Building resilient renewable power generation portfolios: The impact of diversification on investors' risk and return

Simon R. Sinsel*, Xuqian Yan, Annegret Stephan

Swiss Federal Institute of Technology Zurich (ETH Zurich), Department of Management, Technology, and Economics, Group for Sustainability and Technology, Weinbergstrasse 56/58, 8092 Zurich, Switzerland

* Corresponding author: Phone: +41 44 632 98 89, E-mail address: ssinsel@ethz.ch (S. Sinsel)

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Abstract

Over the coming years, variable renewables such as wind and photovoltaics will become increasingly exposed to market risks due to the gradual reduction in policy support. Building diversified portfolios of variable renewables and complementary technologies such as storage (i.e. technological diversification), and in different regions (i.e. geographical diversification) seem to be promising options to mitigate these risks. The extant literature, however, does not provide a comprehensive comparison of these two diversification strategies. Using actual production data from eight wind and photovoltaics plants across Germany from 2015 until 2017 and a storage unit for arbitrage operations, we build a quantitative model to evaluate the impact of these strategies on investors' risk and return. In our analysis, we compare the results of two scenarios: the first with actual prices and the second which assumes prices reflecting higher shares of variable renewables in the power system. In doing so, our study provides the following important insights for investors: (1) technological diversification largely yields lower risk levels than geographical diversification, (2) maximizing the capacity factor of wind and photovoltaics is an effective way to mitigate risk, and (3) while technological diversification with another variable renewable technology is more effective under current conditions, storage gains importance for mitigating risk in times of high shares of variable renewables.

Keywords

Variable renewables; Renewable integration; Storage; Diversification; Risk mitigation; Investor perspective

Nomenclature:

VRE	*Variable renewable energy sources*
FITs	*Feed-in tariffs*
MPT	*Modern portfolio theory*
CVaR	*Conditional value at risk*
PV	*Photovoltaics*

1 Introduction

Over the last decades, investments in variable renewable energy sources (VRE) such as wind and solar photovoltaics (PV) have significantly increased worldwide [1,2]. VRE have specific features, which differentiate them from conventional power generation technologies; most fundamentally, VRE are not dispatchable and exhibit geographically correlated production patterns [3]. As a result, power generation from VRE can only partially match power demand. This circumstance, combined with the low short-run cost of VRE, leads to increasing market price volatility and decreasing market price levels, both of which are intensified as VRE penetration continues to increase [4,5].

Thus far, VRE investors have not been confronted with these challenges since they benefit from support policies such as feed-in tariffs (FITs), which guarantee a prioritized feed-in of renewable power and provide well predictable revenues over a specified period of time [6,7]. Due to the falling cost of VRE, however, many national governments have started to reduce and even phase out VRE deployment support [8]. While the falling cost of VRE may help to maintain profit levels for VRE investors, reduced policy support increases the risk for investors. More specifically, the phase-out of a guaranteed feed-in and predictable remuneration exposes VRE revenues to market forces and hence increases market risk[1]. Higher risk levels, in turn, will increase the cost of capital for VRE projects, reducing their attractiveness compared to other investment options. VRE investors therefore will have to identify ways to cope with the increasing market risk. Failure to do so may deter VRE investments and therefore potentially jeopardize meeting national or international renewable or climate change targets [9].

One risk reduction approach for VRE investors is to diversify their generation portfolio to better match power demand. In the context of VRE, this can be achieved via two diversification strategies: technological and/or geographical diversification [10]. *Technological diversification* means investing in different VRE technologies or in complementary technologies that modify the generation profile of VRE technologies (e.g. storage technologies), while *geographical diversification* entails spreading investments across different regions. For investors, the latter strategy seems preferable since it does not require new technological capabilities which are typically difficult to achieve [11]. At the same time, geographical diversification may be less effective compared to technological diversification since technological risks cannot be hedged with geographical diversification.

[1] Note that in general, technology investments are also affected by other risks such as project development risks, technological risks, legal risks, decommissioning risks or force majeure risks [63], which can occur before, during or after the project lifetime. The reduced policy support, however, typically affects the market risk occurring during the operational phase, which is hence the focus of this study.

To allow for strategic decision-making, investors need to evaluate how each strategy contributes to risk mitigation, hence necessitating a direct comparison of these strategies. While several studies investigate the value of diversification for optimizing risk and return of power generation technologies [10,12–16][2], a direct comparison of both diversification strategies focusing on VRE is lacking so far.

Extant empirical studies on efficient portfolios for power generation technologies have focused on conventional power generation sources as inputs [13] or the combination of conventional power generation technologies and VRE [12,15]. Studies that exclusively focus on renewable power generation either do not consider technologies that are complementary to VRE [14,17], or do not include geographical diversification effects [16]. Studies that incorporate geographical aspects into diversification issues typically take a system perspective and do not provide specific recommendations for VRE investors [14,18,19]. One recent study combines both diversification effects [10]. However, it takes the perspective of market intermediaries, which prevents conclusions regarding VRE investors because business decisions of market intermediaries are characterized by shorter time frames compared to investors [20]. Moreover, this study overlooks the potential of technological diversification with complementary technologies; storage in particular has started to diffuse substantially, representing a promising technology to balance power supply and demand [21] and therefore reduce risk [22,23]. Lastly, Gersema and Wozabal [10] take average generation data of a certain region as opposed to individual plant data, likely leading to an underestimation as to the contribution of geographical diversification. Hence, while the mentioned studies provide insight into the effect of the individual diversification strategies, the scope of the analysis, the choice of the respective technologies and the choice of aggregated data prevents conclusions on the contribution of the different diversification strategies for risk mitigation in VRE investments. In this study, we address this gap by analyzing *how technological and geographical diversification affect the risk and return of variable renewable power generation portfolios.*

To answer this question, we build a model based on the concept of modern portfolio theory (MPT) [24] using empirical electricity feed-in data from eight existing wind and PV plants at different locations from 2015 to 2017. In addition, we include a storage module in the model to specifically investigate the contribution of complementary technologies to VRE. While a theoretically well diversified portfolio would include assets from various industries and technologies according to MPT [24], our VRE investor is restricted to the power sector and the selected technologies. In doing so, we assume a typical VRE investor who is less familiar with investment opportunities in other sectors [25], and who wants to invest in technologies relevant for future low-carbon power systems [26][3]. Our analysis focuses on Germany, as it has experienced a strong expansion of VRE in the recent decades largely attributed to its favorable policy support [1]. Over the last years, however, the German policy environment has undergone a paradigm change towards integrating VRE into existing power markets [8]. At the same time, Germany maintains ambitious future renewable goals [27], making it a highly applicable case for our analysis.

[2] DeLlano-Paz et al. [28] provide a comprehensive overview of studies that investigate the effects of diversification in the energy sector.

[3] Note that we do not consider traditional or fossil fuel based power production technologies given that many countries have started to phase out these technologies [64–66], and that they have become less profitable due to the prioritized feed-in of VREs in many countries [57,67].

Both diversification strategies can result in risk mitigation, as they allow for the combination of non-perfectly correlated production patterns and hence revenues[4]. In the case of technological diversification, the differences in VRE production patterns result from the different natural sources that are used by both technologies, i.e., solar irradiation is at its maximum during the summer months, while the windy season in Germany occurs during the winter months. In the case of geographical diversification, the differences in power production patterns result from varying weather conditions in different locations [19].

To assess potential diversification benefits, we compare two scenarios, each without policy support and hence maximum market risk exposure for both VRE plants and storage. The first scenario uses market prices from 2015 to 2017, while the second scenario assumes potential future market conditions considering higher shares of VRE in the power mix.

The remainder of the paper is structured as follows: In Section 2, we introduce our model, present the motivation for selecting our research case and describe the sources of our input data, including the treatment measures for their use within our model. In Section 3, we present the results of our analysis, followed by a discussion from the perspectives of both VRE investors and policy makers in Section 4. In Section 5, we conclude, discuss the limitations of our analysis and suggest areas for future research.

2 Methods and materials

2.1 Risk and return indicators

Our model calculates the risk and return performance of portfolios composed of wind and PV plants at different locations, as well as an energy storage unit. Building upon the insights of MPT, we can identify a finite set of portfolio combinations that define the so-called efficient frontier, which exhibits the best possible return at a given risk level or vice versa [24].

A key differentiator between the studies that apply MPT in the power sector is the choice of the risk and return indicators [28]. The choice is typically motivated by the specific research question, target audience and available data. In terms of return indicators, three groups of studies can be distinguished. One group of studies determines risk-return frontiers, in which return is measured, for example, with the net present value or inverted production cost which is assumed to be positively correlated with return. A second group of studies determines risk-cost frontiers, in which production cost is used as a proxy for return. A third group uses energy production as the return indicator [28]. The choice of risk indicator is typically closely linked to the choice of the return indicator. Studies typically use the variability of portfolio returns [e.g. ,13], the variability of portfolio costs [e.g. ,12], or production variability [e.g. ,14].

For this study, the chosen risk and return indicators need to be relevant for VRE investors. We therefore used financial indicators as opposed to physical indicators, e.g. energy production, for risk and return. For the return indicator, we followed Gersema and Wozabal [10] and chose mean revenue as the return indicator. A profit-oriented indicator would not work in all cases as VRE and storage portfolios are currently not necessarily

[4] The only case in which revenues would be perfectly correlated despite not-perfectly correlated production patterns is if differences in power production were perfectly balanced by differences in market prices. We assume that this is not the case.

profitable without policy support [29]. Taking revenues as a proxy for profit is reasonable since revenues and profits for both VRE and storage technologies are strongly correlated due to the high share of capital versus the operating cost of these technologies[5] [30]. This is different for conventional power generation technologies, which have significant operating cost that largely depend on varying fuel prices. Due to this circumstance, conventional power generation technologies can have high revenues but low profits due to high fuel prices.

For the risk indicator, one that reflects variability and focuses on downside risks seemed most reasonable for our analysis for two reasons. First, increasing fluctuation of revenues is the main consequence of ceased policy support for VRE and a central motivation of our analysis.

Second, depressed revenues constitute a significant risk for VRE and storage operators since such projects are increasingly debt-financed [25] and require timely debt-serving to remain economically viable [10,31]. Considering that debts are usually repaid on a monthly basis, we use a monthly time scale for both risk and return indicators. More specifically, we use the conditional value at risk (CVaR) of monthly revenue in our model. We chose the CVaR for three reasons: First, in comparison to simpler indicators like the standard deviation, the CVaR solely focuses on extreme downside risks, i.e. events that are beyond the expected level of variation and that significantly affect investors. Second, the CVaR is a coherent risk measure[6], which is an important theoretical prerequisite for its use in an MPT model [32]. Third, the CVaR is widely used in investment decisions and energy trading [10,33] which favors the applicability of our results in industry.

The CVaR is the expected revenue of a specified quantile of revenues. In our example, it represents the expected revenue of the worst 10% of the analyzed monthly revenues. In contrast to other risk indicators such as standard deviation, the higher the CVaR value, the lower the risk. As such, the CVaR is positively correlated to the mean revenue, which makes diversification strategies that involve high revenue plants preferable when comparing efficient frontiers solely on an absolute scale. To deal with this issue analytically, we compare our results both on absolute and relative scales.

2.2 Research case & data

We applied our model to the case of Germany, which has experienced a strong growth in VRE share over the past decades, largely due to strong policy support [1]. VRE investors in Germany, however, face multiple growing risks and uncertainties that need to be mitigated. Over the last years, Germany has significantly lowered its policy support, e.g. via a shift from FITs towards tendering [34], which constitutes a major shift in the business environment of investors [8].

Simultaneously, VRE have had a growing impact on the German power market. Average prices in the wholesale electricity market have decreased and weekly power price volatility has increased due to the increasing share of VRE over the last years [5,35,36]. At the same time, technological and geographical diversification seem to be

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[5] The only factor that constitutes a larger share of operating costs for VRE is the land lease which, under the assumption of a perfect market, could lower the profitability of good VRE locations and thereby diminish the correlation to revenues. The determination of land lease differs across countries. We will therefore evaluate the impact of the land lease on the correlation of profit and revenue when introducing the research case.

[6] A risk measure is coherent if it satisfies four axioms: monotonicity, subadditivity, positive homogeneity and translation invariance [32].

promising mitigation strategies because the majority of VRE generation capacity in Germany is owned by investors that only own single plants [37].

While the land lease of VRE plants could theoretically lower the profitability of good VRE locations and thereby diminish the correlation to revenues, reality shows that assuming a strong correlation between profit and revenue remains valid. The land lease, the foremost operating cost driver in Germany, is variable with land owners normally charging 3-6% of the monthly revenue beyond a base lease [38]. However, in total, operation and maintenance cost over the lifetime of a VRE plant are estimated to be well below 10% of the investment cost [39].

To analyze the risk mitigation potential of both geographical and technological diversification, we used empirical generation data from existing utility-scale VRE plants consisting of two technologies at eight different locations in Germany. Within our model, geographical diversification was achieved by building portfolios of a specific VRE plant at different geographical locations. In order to maximize the effect of geographical diversification, we chose plant locations at maximum distances in all four cardinal directions within Germany (see Table 1). The average distance between individual plants of one technology is above 500 km, with a minimum distance of around 150 km between two locations[7]; plant sizes of the existing VRE plans vary between 0.7 and 60 MW. Technological diversification was implemented through the choice of both wind and PV being the dominant VRE technologies in the German market [27].

To evaluate the diversification benefits of complementary technologies, we included energy storage as a further means of technological diversification in our model. Unlike the data from VRE plants, we assume one single storage unit and simulate the activity of the storage unit based on data from literature[8]. While storage can be utilized in several applications complementary to VRE [21,40], the storage unit in our study performs arbitrage between times of higher and lower pricing. To do so, we chose a sodium-sulphur battery due to its low life-cycle cost specifically for this application [41][9].

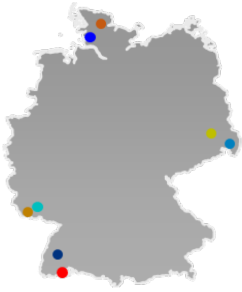
To be able to assemble portfolios, we used standardized investment costs provided by IRENA [29] for the VRE technologies and Luo et al. [42] for the storage unit (see Table 1).

Parameter	**Unit**	**Value**	**Source**
Capital cost wind	EUR/kW	1656	[27]
Capital cost PV	EUR/kW(peak)	994	[27]
Capital cost storage	EUR/kW h	316	[42]

Table 1: Technology investment cost data

In terms of input data, we used the electricity feed-in at the plant level in 15-minute resolution intervals, from the eight existing VRE plants from 2015 until 2017 (cf. Table 2).

[7] In our case, this minimum distance occurs between wind in the west of Germany and in the south of Germany.
[8] We thereby assume that the performance of the storage unit is independent from its location and neglect potential location-specific effects such as temperature differences.
[9] Currently, there are two operational projects in Germany that are based on this technology [68].



Region	Plant type	Technology type
North	PV	Suntech Monocristalline
North	Wind	Enercon E-82 E2
East	PV	Canadian Solar CS6P
East	Wind	Vestas V90/2000
South	PV	Canadian Solar CS6P
South	Wind	Enercon E-82 E2
West	PV	SolarWorld Polycristalline
West	Wind	Vensys V-112

Table 2: Overview of VRE plants

We treated the data for missing values or times of curtailment with extrapolated data based on local weather conditions and additional information from the operator. Extrapolation was performed by fitting the VRE production data and weather data for the specific location with a smoothing spline function. The average distance between a specific generation plant and the closest weather station is 26 km, with a maximum distance of 62 km. The operation of the storage unit was simulated as part of our model. Table 3 summarizes the relevant technical parameters of the chosen sodium-sulphur battery [42,43].

Parameter	Unit	Value	Source
Round trip efficiency	%	85	[42]
Operation range	%	20-100	[41]
Charge/discharge rate	hrs	6	[41]

Table 3: Storage unit parameters

In order to calculate the risk and return values for each portfolio, we calculated the risk and return of all individual plants based on market data from the German spot market, i.e. without policy support, from 2015 to 2017 [44]. We focused on the spot market, i.e. the day ahead, as opposed to the intraday market, since approximately 90% of produced power is traded on the spot market and the average deviation between the spot market and the intraday market on an hourly basis is about 1% [45][10]. In line with the German spot market [44], we also trade on an hourly basis. This data was the basis for the current market price scenario.

Evaluating the effects of geographical and technological diversification for high VRE shares such as 40-50%, i.e. the future scenario, required adjusting the price time series. Based on analyses of the impact of current VRE shares on electricity prices, scholars predict changes along two dimensions: (1) a reduction of the mean power price, the so-called ‘merit-order effect’ [5,35] and (2) an increase in short-term power price volatility [36]. The extent of both changes depends on a number of factors, such as the overall generation portfolio, renewable generation patterns and available transmission interconnection capacities, and is therefore highly market specific. For the case of Germany, there are currently no studies that provide useable estimates for both dimensions. Therefore, we base our assumptions of the future market scenario on values from a study on the Californian power market [46], which estimates a 35% reduction of mean power prices and a 30% increase in price volatility, i.e. its standard deviation[11]. Considering the uncertainty of these estimates, specifically in terms of market price volatility, we performed robustness checks with substantially higher and lower volatility levels

[10] By using this simple trading strategy, we exclude the possibility of hedging revenue risk as proposed, e.g., by Kristiansen [60].

[11] The values correspond to a scenario with high wind penetration, which results in similar VRE market shares compared to Germany.

(see Appendix A for a comparison of both scenarios as well as robustness checks). Note that while the shares of VRE power production are quite similar in both locations, California has higher shares of gas and hydro power [47] and hence seems to be more likely to balance future high shares of VREs. Since California could therefore have lower price volatilities, we consider the high volatility robustness check more relevant for the German market.

2.3 Modelling framework and computation

The model was implemented in MATLAB R2017b. The output of the model, the average monthly revenue R and the defined CVaR of the worst 10% quantile of monthly revenues of a given portfolio c, was calculated in three stages: the investment stage, the portfolio stage and the market stage (Figure 1). In the *investment stage*, we generated random portfolio vectors c_i, which consist of the capacity [kW] invested in the different plants, and the capacity of the storage unit [kW h] in Eq. (1).

$$c_i = \begin{pmatrix} c_{PV,north} \\ c_{Wind,north} \\ c_{PV,east} \\ \vdots \\ c_{Storage} \end{pmatrix} = \begin{pmatrix} b_{PV,north} * i_{PV} \\ b_{Wind,north} * i_{Wind} \\ \vdots \\ b_{Storage} * i_{Storage} \end{pmatrix} \text{ with } \sum_{i=1}^{9} b_i = B \qquad (1)$$

c_i was calculated through randomly allocating a set budget B of €10m[12] to the different plants and the storage unit b_i. The individual capacities of each portfolio therefore depend on the specific investment costs i of the different plants. For generating the portfolio vectors, the budget was first randomly allocated to the available plants and the storage unit. Given that investment shares can vary between 0 and 100%, the modelled portfolio capacities can theoretically range between 0 kW to about 6MW (wind), 10MW (PV), and 32 MWh (storage). In order to identify the efficient frontier and then analyze the portfolio composition along the efficient frontier, we used a genetic algorithm to identify the best performing portfolios in two steps. In the first step, we identified the portfolio with the maximum revenue. Finding this portfolio was relatively straightforward since it is a non-diversified portfolio composed of one plant. In the second step, starting from this portfolio the algorithm allocated two percent of the budget in each of the other plants and subsequently chose the best performing portfolio in the second step. This process was repeated until the lowest level of risk was reached, i.e. when a further diversification step did not yield a lower risk level. In between the two-percent-steps, a linear interpolation was used to approximate the portfolio composition along the efficient frontier. In total, we simulated nearly 9,000 portfolio iterations for each current and future market price scenario. For our analysis, the portfolios could be diversified either geographically, technologically, or along both dimensions. We refer to the latter as “fully diversified”. Geographically diversified portfolios are composed of one VRE technology at different locations (e.g. wind in the north and the east of Germany), while technologically diversified portfolios are composed of both VRE technologies at one location as well as the storage unit as a complementary technology. Fully diversified portfolios allow for a combination of all available technologies and locations.

[12] We chose a budget of €10m as a standard size for a stand-alone utility-scale VRE plant.

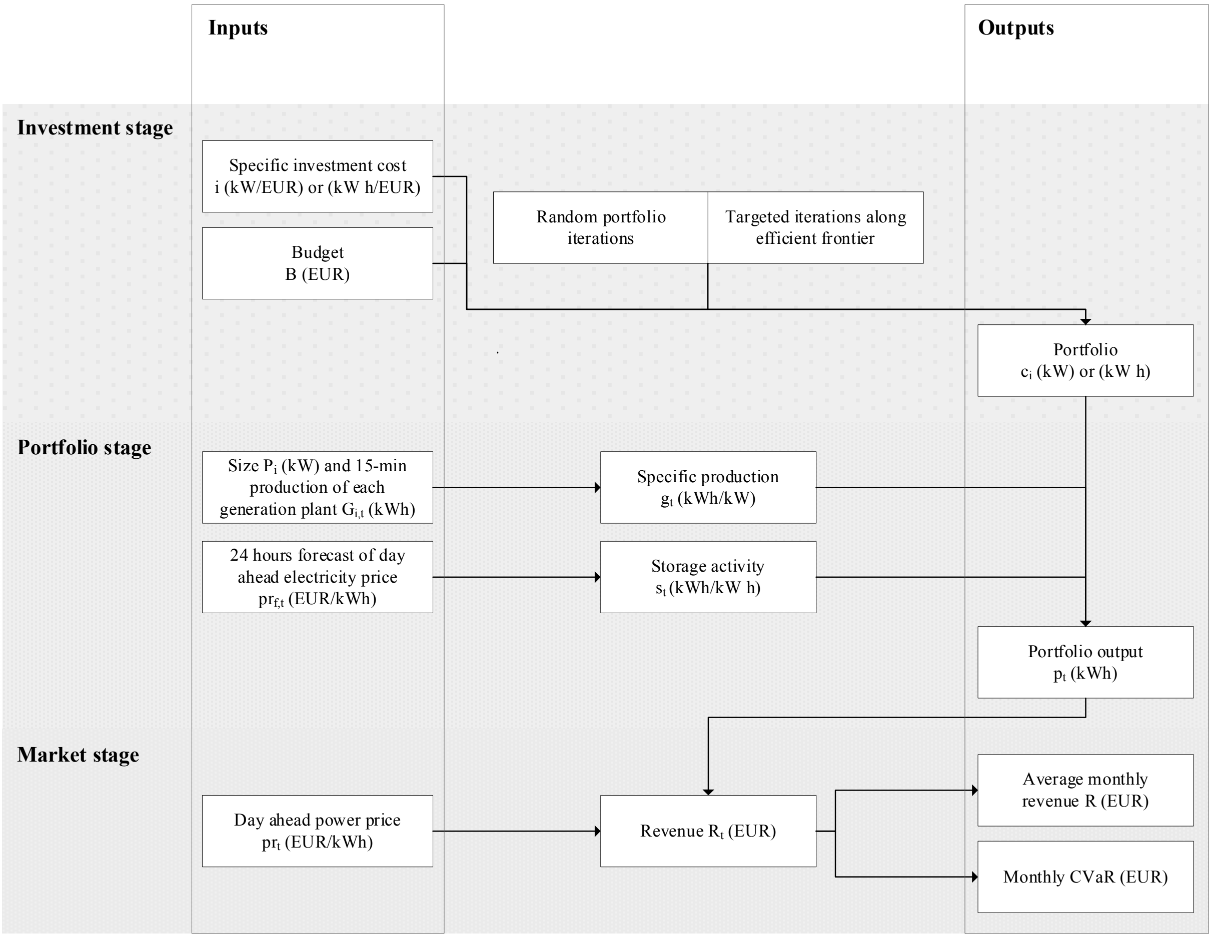


Figure 1: Model overview

The power production p_t of the different portfolios at time *t* was calculated in the *portfolio stage*. p_t is the sum of the specific production g_t of the VRE plants at time t and the storage activity s_t multiplied by the portfolio vector in Eq. (2).

$$p_t = c^T * (g_t + s_t) = c^T * \begin{pmatrix} g_{PV,north,t} & & 0 \\ g_{Wind,north,t} & + & 0 \\ \vdots & & \vdots \\ 0 & & s_t \end{pmatrix} \tag{2}$$

The specific production vector g_t of the VRE plants at time t represents the generation data $G_{i,t}$ normalized with the installed capacity P_i of each plant. The storage activity s_t was generated using a heuristic for arbitrage operations [48]. This heuristic uses future power prices for the upcoming 24 hours $pr_{f,t}$ and charges or discharges the storage unit at times when power prices deviate from the rolling average by more than a specified dead band of 10% (see Appendix B for an illustration of s_t). The possibility of charging and discharging, however, remains dependent on the overall capacity and charging level at a specific point in time. According to Connolly et al. [48], this heuristic generates 80% of the revenue compared to an optimal operation strategy with a perfect price forecast over an entire year[13]. As such, the storage unit operates solely dependent on market price signals as opposed to other signals such as VRE generation. However, this is reasonable since it establishes a

[13] While the efficiency of this heuristic could be improved by optimizing the operation dead band, we assume that this inefficiency is offset in reality by the forecast inaccuracy that we currently did not consider as part of our model.

clear delineation between the generation (i.e. wind and PV) and storage plants with regards to their risk and return contribution[14].

In the *market stage*, the monthly average revenue R and the monthly CVaR for each portfolio combination were calculated based on the portfolio production and power price time series for the two analyzed scenarios. Revenue and CVaR were calculated based on 36 equalized months (730 hours per month) in order to avoid additional variance through the varying lengths of calendar months. Due to the discrete nature of the data, we used the approach proposed by Rockafellar and Uryasev [49] to calculate the CVaR of the worst 10% quantile of monthly revenues. As output, each portfolio combination was plotted on a risk/return graph in which the efficient frontiers are identified as the concave envelopes around the portfolio combinations of maximal revenue at a given risk level. To answer our research question, we compare the efficient frontiers, more specifically the two extreme points on each frontier, of technologically and geographically constrained portfolios against unconstrained portfolios.

2.4 Robustness checks

To verify the robustness of our results, we run the model with changed input parameters (±10% ceteris paribus) and check their implications on the results. More specifically, we perform robustness checks for the price time series, the investment cost for the different technologies, the impact of the land lease cost, the operation dead band of the storage unit and the CVaR quantiles.

3 Results

In the following, we present the results of the current market price scenario before comparing them to the results of the future market price scenario. For both scenarios, we describe our results in two steps: First, we look at the risk and return characteristics of the individual plants and the storage unit. Then, we illustrate our observations regarding the contribution of geographical and technological diversification to risk mitigation and analyze the portfolio composition along the efficient frontier of a fully diversified portfolio.

3.1 Current market prices

Figure 2 and Table 4 provide an overview of the results for the current market price scenario (see Appendix C for further scatter plots). Figure 2 illustrates the results in absolute terms, while Table 4 includes relative comparisons which help to mitigate the problem of the correlation between CVaR and the return indicator.

When looking at the *individual plants* (Figure 2a), we observe that wind locations vary more strongly in terms of risk and revenue than PV locations. With a CVaR to revenue ratio of close to 53% (Table 4), the wind plant in northern Germany features the lowest risk value of all plants, and is at the same time the best performing plant in terms of monthly average revenues, with close to €38,000 per month. While other wind plants have lower revenue values, the risk performance of wind plants is on average more than 180 percentage points higher than that of PV plants, which is due primarily to the higher seasonality of PV power production (see Appendix D). In addition, the storage device has a slightly higher CVaR to revenue ratio than the most productive wind

[14] Making storage operations dependent on VRE plant operation would only make sense if a transfer price lower than the market price was assumed for charging the storage. This would, however, dilute the performance contributions for investors, which is generally considered undesirable.

location (Table 4). However, the average revenue is the lowest of all analyzed plants. This is largely due to the relatively rare arbitrage possibility which leaves the storage device to idle approximately 60% in the observed period (cf. Appendix B). Besides the performance of the storage device, we can conclude in general terms that maximizing the capacity factor, i.e. the ratio of maximum generation capacity to actual average generated power, is favorable for investors from both a risk and return perspective since it not only increases the average revenue but also disproportionally decreases risk (see Appendix E for details of the relationship between capacity factor and risk performance).

Attempting to efficiently combine either wind or PV plants at different locations, i.e. *geographical diversification* (red and blue dotted lines in Figure 2b), does not provide significant risk mitigation benefits[15]. This indicates that weather conditions seem to affect the power generation of wind and PV plants across Germany as opposed to only having regional impact. The monthly revenues of wind and PV plants across locations are positively correlated, i.e. monthly revenues change more or less simultaneously and one plant cannot compensate for the revenue reduction in another (see Appendix F). Compared to wind portfolios, PV portfolios offer a slightly larger risk reduction potential in the portfolio of maximum revenue (cf. Table 4).

In presenting the results for *technological diversification*, we first look at portfolios that are only composed of PV and wind plants at specific locations (dashed green lines in Figure 2c; largely hidden behind full green lines). Overall, we find that technological diversification of VRE plants has a high potential for risk mitigation. In our analysis, the level of risk mitigation, i.e. the horizontal length of the efficient frontier in Figure 2c, depends on the correlation of the monthly revenues and the mean revenue differences of the respective plants in the portfolio. While the correlation coefficient is negative for all PV and wind plants at the different locations (Appendix F), the revenue of technologically diversified portfolios differs considerably between locations. For example, in the west, both plants have similar average revenue performance. Hence, we find the highest risk mitigation potential at this location (west) with 166 percentage points decrease of risk at a less than 1 percentage point loss in revenue, when comparing the portfolio of maximum revenue with the portfolio of minimum risk (see Table 4 and the dashed dark green line in Figure 2c). For locations where the individual plants feature larger revenue differences, as for example in the eastern locations, the potential for risk mitigation decreases. When we allow for storage to be included in technologically diversified portfolios (full green lines in Figure 2c), we find that storage has a marginally positive effect on the CVaR/revenue ratios in minimum risk portfolios. However, adding storage to any portfolio always results in a slight decrease in average revenue.

Finally, we look at the *fully diversified*, i.e. geographically and technologically, portfolios with and without storage (full and dashed black lines in Figure 2d). Similar to the case of technological diversification, the negative revenue correlation for both VRE technologies offers greater potential for risk mitigation than geographical diversification. The fully diversified portfolio with minimum risk has the best CVaR/revenue ratio of all portfolios with more than 75%. This comes at a trade-off between maximum revenue and minimum risk, with a relative decrease in risk by 20 percentage points and a resulting decrease in revenue of 17 percentage points (Table 4). Including storage only reaps marginal benefits in terms of risk mitigation since it produces too little revenue under current market prices in comparison to VRE plants. When analyzing the compositions of the fully diversified portfolios along the efficient frontier (see Figure 3), we find that these portfolios contain

[15] As risk decreases with an increasing CVaR, the efficient frontiers in Figures 2 and 4 are tilted to the right.

combinations of locations with the highest revenue of each technology (wind north and PV south), together with an increasing share of the geographically most distant wind plant (wind south) in the minimum risk portfolio.

When *comparing geographical and technological diversification*, we find that, regardless of technology or location, technological diversification leads to better risk mitigation compared to geographical diversification. To illustrate this, we take the example of an investment in PV in southern Germany, which is the plant with the highest revenues for PV. As described previously, there is a relatively low risk reduction potential when diversifying PV in different regions. With technological diversification at the same location, however, we find an improvement potential in both risk and revenue (266 and 6 percentage points, respectively) in the portfolio of minimum risk.

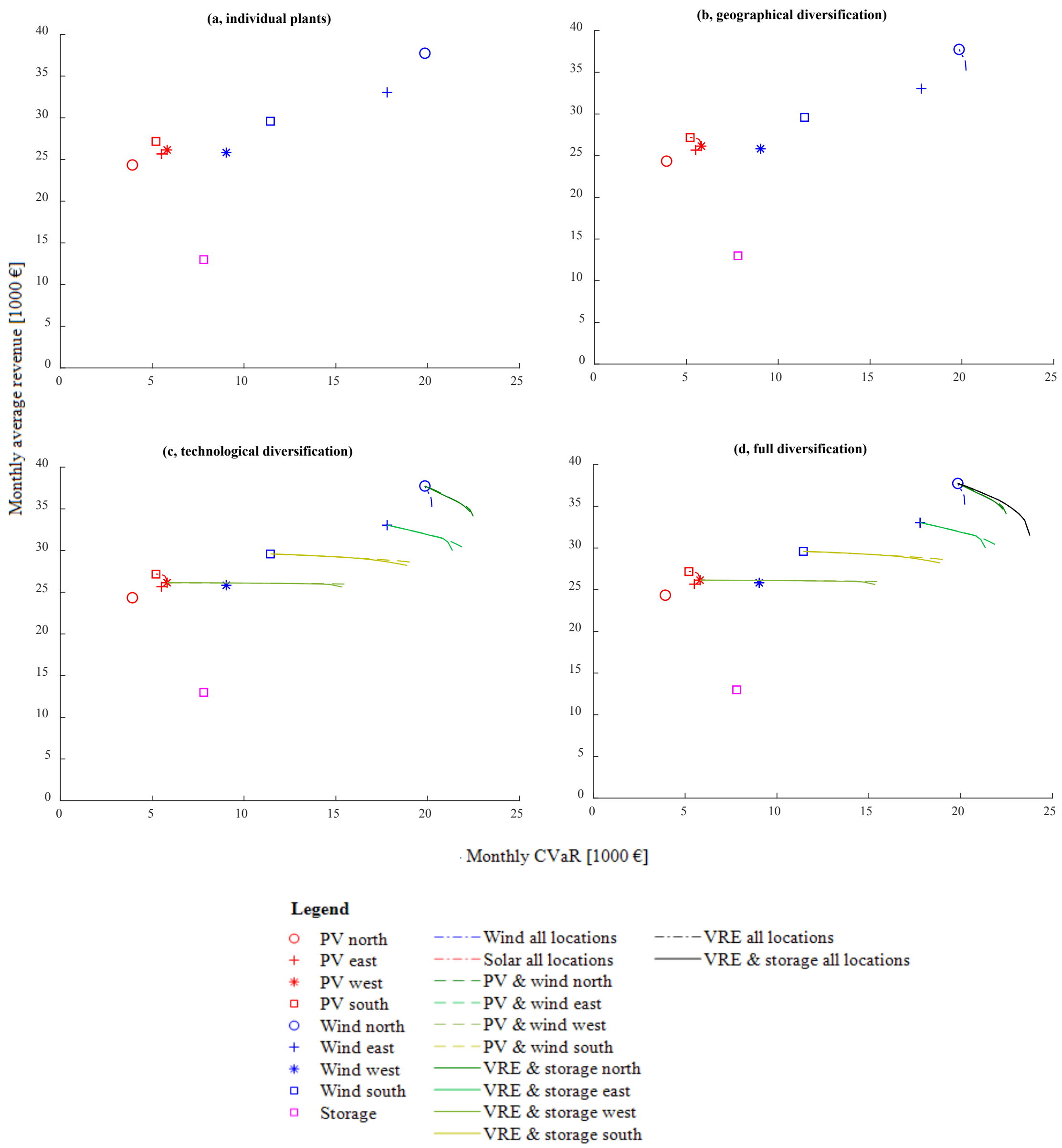


Figure 2: Portfolio performance (risk and return) for current market prices

	Maximum return				
	Revenue [k EUR]	Relative revenue to maximum return	CVaR [k EUR]	Relative risk to maximum return	CVaR/Revenue ratio
Wind north	37.7	-	19.8	-	52.58%
PV south	27.2	-	5.2	-	19.16%
Storage	13.0	-	7.8	-	60.11%
Wind all locations	37.7	-	19.8	-	52.58%
PV all locations	27.2	-	5.2	-	19.16%
PV & wind west	26.1	-	5.8	-	22.24%
PV & wind south	29.6	-	11.4	-	38.65%
VRE & storage west	26.1	-	5.8	-	22.24%
VRE & storage south	29.6	-	11.4	-	38.65%
VRE all locations	37.7	-	19.8	-	52.58%
VRE & storage all locations	37.7	-	19.8	-	52.58%
	Minimum risk				
Wind north	-	-	-	-	-
PV south	-	-	-	-	-
Storage	-	-	-	-	-
Wind all locations	35.2	-6.7 pp.	20.2	1.9 pp.	57.45%
PV all locations	26.1	-3.8 pp.	5.8	11.7 pp.	22.24%
PV & wind west	26.0	-0.6 pp.	15.5	166.0 pp.	59.52%
PV & wind south	28.6	-3.3 pp.	19.0	66.4 pp.	66.48%
VRE & storage west	25.6	-2.0 pp.	15.3	164.0 pp.	59.91%
VRE & storage south	28.2	-4.7 pp.	18.9	65.1 pp.	66.92%
VRE all locations	31.7	-16.0 pp.	23.7	19.7 pp.	74.91%
VRE & storage all locations	31.5	-16.6 pp.	23.8	19.8 pp.	75.49%

Table 4: Risk and return characteristics of portfolios at current prices

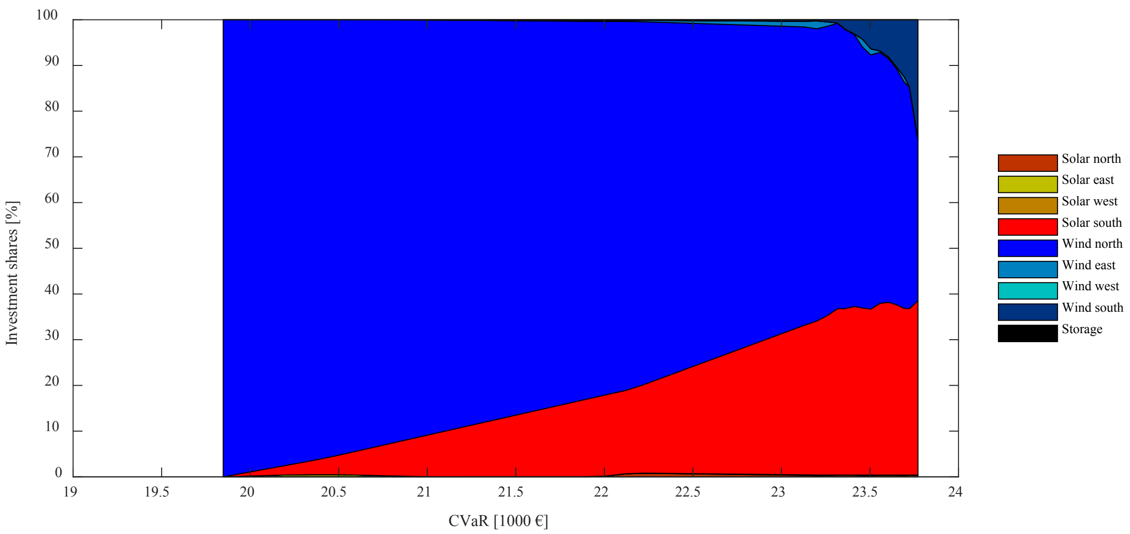


Figure 3: Portfolio composition along the efficient frontier of fully diversified portfolios

3.2 Future market prices

Figure 4 and Table 5 provide an overview of the results for the future market price scenario. When describing the results of this scenario, we proceed in a similar order as before and directly compare our findings with the current price scenario.

For *individual plants* (Figure 4a), we observe an average drop in revenues for all VRE plants of 41%, which is 6 percentage points higher than the mean drop of the power price by 35%. This is realistic since a higher VRE penetration will also lead to a lower market value of VRE production [50]. The reduction of the average revenue is in line with a reduced CVaR across all technologies. However, individual CVaR decreases differ by technology, as evident from the CVaR/revenue ratios. More precisely, the CVaR/revenue ratio of wind assets decreases by approximately 65 percentage points compared to the current market price scenario, while the CVaR/revenue ratio of PV assets slightly improves (compare Tables 4 and 5). Together with the lower revenue, this means that the risk of investing in wind technologies will increase in the future. In part, this can be explained by the negative correlation between wind infeed and electricity prices compared to the slightly positive correlation for PV[16]. Another reason for the increase of risk for wind plants compared to PV plants is that the CVaR of PV plants is generally low due to its seasonality. The anticipated changes in prices could therefore have a stronger impact on the CVaR of wind. In contrast to the revenue drop of VRE plants, storage improves both its revenues and its risk performance compared to the current market price scenario (cf. Tables 4 and 5), making it the lowest risk investment option in this scenario.

The risk mitigation potential for *geographical diversification* remains similar in the future price scenario (Figure 4b) compared to the current price scenario. Although the risk mitigation potential for wind plants increases due to the decreased risk/return differences between locations, geographical diversification of PV plants still yields higher relative gains.

The risk mitigation potential for *technological diversification* of PV and wind, however, decreases compared to the current price scenario (Figure 4c) due to decreasing negative revenue correlations. In western locations, for example, risk can only be reduced by 60 percentage points (Table 5) compared to 166 percentage points in the current price scenario (Table 4). With further increasing shares of VRE in power systems, risk mitigation effects of technological diversification with VRE will likely continue to decrease. By contrast, the inclusion of storage in technologically diversified portfolios bears a high potential for risk mitigation (Figure 4c). While storage only results in a marginal contribution at current prices, certain efficient portfolios are primarily composed of storage, such as in western and southern locations[17]. In other locations with a high wind performance, such as in the east of Germany, storage can help to reduce risk up to 95 percentage points at a loss of 3 percentage points in revenue.

Fully diversified portfolios with and without storage feature a similar picture (full and dashed black lines in Figure 4d). While the effect of diversification on all VRE plants is considerably reduced at future market prices, the inclusion of storage offers the potential to reduce risk by an additional 58 percentage points at a loss of close

[16] The Spearman correlation coefficient of the production of wind north and current electricity prices is -0.26, and the coefficient of PV south and electricity prices is 0.11. Both are significant on a 95% confidence level.
[17] Efficient portfolios that combine VRE and storage in western and eastern locations only have very short frontiers that originate at the storage unit.

to 6 percentage points in revenue. The risk mitigating effect of storage also becomes evident when looking at the portfolio composition along the efficient frontier. In comparison to the current market price scenario, where wind in the east and north and PV in the south contribute to the minimum risk portfolio (Figure 3), the minimum risk portfolio at future prices (Figure 5) almost exclusively comprises storage and PV south, which has the highest revenue of all PV plants and the second-highest negative revenue correlation with storage among all plants.

When comparing *geographical* and *technological diversification*, we find that the relative benefit depends on the technology. Compared to technological diversification, geographical diversification is more favorable for wind locations in the north of Germany, and less favorable for PV power plants. The higher attractiveness of geographical diversification for wind assets is, at least for our selected locations, largely due to the revenue difference between wind and PV in the north. When storage is included in technologically diversified portfolios, we find that the role of storage technologies and probably also other complementary technologies for risk mitigation in VRE portfolios will increase, while the benefits of diversification with other VRE technologies will likely decrease.

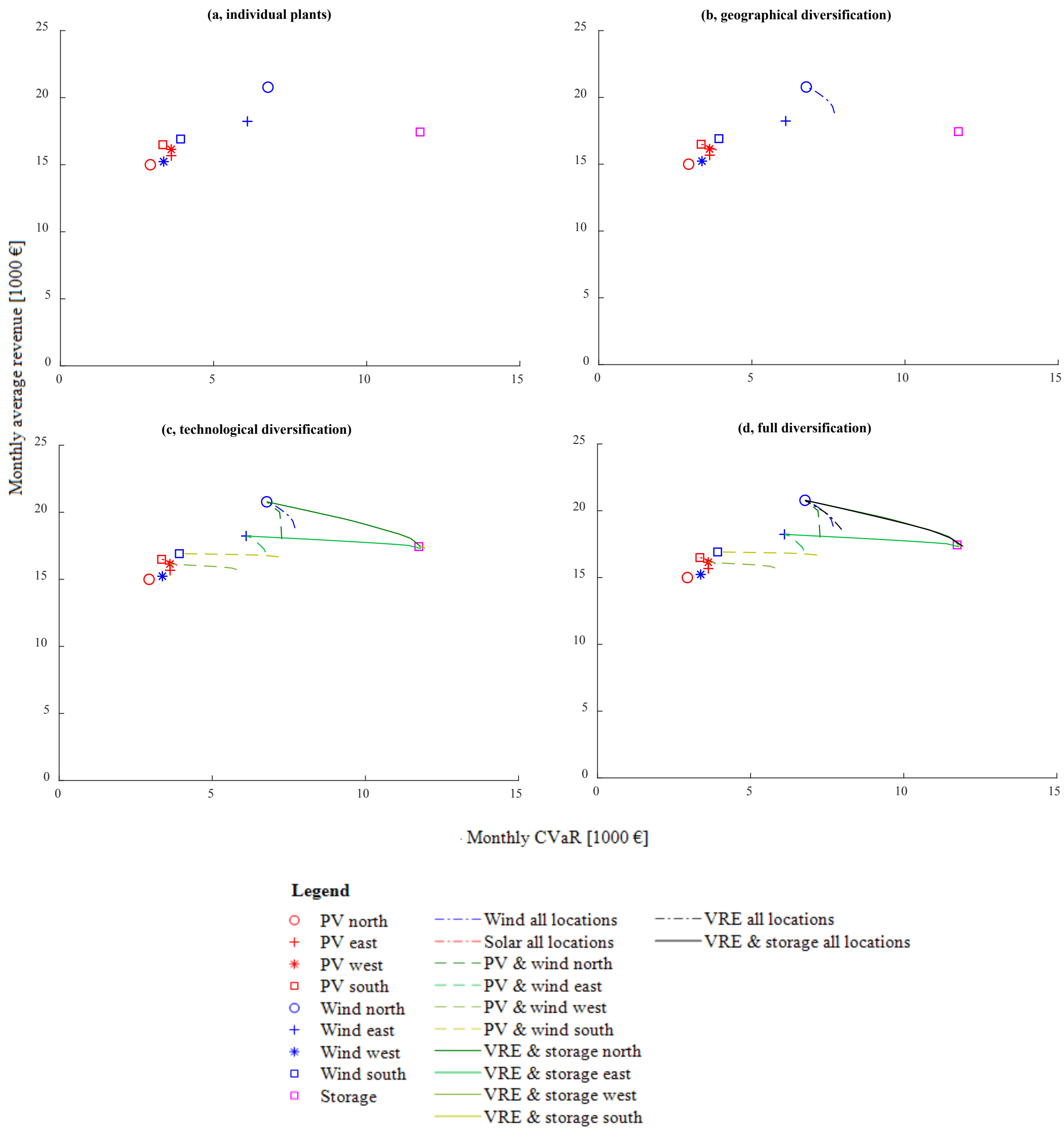


Figure 4: Portfolio performance (risk and return) for future market prices

	Revenue [k EUR]	Relative revenue to maximum return	CVaR [k EUR]	Relative risk to maximum return	CVaR/Revenue ratio
	Maximum return				
Wind north	20.8	-	6.8	-	32.61%
PV south	16.5	-	3.3	-	20.27%
Storage	17.4	-	11.7	-	67.33%
Wind all locations	20.8	-	6.8	-	32.61%
PV all locations	16.5	-	3.3	-	20.27%
PV & wind west	16.1	-	3.6	-	22.41%
PV & wind south	16.9	-	3.9	-	23.20%
VRE & storage west	17.4	-	11.7	-	67.39%
VRE & storage south	17.4	-	11.8	-	67.42%
VRE all locations	20.8	-	6.8	-	32.61%
VRE & storage all locations	20.8	-	6.8	-	32.61%
	Minimum risk				
Wind north	-	-	-	-	-
PV south	-	-	-	-	-
Storage	-	-	-	-	-
Wind all locations	18.8	-9.4 pp.	7.7	13.6 pp.	40.91%
PV all locations	16.0	-2.7 pp.	3.8	15.1 pp.	23.99%
PV & wind west	15.7	-2.6 pp.	5.8	60.4 pp.	36.90%
PV & wind south	16.7	-1.4 pp.	7.2	82.7 pp.	42.97%
VRE & storage west	17.4	-0.1 pp.	11.8	0.7 pp.	67.93%
VRE & storage south	17.3	-0.9 pp.	11.9	1.6 pp.	69.16%
VRE all locations	18.6	-10.5 pp.	8.0	17.6 pp.	42.88%
VRE & storage all locations	17.4	-16.5 pp.	11.9	75.9 pp.	68.70%

Table 4: Risk and return characteristics of portfolios at future prices of fully diversified portfolios

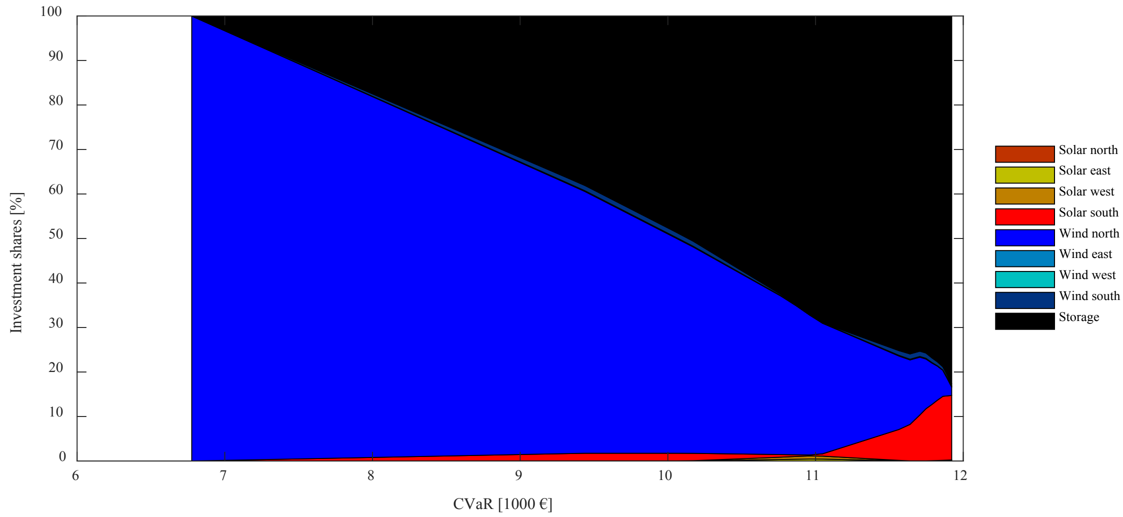


Figure 5: Portfolio composition along the efficient frontier of fully diversified portfolios

3.3 Robustness checks

In addition to the previous scenarios, the model was run with various input variables, namely different price time series, investment costs, reduced revenues representing the different impact of the land lease on efficient portfolio compositions, operation dead bands for the storage device, and CVaR quantiles.

While our model is invariant to changes in the latter three variables, the model is sensitive to the price time series and investment cost. Changes in the price time series, on the one hand, either attenuate or amplify the developments we identify in the future price scenario (cf. Appendix A). Changes in investment cost of different plants, on the other hand, influence (1) location and length of the efficient frontiers for different diversification strategies and (2) the efficient portfolio composition. The box plots in Appendix G, however, confirm the limited impact of these changes. Overall, the relative contribution of the different diversification strategies remains similar in all robustness checks.

4 Discussion

In the following, we reflect on the implications of our findings on three levels. First, we derive specific diversification strategies for VRE investors in general and different types of VRE investors in specific. Second, we outline the consequences of our findings for the actor structure of the power sector. Third, we highlight relevant conclusions for the future diffusion of VRE and complementary technologies like storage, which might be relevant for the strategic planning of power sector players and policymakers.

First, our analysis reveals viable risk mitigation options regarding market risk for VRE investors, despite a general increase in (market) risk when policy support is continuously reduced in the future. The results of our case study indicate that technological diversification is preferable to geographical diversification for risk averse investors. This is even more so since the benefits of geographical diversification are more difficult to obtain in comparison to technological diversification which, in our case, is based on portfolios of two plants, whereas geographical diversification is based on portfolios of four plants. However, the choice of technologies for technological diversification varies depending on the timing. In the short term, technological diversification should occur via another VRE technology (i.e. PV or wind respectively); assuming increased price volatility in the longer term, storage should be included in portfolios. Technological diversification means that financial investors need additional capabilities in the valuation of different technologies, while plant owners need to acquire a new set of capabilities in constructing, operating and maintaining the different technologies. This could be challenging as the technologies differ substantially – especially when (battery) storage comes into play.

More specifically, our findings have different implications for different types of investors, namely commercial/public investors and private investors. While the focus of our analysis has been on large scale—and therefore most likely commercial/public—investors, we attempt to draw implications for private investors as well. Our recommendations are thereby based solely on economic criteria as opposed to behavioral or social criteria that may also influence private and commercial/public investment decisions. In addition to distinguishing investor types, we further differentiate between investors that already own plants (i.e. that want to extend their portfolio) and new investors (i.e. that build a portfolio from scratch).

Public/commercial investors typically accept higher levels of risk than private investors [25]. Our findings indicate, that investors that already own plants or stakes in plants are best served by investing in high revenue wind power, provided that such projects can be developed or acquired at reasonable cost. In doing so, they either maintain or improve their risk and revenue position and profit from reaching high capacity factors at these locations. Investing in wind locations with a high capacity factor will also guarantee high revenues in the future, as evident from the future price scenario. New public/commercial investors should either secure wind power plants with a high capacity factor if they accept higher levels of risk, or they should postpone their investments until arbitrage with storage becomes a viable business case for them in order to mitigate risk. They should choose either one of these two options since our results suggest that a combination of storage and wind power in a portfolio does not make sense for minimizing risk due to the positive correlation of the output of both plants.

Private investors, including farmers, who own more than 40% of the installed renewable energy capacity in Germany [51][18], have a lower low risk-bearing capacity [25]. They hence are specifically vulnerable to increasing risk if policy support is continuously reduced[19]. At the same time, private investors have comparatively limited capital at their disposal, which makes diversification difficult to achieve. Our results show that only plants that produce high revenues are favorable for risk mitigation in the short term. Diversification in the short term is therefore difficult to achieve for private investors, because the largest share of private investors already own PV plants [27] and wind is typically less scalable than PV and hence comes at relatively high capital cost. In the longer term, however, our findings indicate that these investors could consider adding storage to their portfolio. While private investors have started to adopt small storage devices for optimizing self-consumption [52,53], arbitrage opportunities have been less attractive so far due to lower economic viability [54]. For new private investors, our results indicate that investments in PV plants with a high capacity factor, i.e. in the south of Germany, represent the basis for diversification since PV locations with a high capacity factor are included in minimum risk efficient portfolios in both current and future price scenarios. Dependent on individual risk preferences and available capital, further investments should then either be steered in the direction of storage or wind locations with a high capacity factor. These implications base on the assumption that private investors would directly act in the market and do not need an intermediary as discussed below.

Second, our findings also have implications for the organizational structure of the renewable power sector, which relates back to individual investment decisions. Our results show that diversification will continue to gain importance in the future. Investments in wind or large-scale storage are, however, considerably less scalable than investments in PV. Therefore, the role of intermediaries, which is to combine and operate plants on the market, will gain importance in order to maintain the investment attractiveness of these technologies for small and medium-sized investors [55]. Such intermediaries have already gained importance for providing market access for plants in Germany [20]. Intermediaries, however, have different valuation criteria for VRE investments, as Gersema and Wozabal [10] point out in their analysis on portfolio diversification for virtual power plant providers. They infer that assets from lower annual yield locations are more valuable for operators of virtual power plants since their production patterns have a lower correlation to the market price [10]. This stands in contrast to our results, in which the asset with the highest annual yield constitutes the maximum revenue portfolio. This contradiction is important for the sales strategy of VRE operators and new investors. Our study shows that if investors have the financial resources and the competences to sell their power directly to the market, investing in high-yield locations will be advisable. Smaller scale investors that need an intermediary for selling their power or for diversifying their investment need to consider the lower market value of high-yield

[18] Values from 2016; for more detail, see Appendix H.
[19] Note that the majority of their investments have been profitable due to several years of fixed feed-in remuneration. However, they still have to cope with uncertain future revenues.

locations [50]. Investing in lower yield locations, however, would increase risk and reduce the investment attractiveness of VRE plants when selling power directly to the market.

Finally, our study holds two important implications for the future diffusion of VRE and complementary technologies like storage. First, the reduction of policy support and hence the increasing risk level of VRE investments can change the financial structure of these investments. In the recent past, both policy support and the increasing experience with operating VRE technologies have triggered a rise in debt funding [2,25]. This has broadened the financial base for VRE investments and decreased financing costs for VRE owners since the cost of debt for commercial/public investors is typically lower than the cost of equity [56]. Growing risks have the potential to revert this process and make VRE investments more dependent on scarcer equity capital, which would increase the cost of VRE projects again and could hence eventually stall further VRE diffusion, which is highly relevant for the strategic planning of power sector players and policymakers. Second, our findings relate to spatial diffusion patterns of VRE and the need for complementary technologies. Assuming that investors pursue risk mitigation as proposed by our findings, investments or upgrades of existing plants in locations with high capacity factors (e.g. wind in northern and solar in southern Germany) would increase substantially, provided that new locations for investment would be available. Since storage will only be economically viable at higher VRE shares, additional power transmission and distribution capacity to transmit power from production locations to demand centers will be needed until then. Strategically located storage could help to both mitigate grid congestion and support risk mitigation of VRE investors. Therefore, enabling business models in which storage can provide these different services is advisable and could prevent stranded investments in grid capacity. In line with previous studies [57–59], our study highlights the important role of policy and regulation for the investment attractiveness and diffusion of VREs and complementary technologies.

5 Conclusion

With increasing shares of VREs and decreasing policy support, VRE operators are facing considerably increasing market risks in the near future. Building diversified portfolios is one approach to hedging these risks. This study attempts to evaluate the contribution of two diversification strategies for VRE investors, geographical and technological diversification. To do so, we build a model based on MPT with data from eight VRE plants in different locations and a storage unit for arbitrage operations in Germany. In this model, we define return as average monthly revenue, and risk as the CVaR of monthly revenues at 90% and compare two price scenarios: the first with actual prices from 2015 until 2017, and the second with assumed future prices that reflect higher shares of VRE. When analyzing the efficient frontiers for the different diversification strategies, we derive three main conclusions: (1) Technological diversification is mostly the better risk mitigation strategy compared to geographical diversification; (2) overall improvement of the capacity factor is important for mitigating risk, and (3) in the shorter term, technological diversification with another VRE technology is the best option, whereas in the longer term, a decrease in average prices and increase in price volatility results in both increased revenues and risk performance for storage, making it the best option to minimize risks. Diversifying portfolios is not straightforward, specifically for smaller scale investors, who typically have a lower risk-bearing capacity. Intermediaries that could help smaller scale investors to diversify their portfolio, however, have different valuation criteria for optimizing portfolios than large scale investors, which may reduce the attractiveness of VRE investments for the former. On the societal level, the increasing risk levels of VRE investments could negatively affect deployment of VRE in comparison to conventional energy investments and lead to an increasing need for energy transmission and distribution capacities.

However, our study does not come without limitations, which should be addressed in further research. First, our study solely focuses on revenue, i.e., market, risk as the dominant form of risk for VRE investments. While there are a number of other risks connected to VRE investments, increasing risk due to decreasing policy support is a salient topic in current debates and can largely be translated into revenue risk. Nevertheless, the evaluation of other VRE investment risks, such as technology risk, curtailment risk or project execution risk, as well as the consideration of the costs of diversification could further strengthen the analysis. At the same time, further analyses could consider complementary measures for revenue risk mitigation, such as advanced trading strategies including forms of hedging [e.g. ,60], markets with higher trading intervals and potentially also short-term volatilities, or an optimized operation of the storage unit.

Second, our method for generating future electricity prices is based on the extrapolation of current trends and does not specifically consider structural changes in electricity price distributions due to higher VRE shares. One example of such a structural change is the so called duck curve in California [61]. This limitation could be addressed through the use of a specifically designed dispatch model for the generation of future electricity prices.

Third, our choice of research case, in terms of geographical extent, the number of locations, the conditions for land lease and the analyzed time span, limits the generalizability of our findings, because it limits the possibility of geographical diversification. Expanding the geographical scope of the analysis, e.g. to Europe as a whole, could result in better performance of geographical diversification compared to technological diversification. Such an expansion should, however, remain limited to the geographical areas that investors would be more inclined to invest in.

In addition to the geographical context, our choice of locations within Germany may constitute a selection bias. Our pick has, however, been random in spite of picking locations in different parts of Germany. It can further be assumed that owners of individual plants optimized their plants according to local conditions. Therefore, we argue that the risk of negative outliers due to bad plant choice is relatively low. The inclusion of more plants (in Germany and beyond) would likely increase the diversification effects, but is unlikely to change our general findings. While greater temporal coverage (our analysis covers three years) could increase the reliability of our findings, we would not expect substantial changes in our general findings. Comparing the plant productivity of the analyzed years with the previous three years includes no signs of significant changes to our results (see Appendix I).

Summing up, our analysis underlines that risk mitigation will become an increasingly important topic for VRE investors. We provide important insights on potential risk mitigation strategies for investors and identify potential pitfalls which should be addressed by policy makers that aim to maintain the pace of the energy transition.

Appendix

Appendix A: Robustness checks for electricity price scenarios

See Appendix Figure A 1, Figure A 2 and Figure A 3.

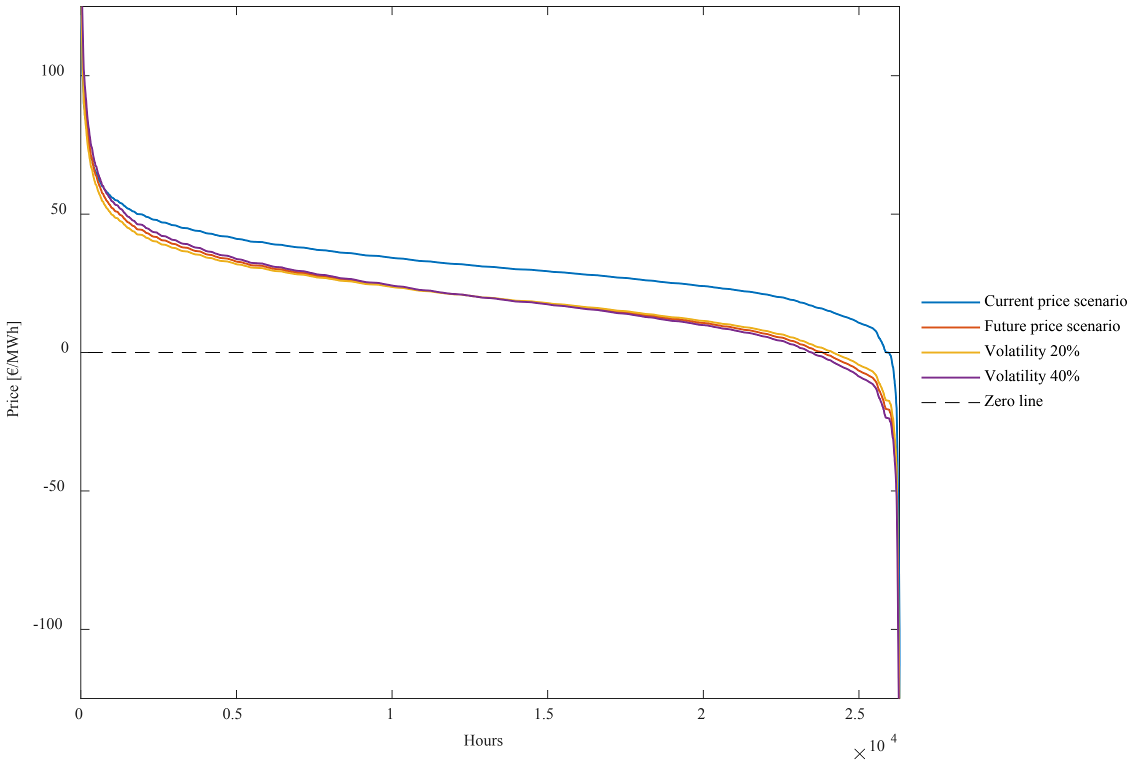


Figure A 1: Price duration curve for current and future price scenarios

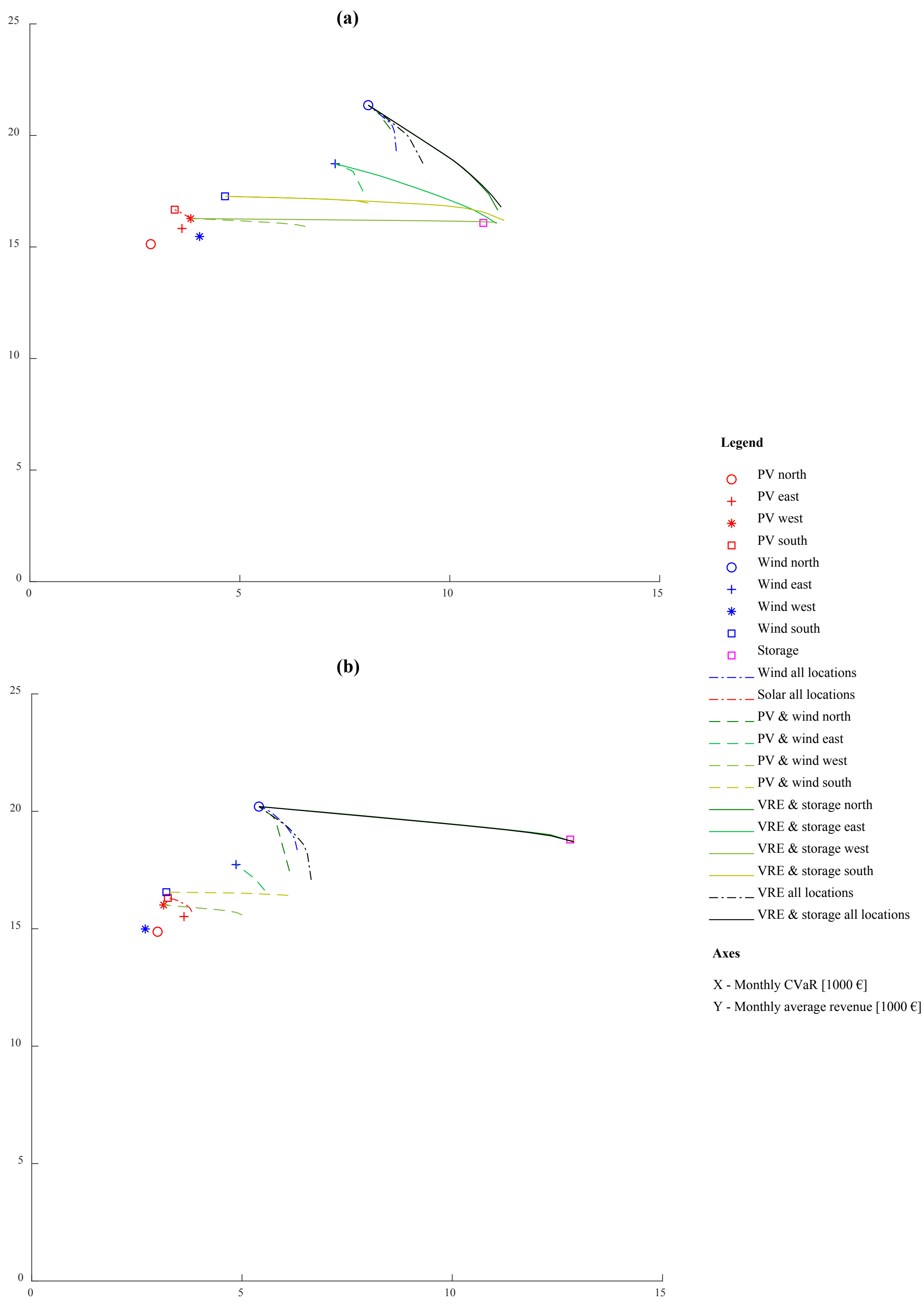


Figure A 2: Efficient frontiers with (a) 20% price volatility increase and (b) 40% price volatility increase

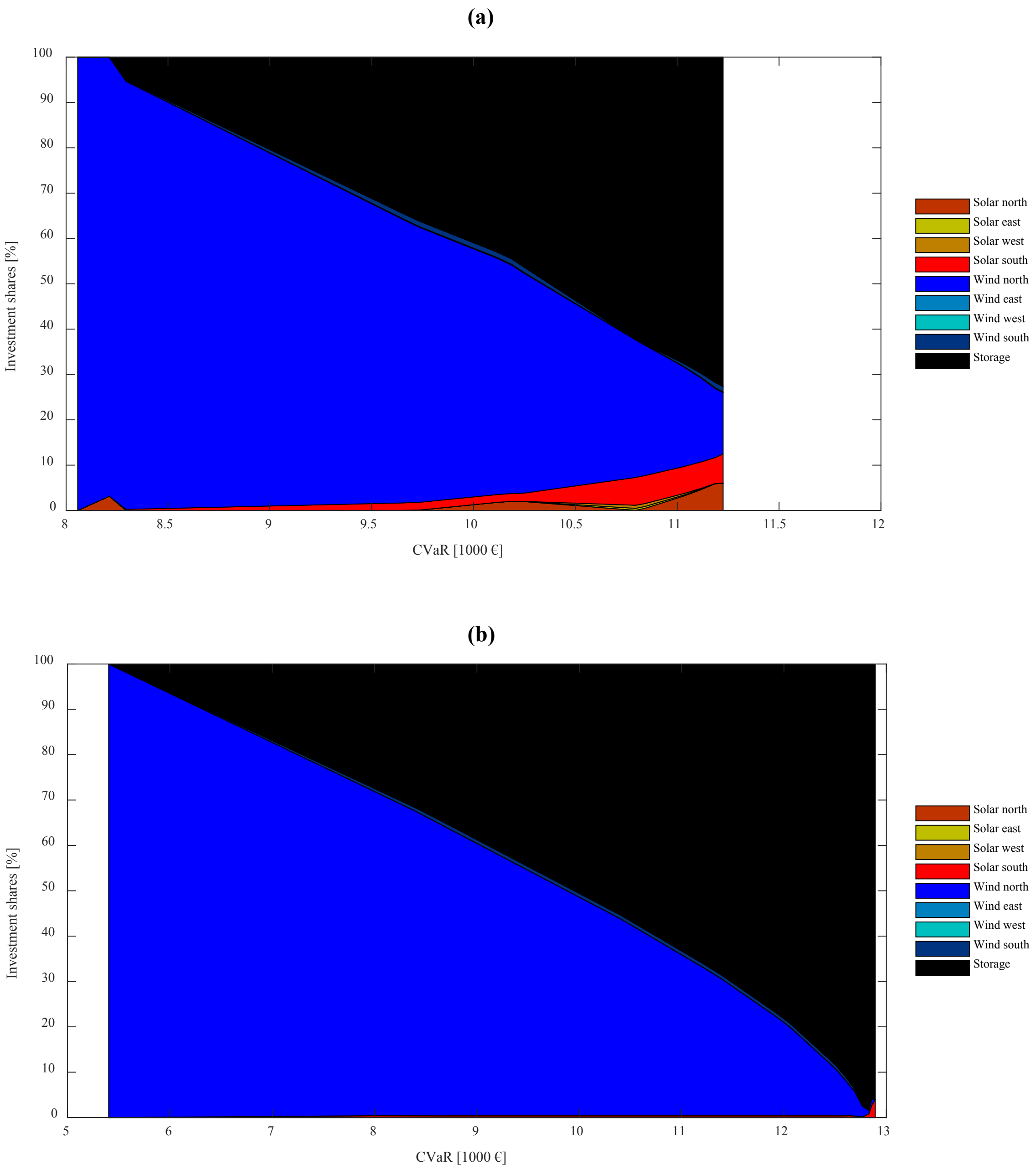


Figure A 3: Portfolio compositions with (a) 20% price volatility increase and (b) 40% price volatility increase

Appendix B: Storage operation

See Appendix Figure B 1.

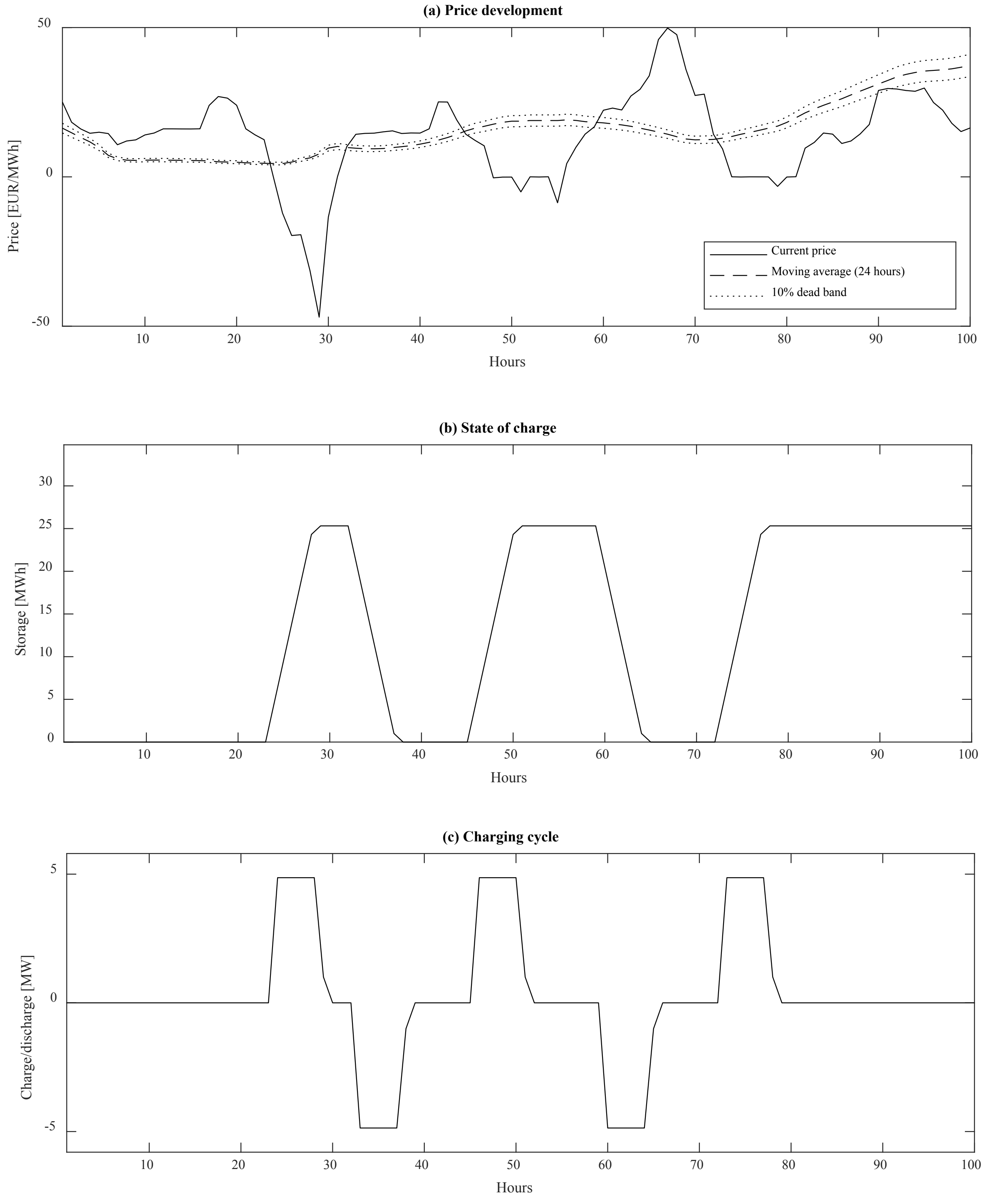


Figure B 1: Illustration of the storage operation (price development [a], state of charge [b], charging cycle [c]) for exemplary 100 hours of the current price scenario

Appendix C: Scatter plots for current and future price scenarios

See Appendix Figure C 1.

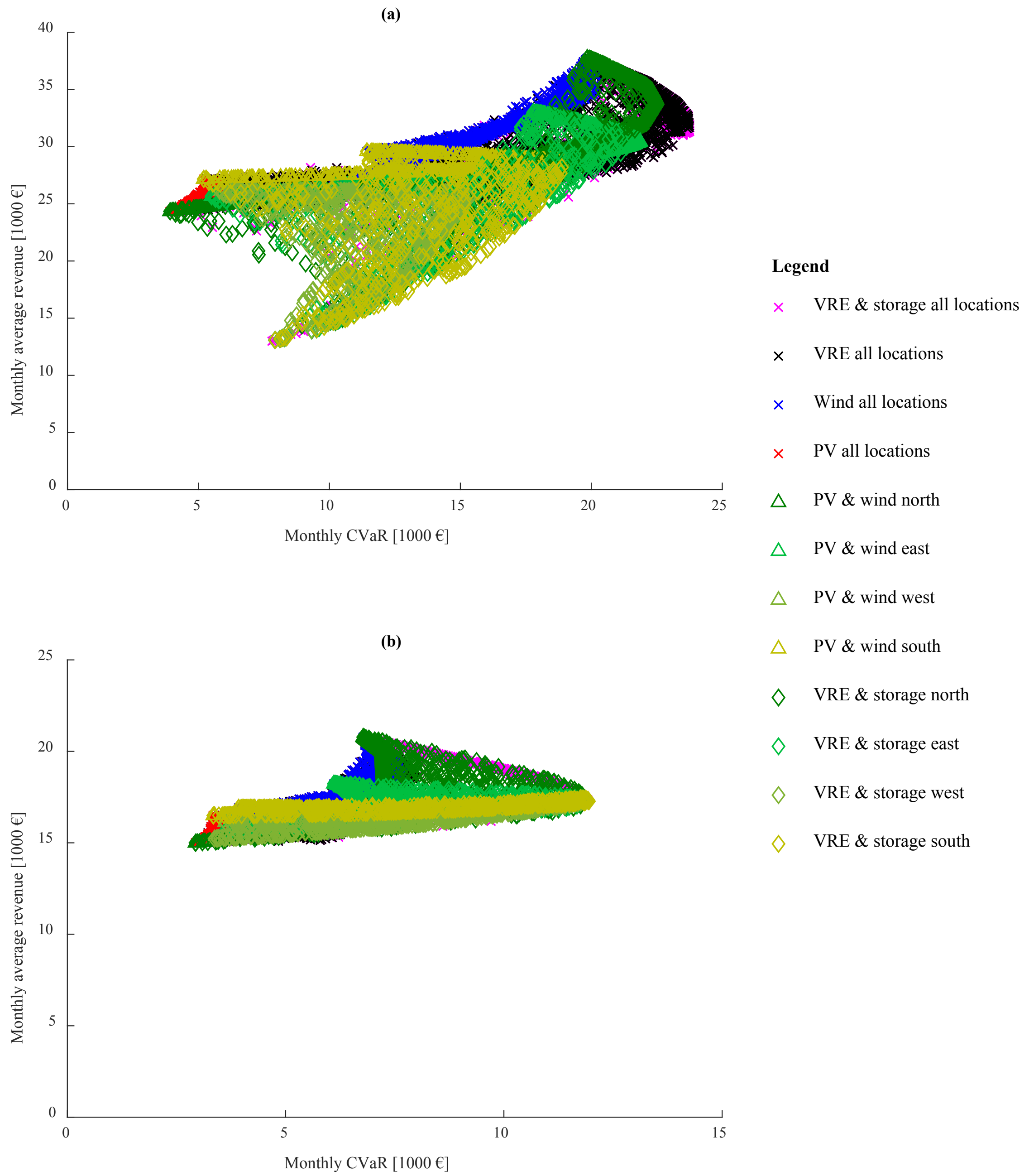


Figure C 1: Scatter plots for current (a) and future (b) price scenario

Appendix D: Seasonality of wind and PV plants

See Appendix Figure D 1 and Figure D 2.

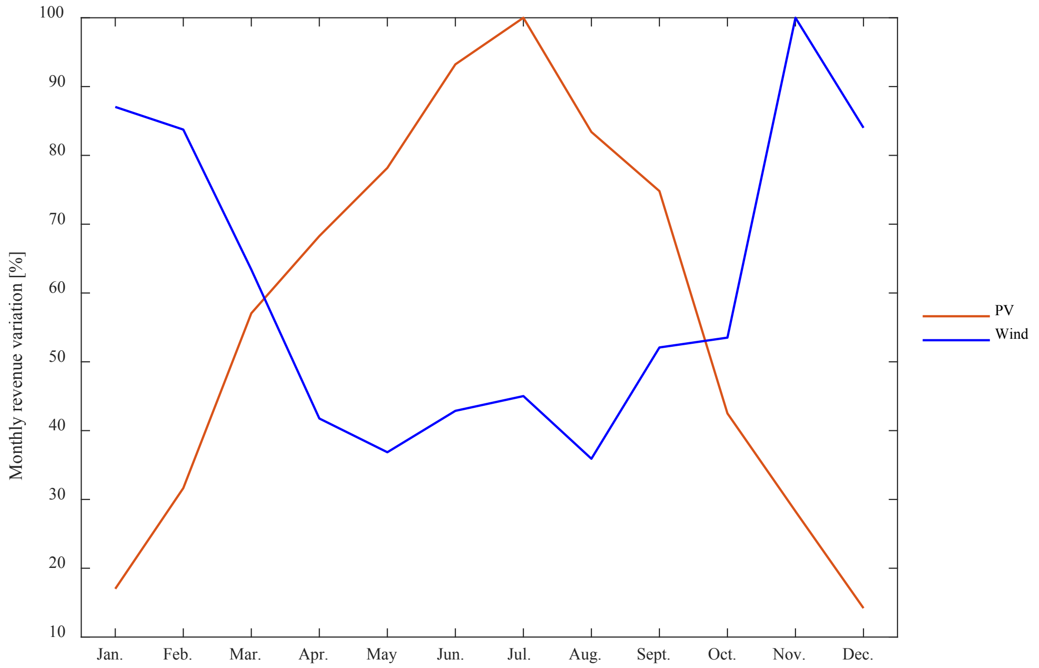


Figure D 1: Monthly revenue variation over all locations (average from 2015 until 2017) for current price scenario

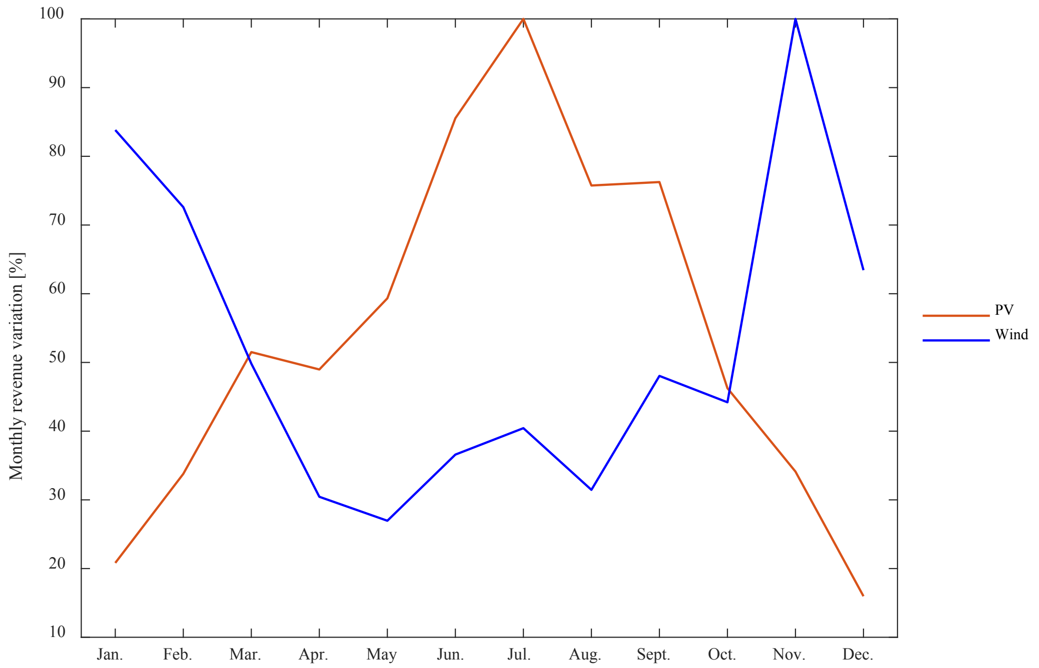


Figure D 2: Monthly revenue variation over all locations (average from 2015 until 2017) for future price scenario

Appendix E: Capacity factors and risk/return performance

Figure E 1 shows the aggregated capacity factors of fully diversified portfolios and their corresponding CVaR and revenue values at current prices.

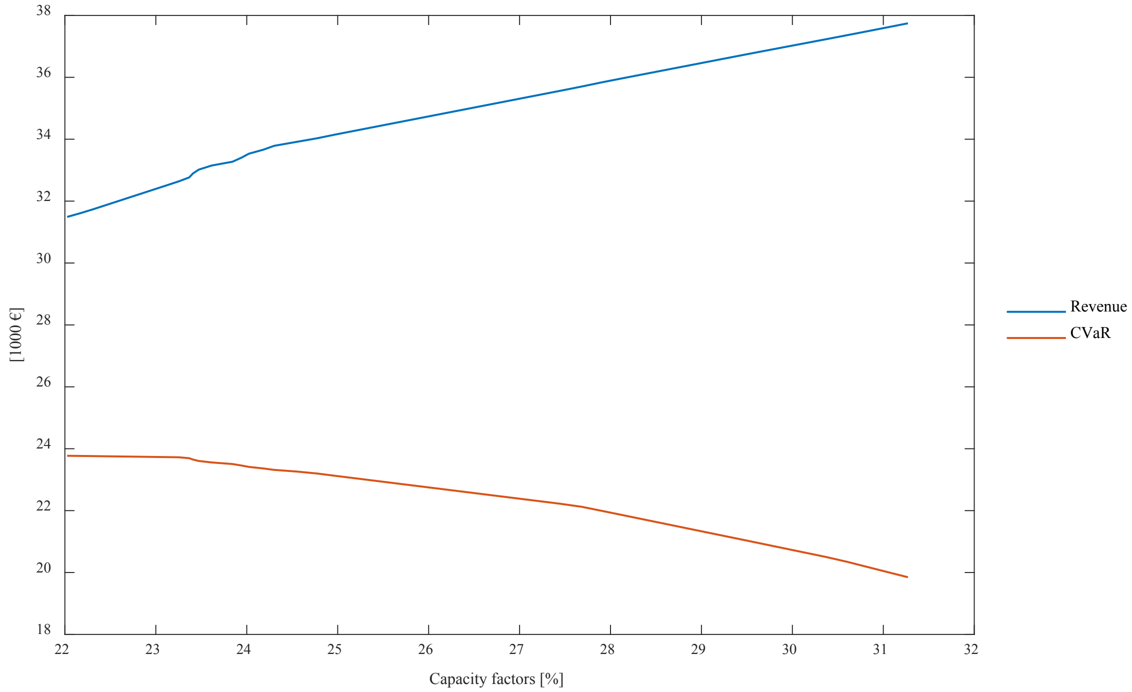


Figure E 1: Capacity factors of fully diversified portfolios and their corresponding CVaR and revenue values at current prices.

Appendix F: Correlation matrices

See Appendix Table F 1 and Table F 2.

	Solar north	Solar east	Solar west	Solar south	Wind north	Wind east	Wind west	Wind south	Storage
Solar north	1	0.97	0.96	0.94	-0.68	-0.71	-0.5	-0.66	-0.52
Solar east	0.97	1	0.96	0.95	-0.68	-0.7	-0.46	-0.64	-0.45
Solar west	0.96	0.96	1	0.96	-0.63	-0.67	-0.42	-0.64	-0.42
Solar south	0.94	0.95	0.96	1	-0.62	-0.66	-0.48	-0.68	-0.45
Wind north	-0.68	-0.68	-0.63	-0.62	1	0.85	0.57	0.65	0.62
Wind east	-0.71	-0.7	-0.67	-0.66	0.85	1	0.6	0.66	0.73
Wind west	-0.5	-0.46	-0.42	-0.48	0.57	0.6	1	0.83	0.54
Wind south	-0.66	-0.64	-0.64	-0.68	0.65	0.66	0.83	1	0.52
Storage	-0.52	-0.45	-0.42	-0.45	0.62	0.73	0.54	0.52	1

Table F 1: Correlation matrix of monthly plant revenues at current prices

	Solar north	Solar east	Solar west	Solar south	Wind north	Wind east	Wind west	Wind south	Storage
Solar north	1	0.96	0.94	0.92	-0.34	-0.35	-0.17	-0.3	-0.29
Solar east	0.96	1	0.96	0.94	-0.21	-0.23	-0.04	-0.19	-0.15
Solar west	0.94	0.96	1	0.94	-0.16	-0.2	0.01	-0.18	-0.1
Solar south	0.92	0.94	0.94	1	-0.22	-0.26	-0.14	-0.29	-0.16
Wind north	-0.34	-0.21	-0.16	-0.22	1	0.86	0.71	0.75	0.6
Wind east	-0.35	-0.23	-0.2	-0.26	0.86	1	0.72	0.72	0.66
Wind west	-0.17	-0.04	0.01	-0.14	0.71	0.72	1	0.89	0.51
Wind south	-0.3	-0.19	-0.18	-0.29	0.75	0.72	0.89	1	0.47
Storage	-0.29	-0.15	-0.1	-0.16	0.6	0.66	0.51	0.47	1

Table F 2: Correlation matrix of monthly plant revenues at future prices

Appendix G: Model sensitivity for changes in investment cost ratios

Figure G 1 shows the portfolio compositions of maximum return (a), medium risk and return (b) and minimum risk (c) when varying the investment cost of the different technologies by ±10%. Figure G 2 illustrates the changes in risk and return values for varying investment cost of the different technologies by ±10%. The number of commutations for both figures is 27.

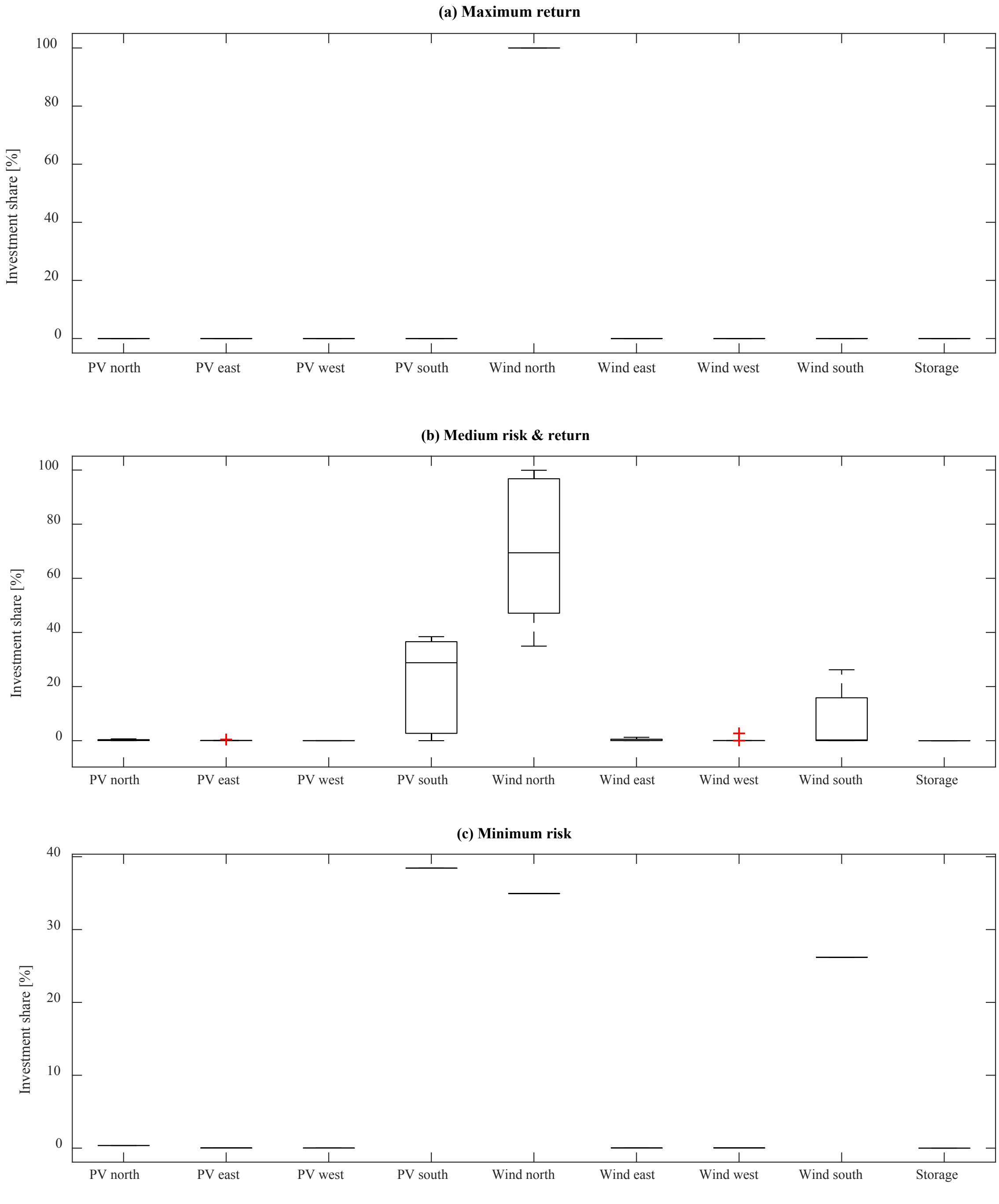


Figure G 1: Portfolio composition at maximum return (a), medium risk and return (b) and minimum risk (c) with varying investment cost ratios

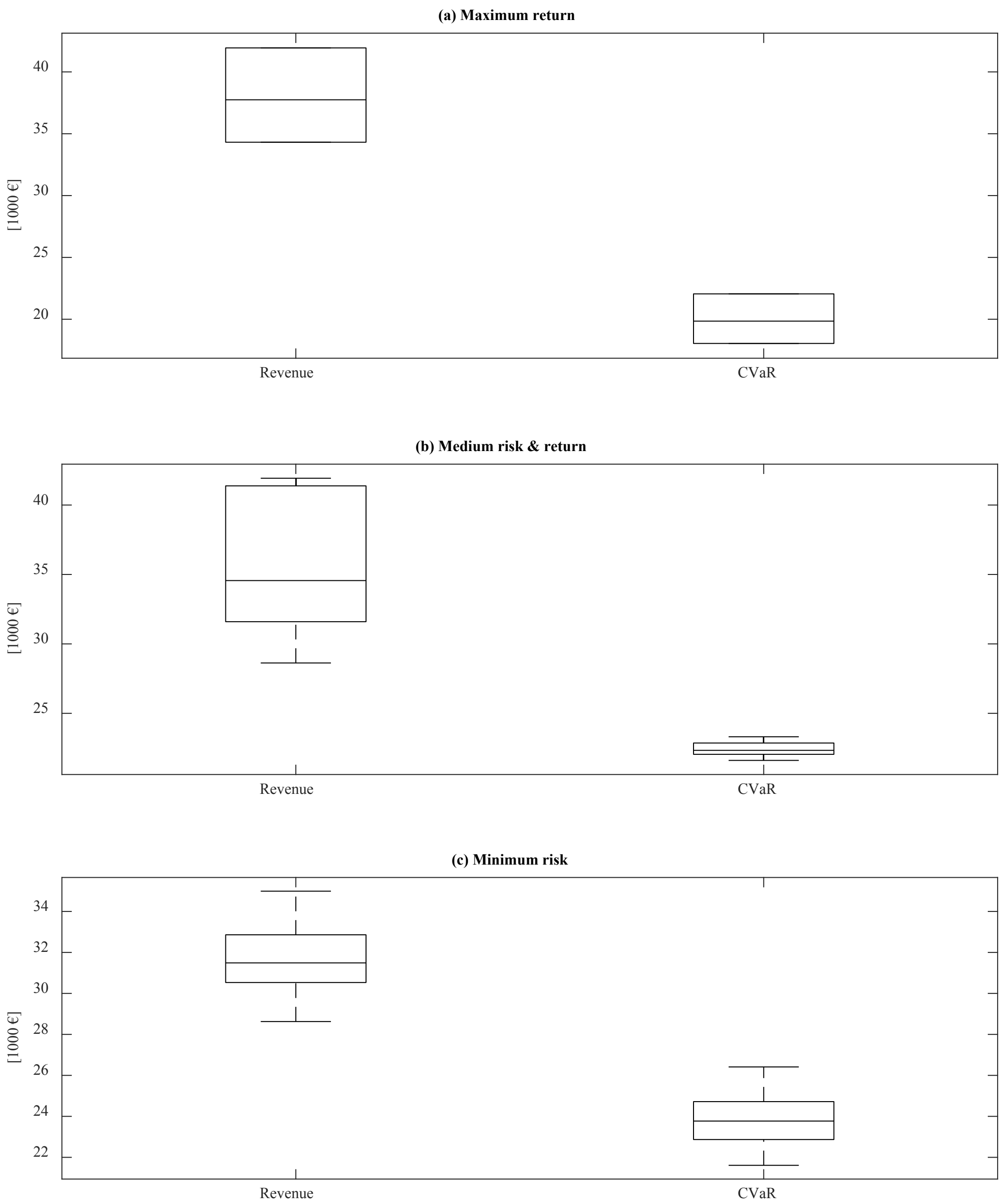


Figure G 2: CVaR and revenue at maximum return (a), medium risk and return (b) and minimum risk (c) with varying investment cost ratios

Appendix H: Ownership structure of German VRE plants 2016

See Appendix Figure H 1.

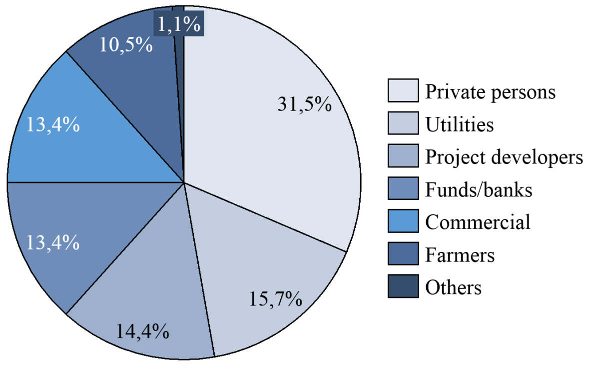


Figure H 1: Share of renewable energy capacity by actor [51]

Appendix I: Comparison of wind and solar productivity from 2015-2017 to previous years

See Appendix Figure I 1.

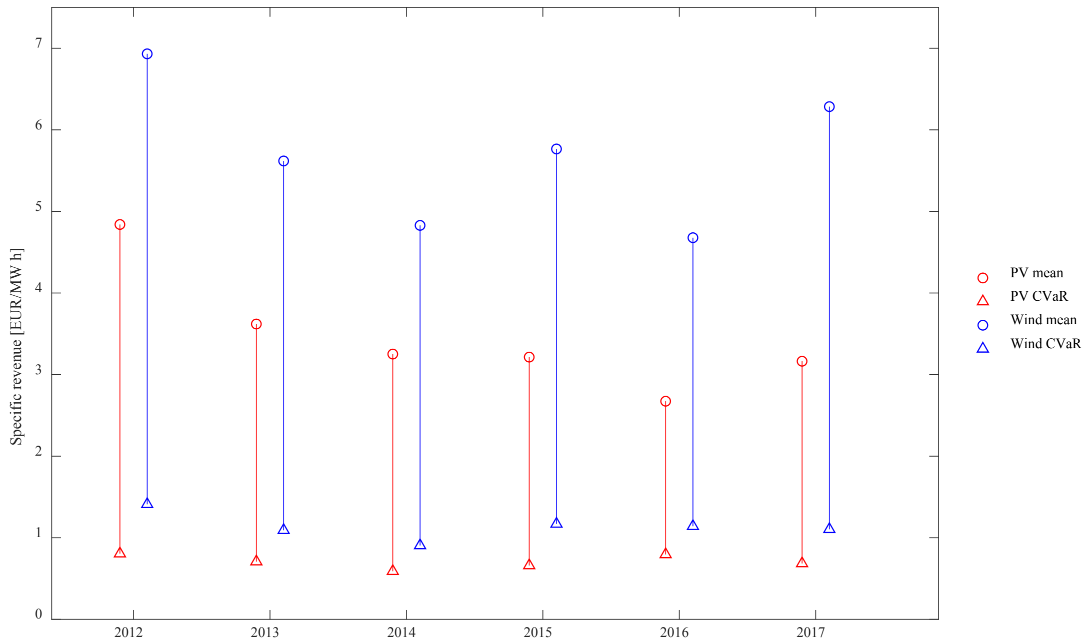


Figure I 1: Mean revenue and CVaR per MW and hour for PV and wind from 2012 until 2017 [62]

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