameters of one year are scaled up or down by their annual risk factors, whereby the expected value is 100%. Hence, each year has the same demand and availability profile and only the magnitude of the parameters are affected by the risk factor. For simplicity, all risk factor expect the renewable availabilities are modelled

[11] Roques et al. (2008) assume quarterly price fluctuations.

with the same stochastic process, which is a Geometric Brownian motion (GBM) with mean reversion (e.g. Blanco & Soronow 2001):[12]

$$rf_{y+1} - rf_y = \theta(rf^* - rf_y)dy + \sigma\varepsilon_y rf_y\sqrt{dy} \quad \forall\, y\,, \tag{20}$$

where rf_y is the value of the respective risk factor in year y. Therefore, the left side of the equation is the change between two years. The equilibrium values of the risk factors are denoted by rf^*. These are the expected values of the respective risk factors, which are the inputs of the first stage. The mean reversion parameter θ determines how fast the risk factors revert to their equilibrium values. Together with the time step dy, the left term on the right side of the equation is the mean reversion component. If, for example, the risk factor lies above its mean, the mean reversion component is negative such that the risk factor is pulled down to the mean value. The right term on the right side of the equation is the random term. The volatility parameter σ determines the influence of the random component on the process. It is multiplied with the standard normal distributed annual error term ε_y, the risk factor value, and the square root of the time step. The resulting distributions of the GBM processes are log-normal distributed. This asymmetric distribution is preferable, because all risk factors cannot be negative (cp. Lynch et al. 2013).

The assumed parameters of the stochastic process and the resulting minimum and maximum values[13] of the generated data are shown in appendix 8.3 for the respective risk factors. The gas price has an expected value of 25.32 €/MWh_{th} and the coal price of 11.7 €/MWh_{th}. It is assumed that the gas price is more volatile than the coal price, which is in line with the literature (e.g. Awerbuch & Spencer 2007). Moreover, the correlation between the gas and the coal price is 0.7, which is in between those coefficients found in the literature (e.g. Awerbuch & Spencer 2007, Roques et al. 2008, Lynch et al. 2013). Correlations between the CO_2 price and the fuel prices and between the demand and all other risk factors are neglected.

The expected CO_2 price in the CON market is 30 €/t and in the RES market 100 €/t. The CO_2 price in the RES market in every Monte Carlo run is simply the CO_2 price of the CON market plus 70 €/t. This implies that the price has the same absolute standard deviation in both markets, but a lower relative standard deviation in the RES market. This might not be realistic, because a higher absolute price potentially fluctuates also more in absolute terms (as e.g. in Lynch et al. 2013). However, taking the same relative standard deviation implies a strongly

[12] The process is modelled in excel to generate for every Monte Carlo run and year one value for each risk factor. The data are then an input in the GAMS model which is solved 1000 times for each Monte Carlo simulation.
[13] Clearly, the minimum and maximum values deviate slightly for each risk factor generation. The values in the table 8 are those used in the Monte Carlo simulation.

dispersed CO_2 price in the RES market, which might also not be realistic. But any other assumption regarding the CO_2 price would be arbitrary. Nevertheless, the same absolute standard deviation simplifies the analysis, since the risk factors have the same absolute influence on the profits, which is the reason why this variant is chosen.

As noted in last section, an important assumption in this paper is that all risk factors do not have any trends, which means their expected values are the same over the whole timespan of the model. This is known by the investor such that she has no incentive to invest in capacities after the first model year. This is the reason why a mean reversion process is chosen: The risk factors fluctuate only around their equilibrium values, while the deviations do not trigger new investments. Without the mean reversion component, there would be persistent deviations from the expected values of the first stage. This implies that there should also be investments in the second stage to be theoretically consistent. However, this complicates the analysis, because one needs some investment rule which dictates when new investments are triggered. To put in other words, there would be some assumption needed that determines when the investor recognizes that the risk factor deviations indicate new long-term trends which justify new investments. To avoid theoretical inconsistencies that could arise from such assumptions as, for example, in Lynch et al. (2013) there is no trend in the risk factors and they fluctuate only around their persistent expected values. Clearly, this limits the approach to investment risks emerging due to annual deviations of the risk factors.

While the modelling of prices and the demand with stochastic processes is preferable, since these risk factors have strong autocorrelations, this is not assumed for the renewable availabilities. Instead, the annual availability risk factors for wind and PV are normal distributed in this paper. The annual average availability of wind has a larger spread compared to PV given the German data. Thus, it is assumed that the wind availability has a standard deviation of 6% and PV of 3%. The highest annual deviation from the expected average availability of wind is about ±26% and of PV ±13%. Furthermore, I assume that the annual availability deviations of wind and PV are correlated with -0.15.[14]

The risk factors are grouped in three different scenarios for the sake of analyzing their different influences on the investment risks, which would be more difficult if all risk factors would be part of the same Monte Carlo simulation. Scenario one contains the coal, gas and CO_2 price risk factors. Hence, it is the variable costs risk scenario. In the second scenario, only

[14] Note that this correlation is chosen because it is near to the within year correlation of wind and PV in the used data. Clearly, a coefficient based on annual average availabilities would be more precisely. However, it is unlikely that this would affect the qualitative results of this paper.

the demand risk is analyzed, while the third scenario involves the wind and PV availability risk. Each scenario consists of 1000 Monte Carlo runs in the second stage and is computed for the CON and RES market. A scenario that contains all risk factors might also be of interest to see the overall effects of the considered risk factors. However, this is out of scope of this paper.

5.1.3 Risk Integration in the Model

One result of the second stage are the CVaRs of the different plant types. The aim of the third stage is to analyze the effect of the risk integration on the investment decisions. For this purpose, the model described in section 5.1.1 is extended, which is explained in this section.

Basically, the risk is integrated in the model by using the utility function of the investor given in equation (11). The utility function evaluates the CVaR by the risk aversion factor as costs of risks, which are denoted by $\alpha CVaR$. With this, the risk is a cost factor and it is straight forward to integrate it in the model: The last term of the objective function in (15) is simple extended by the costs of risk and becomes

$$\sum_i (invc_i + \alpha CVaR_i)\, cap_i \,, \tag{21}$$

where $\alpha CVaR_i$ are the costs of risks per MW of plant i which are added to the investment costs $invc_i$. Hence, the costs of risk are interpreted as additional costs of capital. The other term of the utility function of the investor in (11), the expected NPV, is implicitly calculated by the model: Without the risk integration the expected NPV (the economic profit) is zero for each endogenously built capacity, because this is a long-run equilibrium model. When risk is integrated in the model the expected NPV must be positive to compensate for the additional costs of risk. But the risk adjusted NPV, which is here the utility of the investor and given by equation (11), is zero when risk is integrated in the model. Thus, the new long-run equilibrium condition is

$$U_i = E[NPV_i] - \alpha CVaR_i = 0 \quad \forall\, i \,, \tag{22}$$

where the expected NPV, $E[NPV_i]$, is discounted with the same (risk free) rate as in the case without risk, which means it is the same as given in equation (19). As explained in section 4.2.1, the standard way to account for the costs of risk is to adjust (rise) the discount rate. However, this is out of scope of this paper, such that the costs of risks are added to the investment costs, which has been observed elsewhere in the literature (e.g. Fagiani et al. 2013).

Up to this point, the costs of risk are included in the model on a stand-alone basis, since the technology specific costs of risk are added to the investment costs. In the next alternative specification, the model is expanded to include the portfolio costs of risk. For this specification, the CVaR portfolio optimization in (10) is employed on the model from (15) to (18). However, the crucial difference to the basic CVaR portfolio optimization in (10) is that here the aim is to optimize the portfolio of a representative investor for the whole market rather than of a single investor. Therefore, the following modifications are necessary:

Due to the fact that the electricity market model computes the long-run equilibrium the expected portfolio return, discounted with the risk free rate, must always be equal to the portfolio costs of risks. This means the long-run condition becomes

$$U = E\left[NPV_{\mathrm{p}}\right] - \alpha CVaR_{\mathrm{p}} = 0\,, \tag{23}$$

which is the same as in (22) but for the expected portfolio NPV and the corresponding portfolio risk. Therefore, the restriction $E\left[r_{\mathrm{p}}(x_{\mathrm{i}})\right] \geq R$ in (10) that assures that some minimum return is achieved can be neglected here. Moreover, instead of the asset shares x_i in (10), the absolute amount of assets invested is the relevant variable. In the model, the amount of assets is given by the plant capacities cap_{i}. The optimal investments in these assets are calculated within the electricity market model. Hence, the assets share restriction $\sum_i x_{\mathrm{i}} = 1$ in (10) is redundant here. Consequently, the portfolio risk integrated optimization model becomes:

$$\max_{q_{iysh}, cap_i, X_{ysh}, \gamma, aux_k} CS - \alpha\left(\gamma + \frac{1}{s(1-\beta)}\sum_k aux_{\mathrm{k}}\right) \tag{24}$$

$s.t.$

$$\sum_i NPV_{\mathrm{ik}} cap_{\mathrm{i}} + \gamma + aux_{\mathrm{k}} \geq 0, \quad aux_{\mathrm{k}} \geq 0 \quad \forall\, k \tag{25}$$

restrictions (16), (17) and (18) (26)

The consumer surplus CS is the objective function in (15). Furthermore, in (26) are the same restrictions present as in the first stage base model. Thus, the base model from (15) to (18) is extended by the portfolio cost of risk in the objective function, which is α times the term in the brackets in (24), whereby the term in the brackets is in the optimum the β-CVaR of the portfolio. Additionally, restriction (25) is necessary as in the portfolio optimization in (10). Note that instead of the asset share, the capacities are included in restriction (25). For the other notations see section 4.2.2.

The model computes the optimal capacity investments by additionally taking the portfolio costs of risks resulting from these investments into account. Hence, it determines endogenously the portfolio CVaR. The underlying NPV distributions of the plants are taken from the sample s, which is generated in the second stage by the Monte Carlo simulations. The correlations between the plants´ NPVs are implicitly included in this sample such that diversification effects are considered by the model. An important difference to the standard portfolio optimization is that here the representative investor influences with its investments the returns of the assets. However, since perfect competition is assumed in the long-run equilibrium, the investor raises the returns exactly to point where they compensate the costs of the risks.

A limitation of this approach is that the underlying sample for calculating the CVaRs of the portfolio and for the stand-alone risks is fixed. In fact, the investment risks per MW of each plant type change with the production mix. To account for this, an iterative approach can be applied: After the third stage, again Monte Carlo simulations are conducted, but this time with the capacities of the third stage. The new computed NPV samples and the related CVaRs would lead to another production mix. However, this is computationally intensive and out of scope of this paper. Moreover, the aim of this paper is not to calculate exact quantitative effects, but to analyze general effects of (portfolio) risks on investment decisions. For this purpose the explained three stage approach is sufficient.

The whole approach can be summarized as follows. A representative investor maximizes her profits via investments in plant assets that have risky returns. In the first stage she invests according to the expected values of the risk factors, while investment risks are neglected, respectively she is risk neutral. The resulting (base) capacities are used as inputs in Monte Carlo simulations in the second stage to determine the stand-alone investment risks of each plant type measured with the CVaR. In the third stage, the investor maximizes again her profits with the investment decisions, but this time taking also into account the investment risks of the plant types. In order to see diversification affects, the risks are evaluated in the investment decision in a portfolio context and on a stand-alone basis. In the next section, the results of the three stages are presented.

5.2 Results

In this section the results of the numerical model are presented. The outline follows the sequence of the three stages described in the previous sections. The first subsection shortly presents the main results of the two deterministic base runs. In subsections of 5.2.2, the stand-alone risks of one plant of each technology computed by the Monte Carlo simulations of the second stage are examined for the three scenarios. In order to compare the technologies, one representative plant of each technology is defined for which the investment risks are analyzed. The impacts of the risk integration in the investment decisions (third stage) are presented in section 5.2.3.

5.2.1 First Stage: Base Runs

In the following, the results of the deterministic CON and RES market are described to give a general overview of the two markets and to introduce some aspects, which become important later in the risk analysis. Table 1 depicts technology specific outcomes of the two markets.

Table 1 Base results of the CON and RES market

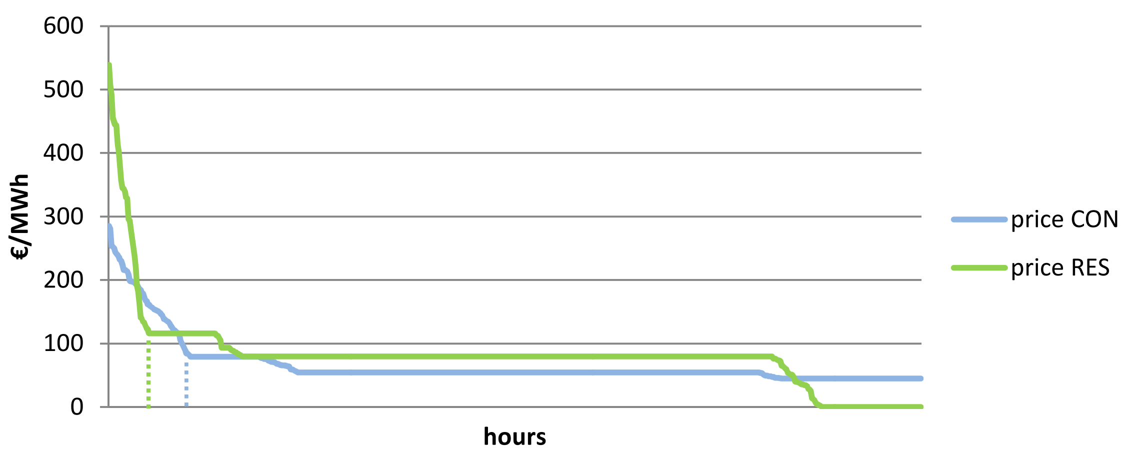
	Share in production		Capacity factor		Average price (€/MWh)	
	CON	RES	CON	RES	CON	RES
Wind	4.9%	58.8%	25.0%	23.7%	64.12	67.52
PV	-	8.7%	-	13.1%	-	80.10
Coal	75.3%	-	83.8%	-	67.24	-
CCGT	18.4%	31.3%	45.2%	43.4%	81.21	107.64
OCGT	0.7%	1.2%	11.6%	7.3%	144.92	220.93

The CON market is dominated by the typical baseload technology coal with a share in the production of 75.3%. CCGT serves as a midload in the CON market and has a much lower proportion, while OCGT is only used as a peaker, when residual demand (total demand minus renewable production) is high. Wind plays a minor role with a share of 4.9% and PV is not build endogenously at all. Increasing the CO_2-price in the RES market up to 100€/t leads to a quite different picture: Now wind has the highest share with 58.8% and together with PV the renewables produce about 67.5% of the total production. The proportion produced by the two gas technologies also rises, while coal is not used anymore, because it is too expansive.

Next, consider that wind has a lower capacity factor in the RES market (23.7% against 25.0%). While in the CON market all wind capacities can be used according to its availability, in the RES market there are hours in which demand is lower than the maximum wind and PV production. In these hours, the wind and PV production is curtailed and thus the capacity factors of both do not reach their maximum according to their availabilities. Note that also the CCGT and OCGT capacity factors decreases in the RES market because the variable renewables have large shares in the production, but they do not reduce the need for fossil capacities accordingly. The reason is the volatile availability of the renewables leading to a dispersed residual demand. Hence, CCGT and OCGT produce less relative to their capacities (lower capacity factors) in the RES market, which is called the utilization effect (Nicolosi 2011).

The last column shows the received average price for one MWh of produced electricity (the output weighted average price) which indicates the market value of an average MWh of the respective plant. Wind produces electricity with the lowest market value in both markets. Since wind has zero variable costs (left in the merit order), a higher wind availability (and hence production) shifts the total supply curve to the right, which lowers the price and vice versa. Therefore, wind produces less if the price is high and more if the price is low. This effect is weaker for PV, because there are less PV capacities and hence the price effect is lower. Moreover, the PV availability is high over the day and zero at night. Since the demand and the electricity prices are higher over the day, PV produces the more valuable electricity compared to wind. Clearly, OCGT receives the highest average price, because it produces only if the prices are high. The average prices of all plants are higher in the RES market due to the increase of the CO_2-price. Consequently, the overall average price in the RES market is with 83.1 €/MWh also higher than in the CON market with 70.2 €/MWh.

Figure 3 Price duration curves of the base runs



Another important difference between both markets is the price formation given in figure 3 by the price duration curves of both markets. These curves plot the by height sorted hourly prices of one year from the highest in the left to the lowest price in the right part of the figure. Note that in the base scenarios all years are identical, due to the assumption of stable input parameters. The curves are characterized by different flat parts which have the height of the variable costs of the plant type that sets the price in the respective hour. In both markets, CCGT most often sets the price, which is the widest flat part of both curves in the figure. The plateau in the left, which is a bit lower than 100 €/MWh in the CON market and bit above 100 €/MWh in the RES market, indicates the hours in which OCGT sets the price. The right plateau in the CON market depicts the hours when the price is given by the variable costs of coal, whereas during the zero price part in the RES market wind and PV sets the price. The prices are more dispersed in the RES market, since additionally to demand fluctuations also the variable renewable production strongly affects the prices. These extremer prices are in line with other predictions about the influence of renewables on the electricity market (e.g. Redpoint 2009; Poyry 2009). However, the number of scarcity hours, indicated by the dashed lines, is higher in the CON market, which has certain risk implications in the here used model.

5.2.2 Second Stage: Stand-Alone Plant Risk

In this subsection, for each scenario the stand-alone investment risks as a result of the second stage Monte Carlo simulations are analyzed. The considered risk measure is the CVaR, while throughout the rest of the paper it is always calculated for a confidence level β of 95%, which is a standard value.

Here the aim is to compare the investment risks of the different technologies on a plant level, which means one plant of each technology. For this purpose the NPVs must be normalized, such that the related plants have an equal size (cf. Roques et al. 2008, Fuss et al. 2012). If one would simply compare the NPV per MW, this would lead to a bias: One MW wind or PV is less than one MW of the fossil fuel plants in terms of the production potential, because the renewables have a lower average availability. Therefore, the MWs are normalized by the expected availability factors of the respective plant, which I term MW^N. Thus, plants of equal expected production potential are compared. Note that this normalization is only done in this chapter for reasons of a more stringent comparison of the plants. As described above, the costs of risk as a model input are on a per MW basis, since the model takes account of the different availabilities of the plants.

5.2.2.1 Scenario 1: Variable Cost Risk

In the following, the Monte Carlo results of the first scenario are presented. Figure 4 shows the probability distributions[15] and table 2 gives the mean and the CVaR of the NPVs for the plants in each market.

Figure 4 NPV probability distributions of scenario 1

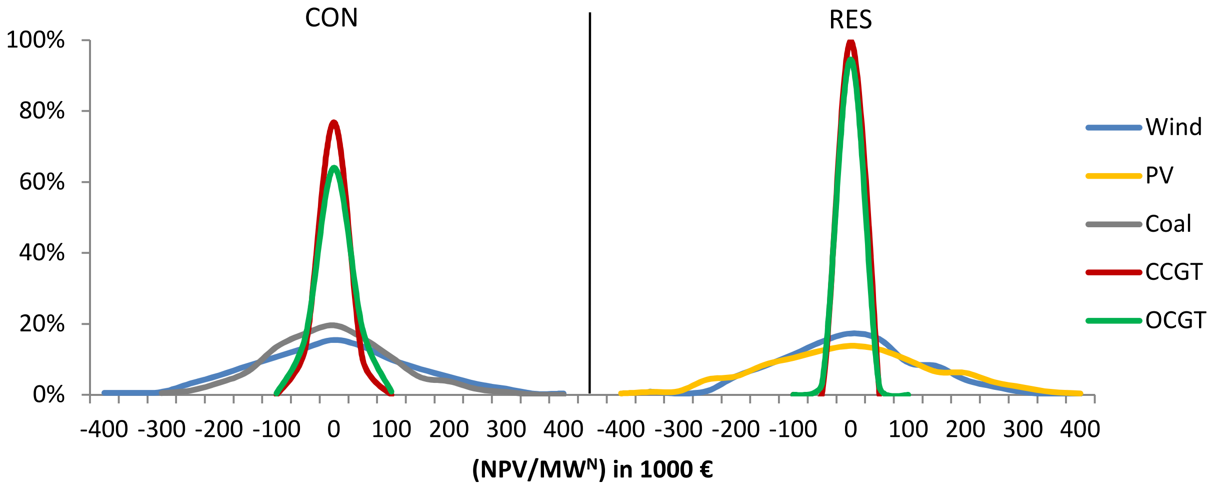


Table 2 Mean and CVaR of scenario 1

(NPV/MW^N) in 1000 €	Mean		CVaR ($\beta = 0.95$)	
	CON	RES	CON	RES
Wind	-1.45	-1.25	287.38	250.26
PV	-	-0.59	-	311.15
Coal	-2.46	-	223.01	-
CCGT	-1.16	-0.51	45.96	17.06
OCGT	1.61	0.27	55.52	27.62

First of all observe that the expected NPVs (the means) are all very close to zero. Thus, positive and negative runs are in terms of their influence on the NPVs approximately in balance for all plants[16]. Considering the NPV distributions and the related CVaRs, one sees that coal is with a CVaR of 223.01 t€ much more risky than the two gas plants in the CON market. Furthermore, wind has a CVaR of 287.38 t€ in the CON market and is even more risky than coal.

[15] Note that the distributions are constructed on a basis of 1000 runs and are not perfectly shaped. However, a greater number of runs should not alter the results in a significant manner.

[16] The expected NPVs are in a range of -2460 € (coal) to +1610 € (OCGT) which is relatively to the investment volumes of the plants negligible.

The main reasons why wind and coal are more risky than the gas plants are their left positions in the merit-order and that a gas plant most often sets the price (see price duration curve in figure 3). In hours of CCGT price setting,[17] a change in the variable costs does not affect the CCGT profits negatively, because CCGT transfers the variable costs directly to the electricity price. If a change in the variable cost of CCGT leads to a shift in the merit-order such that coal instead of CCGT sets the price, this also does not affect the profits of CCGT: The CCGT profits were already zero due to marginal cost pricing. Consequently, the CCGT profits can only be negatively affected in hours with prices higher than its variable costs (mainly hours of OCGT price setting and scarcity hours). For the same reasons, OCGT can only make losses[18] in scarcity hours. However, the variable cost transfer on the price of the price setting plants triggers an electricity price effect, which influences the profits of all plants that also produce in these hours. Since the gas plants most often sets the price and wind and coal also produce in these hours, wind and coal are more risky than the gas plants.

Furthermore, the fact that there are also hours in which coal sets the price, makes wind more risky than coal: In these hours, in contrast to wind, coal is not affected by a change in variable costs since itself sets the price. Therefore, wind has the higher electricity price risk compared to coal. Note that if there would not be the strong correlation between the coal and gas price of 0.7, coal might be more risky than wind. Then very low gas prices could emerge in the same years with very high coal prices, such that the coal profits are affected more than the wind profits in hours when gas plants set the price. Hence, the coal price risks could, with a lower correlation with the gas price, overcompensate the higher electricity price risks of wind. There is a more detailed analysis of a gas price decrease in appendix 8.4.1.

Another observation is the lower risk of CCGT than of OCGT. As explained in appendix 8.4.1 CCGT makes losses when OCGT sets the price and their variable costs are lower than expected. However, the variable costs of CCGT and OCGT always move in the same direction (both have the same cost risk factors) and in general a low variable cost year means higher profits for both such that these years are not directly relevant for the CVaR. But in the opposite case of higher variable costs CCGT makes greater profits (compared to the same base hour) in hours when OCGT sets the price, which in total lowers the CCGT losses in these general bad CCGT years. Another positive effect for CCGT compared to OCGT comes

[17] Clearly, CCGT does not necessary set the price in the same hour of a year in the base run and in a Monte Carlo run, because the merit-order shifts due to the change in the variable costs in the Monte Carlo run. To avoid misunderstandings, in the following the term hour always refers to the hours of the base runs.

[18] Note that the term “losses” is interpreted in this context as “losses compared to the base run”, since in fact the plants make no losses in these hours, but less short-run profits as necessary (i.e. as in the base run). However, for reasons of legibility the term “compared to the base run” is skipped.

through the stable prices and demand in scarcity hours: The price is always given by $p = (A - X)/b$, where A and b are fixed parameters. Due to the fact that the demand X is in many scarcity hours not affected by higher variable costs, the price stays also the same.[19] Since the variable costs of OCGT are compared to CCGT always more influenced by the same change in the gas and CO_2-price, because OCGT has the worse conversion efficiency, and both here considered plants produce the same output, OCGT makes higher losses in scarcity hours.

Next observe that the CVaR is lower for wind, CCGT and OCGT in the RES market. The explanations given yet, show that all losses of OCGT and a large part of the CCGT losses emerge in scarcity hours. Therefore, their lower risk can mainly be traced back to the lower number of scarcity hours in the RES market: CCGT and OCGT gain or lose in each scarcity hour with stable electricity prices (see above) the difference between the expected variable costs and the realized variables costs times the plant size, which is: $(E[vc] - vc) * MW^N$. This holds for each scarcity hour (with stable electricity price) in both markets. Hence, when the same variable cost risk is applied to both markets (which is the case) and scarcity hours emerge more often in the CON market, the losses for CCGT and OCGT are, ceteris paribus, higher in the CON market.

Obviously, wind does not make losses in scarcity hours when the price is stable because it has no change in variable costs and its production stays also the same. Due to the higher number of scarcity hours in the CON market the losses are, ceteris paribus, lower for wind in this market, since there is simply less often the opportunity to make losses (i.e. less hours in which losses can emerge). Consequently, this effect is in diametrical opposition to the gas plants. However, this effect is overcompensated by the lower number of hours in which fossil plants set the price in the RES market, because in these hours wind makes its most losses. As one can observe in the price duration curves above there are many hours in the RES market in which the renewables sets the price to zero and variable cost risks does not play a role. In any other hour, except scarcity hours with stable prices, wind makes losses if the variable costs of the fossil plants decrease and affect the electricity price. In fact in each of these hours by the same amount in the RES and CON market for a given decrease in variable costs. Consequently, if the number of such hours falls the risk is lower for wind in the RES market. The crucial point for the lower risk for wind, CCGT and OCGT is at all, that the number of risky hours for all decreases in the RES market.

[19] The demand, and thus the price is only affected if a scarcity hour of the base run becomes an hour in which OCGT sets the price in consequence of the variable cost increase.

The last important aspect is the higher risk of PV with a CVaR of 311.15 t€ in the RES market against wind with 250.26 t€. The reason for this difference lies in the fact, that PV produces a relative to wind higher share of its total production in hours with higher price risks triggered by the variable cost risks of CCGT and OCGT: PV produces 6.2% of its total production when OCGT sets the price, and 75.6 % when CCGT sets the price against 4.7% and 60.3% for wind, while in scarcity hours both produce only 2.5% of their total shares. Wind has with 19.3% compared to PV with 4.4% a much larger share when itself and PV set the price to zero and there are no price risks.[20] Since both considered plants of the size MW^N have nearly the same annual output,[21] and wind produces relative to PV more in times with lower prices, PV has the higher output weighted average electricity price which is 80.10€ compared to wind with 67.52€.[22] The reason why PV needs a higher average prices per MWh is that it has higher fixed costs per MW^N (or per MWh), because it has a low capacity factor. To sum up, PV must produce more in times with higher prices relative to wind, because it needs higher average prices to cover its fixed costs. Times with higher prices are more risky, because the prices are determined by the volatile variable costs of the gas plants. Hence, PV is more risky than wind.

5.2.2.2 Scenario 2: Demand Risk

In this section, the results of the demand risk scenario are presented. The first important point to mention is that the demand risk is mostly an electricity price risk: A change in demand triggers strong price effects which affect the NPV of the plants, but a lower production level alone (without simultaneous price change) does not affect the plant´s NPVs: Plants that produce less due to a lower demand when the price is stable, are obviously the price setting plants. Since these plants sell the electricity at their variable costs, their profits are not affected by a lower production level. All other operating plants are also not affected, because they still produce the same amount of electricity and receive the same price. Hence, a loss in NPV compared to the expected NPV of an hour is only possible, if a price change triggered by a demand change emerges.

[20] The values belong to the base RES scenario and can differ for each Monte Carlo run, but not in a significant manner. The missing shares leading to a sum of 100% are given by the phases in between two plant types.

[21] This follows directly from the definition of MW^N which is the normalization of the plant size such that they have the same output potential given their average availability. Since wind and PV are almost always utilized according to their availability, they have nearly the same annual output.

[22] Note that this comparison does not hold for the fossil plants, because they are not used according to their availability and hence, have lower outputs.

Figure 5 and table 3 show again the NPV distributions, the mean and the CVaR.

Figure 5 NPV probability distributions of scenario 2

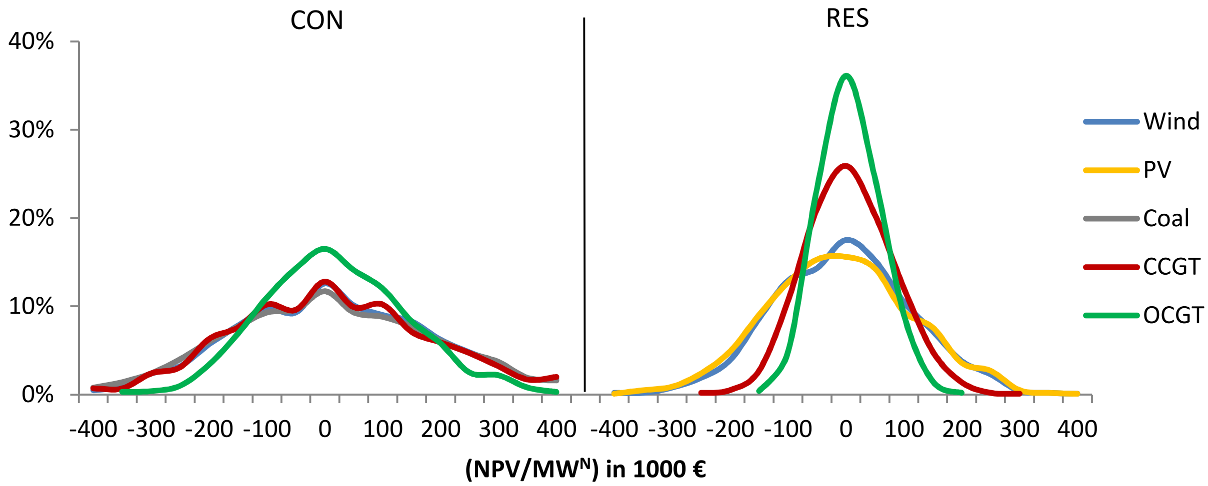


Table 3 Mean and CVaR of scenario 2

(NPV/MW^N) in 1000 €	Mean		CVaR ($\beta = 0.95$)	
	CON	RES	CON	RES
Wind	25.12	-5.05	324.76	250.39
PV	-	-10.74	-	271.04
Coal	18.32	-	357.07	-
CCGT	18.89	7.00	329.99	143.43
OCGT	21.14	7.11	223.77	96.01

Opposed to scenario one, the mean of all operating plants is slightly positive in the CON market. One reason lies in the scarcity hours: A higher than expected demand in scarcity hours fully shifts the price upwards. While the drop of the price in the case of a lower than expected demand is bounded by the variable costs of the plants (mostly by OCGT, see appendix 8.4.2 for a graphical analysis). There are less scarcity hours in the RES market, hence the effect is smaller. Additionally, there are other effects causing a deviation from an expected NPV of zero, which cannot be discussed in the scope of this paper. However, similar to the first scenario the differences between the plants and the deviations from zero are not large.

The differences between the plants in the NPV distributions and the related CVaRs are smaller in the CON market relatively to the first scenario. Under the fossil plants, coal is more risky than CCGT and CCGT more than OCGT. This ranking can be explained by the merit-order: OCGT (right in the merit-order) is only affected by price changes in scarcity times, while coal and CCGT are affected in these hours by the same magnitude in NPV terms, because all plants are fully utilized. In contrast, coal is affected by all price changes (left in the merit-order), while CCGT lies in between coal and OCGT and hence lies also in between them in the risk ranking.

Interestingly, wind is less risky than coal and even a bit less risky than CCGT in the CON market: The price risk is higher in times with higher prices, because the price step between OCGT and CCGT, and hence the influence of a change in demand on the price, is higher than between CCGT and coal. The prices drop most in scarcity hours when the prices are very high, such that the price decline is not bounded by the variable costs of OCGT. As explained in the previous section, wind produces less relative to the other plants in such high price hours and thus, faces a lower scarcity price risk. Nevertheless, wind is affected by all price changes (left in the merit order) and has for that reason only a slightly lower risk compared to coal and CCGT.

As in the first scenario, the risks decrease for wind, CCGT and OCGT in the RES market. Since the highest prices drops emerge in scarcity hours and there is a significant smaller number of a scarcity hours in the RES market, the risk is lower for all plants. For the same reasons given in the last paragraph, namely that wind is less affected by the scarcity price risks but more from risk at lower price levels, it benefits relatively less from the lower number of scarcity hours compared to CCGT and OCGT. Thus, wind is more risky then the two gas plants in the RES market.

Wind is again less risky than PV in the RES market for similar reasons as in the first scenario: On average, PV produces the more valuable electricity compared to wind, or in other words, PV produces relatively more electricity when the prices are higher. As explained above, the electricity price risk is higher at higher price levels, thereof it follows that PV is more risky than wind.

5.2.2.3 Scenario 3: Renewable Availability Risk

Finally, the risk triggered by annual deviations from the expectation of the wind and PV availability is presented. Opposed to scenario one and two, the availability risk transfers into an electricity price and a strong volume (production) risk. Basically, there are two effects of a change in the renewable availability: On the one hand, decreases a lower than expected renewable availability the renewable production, and increases the fossil production (volume risk) and vice versa. On the other hand leads a lower availability to higher prices for all plants (electricity price risk) and vice versa. Hence, a lower (higher) renewable availability is always good (bad) for the fossil plants. For the renewables it depends on the strength of the volume and the price effect, whether the deviation from the expectation leads to gains or losses compared to the base run (see appendix 8.4.3 for a graphical analysis).

Figure 6 and table 4 show the NPV distributions, the mean and the CVaR of the plants.[23]

Figure 6 NPV probability distributions of scenario 3

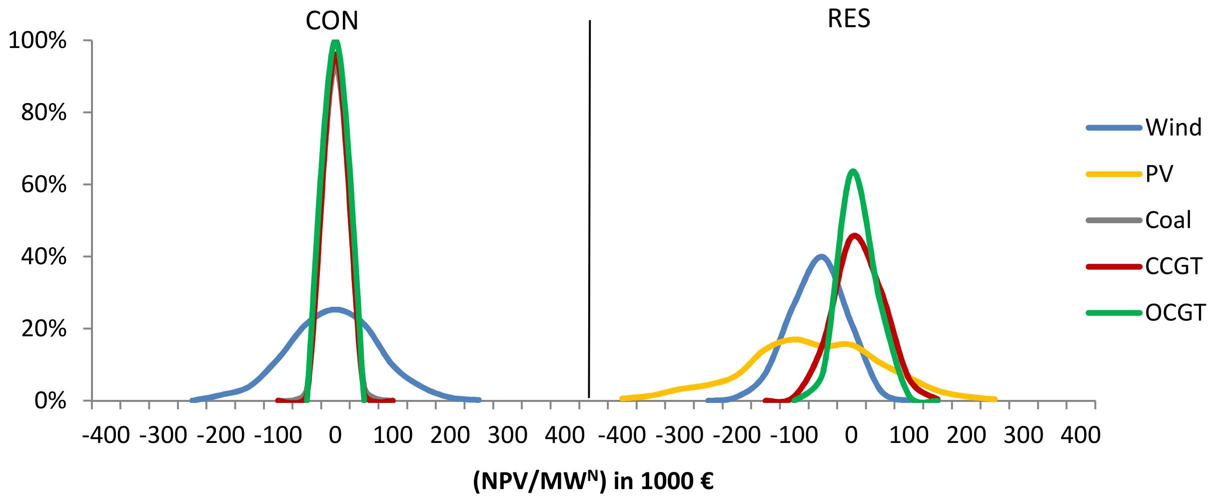


Table 4 Mean and CVaR of scenario 3

(NPV/MW^N) in 1000 €	Mean		CVaR ($\beta = 0.95$)	
	CON	RES	CON	RES
Wind	-2.69	-59.03	162.79	162.99
PV	-	-68.25	-	321.04
Coal	0.10	-	28.38	-
CCGT	0.26	13.65	23.94	66.87
OCGT	0.68	11.46	15.50	38.54

The mean of all plants is very close to zero in the CON market, since the positive and negative runs of all plants almost compensate each other. In the RES market, the means deviate significantly from zero, which will be explained later on. The overall impact of the availability risks on the NPVs is lower compared to the first and second scenario for all plants in the CON market, indicated by the tighter NPV distributions and lower CVaRs. For the three fossil plants, the reason is simply the low share of renewables in the CON market, which implies only a small electricity and volume risk. Wind also has only a small electricity price risk, but bears of course a high volume risk. Thus, wind is much more risky than the fossil plants in the CON market. However, in the RES market the availability risk impacts changes dramatically.

[23] The NPV distribution of coal lies under the curves of CCGT and OCGT in figure 6.

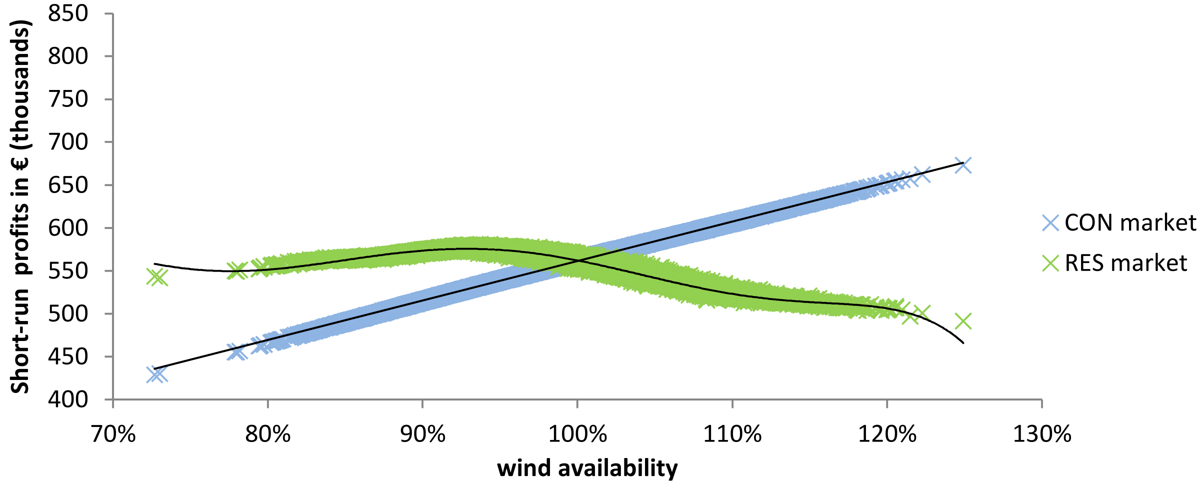
A first difference compared to the CON market is the slightly lower volume risk for wind in the RES market: In the RES market, wind is not fully utilized according to its availability. While wind has a capacity factor of 25% in the CON market, it is only 23.7% in the RES market. Consequently, there are some hours with wind curtailment in which a lower than expected availability does not or with lower magnitude affect the wind production. Clearly, the opposite is also true: A higher than expected wind availability has no effect in hours that already have wind curtailment. In contrast, the volume risk for fossil plants increases in the RES market, because the share of the renewable production is much higher and thus also the replacement of fossil by renewable electricity, when the availability is higher than expected. Taking the standard deviations of the annual capacity factor over all runs as an indicator, one can measure the volume risks: For wind the standard deviation is 1.51 percentage points in the CON market compared to 1.16 in the RES market, while it is 0.42 (0.37) for CCGT (OCGT) in the CON market and 3.06 (1.08) in the RES market (see table 9 in appendix 8.4.4)

The other main difference, compared to the CON market, comes from the much larger electricity price effects of the renewable availability in the RES market: The same increase (decrease) in availability triggers a larger price decrease (increase) in the RES market, due to the higher share of wind and additionally PV production in the total production. Considering the standard deviation of the annual output weighted average price over all runs as an indicator for the price risks, this becomes obvious: While it is less than one euro per MWh for all plants in the CON market, it becomes 5.15€/MWh for wind, 1.31€/MWh for CCGT and 3.70€/MWh for OCGT in the RES market (see table 9 in the appendix 8.4.4).[24] The higher electricity price risk together with the higher volume risk raise the investment risks of CCGT and OCGT by a factor of more than two in the RES market (but the risks are still on a moderate level).

Opposed to the gas plants, wind has with a CVaR of 162.99 t€ nearly the same risk as in the CON market. Interestingly, the whole risk pattern for wind changes in the RES market, as can be seen in figure 7, that plots the (undiscounted) yearly wind short-run profits of all runs against the wind availability for the CON and RES market.[25]

[24] Conclusions about the overall investment risk of a plant solely on the basis of these volume and price risk measures are not feasible. Nevertheless, they are useful to indicate volume and price risk differences between the two markets.
[25] This is a simple scatter plot that ignores the slightly negative correlation between the PV and wind availability of -0.15. Thus, one cannot simply draw causal conclusions about the effect size between the availability and the price that is in a linear regression given by the slope of the trend line, since this would lead to an endogeneity bias. However, the bias is in this case rather small, because the impact of the PV availability on the wind short-run profits is small and the correlation between PV and wind availability low. Moreover, scatter plots are used to show basic effects and not to calculate precise casual effects. Consider this also in the availability scatter plots in the appendix.

Figure 7 Relationship between wind availability and short-run profits of wind



There is a positive linear relationship between the availability and the short-run profits in the CON market: The higher the availability of wind, the higher the profits. Therefore, the impact of the positive volume effect is always larger than the impact of the negative price effect. In contrast, there is a non-linear relationship[26] in the RES market: From the perspective of the expectation (100% availability), a moderate lower availability raises the short-run profits and hence the price effect is larger than the volume effect. But at very low availability levels the volume effect becomes stronger compared to the price effect, such that the short-run profits decrease again. Going the other direction, a higher than expected availability (>100%) drops the short-run profits, thus, the negative price effect overcompensates the positive volume effect.

Next observe that PV is again more risky than wind in the RES market. In this scenario, the risk of PV is with a CVaR of 312.04 t€ even nearly twice as high as wind with a CVaR of 162.99 t€. The main reason for this large difference is as follows: As noted above, the wind availability triggers a large price effect, while this happens only to a much lower extent for PV (see figure 19 and 20 appendix 8.4.4). From the perspective of the wind plant is the negative volume effect of a bad wind availability year partly or even more compensated by a positive price effect. Furthermore, the negative price effect of a good wind availability year is partly compensated by a positive volume effect. In analogy to the gas self-hedge for its variable costs, one can say that wind is also partly self-hedged. In contrast, these compensations effects are lower for PV due to its lower price effects. Clearly, in a market with a higher PV and a

[26] Note that the trend line for the RES market in the figure does not perfectly fit the data. In fact, a polynomial of degree six is used, since lower degrees lead to strong deviations.

lower wind share in total production, the compensation effects would be stronger for PV and lower for wind.

Finally, observe in table 4 that the mean NPVs for wind and PV are negative in the RES market. The reason behind wind can directly be seen in figure 7: The negative effects of a higher than expected wind availability are stronger than the positive effects of a lower than expected availability. Hence, the strong price effects in the case of higher than expected availabilities cause the negative means. For PV such clear graphical observations cannot be made. Instead, consider that PV makes higher profits the higher its availability and vice versa as can be seen in figure 21 in appendix 8.4.4. But the gains from a higher availability are lower than the losses from a lower availability, which causes the slightly non-linear trend line in figure 21. The reason is that high availabilities often cannot be fully translated accordingly into higher production, because demand is too low and hence, only the curtailment rises. On the opposite, a lower PV production is always possible, though in some hours a lower PV availability does not lead to a lower production, since there is some renewable curtailment. However, this effect is smaller than the increased curtailment due to a higher availability, thus, PV has a negative mean. Clearly, the same considerations hold also for wind, but wind makes losses with high availabilities and the price effects are more important for wind in the RES market. Note that CCGT and OCGT have slightly positive NPV means in the RES market, which is a direct consequence from the upper bounded renewable production in many hours: CCGT and OCGT are always harmed by high renewable productions and profits from low productions. Therefore, if a higher renewable availability leads to higher renewable production by a smaller extent, than a lower availability to lower production, CCGT and OCGT have positive means.

5.2.3 Third Stage: Impacts of Risks in Investment Decisions

In the last three sections, the results for the stand-alone investment risks on a plant level measured with the CVaR were presented. In this section, the outcomes of the third stage model runs are examined. In these runs the investment risks, found in the second stage, are evaluated by risk aversion factors such that they yield the costs of risk (αCVaR) which are included in the investment decisions (see section 5.1.3). The perspective is changed from the plant level (previous sections) to the whole market level. This means that the influence of the costs of risk on the shares of each technology in total production is analyzed. To avoid misunderstandings, the term plant refers in this section to all plants of one technology or, interchangeable, to one plant type. In order to show the diversification effects, the results of the investment decisions that take account of portfolio risks are confronted with the decisions that consider only stand-alone risks.

In reality there are different investors with different preferences about risks and return, but in this analysis is only one representative investor. For the purpose to account for different preferences, the third stage model runs are computed for different risk aversion factors. More precisely, risk aversion factors α of 0.5, 0.75, 1 and 2 are assumed and compared to the risk-neutral ($\alpha = 0$) base runs. These risk aversion factors are higher than in Fagiani et al. (2013), who chose a range of 0.25 to 1.25, but by far lower than in Roques et al. (2008). Roques et al. (2008) calculate optimal portfolios for a risk aversion up to 100, while they see a factor of 10 as a medium risk aversion coefficient.[27] However, in reality such high risk aversion factors are unlikely to find (cp. Green 2007) and thus not part of this analysis.

Exclusively the results of the first and third scenario are presented. The results of the second scenario (demand risk) are neglected, because the NPVs of all plants are almost perfectly positive correlated due to the fact that all make higher (lower) profits in high (low) demand years. Hence, there are no diversification effects. Since additionally the results of stand-alone risk incorporation do not have any further insights compared to the other scenarios, the demand risk scenario is neglected.

Note that the differences between the expected NPVs (the means of the previous sections) are not integrated in the third stage model. Thus, I assume that all plant types have expected long-run profits (i.e. NPVs discounted at the risk free rate) that equal their costs of risks (see section 5.1.3). This is theoretically more appealing than lower or higher expected NPVs, because these would not emerge in a long-run equilibrium. Clearly, with this I neglect a difference between the plants types found in the second stage. However, this is almost irrelevant for the first scenario because the differences in the means are negligible. Moreover, this paper is about the impacts of (the costs of) risk in an equilibrium setting. The abstraction from differences in the expected NPVs makes this analysis more convenient, since the findings can be solely traced back to the influence of risk.

[27] Additionally, Roques et al. (2008) take the variance as a risk measure, which results in higher values compared to the CVaR. The likely reason why they choose these high costs of risk is to show the general effects of risk on the portfolio mix, though they do not mention this. Low risk aversion factors have only little influence in their analysis.

5.2.3.1 Scenario 1: Variable Cost Risk

At first, the results of the variable cost risk scenario are presented. Table 5 shows the correlation matrix of the NPVs of all operating plant types for the CON and RES market. Although it is not a direct input as in other portfolio optimizations (see section 5.1.3), it depicts the hedging possibilities between the plants also for this analysis.

Table 5 Correlation matrix of scenario 1

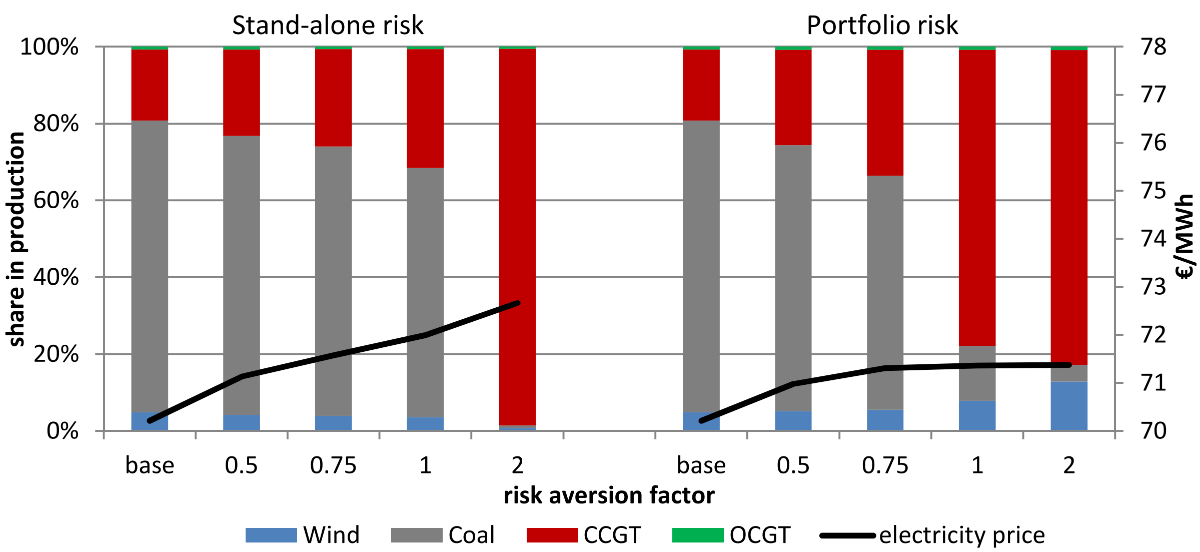
	CON market				RES market			
	Wind	Coal	CCGT	OCGT	Wind	PV	CCGT	OCGT
Wind	1				1			
PV	-	-	-	-	1	1		
Coal	0.705	1			-	-	-	-
CCGT	-0.994	-0.775	1		-0.995	-0.994	1	
OCGT	-0.995	-0.773	0.999	1	-1	-1	0.995	1

The NPVs of wind and coal move into a similar direction in the CON market, indicated by the high correlation coefficient of 0.705. At a first glance, this might be counterintuitive since a high CO_2 and coal price, everything else equal, leads to more profits for wind and less profits for coal. But the overwhelming risk factor is the gas price: Compared to the coal price, it is absolutely higher and more volatile. Compared to the CO_2 price, it has even a lower absolute standard deviation, because it has the same percentage annual volatility and is in absolute numbers lower (see appendix 8.3). However, the CO2 price is per ton and must be multiplied by the emission factor which is 0.21 for both gas plants and 0.33 for coal to calculate the variable costs such that the CO_2 price risk leads to less dispersed variable costs compared to the gas price. Since gas plants set most often the electricity price, the gas price has the strongest influence on the electricity price and with this on the NPVs of coal and wind. Consequently, wind and coal mostly make higher profits if the gas price is high and vice versa. The correlation between wind and the two gas plants is almost perfectly negative, because high gas or CO_2 prices cause profits for wind and losses for the gas plants, while the coal price is less relevant for the wind profits and also strongly positive correlated with the gas price. In contrast, the lower negative correlation between coal and gas plants can mainly be explained by the influence of the coal price, which can cause more gains for coal, even if the gas price decreases and the gas plants also make more profits. The almost perfect correlation between the two gas plants is intuitive due to the fact that both have the same risk factors. Given the variable cost risks, coal is a good hedge for gas, but wind is the better hedge for gas. Coal and wind can only slightly be used as hedges.

Now consider the correlation matrix of the RES market, where all coefficients have extreme values: Wind and PV are perfectly positive and both renewables are (nearly) perfectly negative correlated with both gas plants, while the later are again almost perfectly positively correlated. This is intuitive, because a change in the gas and CO_2 price causes opposing effects on the profits of the renewables compared to the gas plants. Thus, both renewables are again very good hedges for the gas plants, while within renewables and gas plants hedging is nearly impossible.

Next the main results of the risk incorporation in the investment decisions of the CON market are presented in figure 8.

Figure 8 Results of the risk integration in the CON market of scenario 1



The bars show the share of each technology in total production for different risk aversion factors α in the range of zero (base) to two. The five bars on the left depict the results for the investment decisions containing stand-alone risk and the five bars on the right containing portfolio risk. The risk factors for the two base bars are zero, thus the bars are equal and show the result for the CON base run without risk (first stage). The black lines belong to the right y-axis (€/MWh) and show the output-weighted average electricity prices for consumers for the different risk aversion factors.[28]

If investors only consider stand-alone risk, the CCGT share increase from 18.5% in the base run to 31% with a risk aversion factor of one and becomes almost 100% with a factor of two.

[28] All values are for the first model year. Since all years are identical, the shares and the average price are also valid for all other years.

Clearly, CCGT has the lowest risk and hence relatively gains compared to the other plants. It mostly replaces coal: The coal share drops from 75.9% (base) to 64.8% ($\alpha = 1$) and is near to zero with a risk aversion of two. The wind share decreases up to a risk aversion of one only slightly from 4.9% in the base run to 3.6% (for $\alpha = 1$), while wind is like coal almost completely out of the market with a risk aversion factor of two.

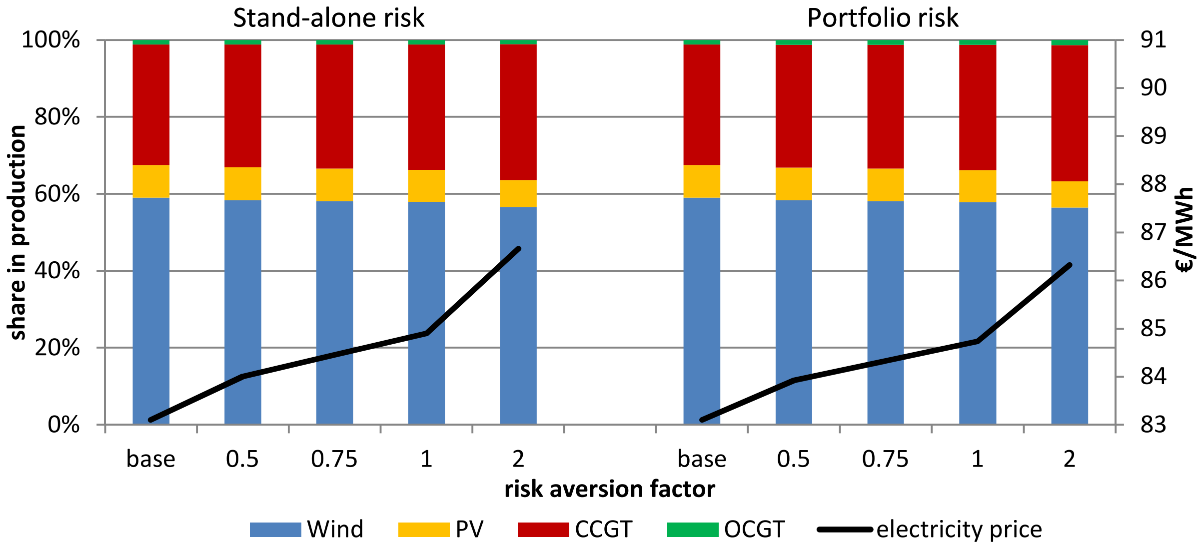
Lastly, it can be seen that the effects on the OCGT shares are negligible. The relative changes in the costs between OCGT and the other plant types are too small to cause significant effects. Independently of the risk aversion factor, OCGT is used only in some hours with very high residual demand.

Under portfolio risk, the coal share drops even more for risk aversion factors up to one: Now its share is only 14.3% for a factor of one compared to 64.8% under stand-alone risk. However, coal has with a share of 4.3% for a factor of two a larger production compared to stand-alone risk. This means that the good diversification potential of coal and CCGT is only effective for a large risk aversion. The reason is that wind is the better hedge for gas plants: If CCGT makes losses, wind always makes profits and vice versa, such that a higher wind share reduces the portfolio risk. Consequently, the wind share increases under portfolio risk even up to 12.9% for a risk aversion of two, which is more than twice as high as in the base case. The CCGT share increases also more for all factors, except for a factor of two.

Intuitively, the average electricity price always rises with higher risk aversion factors, since a higher factor means that the same CVaR has higher costs of risk. Due to the diversification effects, the overall portfolio costs of risk are lower compared to the stand-alone risk. Therefore, the price increase is up to 1.30 €/MWh lower ($\alpha = 2$) under portfolio risk.

Figure 9 depicts the effects of the risk integration on the production shares and the average price in the RES market.

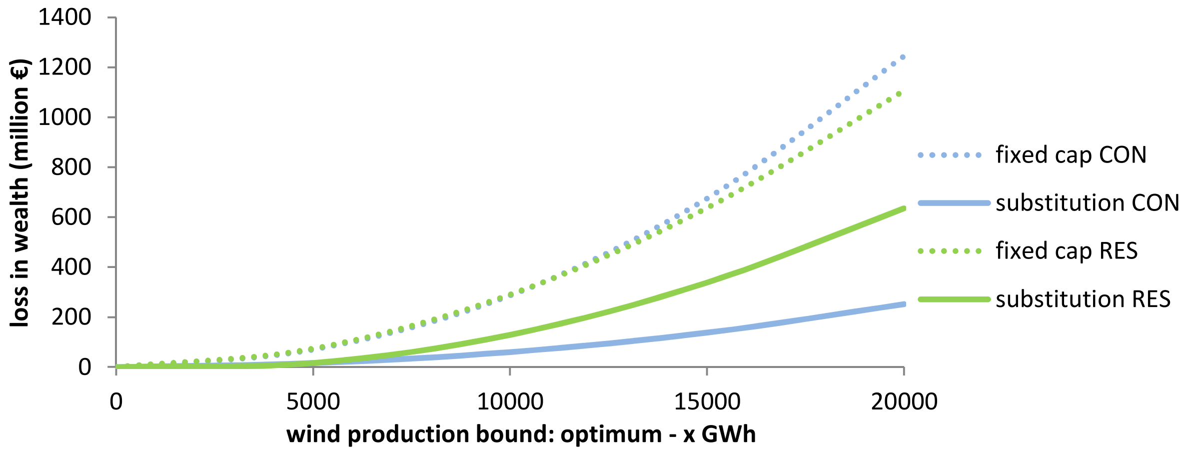
Figure 9 Results of the risk integration in the RES market of Scenario 1



Obviously, the risk effects are much smaller for both stand-alone and portfolio risk. There are only some minor effects: The wind share decrease up to 2.4 and the PV share up to 1.6 percentage points compared to the base case for a risk aversion factor of two under stand-alone risk. These small declines are nearly fully compensated by CCGT, while the OCGT share is again stable. Under portfolio risk, the outcome is almost exactly the same: 2.6 percentage points instead of 2.4 for wind and 1.7 instead of 1.6 for PV. At a first sight this result might not be intuitive, because approximately the same risk for wind in the CON market forced wind almost completely out of the market for a risk aversion factor of two. Moreover, the risk of PV is even double as high and reaches the highest value of all plants over all scenarios, but is also almost not reduced. I contribute these stable production shares to the following reason explained for the wind share:

Figure 10 plots the loss in the consumer surplus (wealth) when the wind production is bounded to its optimum, minus the values on the x-axis for the CON and RES market. This means there is an upper bound on the wind production below its optimum, which becomes more binding to the right. It is further distinguished between the case where the other non-wind capacities are fixed to their optimal base run values ("fixed cap") and the case where the other capacities can be freely adjusted in response to the wind production upper bound ("substitution").

Figure 10 Loss in wealth due to bounded wind production



In the fixed cap case, the losses in both markets are nearly the same and diverge only slightly at stricter bounds, but this is not important for the argument.[29] The main point is that when the other capacities can be freely adjusted or in other words, substitute the wind production, the loss in wealth is much lower in the CON market (substitution CON), but still high in the RES market (substitution RES). Hence, the substitution curve of the RES market is steeper than the one of the CON market. This means, forcing out the same amount of wind in both markets is more expensive in terms of wealth in the RES market when the wind production can be substituted by the other plants. If one relates this to the integration of the costs of risk in the model, one finds the reason for the stable production shares: Adding the same costs of risk to the investment costs of wind in both markets will decrease the wind production less in the RES market compared to the CON market. The reason is that substituting wind is more expensive in the RES market and hence needs higher additional costs of risk for the same reduction in production. To put in other words, the wealth in the RES market is more sensitive to the wind production compared to the CON market when the other capacities are endogenous. Therefore, higher costs of risks are needed to end up in the same decrease in the wind production. The same holds for the PV production in the RES market. Hence, the high costs of risk do not affect the production shares much in the RES market.

However, it remains the question why the wealth is more sensitive to the wind (and PV) production in the RES market. Potentially, this can be traced back to the difference in the cost structure of the plants: In the CON market coal is also profitable and thus present in the market, whereas coal is by far too expensive in the RES market and thus very high cost

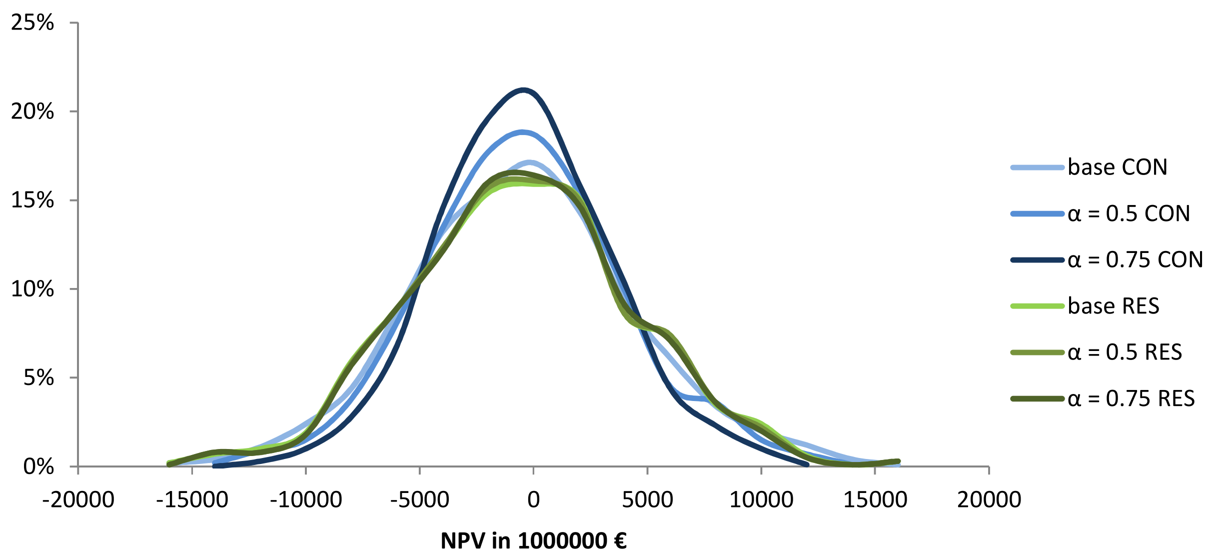
[29] The greater loss in the CON market at stricter bounds can be explained by the higher capacity factors in the CON market. Since the capacities of all other plants are fixed (and not their output) the CON capacities can substitute less wind production without expanding the capacities. Hence, the loss is lower in the RES market.

increases of the other plants would be needed for coal to come into the market. Coal has a more similar cost structure to wind than to CCGT. Coal has high fixed costs and low variable costs, though not that high fixed and not that low variables costs like wind. Important is that the difference in the cost structure between coal and wind compared to CCGT and wind is smaller. Moreover, in the RES market, which is defined through high CO_2 prices, the variable costs of CCGT are even higher such that the difference in the cost structure compared to wind further increases. This means in the CON market, wind has with coal an opponent technology, which is more similar to itself than the opponent in the RES market, which is CCGT. Therefore, coal and wind are in the following seen as better substitutes compared to wind and CCGT, which are denoted as better complements. Obviously are OCGT and wind even better complements (or worse substitutes). If this explanation is accepted, it can be seen why wealth is more sensitive to the wind production in the RES market than to the wealth of the CON market: Forcing out some wind production below its optimum is easier to substitute by coal in the CON market than by CCGT in the RES market, because CCGT is a compliment for wind. Clearly, this interpretation and the wording (substitute and complements) are rather vague and should be studied in more detail, but this is out of scope of this paper. However, since this helps to interpret and describe the results this explanation and wording is used in the following.

The fact that the wind and PV production decreases slightly more under portfolio compared to stand-alone risk (see above), though both renewables are very good hedges for both gas plants, can be explained as follows: Since there are only renewables and gas plants already in the base run, there are no further diversification potentials. Indeed, if the investor considers portfolio risk, the risk for the two gas plants decreases compared to the stand-alone risk, while it stays the same for the renewables: The portfolio optimization (see section 5.1.3) gives the 50 worst Monte Carlo runs of the 1000 (95% confidence level) in terms of NPV of the whole portfolio of the market. The renewables have by far the higher cost of risk and additionally a larger share in the production compared to the gas plants. Therefore, the 50 worst runs of the whole portfolio are identical with the 50 worst runs of the renewables. Due to the almost perfect negative correlation between the renewables and the gas plants, the gas plants have in these runs almost their 50 highest NPVs. This means that the risk contribution of the gas plants to the portfolio is positive (lowers the risk) and strongly negative for the renewables. While under stand-alone risk the renewable have the same costs of risk and the gas plants have also some costs of risk. Hence, the reduction of the renewables is higher under portfolio risk. Note that this is in line with the expectation about the portfolio optimization. However, the overall effect is rather small, due to the only slightly positive contribution of the gas plants to the portfolio risk and the above described bad substitution conditions.

Finally, observe that the electricity price increase is larger in the RES market compared to the CON market: For a risk aversion factor of two, the price rises about 3.56 €/MWh under stand-alone risk and about 3.22 €/MWh under portfolio risk in the RES market, which is 1.12 €/MWh more for stand-alone risk and 2.06 €/MWh for portfolio risk compared to the CON market. The higher price increase in the RES market reflects that the overall costs of risks for all capacities are higher than in the CON market. Thus, though the CVaRs for wind, CCGT and OCGT are lower per MW^N in the RES compared to the CON market (see section 5.2.2.1), the whole risk in the market is larger. The reason is the high share of risky wind and PV in the RES market, which replaces most of the coal production of the CON market. Note that the wind risk is with a CVaR of 250.26 t€ in the RES market still higher than the risk of coal with 223.01 t€ in the CON market. Together with the most risky technology PV the overall risk is higher in the RES market. This can also be seen in figure 11 which plots the portfolio NPV distributions of all capacities in the CON and RES market for different risk aversion factors when investors face portfolio risk.

Figure 11 NPV distribution of the whole portfolio under portfolio risk of scenario 1



The base distribution ($\alpha = 0$) is slightly broader for the RES compared to the CON market. When investors are risk averse and minimize portfolio risk, the CON distribution becomes tighter the higher the risk aversion gets: Plants with lower portfolio risk (CCGT, wind) replace plants with higher risk (coal) such that the overall risk decreases. In contrast, the integration of risk in the RES market does not change the distribution significantly. As described above, the production mix stays almost the same and thus, also the NPV distribution of the whole portfolio. The downside of the stable production share is that the costs of risk cannot be significantly reduced and nearly fully add up to the electricity price. Clearly, it is positive in terms of risk, that the renewables and the gas plants are very good hedges. However, although their shares are already high in the RES market when risk is not considered (base), the overall portfolio risk is slightly higher compared to the CON market. Moreover, this risk can be further reduced in the CON market, while in the RES market the risk reduction is more expansive in terms of wealth (as explained above). While more expansive means that a substantial reduction of the renewable share by increasing the gas share – which is obviously the only possible way to reduce the risk – is very costly, because the renewables and CCGT are bad substitutes. Thus, the complementarity of renewables and the gas plants makes it hard to lower the risk. To put in other words, a good substitute for renewables that profits are additionally not highly positive correlated with the renewables´ profits is missing to lower the risk substantially. At all, the overall risk is higher and can hardly be reduced in the RES market and hence, the electricity price raises more compared to the CON market.

5.2.3.2 Scenario 3: Renewable Availability Risk

This subsection deals with the results of the risk integration in the investment decisions for the renewable availability risk. In the following table the correlation matrix is presented.

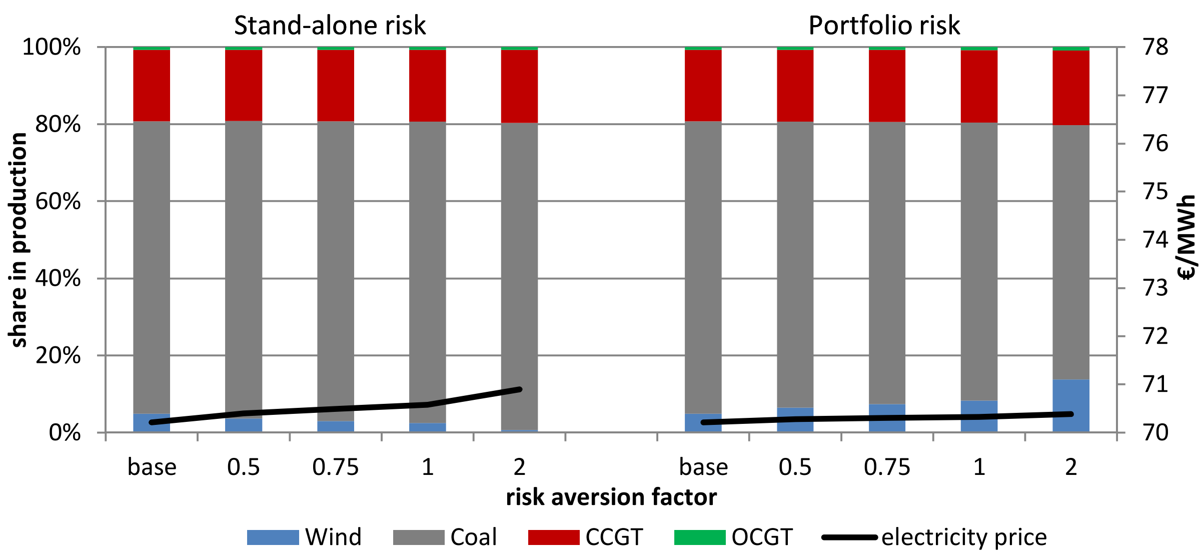
Table 6 Correlation matrix of scenario 3

	CON market				RES market			
	Wind	Coal	CCGT	OCGT	Wind	PV	CCGT	OCGT
Wind	1				1			
PV	-	-	-	-	0.877	1		
Coal	-0.993	1			-	-	-	-
CCGT	-0.992	0.999	1		0.855	0.907	1	
OCGT	-0.996	0.999	0.999	1	0.832	0.897	0.999	1

Like in the first scenario, the coefficients for wind and the two gas plants are near to minus one in the CON market, which means they are almost perfect hedges. A major difference to the first scenario is that wind and coal are with a coefficient of -0.993 also very good hedges. As described in section 5.2.2.3, wind makes more profits with higher availabilities in the CON market, while at the same time all fossil plants make less profits and vice versa. Therefore, all fossil plants make more or less profits under the same conditions and have correlation coefficients with each other of almost one. The coefficients for wind in the RES market change dramatically: Now higher wind availability means fewer profits for all plants, which can be traced back to the strong price effect of the wind production. But wind makes also losses compared to the RES base run if its availability is very low. Thus, wind has strongly but not perfectly positive correlation coefficients with the other plants. The correlation between PV and the gas plants is even stronger, because it makes more profits like the gas plants if the wind availability is low, while its own availability is compared to the wind availability only of minor importance. It follows that both renewables are bad hedges for both gas plants in the RES market. Intuitively, the correlation between CCGT and OCGT is again almost perfectly positive in both markets.

Next consider the impact of the risk incorporation in model on the shares in production and the electricity price in figure 12

Figure 12 Results of the risk integration in the CON market of scenario 3



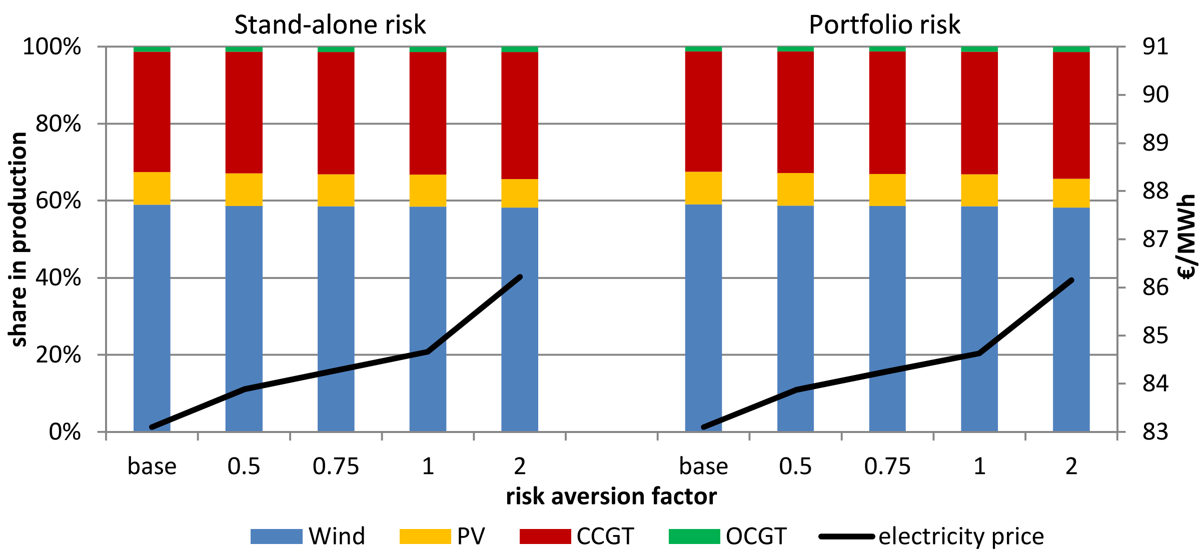
Under stand-alone risk, the wind share slightly decreases until it is nearly vanished with a risk aversion factor of two, because wind is the only technology with a substantial risk. Interestingly, it is mainly replaced by coal which is contributed to the better substitution conditions between coal and wind compared to wind and CCGT (see previous section). Hence, the shares of CCGT and OCGT remain approximately at their initial base values.

As in the first scenario, the wind production share raises when the investors consider portfolio instead of stand-alone risk, here even up to 13.8% ($\alpha = 2$). Wind replaces mostly coal which share drops down by ten percentage points to 66% for a risk aversion factor of two. The reason is the very good hedging possibility between coal and wind. Note that this also holds for CCGT and wind, but coal is compared to CCGT the better substitute for wind. Thus, coal replaces wind when wind becomes relatively more expansive (stand-alone risk) and wind replaces coal when wind becomes relatively less expansive (portfolio risk).

The electricity price increases only very slightly due to the risk integration by a maximum of 0.68 €/MWh ($\alpha = 2$), because only wind is directly affected by the availability risk, while the other plants are indirectly affected via the electricity price and the production volume. However, the wind share in the total production is low, thus there are only little price and volume effects for the fossil plants. It follows that the overall risk in the CON market is low and hence, the price increases only slightly. Under portfolio risk the price increase is even lower, since the investors diversify some risk away.

Figure 13 depicts the results for the risk integration in the model.

Figure 13 Results of the risk integration in the RES market of scenario 3



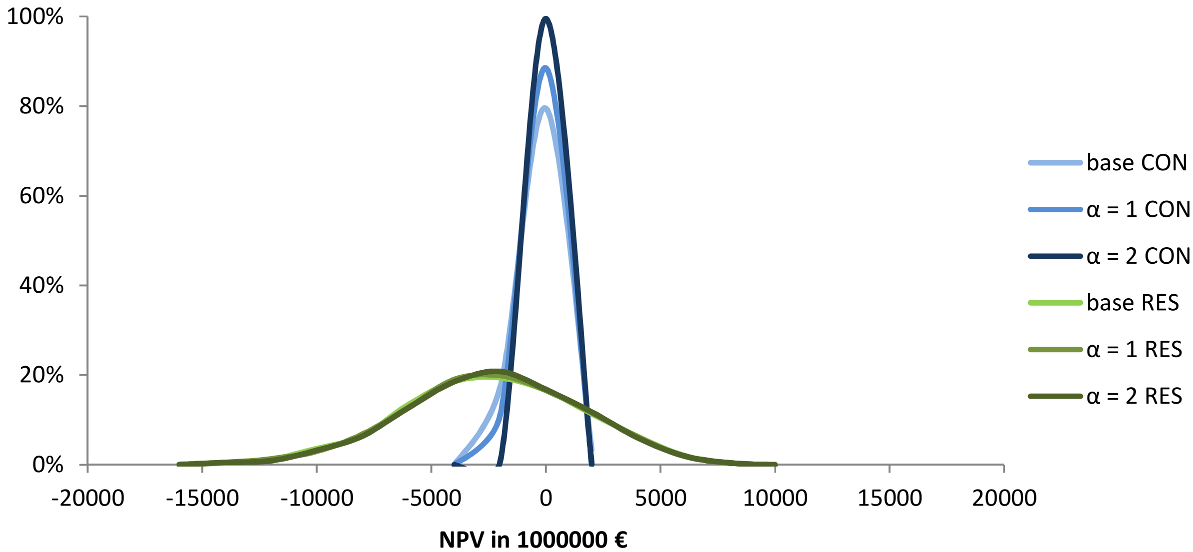
Similar to the first scenario there are only little impacts on the production shares. If the investment decisions contain stand-alone risk, the wind share decreases up to 0.8 percentage points for a risk aversion factor of two compared to the base run. The PV share drops for the same risk aversion a bit more by 1.1 percentage points, because the CVaR of PV is approximately by a factor of two larger compared to the CVaR of wind. The lower renewable shares are again mainly replaced by CCGT, which share raises by 1.8 percentage points for a risk aversion of two. The reason for this negligible impact can, like in the first scenario, mostly be contributed to the bad substitution possibilities: CCGT and especially OCGT are good complements of the renewables, while coal as a better substitute, is too expansive in the RES market and thus no option. Another reason is the lower difference between the risks of the technologies compared to the first scenario. CCGT and OCGT have more risk, and wind less risk compared to the first scenario, which makes their costs of risk more similar and thus its influence on the production shares.

Under portfolio risk, the shares in the production are almost exactly the same as under stand-alone risk, which means there is no significant incentive to decrease the renewable shares compared to stand-alone risk, which is opposed to the first scenario (see previous section). At a first sight, this might be counterintuitive: In the first scenario, the renewables and the gas plants are very good hedges but in this scenario not. Nevertheless, there is a stronger incentive to decrease the renewable shares more in the first scenario under portfolio risk compared to stand-alone risk than in this scenario. The reason is that in the first scenario the gas plants reduce the portfolio risk, while they add risk to the portfolio in this scenario. This follows from the strong positive correlation between the renewables and the gas plants: In the first scenario, CCGT and OCGT make profits in the 50 worst Monte Carlo runs, but in this scenario they also make losses like the renewables, because the renewables and gas plants are strongly positive correlated. Thus, there is no further significant incentive to decrease the renewable shares beyond the reduction under stand-alone risk when portfolio risk is considered. However, again it has to be mentioned that the incentive to reduce renewables more under portfolio risk has only a little impact, also in the first scenario, because of the bad substitution possibilities.

Consequently, the increase of the electricity price is very similar under stand-alone and portfolio risk. The maximum price increase compared to the base run for a risk aversion factor of two is by about 3.10 €/MWh for both stand-alone and portfolio risk. With this, the price raises up to 2.40 €/MWh more compared to the CON market, which indicates the overall higher risk in the RES market. Clearly, the overall greater risk in the RES market can be explained by the fact that the shares in the production of wind and PV, which bring the availability risk into the market, are much higher.

The overall higher risk in the RES market can also be seen in figure 14, which shows again the NPV distribution of all capacities in the CON and RES market for the base runs and when investors consider portfolio risk. Note that opposed to the figure for the first scenario, higher risk aversion factors are chosen to make the effects more visible.

Figure 14 NPV distribution of the whole portfolio under portfolio risk of scenario 3



Obviously, the overall risk is much lower in the CON market in all scenarios, indicated by the broader NPV distributions in the RES market. The fact that all three distributions of the RES market are located almost one above the other reflects the bad diversification possibilities. In contrast, the risk in the CON market is reduced a bit by diversification, such that the NPV distributions become tighter the higher the risk aversion gets. Note that all and especially the RES market curves have a negative mean due to the negative mean of the renewable capacities (see section 5.2.2.3).

6 Discussion and Implications

In this chapter, the main findings of the numerical analyses are summarized and discussed in the context of the related literature. Moreover, implications for the design of future renewable dominated electricity markets are discussed.

The stand-alone risk analysis of the second stage confirms the findings of Roques et al. (2008) and Lynch et al. (2013) that gas is related to its variable costs self-hedged: Gas plants are often the price-setting plants, which is also the case in many real markets. Hence, they can often transfer higher variable costs directly to the consumers via the electricity price, and are compared to the other plant types less risky. This has also implications for the other plants: When the volatile gas price is transferred to the electricity price, the profits of plants that are also producing in these times are directly affected by this volatility. Consequently, the model approves that plants with low variable costs and high fixed costs (left in the merit-order) are exposed to strong electricity price risks (e.g. Gross et al. 2010; Finon 2012). This mainly explains the high stand-alone investment risks of coal and especially renewables found in the analysis.

Another observation is the higher investment risk for PV compared to wind in all scenarios. This can be traced back to the timing of the production: PV produces, compared to wind, a higher share of its production during the day when prices are high. In these times the price risk is higher in the model. However, this also holds for many real electricity markets: The merit-order becomes steeper to the right which indicates increasing short-run marginal costs (see e.g. Cludius et al. 2014 for a stylized German merit-order). These steep parts of the merit-order contain a higher price risk than flatter parts mainly for two reasons: The same shifts in the residual demand trigger larger price changes and most of the plants of the steep parts have low conversion efficiencies which also trigger large price effects due to variable cost fluctuations. In the model, this is represented by a higher step between the variable costs of OCGT and CCGT compared to coal and CCGT (steeper to the right) and by the worse conversion efficiency of OCGT compared to CCGT, which have the same variable cost risk factors. Since PV produces relative more compared to wind in these steep merit-order parts, it is more risky. Moreover, PV has similar hedging opportunities as wind and thus no further portfolio advantages. Therefore, PV is in terms of risk less favorable than wind.[30]

Although PV has a lower volume risk as wind, since the annual average availability of PV has an assumed standard deviation of 3% and wind 6%, the higher investment risk for PV also holds when renewable availability risks are analyzed. The reason why wind is also under these conditions less risky lies mainly in the strong price effect of the wind availability, which leads to compensation effects: The negative price effects on the wind profits triggered by high availability years are at least partly compensated by positive volume effects and vice versa. This can be seen in analogy to gas, where the negative effects of high variable costs years on the gas profits are partly compensated by positive price effects. Hence, this analysis shows that wind is also partly self-hedged, because its volume and price effects go always in diametrical directions (ceteris paribus).[31] It is further shown that the negative price effect in high availability years increases with the wind share such that it dominates the positive (and for wind almost stable) volume effect at some threshold, and is indeed larger in the here analyzed RES market.

[30] This is not necessary the case, because it depends on the actual conditions. If, for example, the annual wind and PV availabilities are strongly negatively correlated in some market, the hedging possibilities change.

[31] Clearly, the same principle could also be applied to other fluctuating renewables like PV. However, wind is probably the most important fluctuating renewable technology in potential renewable dominated electricity markets of the future, at least in Europe.

The described compensation effect is also found by Nagl (2013), though he does not term it self-hedge.[32] Moreover, he finds that the negative price effect in high availability years increases with the steepness of the merit-order. The reasoning behind this is the same as described above for a change in the residual demand in steep merit-order areas. Following Kopp et al. (2012), the merit-order becomes steeper with higher shares of renewable energies, because the need for flexibility increases. Additionally, the capacity factors of the fossil plants are likely to decrease. For these reasons, flexible low fix and high variable costs plants become more important, leading potentially to a steeper merit-order, and thus to more price risks triggered by fluctuating renewable energies. Therefore, the price effect not only increases with the wind share itself, but probably also by a steeper merit-order if the renewable share grows. Consequently, the degree of the wind self-hedge depends on its own share and on the steepness of the merit-order.

One limitation for the generality of the wind self-hedge might be that there is only one wind site in the model whereas in reality there are different wind sites within one electricity price region. Since high wind availability in one site means not necessary that the same is true for the other sites, low volumes and prices can emerge at the same time in one site such that there is no self-hedge. However, it is likely that there is a high correlation between the sites of one price zone. Moreover, investors have an incentive to diversify their wind portfolios regarding different availabilities at different sites, because with this they can lower their revenue risk as shown by Green & Vasilakos (2010). This means they invest in different plant sites, which availabilities are not perfectly correlated and thus can be used as hedges (Roques et al. 2010; Hiroux & Saguan 2010). In this sense, a perfectly diversified investor has wind farms at all relevant sites, which justifies the fact that there is only one site in the model. Hence, the wind self-hedge also lowers the wind investment risk in real electricity markets if one assumes rational well diversified investors.

A further outcome of the variable cost and demand risk scenario of the second stage is the lower investment risk for both gas plants in the RES market compared to the CON market. In the model context, this result can be contributed to the lower number of scarcity hours in the RES market. Since in these hours the effect of the variable costs and demand risks on the gas profits is very high, but the magnitude of the effect is per hour the same in both markets, the investment risks are higher with more scarcity hours (CON market). Although this finding is correct, the main risk of scarcity hours is not included in the model: There is only one demand

[32] In contrast to this paper, he analyses the compensation effect within a fixed bonus and quota support scheme (see section 2). However, the principle of the negative correlation between volumes and electricity prices is the same.

profile in the model which is scaled up and down to represent risk. This modelling leads to a relative low risk due to scarcity prices, because they occur with certainty in every year, while only their number and height is risky. A more realistic approach is to model different demand profiles. With this their number and height varies significantly more by year. It is even possible that they do not occur for years (Pyory 2009). Under this more realistic demand risk, a scarcity hour pattern with an expected higher number and lower prices per year, as in the CON market, is general seen as less risky (e.g. Stoft 2002; Winkler & Altmann 2012). Hence, the demand risk leads potentially to higher investment risks for the gas plants in the RES market and the above described finding might be misleading.

In contrast, in the renewable availability scenario the volume and price risks of the gas plants increase significantly with the renewable share, leading to a higher investment risk for CCGT and OCGT. This is in line with the model results of Poyry (2009) and Redpoint (2009) for Great Britain. Due to the (interannual) variable production of the renewables, the number and height of scarcity hours becomes less predictable in renewable dominated markets. Especially investments in peaker plants (OCGT) that only make short-run profits in scarcity times could be deterred under such conditions. Therefore, the findings indicate the higher need for capacity mechanisms in renewable dominated markets, because these can lower the investment risks (cp. Steggals et al 2011). For example, the widely discussed capacity market of Cramton & Ockenfels (2012) transfers the risky scarcity rents into safer capacity payments. However, the basic economic reasoning of capacity markets is a market failure regarding the flawed short-term demand elasticity: When capacity is scarce, consumers do not lower their demand accordingly, which leads to involuntary black-outs. In this sense, high investment risks alone do not justify the introduction of capacity markets (cp. Joskow 2006). Before such a wide market design extension should be implemented, it must be ensured that the demand elasticity is indeed insufficient in the long-term. In the case of sufficient demand elasticity also the potential problem with high investment risks for peakers might be alleviated (Steggals et al. 2011; Green & Vasilakos 2011): Firstly, the need for peak capacities would decrease to achieve an adequate level of reliability, since the demand response would “replace” some peakers. Additionally, a more price elastic demand leads to lower and more scarcity prices. Hence, the prices would be smoother and the investment risks lower (see above). However, even with a sufficient demand elasticity it is not ensured that the market results are not distorted: Rodilla & Batlle (2012) point out that although consumers (i.e. mostly retailers) have incentives to sign long-term contracts to hedge risks, this does not happen up to today in real markets in a sufficient manner. Consequently, the risk allocation is distorted, leading to too much investment risks for electricity producers. Thus, investment decisions might be distorted, with, for example, the consequence of potential investment cycles, which danger the security of supply (see also Arango & Larsen 2011). If investment risks of especially peaker plants further increase in renewable dominated markets, and the risk allocation and the demand elasticity do not improve, a capacity market might be a proper solution. However, these points must be further analyzed in future research.

The results of the third stage show the strong influence of the gas self-hedge. CCGT relatively gains to coal and hence is much more expanded when risk is considered. This is one reason why CCGT plants are expected to be mainly built in the next years, for example in Great Britain (cp. Steggals et al. 2011). Furthermore, the returns of CCGT are strongly negatively correlated with wind returns. Hence, they are very good hedges (cp. Bolinger 2013). This partly explains the strong wind expansion in gas dominated electricity markets like in Texas. However, due to the increasing price effect of the fluctuating wind production the hedging possibilities decrease with higher wind shares as indicated by the RES market correlation matrix for the third scenario. Thus, the incentives for firms with high gas shares in their portfolio to invest also in wind (and PV) decrease with the wind share in the total production. Moreover, even if the good hedging possibilities remain in renewable dominated markets, firms that consider portfolio risk have an incentive to lower their renewables shares compared to a riskless project evaluation. The reason is that renewables are on a stand-alone basis more risky than gas plants and contribute at high renewable shares in the portfolio also more risk to the portfolio.

Moreover, the third stage results indicate that the overall investment risks for the whole RES market are higher compared to the CON market. This, additionally with the high investment risks for renewable plants, has further implications for another market design extension: Some researchers, for example Steggals et al. (2011), Kopp et al. (2012), Winkler & Altmann (2012), discuss if energy-only markets are in general suitable to refinance the costs of renewable energies. One main argument of them is that renewables "cannibalise" (Steggals et al. 2011:1393) their own economics. This means with higher shares of fluctuating renewables, with zero variable costs, the price depress the more they produce. Therefore, Kopp et al. conclude that intermittent renewables "cannot be financed through power markets alone" (2012:243) and see a need for an instrument to finance renewables. But they draw their conclusion on the basis of an optimization model where renewables are exogenous. Hence, the costs of the renewables are not part of the optimization and it is arbitrary if renewables make profits or losses, or in other words, it depends on the assumed parameters (mainly the CO_2 price). In the here used model, renewables are endogenously expanded and consequently make zero profits like the other plant types. It is shown that if renewables are market based expanded, which means here via a high CO2 price, the long-term electricity price increases, which Kopp et al. (2012) do not fully account for.

The cannibalization effect is also found in this analysis, since it is the price effect leading to the described wind self-hedge. Thus, this analysis shows that the short-run price depressing effect is not necessary a problem for renewable energies. In fact it depends on how strong the price effect is (cp. Nagl 2013). Nevertheless, the price effect increases with the share of renewables and additionally the merit-order is likely to become steeper (see above). Besides other reasons, this might be indeed a problem for integrating renewables in the energy-only market. However, the problem does not arise per se out of the zero variable costs of renewables, but out of the related high investment risks:

The argument given above, that the risk allocation might be distorted, is especially relevant for capital intensive plant types like renewables. If capital intensive plants cannot hedge their investment risk in a sufficient manner, there might be socially suboptimal investments in them, which is shown by e.g. Awerbuch & Spencer (2007), Roques et al. (2008) and Ehrenmann & Smeers (2011), while it is analytically proven by Meunier (2013). They further point out, like also shown in this paper, that instead low capital and high variable costs are more expanded, in particular gas plants due to their self-hedged. This might be in fact inefficient, since with more capital intensive plants the electricity price might be lower and additionally gas plants bring risk into the market through their highly volatile fuel price (Awerbuch & Spencer 2007). Hence, if the risk allocation is indeed flawed due to the absence of, for example, sufficient long-term contracts, this might be a case for a market design extension (see above). Especially for renewables with their unpredictable production it is questionable if they can participate in forward markets to hedge their risks. They are additionally likely to be the most risky plant types, as indicated by this analysis, and hence mostly be affected by a lack of hedging possibilities. If the above mentioned capacity market is also a proper instrument to reduce the risks for renewables is questionable. Due to their uncertain production they cannot contribute in a similar manner to the reliability, and hence would gain less from a capacity market (Cramton & Ockenfels 2012). Therefore, another instrument that stabilizes the revenues for renewables might be necessary. In the literature, different instruments like quota systems and tenders are discussed (e.g. Winkler & Altmann 2012; Klessmann et al. 2013). It is also possible that the current emission trading scheme of the European Union alone is sufficient to finance high shares of renewable energies. In particular if better hedging instruments for renewables in the forward market are developed. Even without hedging possibilities, this analysis showed that the renewable share is rather stable under a CO_2 price regime when risk is integrated in the model. However, this result must be treated with caution, because a simple model framework is used. Moreover, the investment risks of renewables might be much higher in reality, since there are more risk factors and the magnitude of the modelled factors can be higher. Especially the CO_2 price itself is rather stable in the model. Clearly, this is a basic condition for an effective CO_2 price in the long-term, but in fact not realized today.

7 Conclusions

The main research interest of this paper is to analyze the investment risks in an electricity market dominated by renewable energies and compare them to the investment risks of a market with high shares of fossil fuel plants. For this purpose, a three stage process is applied: In the first stage, the optimal capacities for given expectations about risk factors are calculated for a risk neutral investor by using an investment and dispatch model. In the second stage, these capacities are fixed and the model is used in a Monte Carlo simulation where the risk factors attain different values in every modelled year. This results in NPV distributions and related risk measure values (CVaR) for each plant type. By assuming a utility function for a representative investor, the CVaRs are evaluated as costs of risks and integrated in the investment and dispatch model. In order to show diversification incentives, it is distinguished between a risk evaluation on a stand-alone and on a portfolio basis.

The model outcomes show that wind and especially PV are compared to the fossil plant types more risky on a stand-alone basis. In particular the gas plants are by far less risky, because they are self-hedged. Moreover, renewables and gas plants are very good hedges such that wind capacities are added to gas dominated portfolios above their deterministic share to lower the portfolio risk. But with increasing wind shares in the total production the hedging possibilities become worse, since the negative price effect of high wind availabilities affects the profits of gas and wind negatively at the same time. However, the renewables are also with good hedging conditions unfavorable in terms of risks compared to gas in a pure market setting. If this leads to suboptimal renewable investments, since other hedging possibilities are in many electricity markets flawed, this has important policy implications. An additionally financing mechanism like tenders or quota systems might be a proper option to de-risk the renewables in this case.

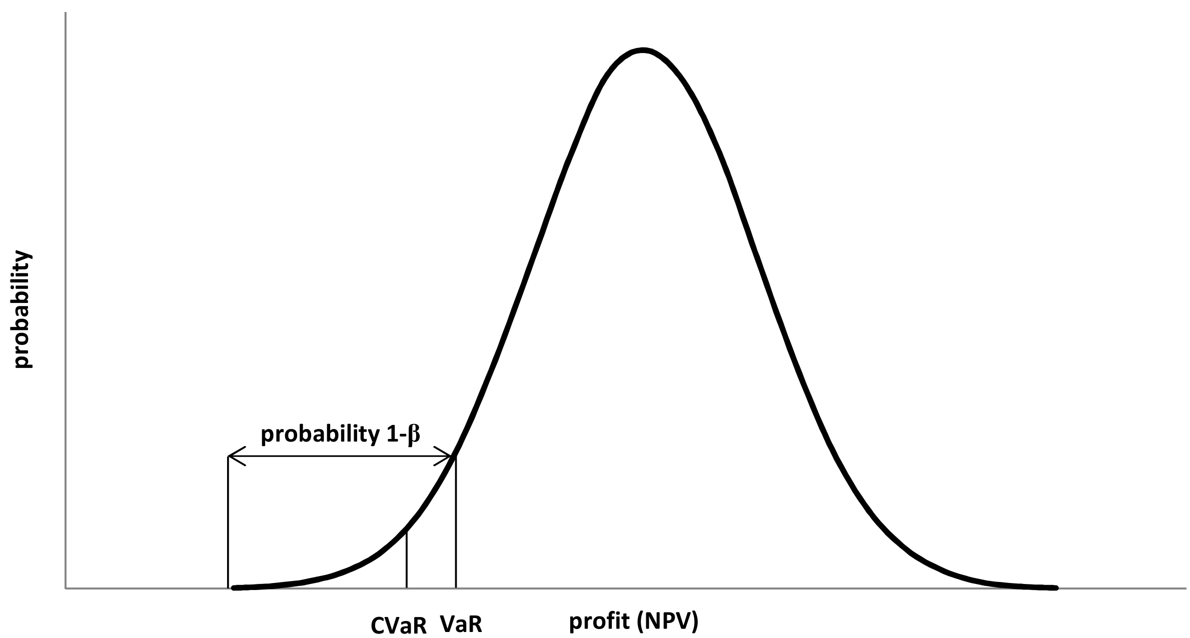
Another significant finding is the increase of the price and residual demand volatility in the renewable dominated market due to the variable production volumes. This is especially for peaker plants in combination with the at all lower number of scarcity hours in the renewable market problematic, since their investment risk further increase. Again, the current imperfect hedging possibilities and additionally the lack of demand elasticity can lead distorted investment incentives and thus blackouts can emerge. Currently discussed capacity mechanisms might be a useful market design extension.

However, if indeed new market design elements are necessary, further research is needed. Important open questions are, for example, to what degree renewables can participate in long-term markets to hedge their risks. In the case if they cannot participate sufficiently, might it be more efficient to spread some of their risks on the consumers? A further interesting question in this regard is if the risk spreading of a capacity market, designed for ensuring long-term security of supply, decreases also the investment risks for renewables or if they do not profit significantly from it due to their unpredictable production.

8 Appendix

8.1 Conditional Value at Risk

Figure 15 VaR and CVaR



Source: Based on Fagiani et al. (2013:653)

8.2 Model Data

Table 7 Model data

	Wind	PV	Coal	CCGT	OCGT
Investment costs (€/MW)	1050000	900000	1250000	880000	600000
O&M costs (€/MW_{yr})	44000	12000	36000	22000	12000
Construction time (yr)	2	1.5	3.5	2.5	2
CO_2 intensity (t/MWh_{th})	0	0	0.33	0.21	0.21
Conversion efficiency (%)	100	100	48	58	40
Availability (%)	$E[25]$	$E[13.5]$	85	85	85

8.3 Risk Factors

Table 8 Risk factor properties

	Volatility σ	Mean rev. rate θ	Min	Max
Coal price	0.15	5	9.62 €/MWh_{th}	14.23 €/MWh_{th}
Gas price	0.25	5	17.18 €/MWh_{th}	35.38 €/MWh_{th}
CO_2 price CON	0.25	5	20.66 €/t	42.77 €/t
Demand	0.06	5	92.1%	108.5%

8.4 Further Explanations for the Second Stage

8.4.1 Scenario 1: Gas Price Effects

Figure 16 Effect of a gas price decrease when OCGT sets the price

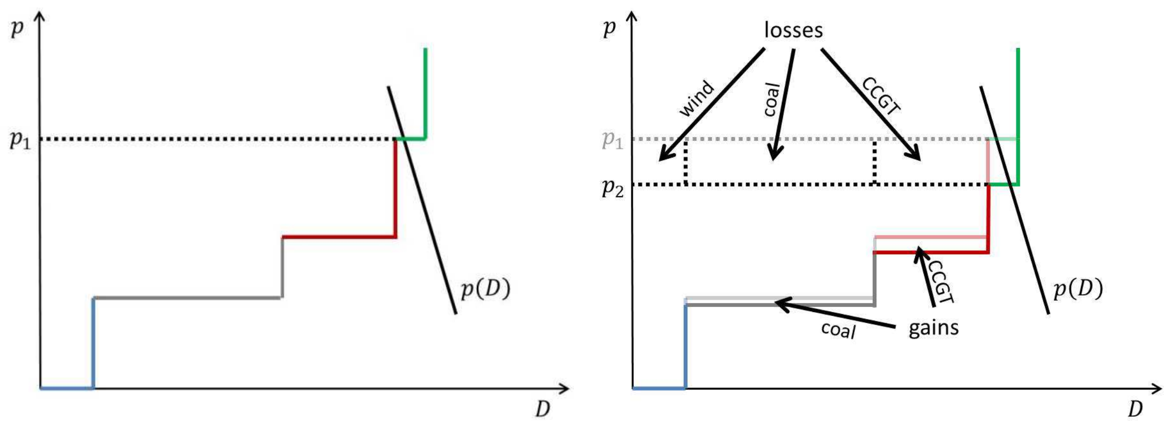
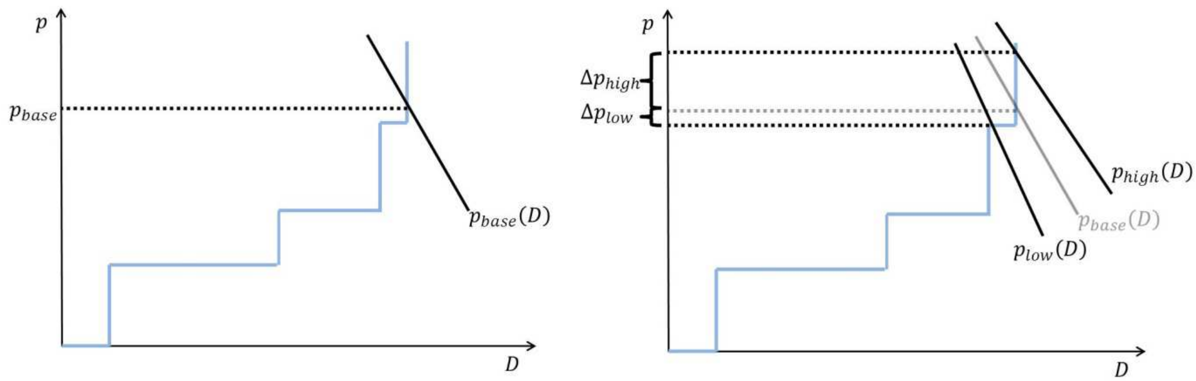


Figure 16 depicts typical effects of a gas price decreases, here for the CON market. Note that the actual proportions given in the model differ from this stylized figure. The different colored parts of the merit-order indicate the different plant types, where the assignment is the same as in the whole paper. The left hand merit-order shows the equilibrium before the fall of the gas price (i.e. for the base run) with the electricity price p_1. The right hand merit-order depicts the equilibrium with the gas price decrease, where the light lines are the same as in the left hand merit order. Since OCGT sets the price in both situations, it makes no gains or losses compared to the base case: The price decreases to p_2, which is exactly the variable cost of OCGT. Wind, coal and CCGT receive a lower price for the same produced electricity and thus make lesser revenues (losses in the figure). Mind that though the three loss areas have different sizes, the losses for coal and CCGT are exactly the same, because I compare plants of equal size given by MW^N. Given the same plant size, coal and CCGT lose both $(p_1 - p_2) * MW^N$, because they are fully utilized. Wind might loss more or less, but if one assumes that this is an average availability hour wind produces also MW^N and loses the same amount as coal and CCGT. However, CCGT and coal have a counter effect (gains in the figure): CCGT is a gas plant and hence its variable costs also decreases, but less than the variable costs of OCGT, because CCGT has a higher conversion efficiency. Due to the correlation of the coal and gas price of 0.7, it is likely that also the coal price decreases, which leads to the coal gains. In the figure, both coal and CCGT make net losses, because their revenue losses are greater than their variable costs savings (gains). The wind net losses are higher because it has no counter effect.

Note that there are many years in which the variable costs of coal increase more than those of the gas plants or even increase when the variable costs of the gas plants decrease. The reason is that the gas and coal prices are not perfectly positive correlated and the CO_2-price, which also enters the variable costs, hits the variable costs of coal more than those of the gas plants due to the higher carbon intensity of the former. In such years when a gas plant sets the price, coal has higher net losses compared to wind. However, the main reason why wind is more risky than coal is that there are also many hours in which coal sets the price (see price duration curves in section 5.2.1 in figure 3). Clearly, in such situations a change in the variable costs only affects the profits of wind.

8.4.2 Scenario 2: Demand Effects

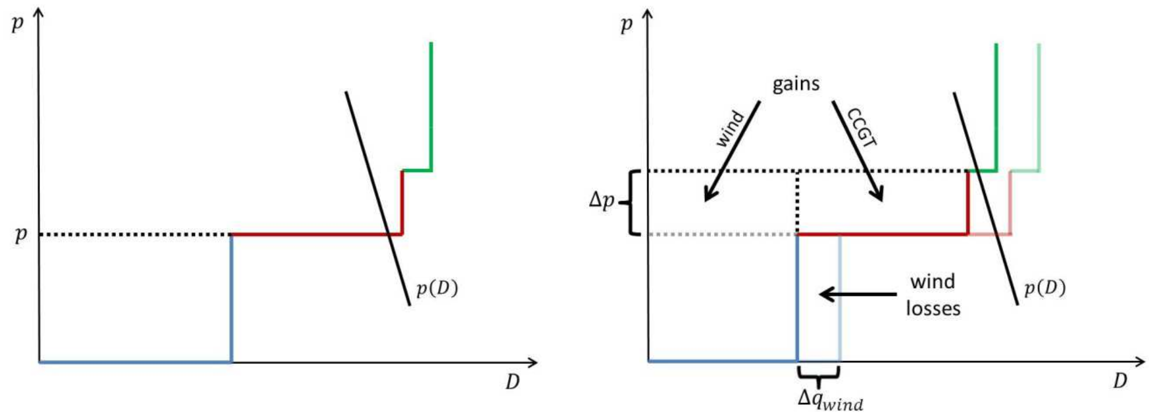
Figure 17 Effect of a change in demand in scarcity hours



The left side of figure 17 shows the merit-order in a typical scarcity hour in the CON market with price p_{base}. The right side depicts the price effects of a demand increase ("high") and decrease ("low") of the same magnitude. Note that the slope of the inverse demand function $p(D)$ also slightly changes due to the change of the parameter b. But this has only minor effects and is not further discussed. Obviously, the price difference to the base or expected demand is higher if the demand increases, which means $\Delta p_{\text{high}} > \Delta p_{low}$. The reason is that the price decrease in the case of the lower demand is bounded by the variable costs of OCGT, while the price increase is not. Clearly, this does not hold for all scarcity hours, because if the expected base price is very high or if the change in demand is low, the bound is not reached. However, this effect causes, ceteris paribus, slightly positive expected NPVs.

8.4.3 Scenario 3: Renewable Availability Effects

Figure 18 Effect of a lower renewable availability



The left part of figure 18 shows the merit order in an hour of CCGT price setting in the RES market (base run). The right part depicts the same hour with a lower than expected wind availability, where the light lines indicate the merit-order with the availability as expected (such as in the left part). PV is for simplicity neglected. The lower wind availability shifts the merit-order to the left, such that no longer CCGT sets the price (left part), but OCGT (right part). The positive price effect of the lower availability is therefore Δp for wind and CCGT. Furthermore, as a consequence of the lower availability, wind sells of course less electricity indicated by Δq_{wind}. CCGT produces more electricity, because it is fully utilized with the lower wind availability, while it was not in the left merit-order. It follows that CCGT only has gains (higher price for more electricity) and wind has a positive and a negative effect on the profits (higher price for less electricity). Obviously, OCGT also produces more electricity due to the lower wind availability. However, OCGT makes no profits, since it sells its electricity exactly to it short-run marginal costs (variable costs).

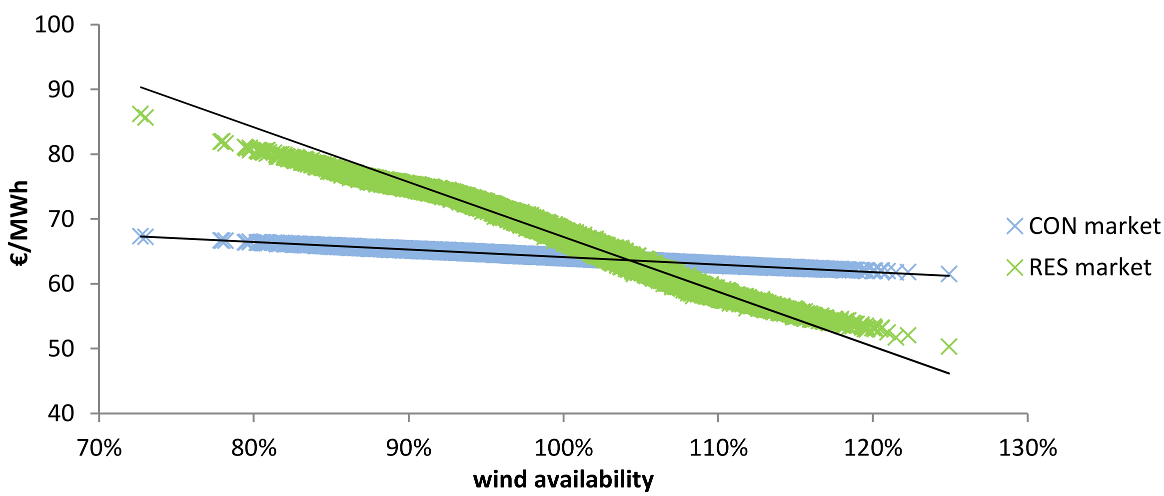
One could easily imagine an hour where a deviation in the renewable availability does not lead to a change in price. In such hours, only the renewables with the lower (higher) availability make losses (gains) compared to the expectation, because they sell less (more) for the same price. For all other plants, the profits are not affected: Either they are still fully utilized if they are not price setting or they produce more/less but sell electricity at their variable costs. However, over the entire year both effects (price and volume risk) emerge for all plants.

8.4.4 Scenario 3: More Data and Illustrations

Table 9 Price and volume risks of scenario 3

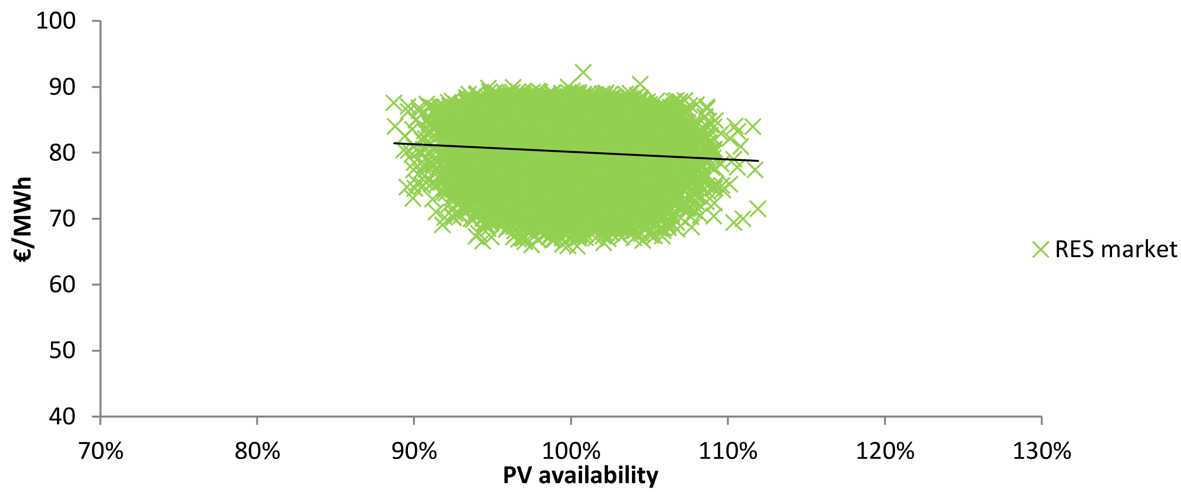
Standard deviations	Average price (€/MWh)		Capacity factor (percentage points)	
	CON	RES	CON	RES
Wind	0.71	5.15	1.51	1.16
PV	-	4.41	-	0.43
Coal	0.57	-	0.06	-
CCGT	0.68	1.31	0.42	3.06
OCGT	0.42	3.70	0.37	1.08

Figure 19 Relationship between wind availability and average electricity price of wind



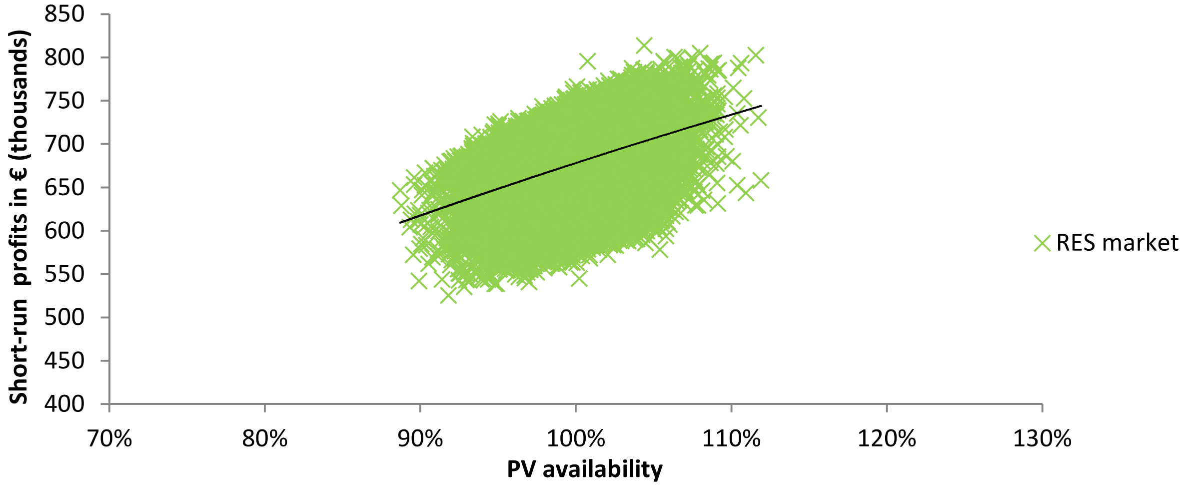
The figure plots the annual output weighted average price of wind of all runs against the wind availability for the CON and RES market. In both markets, the prices decrease with higher wind availabilities, but the effect is stronger in the RES market.

Figure 20 Relationship between PV availability and average electricity price of PV



The figure plots the annual output weighted average price of PV of all runs against the PV availability for the RES market. A higher PV availability comes with a slightly lower electricity price. However, the relationship is weaker and the dispersion is much greater compared to wind in figure 19. This reflects the much stronger impact of the wind availability on the electricity price compared to the impact of the PV availability.

Figure 21 Relationship between PV availability and short-run profits of PV



The figure plots the undiscounted annual PV short-run profits of all runs against the PV availability. The trend line indicates the relationship between the PV availability and the short-run profits. Note that the line is not linear, since the slope decreases slightly with the availability. The overall short-run dispersion is significantly higher in the RES market due to the impact.

9 References

Arango, S. & E. Larsen (2011): Cycles in Deregulated Electricity Markets: Empirical Evidence from two Decades. Energy Policy 39: 2457-2466.

Arnesano, M., Carlucci, A. & D. Laforgia (2012): Extension of Portfolio Theory Application to Energy Planning Problem - The Italian Case. Energy 39: 112-124.

Artzner, P., Delbaen, F., Eber, J.-M., & D. Heath (1999): Coherent measures of risk. Mathematical Finance 9, 203-228.

Awerbuch, S. (2000): Investing in photovoltaics: risk, accounting and the value of new technology. Energy Policy 28: 1023-1035.

Awerbuch, S. & Y. Spencer (2007): Efficient Electricity Generation Portfolios for Europe: Maximising Energy Security and Climate Change Mitigation. EIB Papers 12.

Bar-Lev, D. & S. Katz (1976): A portfolio approach to fossil fuel procurement in the electric utility industry. Journal of Finance 31: 933-947.

Bhattacharya, A. & S. Kojima (2012): Power Sector Investment Risk and Renewable Energy: A Japanese Case Study using Portfolio Risk Optimization Method. Energy Policy 40: 69-80.

Blanco, C. & D. Soronow (2001): Mean Reverting Processes - Energy Price Processes used for Derivatives Pricing & Risk Management. Commodities Now: 68-72.

Blyth, W. (2008): Use of Real Options as a Policy-Analysis Tool. In: Bazilian, M. & F. Roques: Analytical Methods for Energy Diversity and Security. Elsevier.

Bolinger, M. (2013): Revisiting the Long-Term Hedge Value of Wind Power in an Era of Low Natural Gas Prices. Working Paper.

Brigham, E. & P. Daves (2007): Intermediate Financial Management. Thomson/South-Western. Ninth Edition.

Brigham, E. & J. Houston (2009): Fundamentals of Financial Management. South-Western. Twelfth Edition.

Bushnell, J. (2011): Building Blocks: Investment in Renewable and Nonrenewable Technologies. EUI working paper, RSCAS 2011/53.

Cochran, J., Bird, L., Heeter, J. & D. Arent (2012): Integrating Variable Renewable Energy in Electric Power Markets: Best Practices from International Experience.

Conejo, A., Carrión, M. & J. Morales (2010): Decision Making Under Uncertainty in Electricity Markets. Springer.

Cramton, P. & A. Ockenfels (2012): Economics and Design of Capacity Markets for the Power Sector. Zeitschrift für Energiewirtschaft 36: 113-134.

Delarue, E., Jonghe, C., De Belmans, R. & W. D´haeseleer (2011): Applying Portfolio Theory to the Electricity Sector: Energy versus Power. Energy Economics 33: 12-23.

Dixit, A. & R. Pindyck (1994): Investment under Uncertainty. Princeton University Press.

Ehrenmann, A. & Y. Smeers (2011): Generation Capacity Expansion in a Risky Environment: A Stochastic Equilibrium Analysis. Operations Research 59: 1332-1346.

Fagiani, R., Barquin, J. & R. Hakvoort (2013): Risk-based Assessment of the Cost-Efficiency and the Effectivity of Renewable Energy Support Schemes: Certificate Markets versus Feed-in Tariffs. Energy Policy 55: 648-661.

Finon, D. (2012): Institutions and Electricity Systems Transition towards Decarbonisation - The Hidden Change of the Market Regime. Working Paper No. 38-2012.

Fortin, I., Fuss, S., Hlouskova, J., Khabarov, N., Obersteiner, M. & J. Szolgayova (2008): An Integrated CVaR and Real Options Approach to Investments in the Energy Sector. The Journal of Energy Markets 1: 1-25.

Fuss, S., Szolgayova, J., Khabarov, N. & M. Obersteiner (2012): Renewables and Climate Change Mitigation: Irreversible Energy Investment under Uncertainty and Portfolio Effects. Energy Policy 40: 59-68.

Green, R. (2007): Carbon tax or carbon permits: the impact on generators' risks. Working Paper, Mimeo.

Green, R. & N. Vasilakos (2010): Market Behaviour with large Amounts of Intermittent Generation. Energy Policy 38: 3211-3220.

Green, R. & N. Vasilakos (2011): The Long-term Impact of Wind Power on Electricity Prices and Generation Capacity. Discussion Paper No. 11-09.

Gross, R., Heptonstall, P. & W. Blyth (2007): Investment in electricity generation. The role of costs, incentives and risks. Report for the UK Energy Research Centre.

Gross, R., Blyth, W. & P. Heptonstall (2010): Risks, Revenues and Investment in Electricity Generation: Why Policy needs to look beyond Costs. Energy Economics 32: 796-804.

Hiroux, C., & M. Saguan (2009): Large-scale wind power in European electricity markets: time for revisiting support schemes and market designs? Energy Policy 38: 3135-3145.

IEA (2014): The power of transformation - wind, sun and the economics of flexible power systems.

IPCC (2014): Climate Change 2014: Mitigation of Climate Change. Report of the Intergovernmental Panel on Climate Change.

Joskow, P. (2006): Competitive electricity markets and investments in new generating capacity. Working Paper.

Kitzing, L. (2014): Risk implications of renewable support instruments: Comparative analysis of feed-in tariffs and premiums using a mean-variance approach. Energy 64: 495-505.

Kitzing L. & H. Ravn (2013): Support mechanisms and risk: implications on the Nordic electricity system. 10th international conference on the European energy market (EEM 2013).

Knight, F. (1921): Risk, Uncertainty, and Profit. Hart, Schaffner & Marx; Houghton Mifflin Co.

Kopp, O., Eßer-Frey, A. & T. Engelhorn (2012): Can Renewable Energy Sources be Financed Through Competitive Power Markets in the Long Run? Zeitschrift für Energiewirtschaft 36: 243-255.

Lynch, M., Shortt, A., Tol, R. & M. O´Malley (2013): Risk–return Incentives in Liberalised Electricity Markets. Energy Economics 40: 598-608.

Markowitz, H. (1952): Portfolio selection. Journal of Finance 7: 77-91.

Meunier, G. (2013): Risk aversion and technology mix in an electricity market. Energy Economics 40: 866-874.

Nagl, S. (2013): The effect of weather uncertainty on the financial risk of green electricity producers under various renewable policies. EWI Working Paper, No 13/15.

Nicolosi, M. (2012): The Economics of Renewable Electricity Market Integration. An Empirical and Model-Based Analysis of Regulatory Frameworks and their Impacts on the Power Market. PhD thesis. University of Cologne.

Poyry (2009): Impact of intermittency: how wind variability could change the shape of British and Irish electricity markets: Summary report.

Redpoint (2009): Decarbonising the GB power sector: evaluating investment pathways, generation patterns and emissions through to 2030. A Report to the Committee on Climate Change.

Rockafellar, R., & S. Uryasev (2000): Optimization of conditional value at risk. Journal of Risk 2: 21-42.

Rodilla, P. & C. Batlle (2012): Security of electricity supply at the generation level: Problem analysis. Energy Policy 40: 177-185.

Roques, F., Hiroux, C. & M. Saguan (2010): Optimal wind power deployment in Europe - A portfolio approach. Energy Policy 38: 3245-3256.

Roques, F., Newbery, D. & W. Nuttall (2008): Fuel mix diversification incentives in liberalized electricity markets: a mean-variance portfolio theory approach. Energy Economics 30: 1831-1849.

Saenz de Miera, G., Rio Gonzalez, P. & I. Vizcaino (2008): Analysing the impact of renewable energy electricity support schemes on power prices: the case of wind electricity in Spain. Energy Policy 36: 3345-3359.

Schmidt, T. (2014): Low-carbon investment risks and de-risking. Commentary in Nature 4: 237-239.

Sensfuss, F., Ragwitz, M. & M. Genoese (2008): The merit-order effect: a detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36: 3086-3094.

Steggals, W., Gross, R. & P. Heptonstall (2011): Winds of change: How high wind penetrations will affect investment incentives in the GB electricity sector. Energy Policy 39: 1389-1396.

Stoft, S. (2002): Power system economics: designing markets for electricity. IEEE Press; Wiley-Interscience.

Varian, H. (2010): Intermediate Microeconomics: A Modern Approach. Eighth edition. East West.

Winkler, J. & M. Altmann (2012): Market Designs for a Completely Renewable Power Sector. Zeitschrift für Energiewirtschaft 36: 77-92.

„Ich versichere, dass ich die Masterarbeit selbstständig verfasst habe. Andere als die angegebenen Hilfsmittel und Quellen wurden nicht benutzt. Die Arbeit hat keiner anderen Prüfungsbehörde vorgelegen. Es ist mir bekannt, dass ich bei Verwendung von Inhalten aus dem Internet diese zu kennzeichnen habe und einen Ausdruck davon mit Datum und Internet-Adresse (URL) als Anhang der Masterarbeit beizufügen habe."

Oliver Tietjen, Berlin August 2014