Evaluating Investments in Renewable Energy under Policy Risks

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ABSTRACT

The considerable amount of required infrastructure and renewable energy investments expected in the forthcoming years also implies an increasingly relevant contribution of private and institutional investors such as insurers. In this context, especially regulatory and policy risks have been shown to play a major role for investors when evaluating investments in renewable energy and should thus also be taken into account in risk assessment and when deriving risk-return profiles. In this paper, we provide a stochastic model framework in order to quantify policy risks associated with renewable energy investments (e.g. a retroactive reduction of a feed-in tariff), thereby also taking into account energy price risk, resource risk, and inflation risk. The model is illustrated by means of scenario analyses and applied to identify potential country diversification effects within a portfolio of renewable energy investments, which is also of high relevance for the new European risk-based insurance regulatory framework Solvency II.

Keywords: Renewable energy; wind parks; policy risk; diversification; value at risk

1. INTRODUCTION

The increasing expansion of renewable energy to reduce greenhouse gas emissions is one main goal of the Europe growth strategy 2020. To provide incentives for private and institutional investors to invest in renewable energy such as wind parks, the governments typically grant subsidy payments during the life span of the investment projects (e.g. feed-in tariff (FIT)) (Turner et al. (2013, p. 6)). In this context, policy risks have been identified as one of the most prominent risks as the uncertain future of the policy support schemes for investments in renewable energy

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projects implies a high degree of uncertainty regarding future cash flows (Micale et al. (2013), Jin et al. (2014), Gatzert and Kosub (2014)). In Spain, Bulgaria, Greece, and the Czech Republic, for instance, the guaranteed feed-in tariffs have recently been reduced retroactively for solar parks, thus implying a considerable reduction of investors' returns.

Hence, policy (or political) risks play a major role for investors when evaluating investments in renewable energy projects and should be taken into account when establishing risk models and when deriving risk-return profiles. In this context, especially country diversification effects may help to reduce regulatory and policy risks associated with renewable energy investments in different countries for diversified portfolios. This is also of relevance for Solvency II, the new European risk-based regulatory framework for insurers being introduced in 2016. For insurers seeking new investment alternatives, especially the stability of long-term cash flows plays a major role along with the question of policy risk as described above, as well as regulatory risks, i.e. how different types of infrastructure investments are treated under Solvency II. Against this background, the aim of this paper is to develop a model to quantify policy risks based on a qualitative risk assessment by experts using fuzzy numbers, which will be applied to identify potential country diversification effects that may reduce the overall risk of a portfolio of renewable energy investments. We thereby also take into account energy price risk, resource risk, and inflation risk.

Policy support schemes (see Meyer (2003) for an overview of different support schemes such as feed-in tariffs, feed-in premiums or the tender system) as one main incentive for renewable energy investments have been studied in various dimensions in the literature, including real (regulatory) option approaches and first insight regarding policy risks for various countries (e.g. Boomsma, Meade and Fleten (2012), Brandstätt, Brunekreeft and Jahnke (2011), Campoccia et al. (2009), Holburn (2012), Kitzing (2014), Monjas-Barroso and Balibrea-Iniesta (2013). In addition, Gatzert and Kosub (2014) provide an overview of risks and risk management solutions for renewable energy projects with focus on onshore and offshore wind parks and identify relevant gaps in risk transfer. Their results show that especially policy and regulatory risks represent major barriers (see also Jin et al. (2014), Micale et al. (2013))) and that diversification is among the most important tools for risk mitigation and used in various dimensions.

Overall, while previous literature has emphasized that policy (political) and regulatory risks are among the most relevant risks for investments in renewable energy projects, risk mitigation and transfer is highly challenging (see Gatzert and Kosub (2014)). In the literature, the definitions and distinctions between political, policy, and regulatory risks differ. Smith (1997) defines traditional political risks as the risks related to expropriation, currency convertibility and transferability, as well as political violence, and regulatory risks as the risks arising from the application and enforcement of regulatory rules, both at the economy and the industry (or project) level, including rules contained in contracts with governments, in laws, and in other regulatory instruments. Brink (2004) further analyzes political risks and distinguishes political risk factors depending on economic, political and social factors. Further (empirical) analyses of specific aspects of policy and regulatory risks as well as risk drivers are studied in Alesina and Perotti (1996), Barradale (2010), Fagiani and Hakvoort (2014), Holburn (2012), Hitzeroth and Megerle (2013), Lüthi and Prässler (2011) as well as in Lüthi and Wüstenhagen (2012), who conduct an empirical survey on stated preferences among photovoltaic project developers and derive their willingness-to-accept for certain policy risks. In addition, Bürer and Wüstenhagen (2008) study venture capital investments in clean technology and illustrate active and passive risk management strategies to manage regulatory risks. Sachs, Tiong and Wagner (2008) include regulatory risks into their political risk analysis and use a method based on fuzzy numbers to quantify regulatory risks based on qualitative information acquired from experts. Reuter et al. (2012) also study the probability of feed-in tariff reductions as one application of their renewable energy investment approach, but without modeling the underlying risk factors and with focus on investment incentives instead of a risk assessment of existing projects in the operating phase. With focus on regulatory risks frequently occurring in infrastructure projects, Bond and Carter (1995) distinguish two cases: (1) tariff adjustments not being permitted or made on time (in case of inflation or devaluation, for example), where companies can hedge against this risk by implementing automatic adjustments into contracts, but ultimately complying with these obligations lies with the government or its state owned enterprises; and (2) regulatory changes, which, for instance, include possible changes in environmental regulations that may impact many infrastructure companies and their lenders. In general, policy risk can be expected to further increase in the future as pointed out by Turner et al. (2013, p. 7), who see a trend towards combining regulatory certainty with market-based components, as states change their support schemes to achieve cost reduction and a fairer distribution of risks.

The purpose of this paper is to contribute to the literature by developing a model framework for studying policy risks and country diversification effects for investments in renewable energy projects. In contrast to previous work, we take into account risk factors that drive policy risk in the model (e.g., political stability, economic stability, public acceptance) and apply scenario analyses regarding the likelihood and impact of the considered policy risk scenarios (e.g. retroactive reduction of feed-in tariff) to illustrate the model. Based on this, we derive risk-return profiles and compare different risk measures of renewable energy investments for the case of wind parks using simulation techniques, thereby also taking into account country diversification effects regarding policy risks.

The quantification of policy risks is challenging, and relying on expert estimations will typically be necessary as the number of comparable events, which can be used to quantify policy or political risk and to calibrate the model, is typically not sufficiently large. This is also stated by Brink (2004), for instance, who points out that the measurement and observation of political risk to a great extent depends on subjective human judgment. Therefore, if objective probabilities for policy risk factors cannot be obtained, one needs to revert to experts (see also Sadeghi, Fayek and Pedrycz (2010)). In this paper, we will make use of fuzzy set theory, which provides a methodology for 1) handling subjective and linguistically expressed variables and 2) for representing uncertainty in the absence of complete and precise data (see Sadeghi, Fayek and Pedrycz (2010)). The use of expert estimations and fuzzy numbers for quantifying qualitative information on risk (i.e. expert estimates) is also done by, e.g., Sachs, Bellinger and Tiong (2008), Sachs and Tiong (2009), Sachs, Tiong and Wagner (2008), Sadeghi, Fayek and Pedrycz (2010), and Thomas, Kalidindi and Ganesh (2006). Regarding the cash flow model, we extend the approach in Campoccia et al. (2009) and follow Monjas-Barroso and Balibrea-Iniesta (2013) to model energy prices at the exchange using a mean-reverting process, which can also be extended. Inflation risk is modeled using the Vasicek (1977) model. The developed model will be exemplarily applied to the evaluation of onshore wind parks including a risk of a retroactive reduction of a feed-in tariff, but it can also be applied to other renewable energy investments such as solar parks, for instance, and also take.

The paper is structured as follows. Section 2 presents an approach for the quantification of policy risk based on expert opinions and fuzzy numbers and Section 3 provides a model for modeling cash flows of renewable energy investments including market risk, resource risk, inflation risk and policy risk. Section 4 presents the calibration of the model to the case of France and Germany as well as the results of the numerical scenario analyses. Section 5 concludes.

2. MODELING AND ASSESSING POLICY RISK OF RENEWABLE ENERGY INVESTMENTS

As described before, the definitions of policy, political and regulatory risks differ. In what follows, we consider developed countries and use the term “policy risks”, thereby focusing on retroactive adjustments of support schemes of the investments in renewable energy (e.g., a retroactive FIT reduction) as has been observed in Bulgaria, the Czech Republic, Greece, Italy, and Spain, for instance.

General procedure

To quantify policy risk, it is common to first identify driving risk factors (see, e.g., Brink (2004) and Sachs, Tiong and Wagner (2008)). For instance, one could consider the categories stated by Brink (2004) (political, economic and social) and assume one relevant risk factor in each category (e.g. political instability, economic instability, decline of public acceptance). Each of these risk factors is assessed by experts, who estimate the probability of occurrence and the impact, according to the following procedure as laid out in Thomas, Kalidindi and Ganesh (2006) by performing three steps: 1) Scenario modeling (in our case, policy risk scenarios that depend on the specific country and the respective policy support scheme, e.g. a feed-in tariff (FIT) reduction of α% or a change in the drift or volatility of a green certificate price process) along with an identification of the relevant risk factors driving policy risk, which will be used to obtain probabilities for the policy risk involving estimations of experts, 2) fuzzy Delphi probability prediction (by means of the commonly used Delphi technique for expert estimations, see, e.g., Hsu and Sandford (2007)), i.e. the likelihood of occurrence and impact of the risk factors associated with the policy risk scenario are coded with fuzzy numbers and then aggregated, and 3) (quantitative) risk impact evaluation using simulation techniques.

Likelihood and impact of risk factors

In what follows, we assume that $m = 1,\ldots, M$ (independent) risk factors r_m (e.g., political or economic instability, decline of public acceptance) were identified that impact the risk of respective policy risk scenario s (e.g., FIT reduction of α%). Following Thomas, Kalidini and Ganesh (2006), Kafka (2008), and Sachs and Tiong (2009), N experts are first asked “what is the likelihood that the risk factor occurs?” in order to obtain the likelihood of occurrence $P(r_m)$ per unit of time of the respective risk factor m. The unit of time has to be chosen carefully in order to account for estimation biases (see Kafka (2008)). The experts estimate the likelihood of occurrence of each risk factor with a linguistic variable (extremely low, very low, low, medium, high, very high, extremely high), which is then transformed into a trapezoidal fuzzy number[1] (Sachs and Tiong, 2009). The experts next estimate the conditional probability that the policy risk scenario occurs given the occurrence of risk factor *m*, denoted with $P(s \mid r_m)$, by answering the question “given that the risk factor occurs, what is the likelihood that it causes the policy risk scenario?” These estimations are updated following the Delphi technique (see Thomas, Kalidindi and Ganesh (2006)), where experts receive the average of the responses of the other experts and are allowed to reconsider their first estimations. Combining the resulting estimations, one can then derive the probability of the event (“risk factor *m* causes the policy risk scenario *s*”).

Fuzzy numbers: Assessing the likelihood

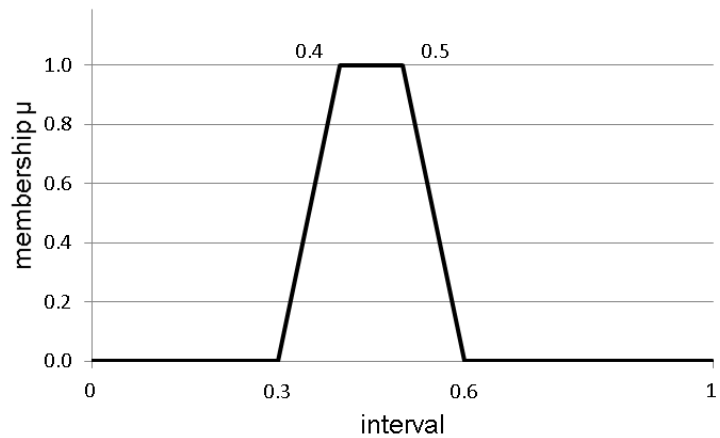
One challenge is to transform these linguistic values into a probability, since a response of “medium” does not necessarily exactly mean a probability of 0.5, for instance. Thus, fuzzy set theory is used by coding each linguistic response with a trapezoid fuzzy number whose membership function $\mu(x)$ is defined by a quadruple (a,b,c,d) through

$$\mu(x)=\begin{cases} 0 & x<a \vee d\le x \\ \frac{x-a}{b-a} & a\le x<b \\ 1 & b\le x<c \\ \frac{d-x}{d-c} & c\le x<d, \end{cases}$$

where *a* and *d* reflect the range associated with the linguistic value (e.g. “medium”) as exemplarily shown in Figure 1, where a “medium” is not below 0.3, not higher than 0.6, and definitely between 0.4 and 0.5 (Sachs, Bellinger and Tiong (2008)).

[1] There are also other types of fuzzy numbers, which can be used, e.g., Thomas, Kalidini and Ganesh (2006) use triangular fuzzy numbers. We follow Sachs and Tiong (2009) and use trapezoidal fuzzy numbers as this is slightly more general (trapezoidal fuzzy numbers contain triangular fuzzy numbers).

Figure 1: Illustration of a trapezoidal fuzzy number representation of the linguistic value "medium"



The numerical representation of linguistic values is referred to as the "knowledge base" in Sachs and Tiong (2009) and must be identified before conducting the survey by collecting numerical opinions on the linguistic values. We later make use the values stated by Sachs and Tiong (2009, p. 60). The responses of the N experts for each risk factor are aggregated by assigning a weight c_n (e.g., $1/N$) to each expert opinion, i.e.

$$x_m = \sum_{n=1}^{N} c_n \cdot x_{m,n} \text{ with } \sum_{n=1}^{N} c_n = 1, \tag{1}$$

where $x = a, b, c, d$. For instance, in case the opinion of expert n regarding the likelihood of occurrence $P(r_m)$ of risk factor m is "medium", the representation in Figure 1 implies that $a_{m,n}$ = 0.3, $b_{m,n}$ = 0.4, $c_{m,n}$ = 0.5, $d_{m,n}$ = 0.6. Based on the aggregated opinion of the experts, one obtains a fuzzy number representation (with quadruples a,b,c,d) for $P(r_m)$ and $P(s|r_m)$ of each risk factor. For further arithmetic operations on fuzzy numbers and a detailed introduction, we refer to Klir and Yuan (2005).

The fuzzy numbers resulting from Equation (1) are then defuzzified using (see Klir and Yuan (2005))

$$c = \frac{\int_{\mathbb{R}} \mu(x) \cdot x \cdot dx}{\int_{\mathbb{R}} \mu(x) \cdot dx}, \tag{2}$$

where c is the obtained real (also referred as crisp) number. The average and the personal estimations are then presented to the experts, who can use these values for reconsideration and possible revision of their previous estimations (Thomas, Kalidindi and Ganesh (2006)). This procedure is repeated until the coefficient of variation of the estimations is below a defined value, e.g., 0.2. The probability of the policy risk scenario s, $P(s)$, is then given by

$$P(s)=1-\prod_{m=1}^{M}\left(1-P(s\,|\,r_m)P(r_m)\right)\ P(s)=1-\prod_{m=1}^{M}\left(1-P(s\,|\,r_m)P(r_m)\right) \quad (3)$$

Assessing the impact

Thomas, Kalidindi and Ganesh (2006) point out that assessing the impact of the policy risk scenario at a higher level (i.e. no breakdown to risk factors) is generally easier for the experts, i.e. they estimate the impact dependent on the underlying policy risk scenario (e.g., the percentage α of a FIT reduction in Germany). The experts are asked to estimate an optimistic, a most plausible and a pessimistic value (e.g. for α), which are then translated in a triangular fuzzy number (i.e., $b = c$ in terms of trapezoidal fuzzy numbers) (Thomas, Kalidindi and Ganesh (2006)). Again the Delphi technique is used to achieve a consensus between the experts. After the determination of the likelihood of occurrence through Equation (3) and the impact, the obtained fuzzy numbers are defuzzified using Equation (2) in order to obtain a real-valued reduction probability and a real-valued impact on the support scheme. These values can then be used in the simulation analysis.

Discussion of the method

The quantification of risk depending on the experts' opinions is generally difficult as the assessment is subjective and the probabilistic approaches for handling this information often assume more knowledge than is actually available (Guyonnet et al., 2003). Moreover, one has to take into account potential biases in the estimates of the experts and the potential influence of heuristics that are used by the experts (see e.g., Garthwaite, Kadane and O'Hagan (2005)). Nevertheless, many researchers have successfully applied fuzzy numbers for dealing with this issue (see e.g., Thomas, Kalidindi and Ganesh (2006) as standard probability theory is not suitable for modeling the inherent fuzziness of the parameter estimates (Choobineh and Behrens (1992))

In addition, the overall risk may not only depend on estimated probabilities, but also on other random variables (e.g., electricity prices). There are two approaches for combining these two types of uncertainty (see Sadeghi, Fayek and Pedrycz (2010)): a transformation of the fuzzy probabilities to real-valued probabilities as described above, and a hybrid approach. A hybrid approach as laid out in Sadeghi, Fayek and Pedrycz (2010) or Guyonnet et al. (2003) leads to a fuzzy outcome (a fuzzy cumulative distribution function or a fuzzy expected value, respectively), which is difficult to interpret for the decision maker. A transformation to crisp numbers as conducted by Wonneberger, Kistinger and Deckert (1995) and Sachs and Tiong (2009), for instance, has the disadvantage that there are several ways of transforming fuzzy numbers to real numbers. As the approach using a transformation allows a better interpretation, we use the latter with the transformation defined by Klir and Yuan (2005) and also used in, e.g., Thomas, Kalidindi and Ganesh (2006).

3. MODELING CASH FLOWS OF RENEWABLE ENERGY INVESTMENTS INCLUDING POLICY RISK

We focus on the investor's perspective and describe a model which can be used to evaluate investments in renewable energy and to quantify policy risks associated with the investment, given that the wind or solar park is already in operation.[2] In addition, we describe cross-country diversification benefits that may arise within a portfolio of renewable energy investment projects. We focus on the case of feed-in tariffs, which are among the most widely used policy instruments to support renewable energy, especially in the European Union (see Lüthi and Wüstenhagen (2012, p. 2), Campoccia et al. (2009, p. 288)). However, the model can as well be extended to other types of support schemes (e.g., green certificates as implemented in Italy by defining the (possibly stochastic) price of renewable energy and by taking into account the respective policy risk by means of jumps, for instance).

Evaluating investments in renewable energy projects

In what follows, we consider the cash flows resulting from a direct investment in a renewable energy project (e.g. wind or solar parks) in $k = 1,\ldots, K$ countries, which depend on several factors and variables as described in Table 1.

[2] We refer to Lüthi and Prässler (2011) and Lüthi and Wüstenhagen (2012) regarding the impact of policy risks on investors' decisions to invest in wind or solar parks in the first place.

Table 1: Notation and description of variables

Variable	*Description*	*Model / calibration*
$1 + \gamma^k$	Discount factor in country *k*	Constant internal rate of return (IRR)
$P_t^{k,renewable}$	(Monthly) average price of renewable energy received by the operator (in €/MWh)	Depends on policy support scheme in the respective country (here: FIT in different country-dependent specifications) and/or traded energy prices at the exchange; subject to policy risk scenarios
P_t^{ex}	(Monthly) average energy price obtained at the exchange (in €/MWh)	Mean-reverting process
PE_t^k	Produced electricity in month *t* in country *k* (in MWh)	$PE_t^k = L_t^k \cdot CP^k \cdot 720h$
CP^k	Installed capacity in country *k* (in MW)	
L_t^k	(Monthly) load factor in country *k*	Stochastic, taking into account resource risk and interruptions (Abadie and Chamorro (2014))
PI_t^k	Price index describing the development of the price level of the OMSI in country *k*	Vasicek model
$OMSI^k$	Operation, maintenance, staffing and insurance costs in country *k* (in €)	Deterministic (contract with fixed charges), adjusted by the price index
FIT_t^k	FIT at time *t* (subject to policy risk scenarios) (in €/MWh)	Deterministic or stochastic depending on the respective country
T	Investment period (in years)	E.g. 25 years (assumption) (= 300 months)
$T^{S,k}$	Support period for FIT in years (in general $T >= T^S$) (e.g. 20 years in Germany)	Depends on country
τ^k	Point in time where the policy risk scenario occurs	See Section 2 for derivation
α^k	Percentage reduction in FIT in case of policy risk	See Section 2 for derivation

In particular, we follow, e.g., Campoccia et al. (2009) and define the cash flow of the renewable energy project investment in country *k* at time *t* as

$$C_t^k = PE_t^k \cdot P_t^{k,renewable} - OMSI^k \cdot PI_t^k = PE_t^k \cdot f\left(FIT_t^k, P_t^{ex}, \tau^k, \alpha^k, T^{S,k}\right) - OMSI^k \cdot PI_t^k. \quad (4)$$

where PE_t^k denotes the monthly produced electricity in MWh at time *t*, $P_t^{k,renewable}$ is the (monthly average) price obtained for 1 MWh electric energy produced,[3] $OMSI^k$ are costs for operation, maintenance, staffing, and insurance, and PI_t^k denotes the price index, which describes the development of the OMSI price level over time. Analogously to Abadie and Chamorro (2014), we assume that each cash flow is received at the end of month such that t = 1,…, $T \cdot 12$. Using the discounted cash flow (DCF) method (see, e.g., Campoccia et al. (2009)), the (stochastic) present value of the cash flows in Equation (4) at time 0 is thus given by

3 See, e.g., Campoccia et al. (2009) for an overview of different support specifications in various countries.

$$PV^k = \sum_{t=1}^{T\cdot 12} \frac{C_t^k}{\left(1+\gamma^k\right)^{t/12}}, \tag{5}$$

where γ^k is the discrete annual discount factor (typically the weighted average costs of capital (WACC) or the investor's internal rate of return (IRR)).

In addition, we make the following assumptions regarding the variables in Equation (4). The produced electricity PE_t^k generally depends on various factors, especially on the type of renewable energy project and the location, amongst others. We follow Abadie and Chamorro (2014) and model all interruptions and resource risk through the stochastic behavior of the load factor L_t^k, whereby the load factor multiplied with the installed capacity CP^k and the time (i.e., 720h per month) yields the produced electricity, i.e.

$$PE_t^k = L_t^k \cdot CP^k \cdot 720h$$

with

$$L_t^k = g_t^k + L_m^k + \varepsilon_t^k, \quad t = 1,\ldots,T\cdot 12$$

where L_m^k is the long-term average load factor, g_t^k accounts for the seasonality in the respective location and ε_t^k is normally distributed with mean 0 and standard deviation σ_L^k. We do not consider stochastic fluctuations of the operational expenditures (OMSI), as maintenance contracts usually involve fixed charges (except for possible inflation effects as reflected in Equation (4)).

The price $P_t^{k,renewable}$ that the operator of a renewable energy project obtains for renewable energy when selling it to a utility generally depends on the support scheme (e.g. FIT) in the respective country and the type of renewable energy, the prices at the exchange P_t^{ex},[4] inflation risk,[5] and policy risk, among others.

To model energy prices at the exchange, we follow Monjas-Barroso and Balibrea-Iniesta (2013) and use a simple model for tractability reasons, which, however, can be easily extended if

[4] This price is relevant in the following cases: E.g. after the maximum support duration, e.g. 20 years in Germany, when reaching a cap, when the FIT is below the spot market price, and in case of a subsequent switch to the market premium model as in case of Germany, for instance.

[5] In France, for instance, the FIT_t is adjusted depending on a retail price index and thus accounts for inflation; furthermore, independent of the country, inflation risk plays a role for the development of operating costs.

necessary.[6] In particular, we assume that the energy price P_t^{ex} at time t follows a mean-reverting process (under the real-word measure), i.e.

$$dP_t^{ex} = \kappa^{ex}\left(\left(a \cdot t + c\right) - P_t^{ex}\right)dt + \sigma^{ex} dW_t^{ex},$$

where $\left(a \cdot t + c\right)$ is the mean-reversion level, κ^{ex} denotes the speed of mean reversion and W_t^{ex} a standard Brownian motion. Note that for simplicity we assume the same energy prices for the considered countries as we focus on European electricity markets, which are converging and show a cointegrating relationship (Bollino, Ciferri and Polinori (2013)).

Inflation risk is modeled using the Vasicek (1977) model (see, e.g., Falbo, Paris and Pelizzari (2010)), i.e. the inflation rate r^k, relevant for example for $OMSI^k$ or the FIT in case of France is given by

$$dr_t^k = \kappa^{PI,k}\left(b^{PI,k} - r_t^k\right)dt + \sigma^{PI,k} dW_t^{PI,k}, \ k = 1,\ldots,K$$

where $\kappa^{PI,k}$ is the speed of mean-reversion, $b^{PI,k}$ is the long-term mean, $\sigma^{PI,k}$ is the volatility and $W_t^{PI,k}$ $k=1,\ldots,K$ are correlated Brownian motions with correlation coefficients $\rho_{k,l}^{PI}$ ($dW_t^{PI,k} dW_t^{PI,l} = \rho_{k,l}^{PI} dt$). Following Ahlgrim and D'Arcy (2012), the price index PI_t^k is given by

$$PI_t^k = PI_0^K \cdot \exp\left(\int_0^t r_t^k dt\right).$$

Integrating policy risk

In the case of policy risk, we assume a reduction in the feed-in tariff of α^k% at some (stochastic) point in time τ^k during the investment period, i.e. $FIT_t^k \cdot \left(1-\alpha^k\right), t \geq \tau^k$. In case $\tau^k > T^S$, no reduction took place during the support period $T^{S,k}$. The feed-in tariff in Equation (4) is thus given by

$$FIT_t^{k,pol} = \begin{cases} FIT_t^k & , t < \tau^k \\ FIT_t^k \cdot \left(1-\alpha^k\right) & , \tau^k \leq t \leq T^S \end{cases}.$$

[6] Deng and Oren (2006) discuss two main ways to model energy prices at the exchange. While the "fundamental approach" relies on simulation of system and market operation to arrive at market prices, the "technical approach" attempts to directly model the stochastic behavior of market prices from historical data and statistical analysis.

The five-year probability that the FIT is reduced by $\alpha^k\%$ can thereby be obtained through the Delphi technique as described in the previous section or by using scenario analyses.

Risk measures and diversification effects

In the case of investments in several renewable energy projects in different countries $k = 1,\ldots,K$ (e.g. wind farms in Germany and France), diversification effects may arise in case policy risks are not perfectly correlated (which is to be expected) and in case of differences in the support schemes. Hence, for each investment in each country, cash flows must be modeled taking into account the respective input parameters (e.g. produced electricity, costs, support scheme, policy risks based on expert assessment for each country, possibly depending on the type of renewable energy) and then evaluated from a portfolio perspective, such that the present value for the portfolio is given by

$$PV^{Portfolio} = \sum_{k=1}^{K} PV^k = \sum_{t=1}^{T}\sum_{k=1}^{K} \frac{w_k C_t^k}{\left(1+\gamma^k\right)^{t/12}}, with \quad \sum_{k=1}^{K} w_k = 1, \quad w_k \geq 0,$$

with PV^k given by Equation (5) and w_k denoting the share of the wind park in country k in the portfolio. To measure the risk associated with the investment, we use the value at risk (VaR) for a given confidence level β,

$$VaR_\beta\left(PV^k\right) = inf\left\{x \mid F_{PV^k}\left(x\right) \geq \beta\right\},$$

where F_{PV^k} denotes the distribution function of PV^k. Based on this, the economic capital (a cushion to compensate unexpected losses at a given confidence level (see, e.g., Drehmann and Alessandri (2010) and Crouhy, Galai and Mark (2000)) is given by

$$EC_\beta\left(PV^k\right) = E\left[PV^k\right] - VaR_\beta\left(PV^k\right).$$

As a second risk measure, we consider the coefficient of variation as a variance-based risk measure,

$$CV\left(PV^k\right) = \frac{\sigma\left(PV^k\right)}{E\left[PV^k\right]},$$

where $\sigma\left(PV^k\right)$ denotes the standard deviation of PV^k. To measure the diversification effect D, we use the value at risk and obtain

$$D = \frac{VaR_\beta\left(\sum_{k=1}^{K} w_k \cdot PV^k\right)}{\sum_{k=1}^{K} w_k \cdot VaR_\beta\left(PV^k\right)} - 1, \ with \ \sum_{k=1}^{K} w_k = 1, \quad w_k \geq 0,$$

where w_k denotes the share of country k in the portfolio.

4. NUMERICAL ANALYSIS

Input parameters

We calibrate the model to two hypothetical onshore wind farms, one in France (k = 1) and one in Germany (k = 2), which started to operate in January 2014. The installed capacity is assumed to be CP = 1 MW in both wind farms. The involved processes are either calibrated based on available data (load factor, inflation, price of electricity) or parameters are derived from the literature (OMSI) as well as legal requirements (feed-in tariffs).

In case of Germany, the FIT is deterministic during the whole support period, whereby the investor can also switch to the so-called direct marketing in case market prices for the respective type of renewable energy are expected to be higher (the switch must be declared one month in advance).[7] For simplicity, we here assume that $P_t^{2,renewable} = max\left(FIT_t^2, P_t^{ex}\right) \forall t$. In France, the switch is irreversible (i.e. it implies the termination of the power purchase agreement), but in order to increase the comparability we also assume $P_t^{1,renewable} = max\left(FIT_t^1, P_t^{ex}\right) \forall t$, which can also be adjusted. The option to switch between the two schemes (feed-in tariff and direct marketing) may also be implemented using a real option approach as is done in Boomsma, Meade and Fleten (2012), for instance. The feed-in tariff may also be stochastic as in the case of France (k = 1),

[7] The available support schemes in Germany depend on the date of the start-up (begin of operation). Until August 2014, operators had the option to switch between the market premium model and the fixed feed-in tariff (in addition to switching to the direct marketing). Now, the market premium model is obligatory (see EEG 2014 and EEG 2012). Using the market premium model, the operators have to sell the produced electricity at the exchange and receive the sales revenues. Furthermore, they obtain a “market premium” as the difference between the FIT and the (monthly) average price of produced wind energy in Germany. On average, the operators thus obtain the same as when using the FIT, but for individual wind farms the market premium may vary and depend on the specific site (see Grothe and Müsgens (2013)).

where regular adjustments are made depending on a price index. In particular, the French FIT develops according to (see “arrêté du 17 novembre 2008 fixant les conditions d’achat de l’électricité produite par les installations utilisant l’énergie mécanique du vent”)

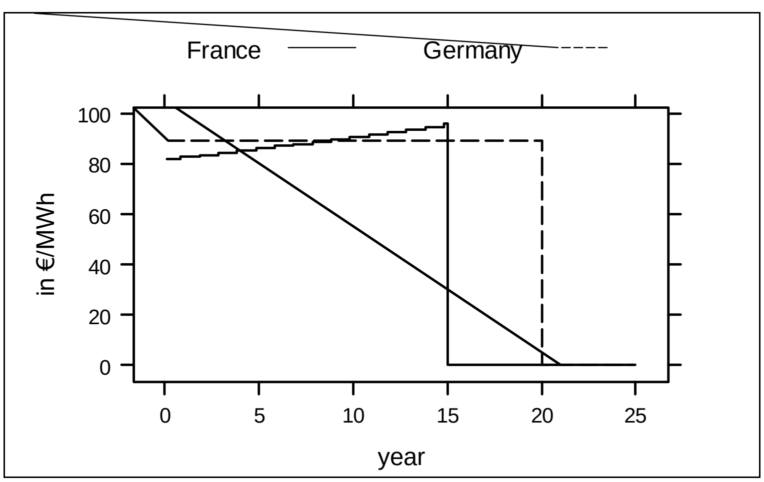
$$FIT_t^1 = FIT_0^1 \cdot \left(0.4 + 0.4 \frac{WI_{t-1}}{WI_0} + 0.2 \frac{PPI_{t-1}}{PPI_0} \right),$$

where WI_t denotes the French wage index of employees working in the electric and mechanic industry in the t-th year (t = 0 denotes the start-up of the wind farm), PPI_t is the producer price index, and the index is updated annually on November 1st. We further assume that OMSI costs, WI_t and PPI_t develop according to the same price index PI_t^1, i.e.

$$FIT_t^1 = FIT_0^1 \cdot \left(0.4 + 0.6 \cdot \frac{PI_{t-1}^1}{PI_0^1} \right).$$

The FITs in Germany and France also depend on the quality of the site of the wind farm. We therefore assume that the two considered wind farms are installed at sites where the operator obtains the full FIT for the entire support period $T^{S,k}$ (i.e., 15 years in France and 20 years in Germany). Figure 2 illustrates the deterministic development of the FIT in Germany and the average (expected) development of the FIT in France based on the assumptions laid out above (e.g. inflation adjustment, put into operation January 2014). As the FIT in France is only updated once a year, the curve is cascading.

Figure 2: Development of FIT in France (expected values) and Germany (deterministic) over the investment period



Of special interest is the policy risk associated with the support schemes and its impact on $P_t^{k,renewable}$. There are several alternatives regarding the modeling of policy risk. In what follows, we assume for simplicity (the model can be easily extended due to its generic presentation) that a retroactive reduction in the FIT occurs at most once during the investment horizon T with a given percentage α^k (which would otherwise have to be estimated based on expert opinions, see Section 2) and that it only refers to cash flows after the reduction takes place. Alternatively, one could also assume a shortening of the support period $T^{S,k}$, but the historical examples discussed in the introduction suggest that a FIT reduction is more common.

For the policy risk assessment, we use scenario analyses to illustrate our approach and assume that the procedure in Section 2 is applied with resulting real numbers as shown in Table 2, which correspond to a five-year reduction probability of 0.0492 in Germany and France (see Equation (3)).

Table 2: Exemplary derivation of the five-year FIT reduction probability (i.e. the policy risk) based on an expert assessment regarding three risk factors

No.	*Risk factor*	*Likelihood of occurrence (Germany / France)* $P(r_m)$	*Likelihood that the occurrence of the risk factor causes the policy risk scenario (Germany / France)* $P(s \mid r_m)$
x^1	Political instability	0.1 / 0.1	0.1 / 0.1
x^2	Economic instability	0.2 / 0.2	0.1 / 0.1
x^3	Decline of public acceptance	0.1 / 0.1	0.2 / 0.2
	Resulting five-year reduction probability (Eq. 3)	Germany 0.0492	France 0.0492

Note that in order to simulate the point in time when a FIT reduction takes place (i.e. when the policy risk occurs), we use a certain time period, e.g. the five-year reduction probability derived as laid out above, and draw the respective five-year period where the FIT reduction occurs, e.g. the first five years or during the second five-year period (year 6 to 10) etc. The month of the FIT reduction is then assumed to be uniformly distributed within this five-year period. For example, if the reduction happens within the second five-year period, the reduction month is drawn uniformly from 61 to 120. Note that these assumptions can also be altered, depending on the support scheme or the country specific settings, for instance.

In regard to resource risk (produced electricity), we use data of the German "Hochfeld-2" wind park available from 2002-2014 (see Production Hochfeld (2015)) to calibrate L_m^k, $g^k(t)$, and σ_L^k using least squares (see Abadie and Chamorro (2014), who calibrate the model based on average values for the entire UK wind energy market). The results for the seasonal component $g^k(t)$ are stated in Table 3 (used for both countries).

Table 3: Estimated seasonal component $g^k(t)$ (resource risk / produced electricity)

t	1	2	3	4	5	6	7	8	9	10	11	12
$g^k(t)$	0.1067	0.0211	0.0463	-0.0301	-0.0459	-0.0521	-0.0675	-0.0665	-0.0398	0.0036	0.0154	0.0832

Furthermore, we assume that the two sides are located far apart from each other and thus assume no (spatial) correlation between the load factors L^k (see, e.g., Haslett and Raftery (1989) for an investigation of the spatial dependence of wind speeds and thus resource risk). In addition, the annual OMSI costs are assumed to be 42,500 € per installed MW (see van de Wekken (2007) for the case of onshore wind parks). The remaining input variables are calibrated using available empirical data. The inflation rates r_t^k are calibrated based on monthly inflation data for France and Germany from 2002-2014 (see http://www.inflation.eu/) and the exchange energy prices P_t^{ex} based on the German EEX Phelix Month Base values from 2002-2014, using the method proposed by Yoshida (1992), respectively. The resulting input parameters are summarized in Table 4.

Table 4: Input parameters (see also Table 1)

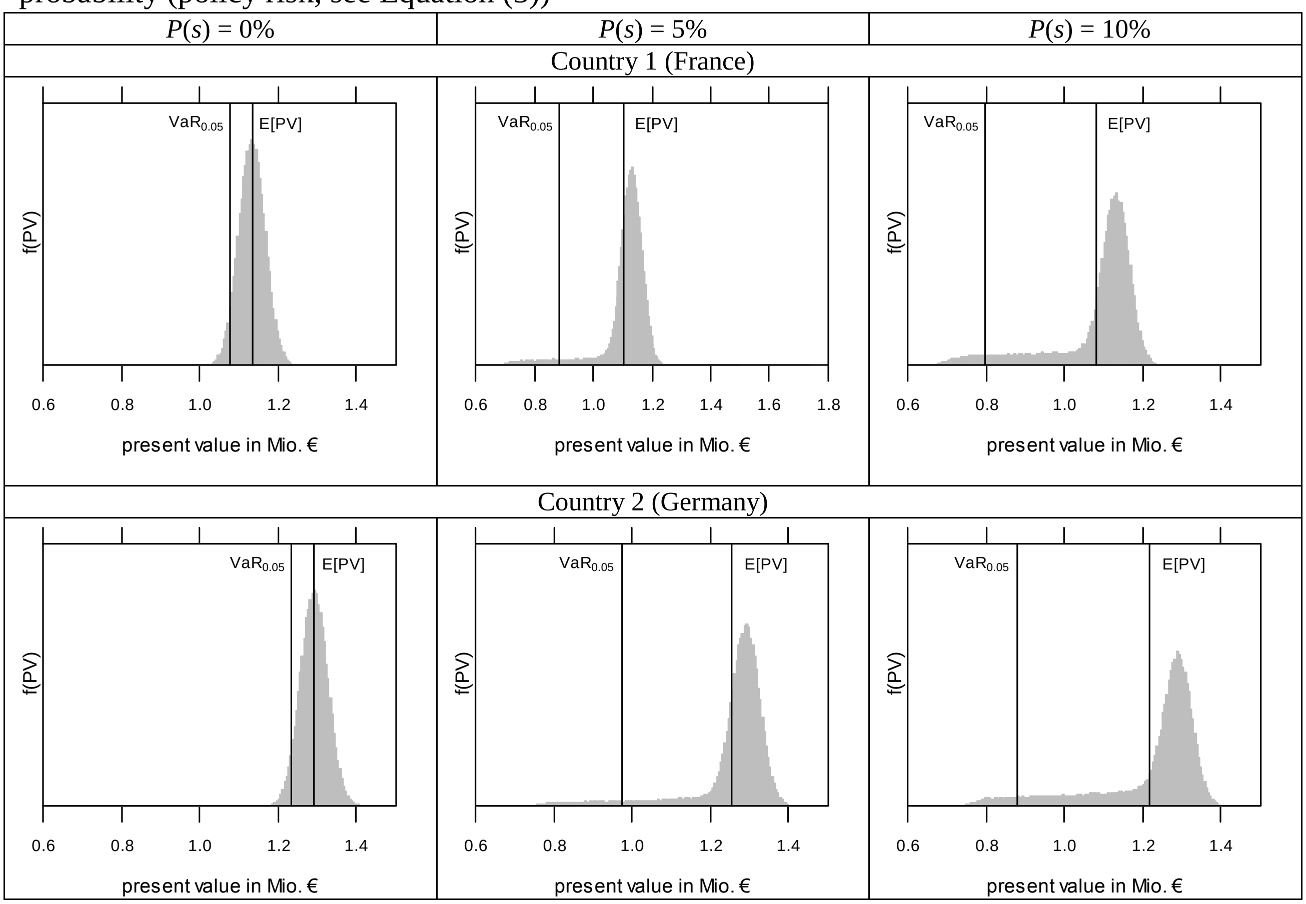
Variable	*Country 1 (France)*	*Country 2 (Germany)*
γ^k	7%	See country 1
P_t^{ex}	$\kappa^{ex} = 0.2095$; $a^{ex} = 0.0582$; $c^{ex} = 36.3227$; $\sigma^{ex} = 7.8754$	See country 1
PE_t	$\sigma_L^1 = 0.0642$; $L_m^1 = 0.2132$; for $g^1(t)$ see Table 3	See country 1
PI_t^k	$\kappa^{PI,1} = 1.3715$; $b^{PI,1} = 0.1239$; $\sigma^{PI,1} = 0.3023$ $\rho_{1,2}^{PI} = 0.2536$	$\kappa^{PI,2} = 1.0368$; $b^{PI,2} = 0.1368$; $\sigma^{PI,2} = 0.2885$ $\rho_{1,2}^{PI} = 0.2536$
CP^k	1 MW	See country 1
$OMSI^k$	42,500 € per year, adjusted with price index PI	See country 1
FIT_0^k	82 €/MWh	89.3 €/MWh
$T^{S,k}$	180 (= 15 years)	240 (= 20 years)
T	25 years	See country 1
α^k	30%	See country 1

All input parameters are subject to sensitivity analyses. Furthermore, a Monte Carlo simulation with 100,000 simulation paths is used to derive the numerical results. To ensure comparability of the results, the random numbers were fixed and various sets of random numbers were tested to ensure robustness of the results.

The impact of policy risk

Figure 3 exhibits the probability distribution of the present value (Equation (5)) for three levels of the five-year FIT reduction probability $P(s)$ (0%, 5%, 10%) (see Equation (3)) for the case of France (country 1, first row) and Germany (country 2, second row). The results show that the inclusion of policy risk can have a considerable impact on the distribution of the present value of cash flows. For instance, the probability distribution in the case without policy risk (left graphs, $P(s)$ = 0%) is rather symmetric (due to the assumptions regarding inflation and resource risk) and without fat tails, while the probability distributions with a positive reduction probability exhibit a heavy-tailed downside risk, which increases for higher reduction probabilities. In addition, one can observe that the expected present value and the value at risk are generally lower in the case of France (country 1, first row), which mainly arises due to the shorter duration of the support period of 15 years instead of 20 years and the additional inflation risk embedded in the feed-in tariff.

Figure 3: Probability distribution of the present value of cash flows depending on the reduction probability (policy risk, see Equation (3))



The strong effect of the characteristics of the respective FIT support scheme on the present value of cash flows can also be seen in Figure 4, which displays the expected value and the value at risk of the cash flows in each year over the entire investment period of 25 years. It can be seen that in the case of France, the expected annual cash flow first increases due to the inflation adjustment, and after the 10th year even exceeds the expected cash flow in the case of Germany, where the expected cash flows are decreasing over time due to the presence of policy risk and inflation adjusted operation, maintenance, staffing and insurance costs. In addition, the expected annual cash flows drop considerably after the end of the respective guaranteed support periods, i.e., 15 years in France and 20 years in Germany. Furthermore, one can observe that the difference between the VaR at the 5% confidence level and the expected value is considerably reduced when the reduction probability $P(s)$ is set to zero, i.e. if policy risk does no longer impact the cash flows. The remaining variability instead arises from inflation risk, energy market price risk as well as resource risk (i.e. the stochastic load factor with regard to the produced electricity) and is similar for both countries due to the fact that the input parameters are generally assumed to be the same except for inflation risk (see Table 4).

Figure 4: Annual expected value and annual VaR of project cash flows over time

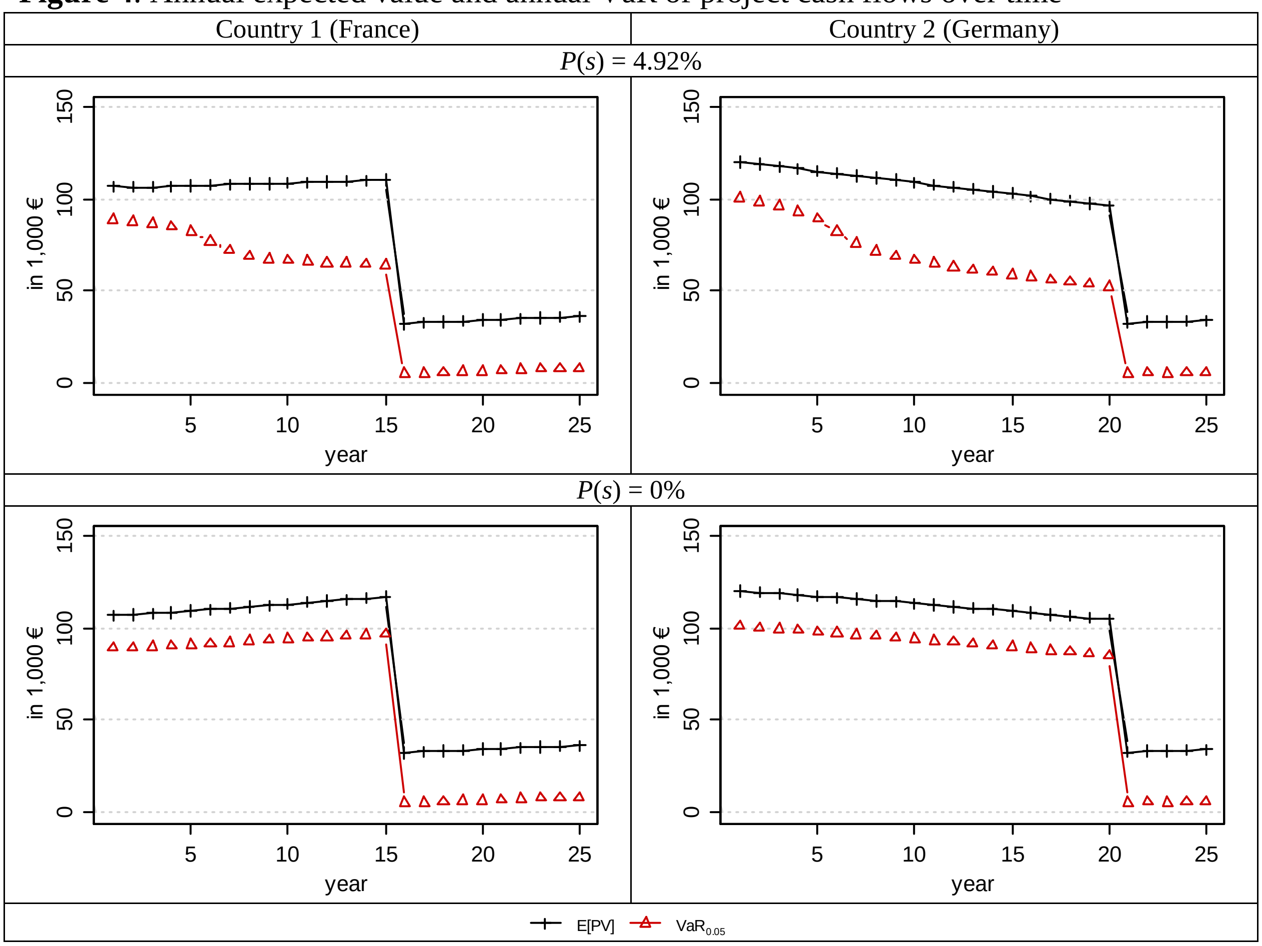


Figure 5 displays the expected present value and the VaR with different confidence levels of 10%, 5%, and 2.5% for different reduction probabilities (see Equation (3)) for the two considered countries. The results show that an increasing reduction probability as expected implies a decrease in the expected present value (upper black line with "+") and a considerable impact on risk. In particular, the VaR shows a similar behavior for all considered confidence levels (i.e., 10%, 5%, 2.5%) in that an increasing reduction probability implies a decrease in the VaR, which is considerably stronger for smaller reduction probabilities and further enhanced for higher confidence levels (e.g. 2.5%). In addition, as already observed in Figure 3, the overall level of the expected present value and VaR are higher in the case of the German onshore wind farm than the one in France in the present setting.

Figure 5: Value at risk and expected present value of renewable energy investments for different FIT depending on the reduction probability (Equation (3))

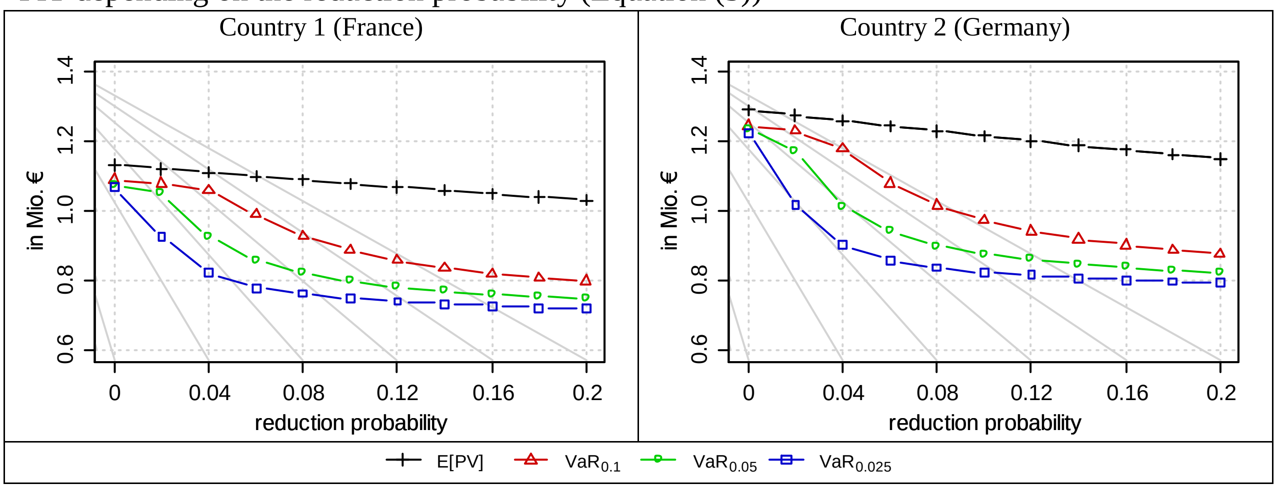
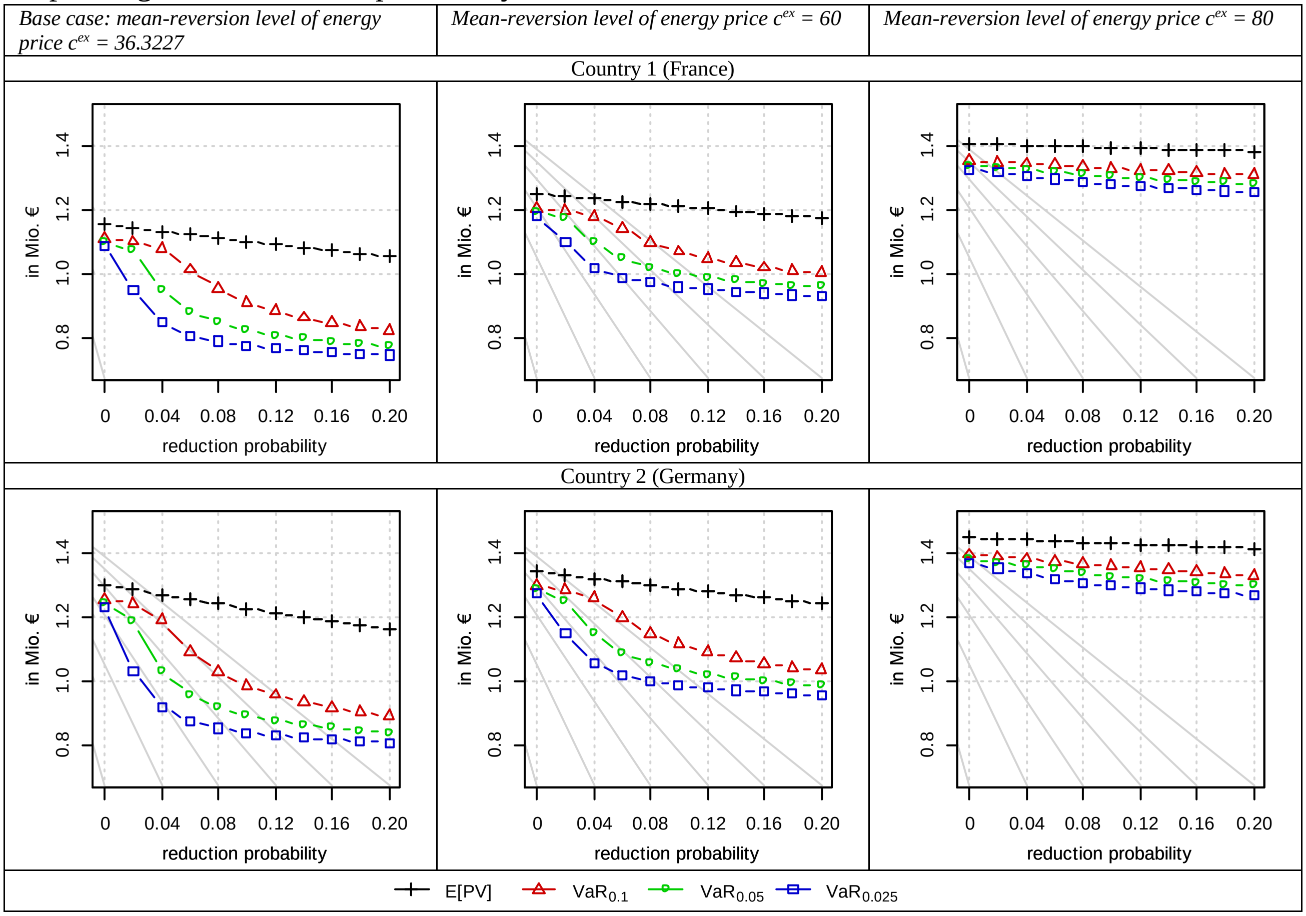


Figure 6 shows the expected value and VaR of the present value of the investment for increasing energy prices. The graphs emphasize the relevance of energy price levels on risk-return profiles of the projects, also due to the assumed possibility to switch between the FIT and the spot market, thus using the more favorable price (see beginning of this section). In case the spot market price approaches the FIT level (right graph, mean-reversion level of energy price of c^{ex} = 80), a FIT reduction – as expected – only has a minor impact, as operators can sell the produced electricity directly at the exchange. Hence, the effect of policy risk is highest for lower energy prices (mean-reversion levels) (see left graphs).

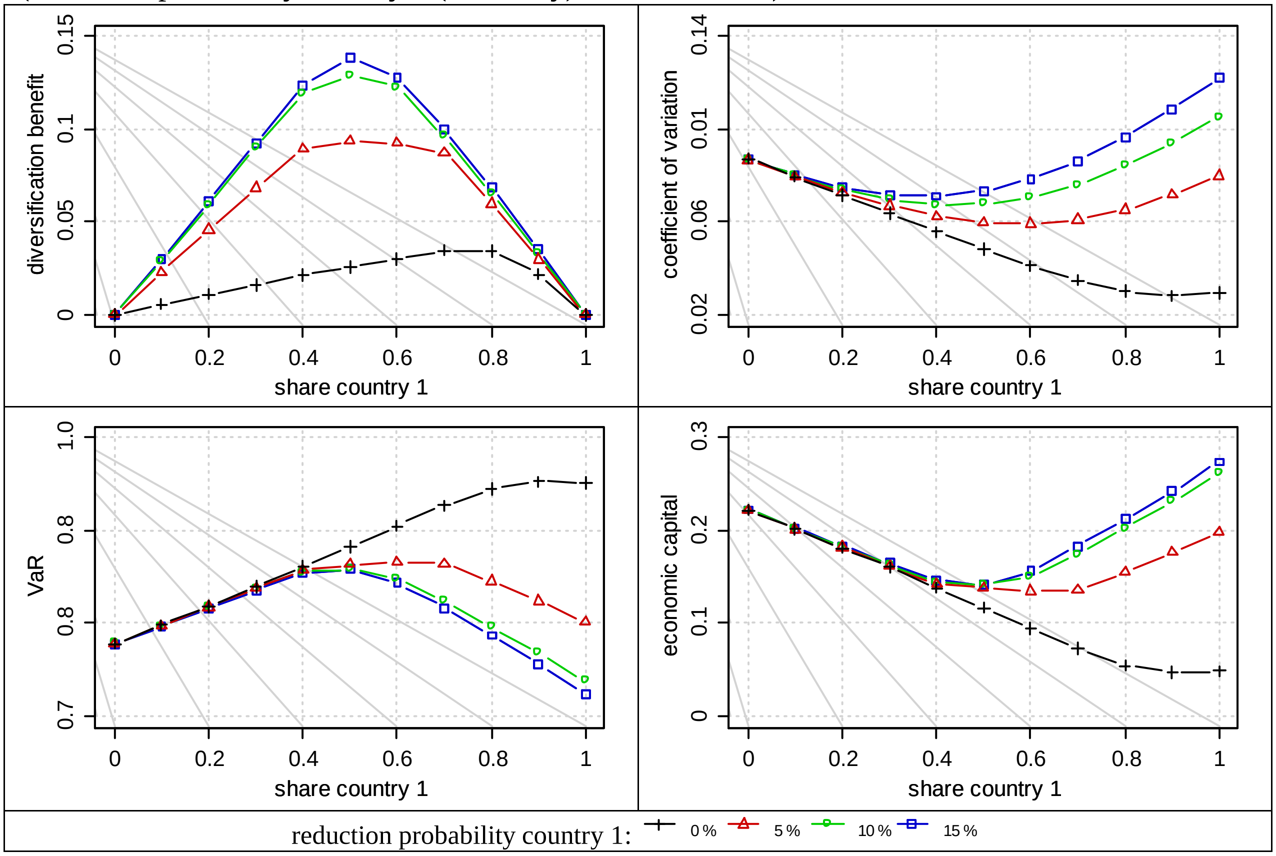
Figure 6: Value at risk and expected value in country 1 and 2 for increasing energy prices depending on the reduction probability



Portfolio considerations and diversification effects

As pointed out by Gatzert and Kosub (2014), diversification plays a crucial role for the management of policy risk associated with renewable energy investments, also due to a lack of alternative risk management measures. Therefore, we next take a portfolio perspective by assuming that an investor invests in both wind farms in country 1 (France) and country 2 (Germany). Figure 7 shows the diversification benefit, the coefficient of variation, the value at risk, and the economic capital for different portfolio compositions and different levels of policy risk. The reduction probability in country 1 thereby varies between 0% and 15%, while the reduction probability in country 2 is fixed at 4.92%.

Figure 7: Diversification benefit, coefficient of variation, value at risk, and economic capital for various reduction probabilities in country 1 (France) depending on the portfolio composition (reduction probability country 2 (Germany) fixed at 4.92%)

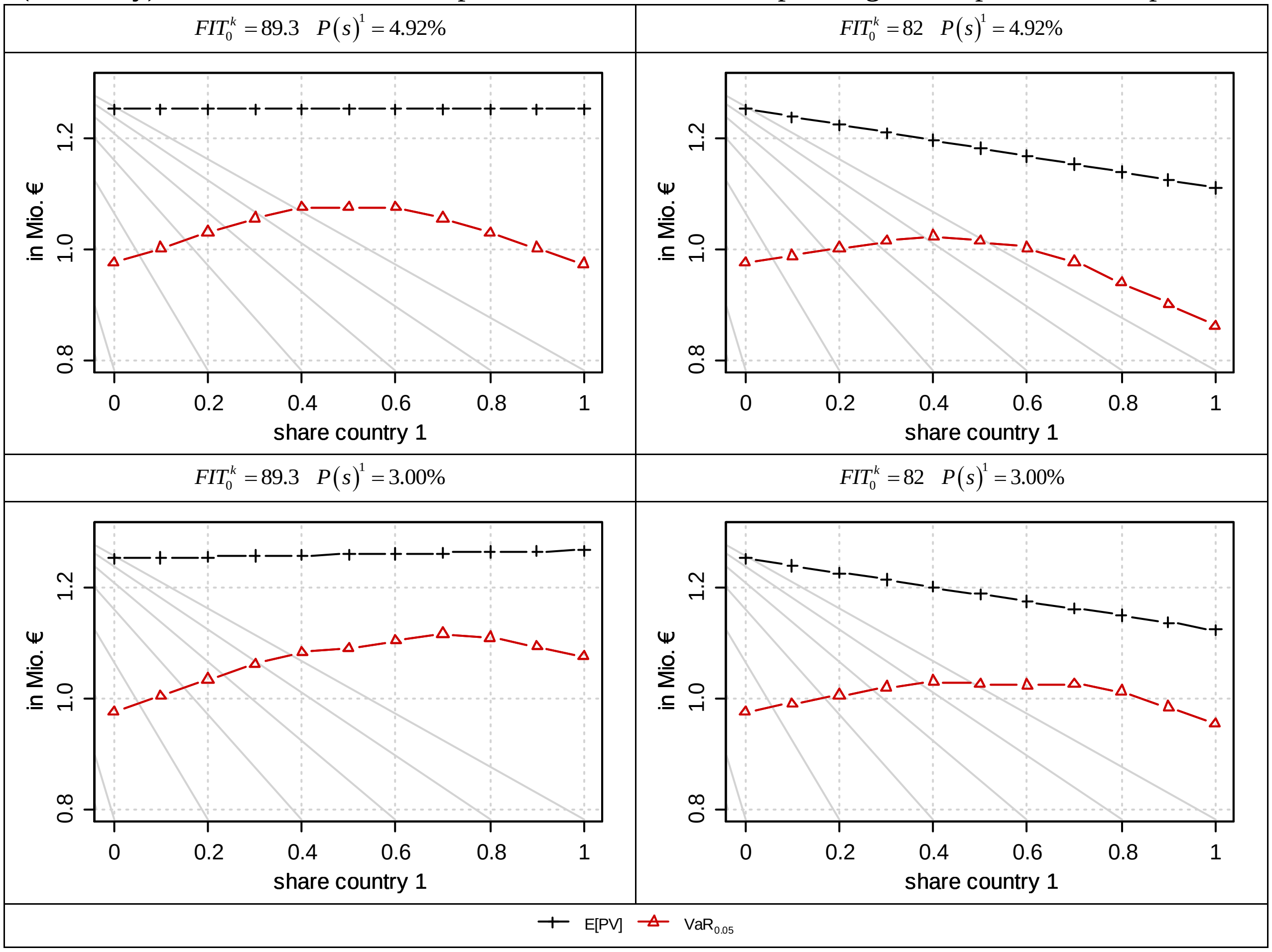


The upper left graph in Figure 7 shows that the diversification benefit (derived using the value at risk, see Section 3) strongly depends on the portfolio composition and the level of policy risk in country 1. For instance, for a low policy risk in country 1 (e.g. 0%, see black line with “+”), the diversification benefit is highest for a high share of about 70% invested in country 1 within the portfolio (since the policy risk in country 2 is fixed with 4.92% and thus higher than in country 1). For a policy risk of 15% (blue line with squares), the highest diversification benefit with about 13.8% is achieved for an approximately equally weighted portfolio. Portfolios with an optimal diversification level also generally exhibit a lower overall risk level, which holds for the considered risk measures VaR and coefficient of variation as well as the economic capital. We also observe that increasing the policy risk from 0% to 5% and to 10% has a much stronger effect on diversification and risk than increasing the policy risk from 10% to 15%. In addition, one has to take into account that even though the diversification benefit increases for higher reduction probabilities, the overall risk level increases as well, but that (relative) diversification benefits are stronger in this case.

The strong impact of policy risk is also emphasized when considering the case where an investor only invests in country 1 (i.e. share in country 1 = 1, i.e. 100%). In this case, the economic capital ranges from 0.037 to 0.269 depending on the reduction probability in country 1, ranging from 0% to 15%. For an investment with an expected present value of 1.13 Mio. (in case of a reduction probability of 0%, see Figure 5) and 1.03 Mio. (in case of a reduction probability of 15%), the required economic (risk) capital thus ranges from 4.85% to 27.50%, which implies a tremendous difference regarding the costs of capital.

Changing policy risk or the FIT level has different effects on the risk-return profile. Figure 9 shows the expected value and value at risk for a portfolio consisting of two countries both calibrated to country 2 (to exclude effects arising from different input parameters) for two reduction probabilities (4.92% and 3%) and two levels of the FIT (89.3 €/MWh and 82 €/MWh). A decreasing reduction probability (from 4.92% to 3%) has only a minor effect on the expected present value. Even when considering the case where an investor only invests in country 1, it is increasing only from 1.25 Mio. € to 1.27 Mio €. However, it does have a considerable effect on the value at risk, which is increasing from 0.97 Mio. € to 1.08 Mio. € in case of investing only in country 1 (see upper and lower left graph in Figure 9). The same holds for the other portfolio compositions, where the VaR increases stronger than the expected value. In contrast, a decreasing FIT (from 89.3 €/MWh to 80 €/MWh) in country 1 has a huge impact on the expected value and the VaR. When considering the case where an investor only invests in country 1, the expected valueis decreasing from 1.25 Mio. € to 1.11 Mio. € and the VaR is decreasing from 0.97 Mio. € to 0.86 Mio. € (see upper right and left graph in Figure 9). Combining these two adjustments (FIT from 89.3 €/MWh to 82 €/MWh and reduction probability from 4.92% to 3%) has a considerable impact on the expected value, but only a minor impact on the VaR (see Figure 9 upper left and lower right graph).

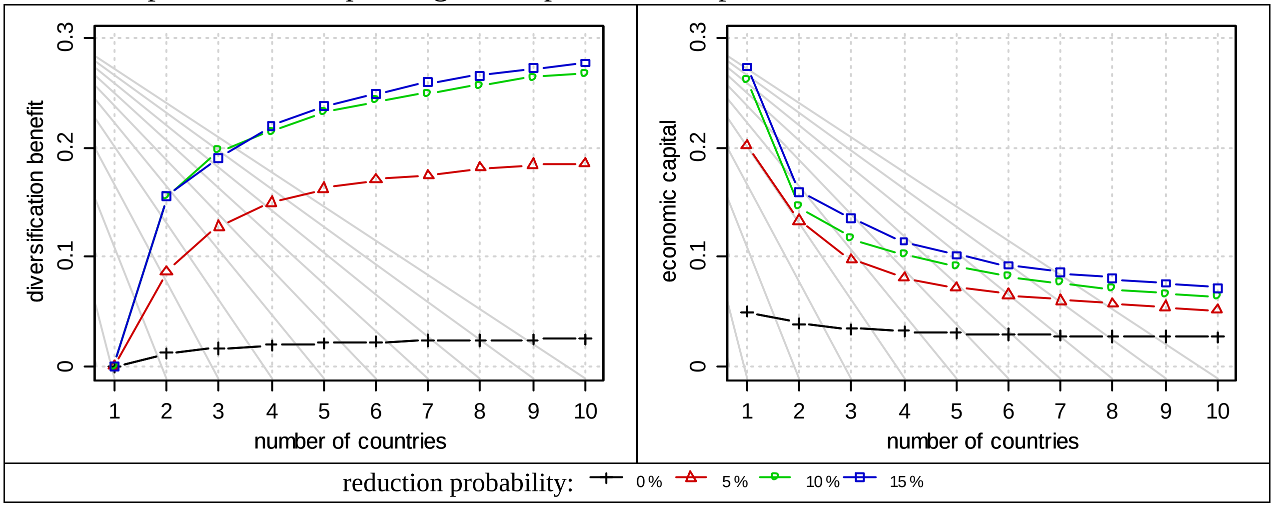
Figure 9: Expected value and value at risk for two hypothetical countries calibrated to country 2 (Germany) for different reduction probabilities and FITs depending on the portfolio composition



We conducted further sensitivity analyses by varying other input parameters, including the impact of the policy risk scenario (i.e. the extent of the FIT reduction) as well as the diversification benefit depending on energy prices, which shows that higher energy prices lead to a lower effect of the FIT reduction and to a decreasing diversification benefit, which is in line with Figure 6.

Finally, the number of countries in the portfolio is increased, thereby assuming an investment in one onshore wind park in each country. Figure 10 shows that the economic capital is decreasing strongly when increasing the number of countries in the portfolio, but that the extent of the diversification benefit is decreasing until a risk level is reached which cannot be further diversified.

Figure 10: Diversification benefit and economic capital for a portfolio with equal shares depending on the quantity of countries (all with parameters of country 1 (France)) for various reduction probabilities depending on the portfolio composition



5. Summary and Policy Implications

Establishing an adequate risk model and conducting risk assessment is of particular relevance for institutional investors such as insurers in order to derive risk capital requirements imposed by regulatory authorities and to ensure a certain safety level. The quality of such risk models will thus have a major impact on the attractiveness of investments in renewable energy due to high costs of capital arising from solvency capital requirements when using the standard model, where an internal model may lead to lower capital requirements (depending on the specific investment). As the previous literature has emphasized that policy risks play an important role, these risks should thus be closely monitored and assessed. Toward this end we provide a model framework for assessing policy risks using fuzzy set theory, which also takes into account energy price risk, inflation risk, and resource risk. While the quantification of policy risks clearly comes with challenges, our approach provides first relevant insight for investors into main drivers and diversification benefits associated with policy risks.

Our results emphasize that policy risk can have a major impact on an investor's risk-return profile. Policy risk is thereby driven by several risk factors and politics should be careful with actions which can worsen one or more of these risk factors. Even a political discussion, e.g., the discussion about a minor retroactive reduction in Germany ("EEG-Soli"), without an actual impact can lead to increasing values of some risk factors (e.g., political instability). This could either decrease the investments in renewable energy and could cause the failing of renewable energy aims, or increase costs as investors generally require a premium for taking the additional risk. Furthermore, politics should behave consistently even in areas not directly link to renewable energy in order to not contribute to an increasing policy risk. Inconsistent behavior towards investors in different areas (e.g., public-private partnerships in the case of infrastructure projects) may cause risk factors to increase. We further show that diversification has a crucial impact on risk-return profiles of investors when dealing with policy risk. In particular when investors use the NPV-at-risk method for investment evaluation, i.e., they choose the investment with the highest VaR, they compose a portfolio consisting of both countries in all of our stated cases. Also, countries with low policy risk can potentially decrease subsidy payments granted to the operators of wind farms, as investments in these countries will nevertheless be taken into account.

In general, we further illustrate that cross-country diversification within a portfolio can contribute to considerably decrease the overall risk level for an investor, but that the extent of the decrease depends on various factors, especially the interaction and dependencies between the involved random variables. In this regard, a limitation of our current approach is the assumption of independence of the underlying risk factors driving policy risk, which in a next step can be calibrated to the actual situation in European countries, for instance, by conducting a qualitative expert assessment as laid out in the paper. Further research should thereby study and take into account dependencies, e.g. by including common risk factors for different countries, and examine the effect of these dependencies on the portfolio. Furthermore, in some countries (e.g., Germany) operators of wind farms can choose between different support schemes (e.g., FIT, market premium model and direct marketing in Germany). Further research could therefore include the option to choose in terms of real options for the operator. Such a real options approach should also include the investment decision itself, i.e., the decision whether to build a wind farm or not.

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