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Evaluating Investments in Renewable Energy under Policy Risks

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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. 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 to quantify policy risks associated with renewable energy investments (e.g. a retrospective 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 simulations and scenario analyses, and it makes use of expert estimates and fuzzy set theory for quantifying policy risks. Our numerical results for a portfolio of onshore wind farms in Germany and France show that policy risk can strongly impact risk-return profiles, and that cross-country diversification effects can considerably decrease the overall risk for investors.

Keywords: Renewable energy; wind farm; policy risk; fuzzy set theory; value at risk

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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 farms, governments typically grant subsidy payments during the life span of the investment projects (e.g. feed-in tariff (FIT)) (Turner et al., 2013). 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 projects implies a high degree of uncertainty regarding future cash flows (Micale et al., 2013, Jin et al., 2014, Gatzert and Kosub, 2015, 2016). In Spain, Bulgaria, Greece, and the Czech Republic, for instance, the guaranteed feed-in tariffs have recently been reduced retrospectively[1] for solar farms, 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. For investors 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. 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 also 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[2] 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 et al., 2012; Brandstätt et al., 2011; Campoccia et al., 2009; Holburn, 2012; Kitzing, 2014; Monjas-Barroso and Balibrea-Iniesta, 2013; Yang et al., 2010), resource risks resulting from wind volatility (e.g., Liu et al., 2011) or curtailment risk (e.g., Jacobsen and Schröder, 2012). In addition, based on a review of risks and risk management solutions for renewable energy projects with focus on onshore and offshore wind farms, Gatzert and Kosub (2016) show that especially policy and regulatory risks represent major barriers (see also Jin et al. (2014) and

[1] The term "retroactive" is often used as a synonym for "retrospective" (see, e.g., Gatzert and Kosub (2015)).

[2] See Meyer (2003) for an overview of different support schemes such as feed-in tariffs, feed-in premiums or the tender system.

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 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, 2016). 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. 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.

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 et al. (2008b) 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. In general, policy risk can be expected to further increase in the future as pointed out by Turner et al. (2013), 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 that allows studying policy risks for investments in renewable energy projects. In contrast to previous work, we explicitly take into account risk factors that drive policy risk in the model (e.g., economic stress or governmental budget constraints), apply the fuzzy Delphi probability prediction method to obtain the likelihood and impact of the considered policy risk scenario (i.e., a retrospective reduction of the feed-in tariff), and conduct sensitivity analyses, thereby taking into account several other risk factors (energy price risk, inflation risk, and resource risk). Based on this, we derive risk-return profiles of renewable energy investments for the case of onshore wind farms using Monte Carlo simulation, thereby also taking into account potential country diversification effects that may contribute to reducing 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 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 et al. (2010)). In this paper, we 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 et al., 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 et al. (2008a), Sachs and Tiong (2009), Sachs et al. (2008b), Sadeghi et al. (2010), and Thomas et al. (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 applied to the evaluation of onshore wind farms regarding the risk of a retrospective reduction of a feed-in tariff, but it can also be applied to other renewable energy investments such as solar farms, for instance.

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 analyses. Section 5 summarizes and discusses policy implications.

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 retrospective adjustments of support schemes of investments in renewable energy (e.g., a retrospective FIT reduction) as has been observed in Bulgaria, the Czech Republic, Greece, Italy, and Spain, for instance.

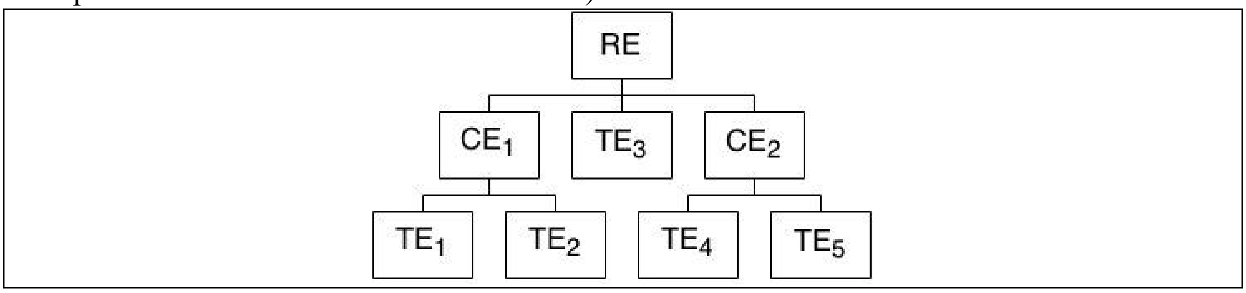
General procedure

To quantify policy risk, it is common to first identify driving risk factors (see, e.g., Brink (2004) and Sachs et al. (2008b)). 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, e.g. following the procedure in Thomas et al. (2006): 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 reduction 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, 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 a fault tree, i.e., a decomposition of a risk event (RE) (e.g., FIT reduction) into risk factors has been identified (see Thomas et al., 2006). The risk factors are either component events (CE) that can in turn depend on additional (lower order) risk factors or terminal events (TE). An example of a fault tree is shown in Figure 1. There are several events that can cause the risk event RE: the terminal event TE_3 can cause the risk event RE directly, TE_1 can cause CE_1 and CE_1 can cause RE etc. We assume there are *L* terminal events and *M* component events in the fault tree.

Figure 1: Example of a fault tree to decompose a risk event (RE) into risk factors (either component events CE or terminal events TE)



Following Thomas, Kalidini and Ganesh (2006), Kafka (2008), and Sachs and Tiong (2009), for every terminal event, N experts are first asked "What is the likelihood that the terminal event occurs within a certain unit of time?" in order to obtain the likelihood of occurrence $P(TE_l)$ per unit of time of the respective terminal event (l = 1,...,L) (note that the unit of time is often neglected, but is also used in, e.g., Kafka (2008)). The unit of time has to be chosen carefully in order to obtain sufficiently high probabilities, as it is challenging to obtain estimates for very rare events (see, e.g., O'Hagan et al. (2006)). The experts estimate the likelihood of occurrence of each terminal event with a linguistic variable (extremely low, very low, low, medium, high, very high, extremely high), which is then transformed into a trapezoidal fuzzy number[3] (Sachs and Tiong, 2009). The experts next estimate the conditional probability that the terminal event or the component event occurs given the occurrence of the preceding terminal or component event in the fault tree (i.e., $P(CE_1 | TE_1)$, $P(CE_1 | TE_2)$, $P(CE_2 | TE_4)$, $P(CE_2 | TE_5)$, $P(RE | CE_1)$, $P(RE | TE_3)$, $P(RE | CE_2)$ given the situation in Figure 1) ("Given that the terminal/component event occurs, what is the likelihood that it causes the component/risk event?"). These estimations are updated following the Delphi technique (see Thomas et al., 2006), where experts receive the average of the responses of the other experts and are allowed to reconsider their first estimates. Combining the resulting estimates, one can then derive the probability of the event "TE_l causes the risk event RE" for l = 1,...,L.

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 A whose membership function $\mu_A(x)$ is defined by a quadruple (a,b,c,d) through

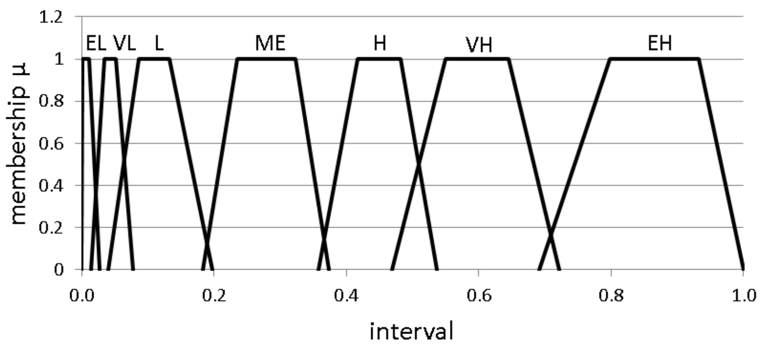
$$\mu_A(x) = \begin{cases} 0 & x < a \vee d \le x \\ \frac{x-a}{b-a} & a \le x < b \\ 1 & b \le x < c \\ \frac{d-x}{d-c} & c \le x < d, \end{cases}$$

where a and d reflect the range associated with the linguistic value (e.g. "medium") as shown in Figure 2, where a "medium probability" is not below 0.183, not higher than 0.373, and definitely between 0.235 and 0.323. The numerical representation of linguistic values must be

[3] There are also other types of fuzzy numbers which can be used (e.g., Thomas, Kalidini and Ganesh (2006) use triangular fuzzy numbers). As is done in, e.g., Abdelgawad and Fayek (2011) and Sachs and Tiong (2009), we use trapezoidal fuzzy numbers as this is slightly more general (trapezoidal fuzzy numbers contain triangular fuzzy numbers).

identified before conducting the survey by collecting numerical opinions on the linguistic values. One can distinguish between direct and indirect methods with one single or multiple experts (see Klir and Yuan, 1995). As, e.g., Sachs and Tiong (2009) we use the direct method with multiple experts. Six PhD students with risk management knowledge were trained on fuzzy numbers and were asked for their opinion regarding the representation of linguistic variables (i.e., a quadruple (a,b,c,d) for every linguistic variable). The resulting fuzzy numbers were calculated by averaging with equal weights (see Klir and Yuan, 1995) and are displayed in Figure 2.

Figure 2: Illustration of fuzzy number representation for linguistic variables from extremely low (EL) to extremely high (EH)



Next, the responses of the N experts for each risk factor (i.e. terminal and component events) 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 $P(TE_l)$ of terminal event l is "medium", the representation in Figure 2 implies that $a_{l,n}^{TE} = 0.183$, $b_{l,n}^{TE} = 0.235$, $c_{l,n}^{TE} = 0.323$, $d_{l,n}^{TE} = 0.373$. Based on the aggregated opinion of the experts, one obtains a fuzzy number representation (with quadruples a,b,c,d) for the occurrence of each terminal event TE and the conditional probability that the risk event RE or the component event CE occur given the occurrence of the lower order risk factors (terminal/component events). For further arithmetic operations on fuzzy numbers and a detailed introduction, we refer to Klir and Yuan (1995).

The (fuzzy) probability of the (policy) risk event RE, $P(RE)$, is then given by one minus the probability that none of the underlying terminal and component events cause RE, i.e. in case of the fault tree in Figure 1,

$$\begin{aligned}P\left(RE\right)=1-&\left(1-P\left(RE\,|\,CE_1\right)P\left(CE_1\,|\,TE_1\right)P\left(TE_1\right)\right)\\ &\cdot\left(1-P\left(RE\,|\,CE_1\right)P\left(CE_1\,|\,TE_2\right)P\left(TE_2\right)\right)\left(1-P\left(RE\,|\,TE_3\right)P\left(TE_3\right)\right)\\ &\cdot\left(1-P\left(RE\,|\,CE_2\right)P\left(CE_2\,|\,TE_4\right)P\left(TE_4\right)\right)\left(1-P\left(RE\,|\,CE_2\right)P\left(CE_2\,|\,TE_5\right)P\left(TE_5\right)\right).\end{aligned} \tag{2}$$

The fuzzy number $P\left(RE\right)$ resulting from Equation (2) is then defuzzified using (see Klir and Yuan, 1995)

$$\mathrm{P}_{RE}^{\mathrm{real}}=\frac{\int\mu_{P(RE)}\left(x\right)\cdot x\cdot dx}{\int\mu_{P(RE)}\left(x\right)\cdot dx}\ , \tag{3}$$

where P_{RE}^{real} 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 et al., 2006). This procedure is repeated until the successive estimations of $P\left(RE\right)$ become reasonable stable (see, e.g., Thomas et al. (2006), Cheng and Lin (2002), and Kaufmann and Gupta (1988)). Therefore, we define the distance between two fuzzy numbers A and B through (see Kuo and Xue, 1998)

$$d\left(A,B\right)=\frac{1}{2}(\beta_2-\beta_1)\int_0^1\left|\bar{A}\left[\alpha\right]^L-\bar{B}\left[\alpha\right]^L\right|+\left|\bar{A}\left[\alpha\right]^U-\bar{B}\left[\alpha\right]^U\right|d\alpha$$

where $\bar{A}\left[\alpha\right]:=\left\{x\,|\,\mu_A\left(x\right)\geq\alpha\right\}=\left[\bar{A}\left[\alpha\right]^L,\bar{A}\left[\alpha\right]^U\right]$ denotes the α-cuts, which are closed intervals, and β_1 and β_2 are given any convenient values in order to surround both $\bar{A}\left[0\right]$ and $\bar{B}\left[0\right]$. Following Cheng and Lin (2002) we assume that the successive estimations are reasonably stable if the distance between the successive estimations of $P\left(RE\right)$ is smaller than 0.2.

Assessing the impact

Thomas et al. (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 a certain country). 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 et al., 2006). Again the Delphi technique is used to achieve a consensus between the experts. After the determination of the likelihood of occurrence through Equation (2) and the impact, the obtained fuzzy numbers are defuzzified using Equation (3) 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 and the potential influence of heuristics that are used by the experts (see, e.g., Garthwaite et al. (2005)). Nevertheless, many researchers have successfully applied fuzzy numbers for dealing with this issue (see e.g., Thomas et al., 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 et al., 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 et al. (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 et al. (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 (1995) and also used in, e.g., Thomas et al. (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 farm is already in operation.[4] In addition, we describe cross-country diversification effects 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; Campoccia et al., 2009). However, the model can as well be

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

extended to other types of support schemes such as 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 farms) in k = 1,…, K countries, which depend on several factors and variables as described in Table 1.

Table 1: Notation and description of variables used in the model

Variable	*Description*
γ^k	Discount factor in country k (in %)
$S_t^{k,renewable}$	(Monthly) average price of renewable energy received by the operator in country k (in €/MWh)
S_t^{spot}	(Monthly) average energy spot price obtained at the exchange (in €/MWh)
PE_t^k	Produced electricity in month t in country k (in MWh)
CP^k	Installed capacity in country k (in MW)
L_t^k	(Monthly) load factor in country k
PI_t^k	Price index describing the (monthly) development of the price level of the OMSI in country k
$OMSI^k$	(Monthly) operation, maintenance, staffing and insurance costs in country k (in €)
$FIT_t^{k,pol}$	FIT at time t (subject to policy risk event) in country k (in €/MWh)
T	Investment period (in years)
$T^{sup,k}$	Support period for FIT in years in country k (in general $T >= T^{sup,k}$)
$P_{RE}^{\mathrm{real,k}}$	Reduction probability, i.e. the probability that during an x-year period the policy risk event (RE) occurs in country k, where the policy risk event is defined as a reduction of the FIT by α^k
τ^k	Point in time where the policy risk event occurs in country k given the reduction probability $P_{RE}^{\mathrm{real,k}}$
α^k	Percentage reduction in FIT in country k in case policy risk event occurs

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

$$C_t^k = PE_t^k \cdot S_t^{k,renewable} - OMSI^k \cdot PI_t^k = PE_t^k \cdot f\left(FIT_t^{k,pol}, S_t^{spot}, \tau^k, \alpha^k, T^{sup,k}\right) - OMSI^k \cdot PI_t^k. \quad (4)$$

where PE_t^k denotes the monthly produced electricity in MWh at time t, $S_t^{k,renewable}$ is the (monthly average) price obtained for 1 MWh electric energy produced,[5] $OMSI^k$ are costs for

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

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 $t = 1,\ldots, T\cdot 12$. 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

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

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, among 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

$$L_t^k = g_t^k + L_{av}^k + \varepsilon_t^k, \quad t = 1,\ldots,T\cdot 12$$

where L_{av}^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 operating expenditures (OMSI), as maintenance contracts usually involve fixed charges (except for possible inflation effects as reflected in Equation (4)).

The price $S_t^{k,renewable}$ 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 S_t^{spot},[6] inflation risk,[7] 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 necessary.[8] In particular, we assume that the energy price S_t^{spot} at time t follows a mean-reverting process under the real-word measure, i.e.,

$$dS_t^{spot} = \kappa^{spot}\left(\left(a^{spot} \cdot t + c^{spot}\right) - S_t^{spot}\right)dt + \sigma^{spot} dW_t^{spot},$$

where $\left(a^{spot} \cdot t + c^{spot}\right)$ is the mean-reversion level, κ^{spot} denotes the speed of mean reversion, σ^{spot} the volatility, and W_t^{spot} 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 et al., 2013).

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

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

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,…, K are correlated Brownian motions with correlation coefficients $\rho_{k,l}^{PI}$, i.e., $dW_t^{PI,k} dW_t^{PI,l} = \rho_{k,l}^{PI} dt$ for countries l and k. Following Ahlgrim and D'Arcy (2012), the price index PI_t^k is given by

$$PI_t^k = PI_0^k \cdot \exp\left(\int_0^t r_s^k ds\right).$$

6 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.

7 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.

8 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.

Integrating policy risk and definition of the policy risk event

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 retrospective reduction in the feed-in tariff occurs at most once during the investment horizon T at some (stochastic) point in time τ^k with a given percentage α^k (which is 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 $T^{sup,k}$, but the historical examples discussed in the introduction suggest that a FIT reduction is more common. The *policy risk event* (RE) in country k is thus defined as

a reduction in the FIT of a certain percentage α^k at some (stochastic) point in time τ^k during the investment period, i.e. after the occurrence of the policy risk event the feed-in tariff is reduced to $FIT_t^k \cdot \left(1-\alpha^k\right), t \geq \tau^k$, whereby the policy risk event occurs only once during the investment period with a reduction probability $P_{RE}^{\text{real,k}}$ as described in Section 2.

In case $\tau^k > T^{sup,k}$, no reduction took place during the support period $T^{sup,k}$. The feed-in tariff in Equation (4) is thus given by

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

The probability $P_{RE}^{\text{real,k}}$ that the FIT is reduced by α^k can thereby be obtained through the Delphi technique (i.e. expert estimates) as described in the previous section or by using scenario analyses, i.e. by varying the probability of occurrence of a policy risk event in the respective country.

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

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

with PV^k given by Equation (5) and w_k denoting the share of the wind farm 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,

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

where F_{PV^k} denotes the distribution function of PV^k. Based on this, the economic capital, i.e., the cushion to compensate unexpected losses at a given confidence level (see, e.g., Drehmann and Alessandri (2010) and Crouhy et al. (2000)), is given by the difference between the expected present value and the value at risk,

$$EC_\beta\left(PV^k\right) = E\left[PV^k\right] - VaR_\beta\left(PV^k\right). \tag{6}$$

To measure the diversification effect D, we use the value at risk and obtain

$$D = \frac{VaR_\beta\left(\sum_{k=1}^{K} w_k \cdot PV^k\right)}{\sum_{k=1}^{K} w_k \cdot VaR_\beta\left(PV^k\right)} - 1, \ \text{with} \ \sum_{k=1}^{K} w_k = 1, \quad w_k \geq 0. \tag{7}$$

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. As our focus is on the impact of policy risk, we assume the installed capacity to be CP = 1 MW for both wind farms in order to have all results in terms of MW.[9] 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).

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[9] The installed capacity of a wind farm is usually higher, e.g., Abadie and Chamorro (2014) assume a value of 50 MW. Different capacities can generally be included in the analysis by multiplying the present values, while in cases where economies of scale are expected, other input parameters may need to be adjusted as well (e.g., OMSI etc.).

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).[10] For simplicity, we here assume that

$$S_t^{2,renewable} = \begin{cases} max\left(FIT_t^{2,pol}, S_t^{spot}\right), & t \leq T^{sup,2} \\ S_t^{spot}, & t > T^{sup,2} \end{cases}.$$

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

$$S_t^{1,renewable} = \begin{cases} max\left(FIT_t^{1,pol}, S_t^{spot}\right), & t \leq T^{sup,1} \\ S_t^{spot}, & t > T^{sup,1} \end{cases},$$

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 et al. (2012), for instance. The feed-in tariff may also be stochastic as in the case of France (k = 1), 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”)

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

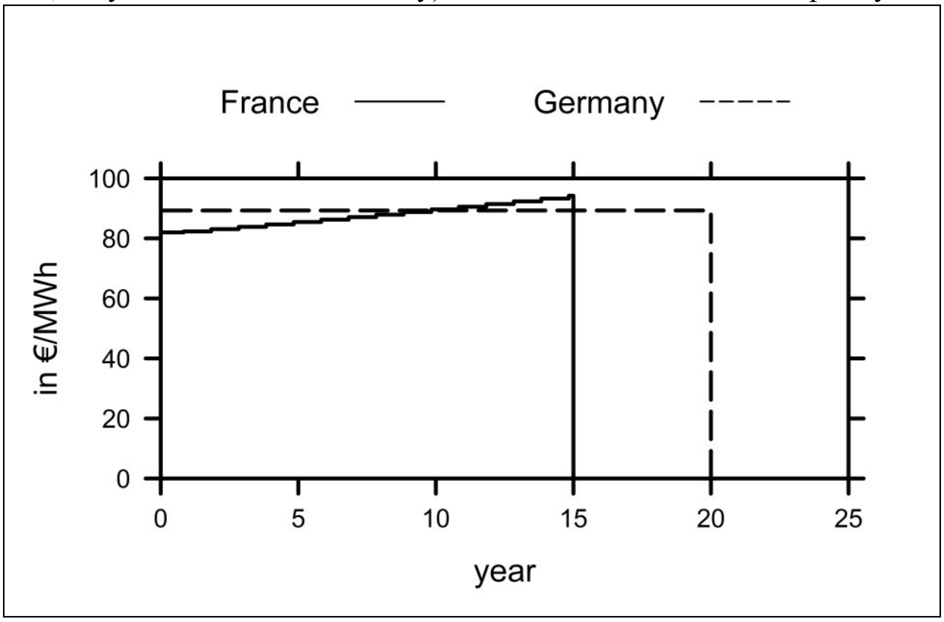
where WI_t denotes the French wage index of employees working in the electric and mechanic industry in the t-th year (t = 0 denotes the start-up of the wind farm), PPI_t is the producer price index, and the index is updated annually on November 1st. For simplicity, we further assume that OMSI costs,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

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

[10] The available support schemes in Germany depend on the start-up date (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 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”, which is 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).

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 $T^{sup,k}$ (i.e., 15 years in France and 20 years in Germany). Figure 3 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, and the specific support period) without the occurrence of a policy risk event. As the FIT in France is only updated once a year, the curve is cascading.

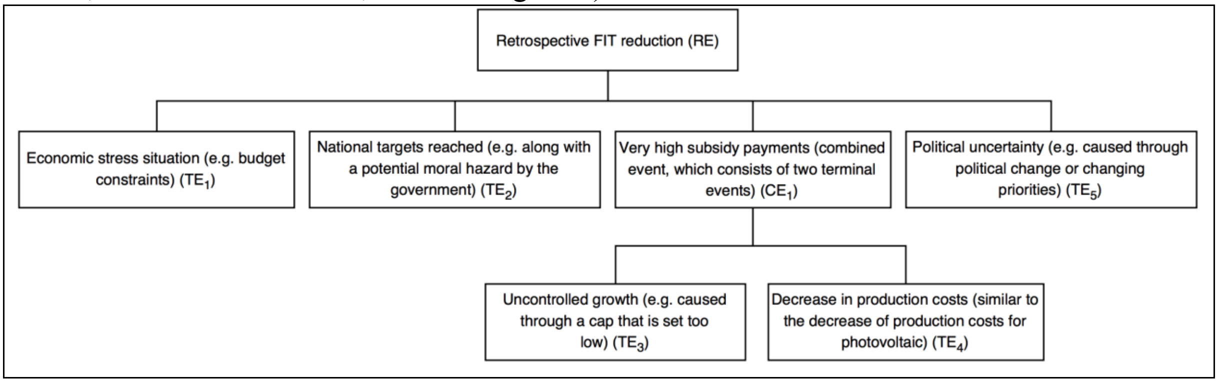
Figure 3: Illustration of the development of FIT in France (expected values) and Germany (deterministic) over the investment period until the maximum FIT support period (15 years in case of France, 20 years in case of Germany) without the occurrence of a policy risk event



Of special interest is the policy risk associated with the support schemes and its impact on $S_t^{k,renewable}$. As laid out in the previous section, in what follows we assume that a retrospective reduction in the FIT occurs at most once during the investment horizon T at some (stochastic) point in time τ^k with a given percentage α^k (estimated based on expert opinions, see Section 2), which only impacts cash flows after the occurrence of the policy risk event.

For the policy risk assessment, we apply the procedure presented in Section 2. For the determination of the driving risk factors (i.e. the terminal and component events) we refer to Gatzert and Kosub (2015) from which we select the most relevant risk factors. The resulting fault tree, which is used for the estimation of policy risk, is stated in Figure 4 containing one component event CE (i.e., very high subsidy payments) and five terminal events TE (i.e., economic stress situation, national targets reached, uncontrolled growth, decrease in production costs, and political uncertainty).

Figure 4: Fault tree for the risk event (RE) "retrospective FIT reduction" (CE = component event; TE = terminal event, see also Figure 1)



To calibrate the model with regard to the currently estimated policy risk for the two considered countries, we asked $N = 4$ experts with four to fourteen years of experience with respect to investments in renewable energy in Europe (more details are provided in Table A.1 in the Appendix) regarding their assessment of the probabilities using the Delphi method as described in Section 2.

The same questions were asked for France and for Germany, and all four experts were asked about both countries. The order of questions asked in each round for the case of Germany are shown in Table A.2 in the Appendix. The questions for the case of France are the same, with "Germany" being replaced by "France", and where the country-specific information and examples were adjusted accordingly (e.g., for question 1, France had an S&P rating of AA at 03/2015). As the unit of time, which has to be chosen carefully (see Section 2), we considered five years and twenty years, where the five-year probability is used in the following numerical analysis. The estimates by the experts for each question are shown in Table A.3 in the Appendix. All experts completed the first round before the aggregated results for the probability of occurrence was calculated using Equations (1) and (2) based on the responses of all four experts, where we used an equal weighting to aggregate the responses. For the second round, each expert obtained the aggregated value (i.e., 8.658% for France and 4.855% for Germany for the five-year probability of occurrence as aggregated across all four experts) and the probability of occurrence calculated using only the personal estimates (see Table A.3 in the Appendix for the values of round 1). Based on this information, the experts could reconsider their estimates.

This procedure resulted in a final five-year reduction probability $P_{RE}^{\text{real,k}}$ of 7.480% in France and 4.455% in Germany after the second round, where the exit condition (see Section 2) was reached as the estimations did not change significantly. The impact evaluation led to a possible reduction size of 13.5417% in France and 13.0417% in Germany (see also Table A.3 in the Appendix). These expert estimates serve as an anchor and as a starting point for our sensitivity analyses, where we vary the five-year probability of occurrence of the policy risk event, and they are intended to provide first central insight regarding the policy risk associated with renewable energy projects in the two considered countries.

Note that in order to simulate the point in time when a FIT reduction takes place τ^k (i.e. when the policy risk occurs), we use a five-year reduction probability derived as laid out above, and draw the respective five-year period where the FIT reduction occurs, e.g. during 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 monthly data of the German "Hochfeld-2" wind farm available from 2002-2014 (see Production Hochfeld, 2015) to calibrate L_{av}^k, $g^k(t)$, and σ_L^k using least squares as is done in Abadie and Chamorro (2014). The results for the seasonal component $g^k(t)$ are stated in Table 2 and are used for the wind farms in both countries.

Table 2: 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 wind farms 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, which results in monthly OMSI costs of €3,541.66 (see van de Wekken (2007) for the case of onshore wind farms). 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 S_t^{spot} are calibrated based on the German EEX Phelix Month Base values from 2002-2014, using the method proposed by Yoshida (1992). The resulting input parameters are summarized in Table 3.

Table 3: Project assumptions and input parameters (see also Table 1)

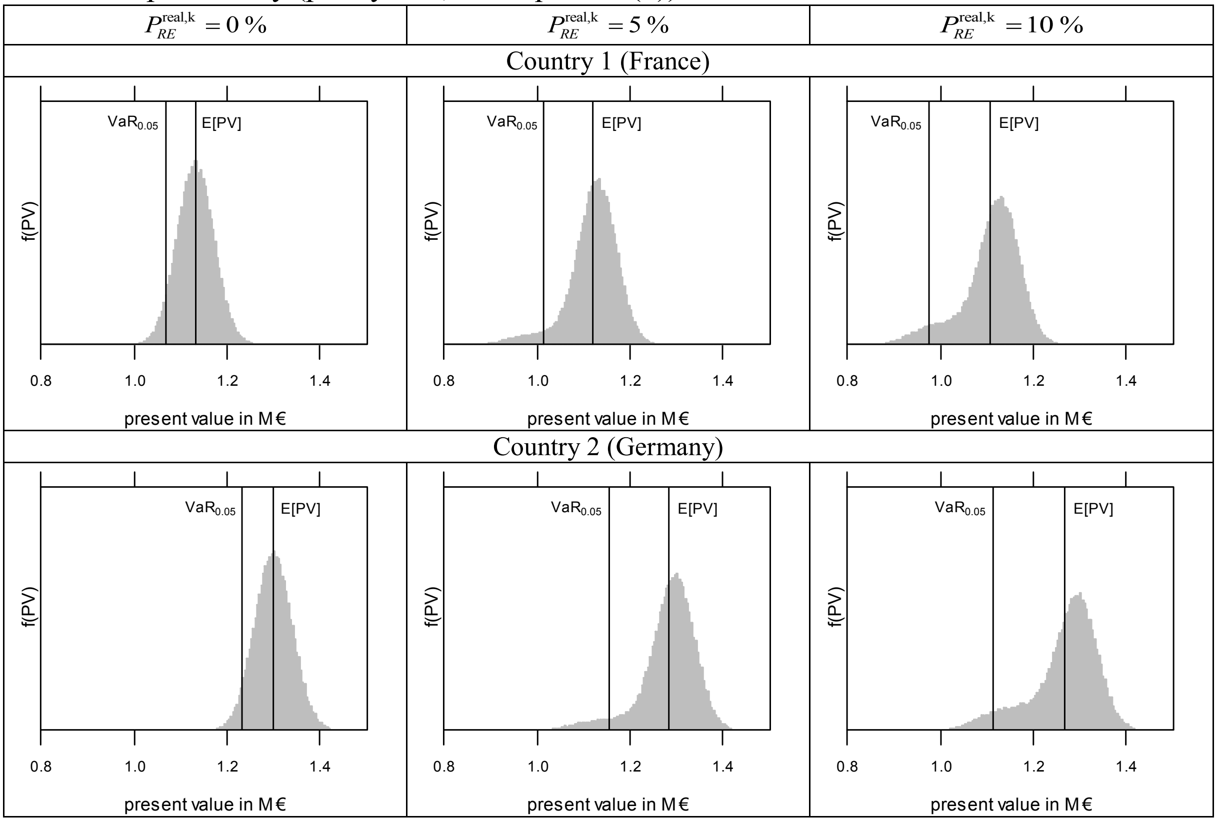
Project assumptions	*Variable / model*	*Input parameters country 1 (France)*	*Input parameters country 2 (Germany)*
Discount factor in country k (in %)	γ^k	7%	7%
(Monthly) average price of renewable energy received by the operator in country k (in €/MWh)	$S_t^{k,renewable} = max\left(FIT_t^{k,pol}, S_t^{spot}\right)$ for $t \le T^{sup,k}$; $S_t^{k,renewable} = S_t^{spot}$ for $t > T^{sup,k}$	$FIT_t^{1,pol} = FIT_t^1$ for $t < \tau^1$; $FIT_t^{1,pol} = FIT_t^1 \cdot \left(1-\alpha^1\right)$ for $T^{sup,1} \ge t \ge \tau^1$	$FIT_t^{2,pol} = FIT_t^2$ for $t < \tau^2$; $FIT_t^{2,pol} = FIT_t^2 \cdot \left(1-\alpha^2\right)$ for $T^{sup,2} \ge t \ge \tau^2$
(Monthly) average energy price obtained at the exchange (in €/MWh)	S_t^{spot} with $dS_t^{spot} = \kappa^{spot}\left(\left(a^{spot}t + c^{spot}\right) - S_t^{spot}\right)dt + \sigma^{spot} dW_t^{spot}$	$\kappa^{spot} = 0.2095$; $a^{spot} = 0.0582$; $c^{spot} = 36.3227$; $\sigma^{spot} = 7.8754$	$\kappa^{spot} = 0.2095$; $a^{spot} = 0.0582$; $c^{spot} = 36.3227$; $\sigma^{spot} = 7.8754$
Produced electricity in month t in country k (in MWh)	$PE_t^k = L_t^k \cdot CP^k \cdot 720h$ with monthly load factor $L_t^k = g_t^k + L_{av}^k + \varepsilon_t^k$	$\sigma_L^1 = 0.0642$; $L_{av}^1 = 0.2132$; for $g^1(t)$ see Table 2	$\sigma_L^2 = 0.0642$; $L_{av}^2 = 0.2132$; for $g^2(t)$ see Table 2
Installed capacity in country k (in MW)	CP^k	1 MW	1 MW
Price index describing the (monthly) development of the price level of the OMSI in country k	$PI_t^k = PI_0^k \cdot \exp\left(\int_0^t r_s^k ds\right)$	$\kappa^{PI,2} = 1.0639$; $b^{PI,2} = 0.1282$; $\sigma^{PI,2} = 0.2956$; $\rho_{1,2}^{PI} = 0.2781$	$\kappa^{PI,2} = 1.3782$; $b^{PI,2} = 0.1239$; $\sigma^{PI,2} = 0.3024$; $\rho_{1,2}^{PI} = 0.2781$
(Monthly) operation, maintenance, staffing and insurance (OMSI) costs in country k (in €)	$OMSI^k$	€3,541.66 per month, adjusted with price index PI	€3,541.66 per month, adjusted with price index PI
FIT at time t (subject to policy risk) in country k (in €/MWh)	FIT_t^k	$FIT_t^1 = FIT_0^1\left(0.4 + 0.6\frac{PI_{t-1}^1}{PI_0^1}\right)$ with $FIT_0^1 = 82$	$FIT_t^2 = 89.3$
Investment period (in years)	T	25 years	25 years
Support period for FIT in country k (in years)	$T^{sup,k}$	15 years	20 years
Five-year FIT reduction probability in country k (in %) used to generate τ^k (policy risk event)	$P_{RE}^{\mathrm{real},k}$	7.480%	4.455%
Percentage reduction in FIT in case policy risk scenario occurs in country k	α^k	13.5417%	13.0417%

All input parameters are subject to sensitivity analyses. Furthermore, 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 5 exhibits the probability distribution of the present value (Equation (5)) for three levels of the five-year FIT reduction probability $P_{RE}^{\text{real,k}}$ (0%, 5%, 10%) (see Equation (2)), which is the same for both France (country 1, first row) and Germany (country 2, second row) to gain insight of what is driving the results. In particular, the graphs show that the inclusion of policy risk can have a considerable impact on the distribution of the present value of cash flows for both countries (going from left to right in Figure 5). For instance, the probability distribution in the case without policy risk (left graphs, reduction probability $P_{RE}^{\text{real,k}} = 0\%$) 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 (right graphs) exhibit heavy-tailed downside risk, which increases for higher reduction probabilities.

Figure 5: Probability distribution of the present value of cash flows depending on the reduction probability (policy risk, see Equation (2))



While policy risk is generally modeled in same way for both countries, the results clearly differ. This can also be seen in Table 4, which assumes the same policy risk scenario for both countries, i.e. the same five-year FIT reduction probability and the same size of the FIT reduction given that the policy risk event occurs, and thus allows a better comparability. The results thereby differ due to the different project economies and the different size of the FIT. In particular, one can observe in Figure 5 and Table 4 that the expected present value and the value at risk are generally lower in the case of France, 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. Table 4 also shows that the relative impact of policy risk events is much stronger for Germany (e.g. last row: value at risk increases by 13.46% in case of Germany as compared to 11.81% in case of France due to the policy risk event 15% FIT reduction and 15% FIT reduction probability).

Table 4: The impact of a FIT reduction on the expected present value (PV) and the value at risk (VaR) for various policy risk event scenarios

Percentage reduction in FIT for both countries α^k	Five-year FIT reduction probability in both countries $P_{RE}^{real,k}$	Expected PV (in M €) and % reduction compared to base case		$VaR_{0.05}$ of PV and % reduction compared to base case	
		France	Germany	France	Germany
0% (base case)	0%	1.132	1.299	1.067	1.233
10%	5%	1.123 (0.80%)	1.286 (1.00%)	1.036 (2.91%)	1.185 (3.89%)
	10%	1.114 (1.59%)	1.273 (2.00%)	1.011 (5.25%)	1.152 (6.57%)
	15%	1.106 (2.30%)	1.262 (2.85%)	0.997 (6.56%)	1.137 (7.79%)
15%	5%	1.118 (1.24%)	1.279 (1.54%)	1.004 (5.90%)	1.135 (7.95%)
	10%	1.105 (2.39%)	1.261 (2.93%)	0.959 (10.12%)	1.087 (11.84%)
	15%	1.092 (3.53%)	1.244 (4.23%)	0.941 (11.81%)	1.067 (13.46%)

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 6, which displays the expected value and the value at risk of the cash flows in each year over the entire support period. It can be seen that in the case of France, the expected annual cash flow (upper lines) first increases due to the inflation adjustment, and after the 11th year even exceeds the expected cash flow in the case of Germany, where the expected cash flows are first higher but then decreasing over time due to the presence of policy risk and inflation adjusted operation, maintenance, staffing and insurance costs. The remaining variability 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 and policy risk (see Table 3).

Figure 6: Annual expected value (EV) and annual value at risk (VaR) of project cash flows over the support period with and without policy risk

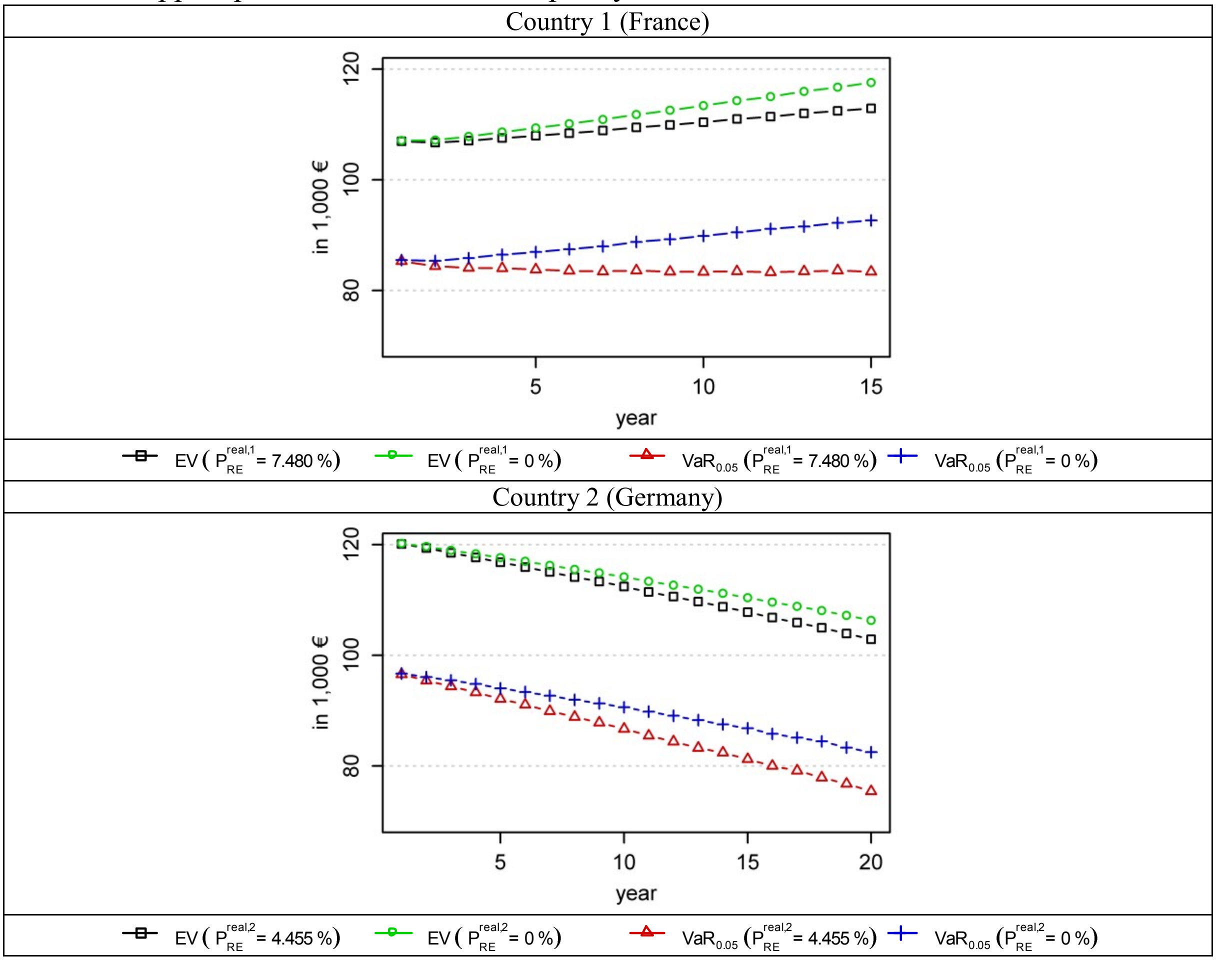


Figure 7 displays the expected present value and the value at risk with different confidence levels of 10%, 5%, and 2.5% for different reduction probabilities for the two countries. The results show that an increasing reduction probability as expected implies a decrease in the expected present value (upper black line with "+") and a considerable impact on risk. In particular, an increasing reduction probability implies a decrease in the value at risk, 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 5, the overall level of the expected present value and value at risk are higher in the case of the German onshore wind farm than the one in France in the present setting.

Figure 7: Value at risk (VaR) and expected present value (E[PV]) of renewable energy investments depending on the reduction probability (Equation (2))

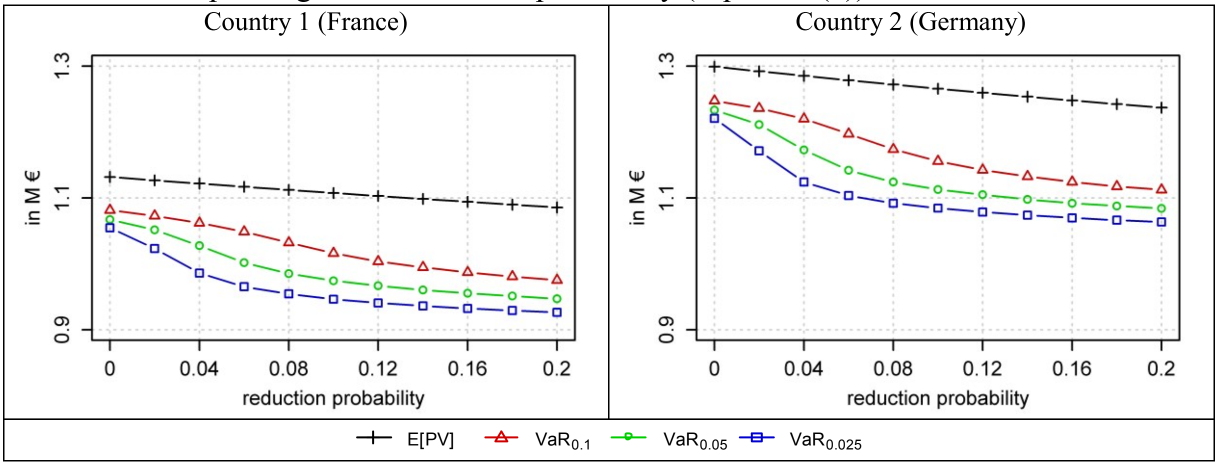
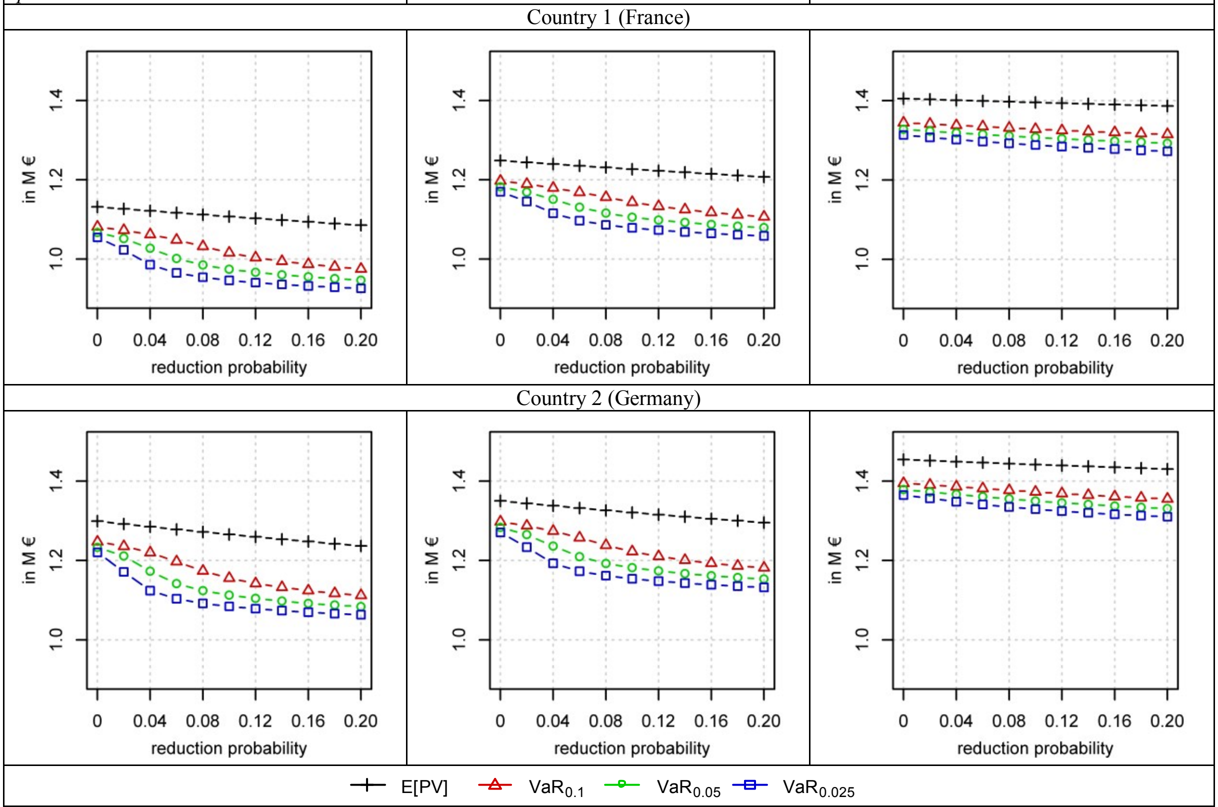


Figure 8 shows the expected value and value at risk of the present value of the investment for increasing mean reversion levels of energy prices (from left to right) and for increasing five-year FIT reduction probabilities between 0% and 20% (expert estimates for Germany: 4.455%; for France: 7.480%). The graphs emphasize the relevance of energy price levels on risk-return profiles of the projects. In case the spot market price approaches the FIT level (right graph, mean-reversion level of energy price of c^{spot} = 80 €/MWh), a possible FIT reduction only has a minor impact on cash flows, as operators have the possibility to switch between the FIT and the spot market and can thus sell the produced electricity directly at the exchange to obtain the more favorable price. Hence, the effect of policy risk is highest for lower energy prices (mean-reversion levels) as can be seen in the left graphs.

Figure 8: Value at risk (VaR) and expected present value (E[PV]) in country 1 and 2 for increasing energy prices depending on the reduction probability

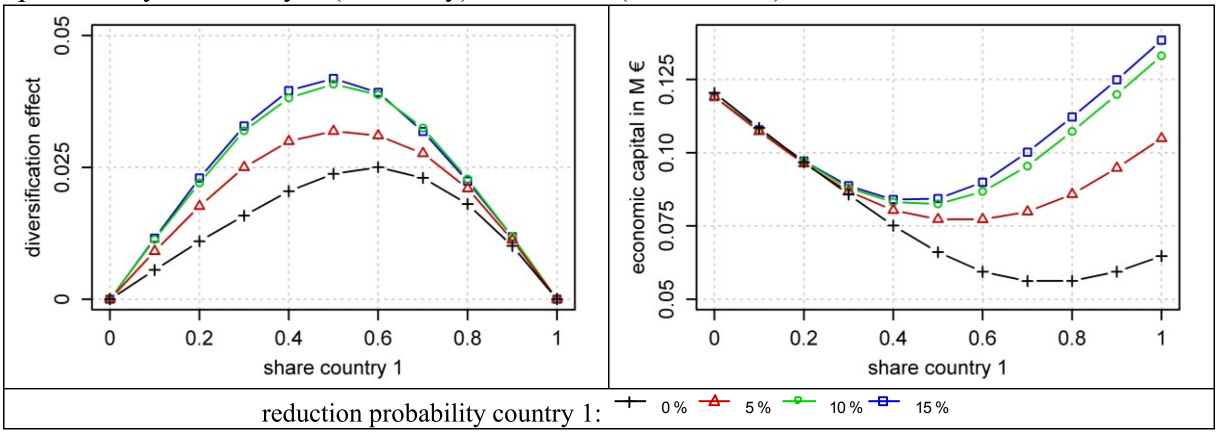
Base case: mean-reversion level of energy price $c^{spot} = 36.3227$	*Mean-reversion level of energy price $c^{spot} = 60$*	*Mean-reversion level of energy price $c^{spot} = 80$*



Portfolio considerations and diversification effects

As shown in Gatzert and Kosub (2016), 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 wind farms in both countries. Figure 9 shows the diversification effect and the economic capital (see Equations (6) and (7)) for different portfolio compositions and different levels of policy risk. The five-year reduction probability in country 1 thereby varies between 0% and 15% (expert estimate: 7.480%), while the five-year reduction probability in country 2 is fixed at 4.455%.

Figure 9: Diversification effect and economic capital for various FIT reduction probabilities of country 1 (France) depending on the portfolio composition and for a given FIT reduction probability of country 2 (Germany) at 4.455% (see Table 3)

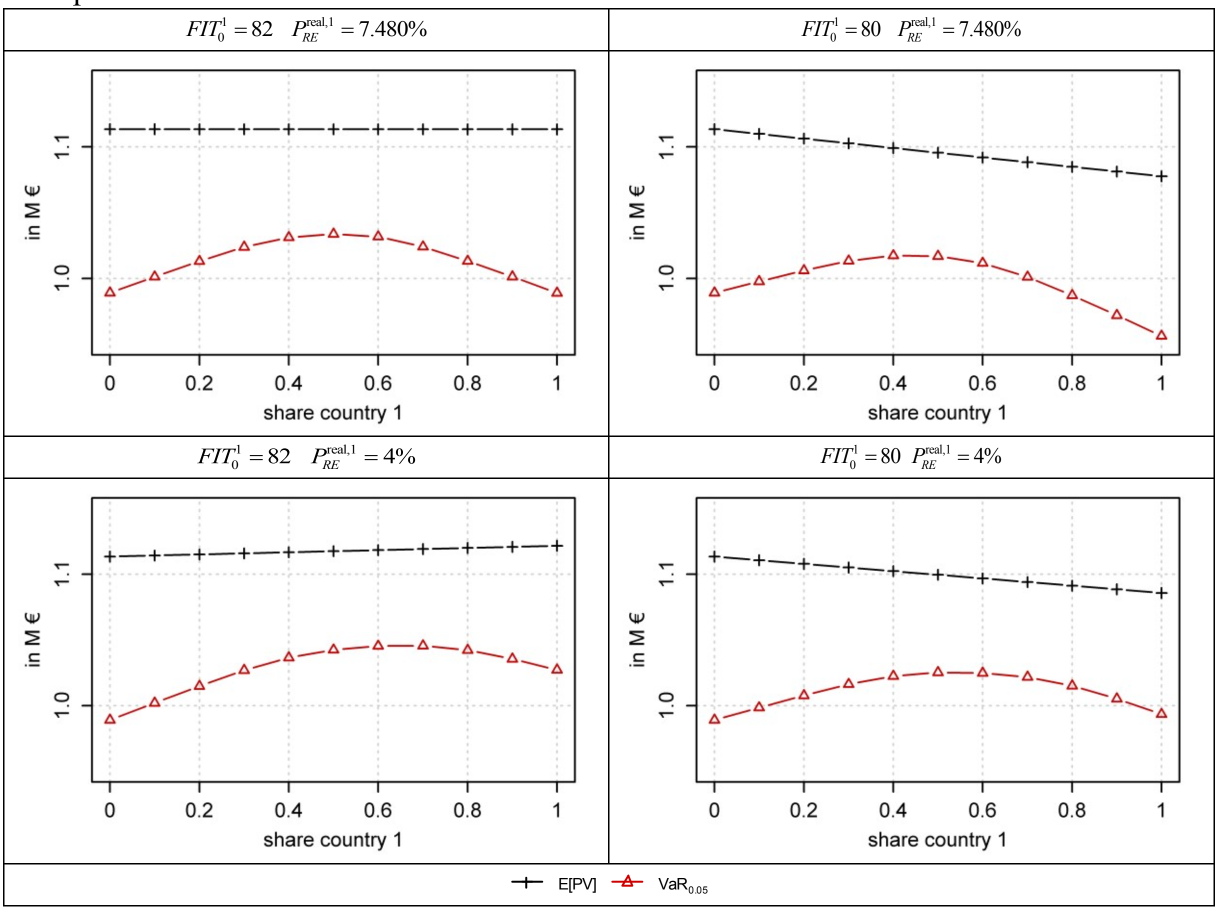


The left graph in Figure 9 shows that the diversification effect strongly depends on the portfolio composition and the level of policy risk in country 1. For instance, for a low policy risk in country 1 (e.g. 0%, see black line with "+"), the diversification effect is highest for a high share of about 60% invested in country 1 within the portfolio since the policy risk in country 2 is fixed with 4.455% and thus higher than in country 1. For a policy risk of 15% (blue line with squares), the highest diversification effect with about 4.18% is achieved for an approximately equally weighted portfolio. Diversification can furthermore lower the necessary cushion for unexpected losses, i.e., the economic capital as can be seen in the right graph. We thereby observe a decreasing marginal diversification effect, i.e., increasing the probability of occurrence of the policy risk event from 0% to 5% and to 10% has a much stronger effect on diversification and economic capital than increasing the policy risk from 10% to 15%. In addition, one has to take into account that even though the diversification effect increases for higher reduction probabilities (see left graph in Figure 9), the overall risk level (e.g., the economic capital) increases as well (see right graph in Figure 9), but that (relative) diversification effects 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 €0.065 million to €0.138 million depending on the FIT reduction probability in country 1, ranging from 0% to 15% (see right graph in Figure 9). For an investment with an expected present value of €1.13 million in case of a reduction probability of 0% (see left graph in Figure 7) and €1.10 million in case of a reduction probability of 15%, the required economic (risk) capital relative to this expected value thus ranges from 5.75% to 12.55%, which implies a tremendous difference regarding the costs of capital.

Changes in the policy risk or in the FIT level have different effects on the risk-return profile. Figure 10 shows the expected value and value at risk at the 5% confidence level for a portfolio consisting of two countries both calibrated to country 1 (to exclude effects arising from different input parameters) for two reduction probabilities (7.480% and 4%) and two levels of the FIT (82 €/MWh and 80 €/MWh). A decreasing reduction probability (from 7.480% to 4%, see upper and lower left graphs) has only a minor effect on the expected present value. Even when considering the case where an investor only invests in one country, it is increasing only from €1.113 million to €1.122 million. However, it does have a stronger effect on the value at risk, which is increasing from €0.989 million to €1.027 million in case of investing only in country 1, thus lowering the economic capital as the difference between expected value and value at risk from €0.124 million to €0.095 million. The same holds for the other portfolio compositions, where the value at risk increases stronger than the expected value.

Figure 10: Value at risk (VaR) and expected present value (E[PV]) for two hypothetical countries, both calibrated to country 1 (France), for various reduction probabilities and FITs in country 1 (parameters of country 2 fixed to French setting), depending on the portfolio composition

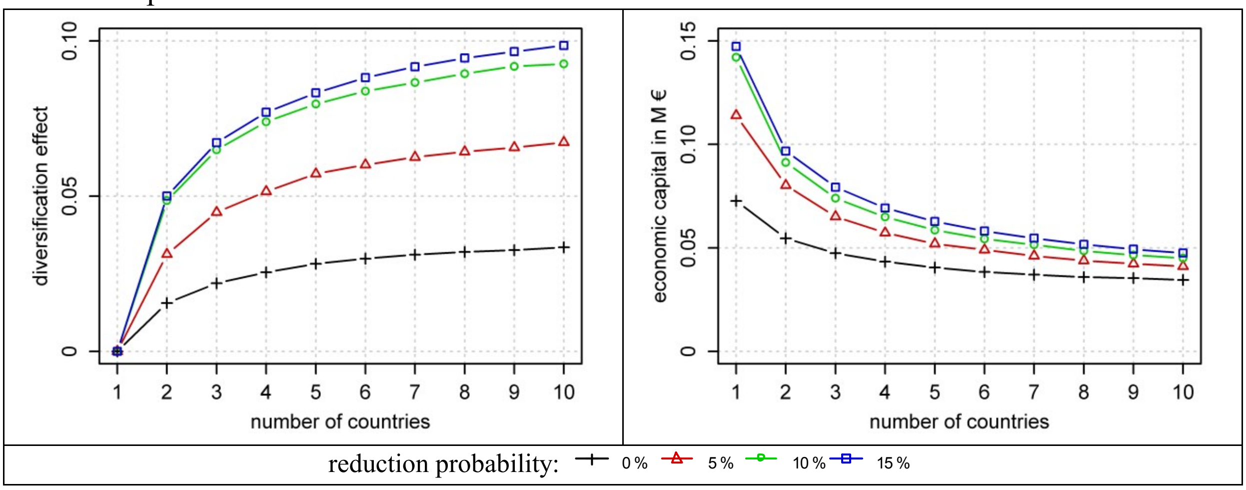


In contrast, a decreasing FIT (from 82 €/MWh to 80 €/MWh) in country 1 has a huge impact on the expected value and the value at risk. When considering the case where an investor only invests in country 1, the expected values decrease from €1.113 million to €1.078 million and the value at risk is decreasing from €0.989 million to €0.956 million (see upper right and left graph in Figure 10). The result is an almost unchanged economic capital of €0.124 million and €0.122 million, respectively. Combining these two adjustments (FIT from 82 €/MWh to 80 €/MWh and reduction probability from 7.480% to 4%) has a considerable impact on the expected value, but only a minor impact on the value at risk (see Figure 10 upper left and lower right graph).

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 effect depending on energy prices, which shows that higher energy prices lead to a lower effect of the FIT reduction and to a decreasing diversification effect, which is in line with Figure 8.

Finally, the number of countries in the portfolio is increased in Figure 11, thereby assuming an investment in one onshore wind farm in each country. The results show that the economic capital is decreasing strongly when increasing the number of countries in the portfolio, but that the extent of the diversification is decreasing until a level is reached which cannot be further diversified, implying a certain remaining economic capital that cannot be further reduced.

Figure 11: Diversification effect 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



5. Conclusion and Policy Implications

As the previous literature has emphasized that policy risks play an important role for the attractiveness of renewable energy investments, these risks should be closely monitored and assessed using adequate risk models. Toward this end, we provide a stochastic model framework for assessing policy risks, which in contrast to previous literature uses fuzzy set theory and thereby also takes into account stochastic energy price risk, inflation risk, and resource risk. We further extend previous studies by studying cross-country diversification effects for a portfolio of wind farm investments. While the quantification of policy risks clearly comes with challenges, our approach provides first relevant insight for investors into main drivers and diversification effects associated with policy risks.

Our findings show that policy risk can have a major impact on an investor's risk-return profile in terms of expected value and value at risk. In particular, our results emphasize that policy risk is a heavy-tailed downside risk, which should be taken into account by investors. As the insurance market for policy risks is very limited, they have to rely on cross-country diversification as one potential risk management tool, which we show can substantially improve the risk-return situation. We further show that the support period has a major impact on the effect of policy risk, as shorter support periods are less exposed to policy risk. Moreover, another relevant factor for the effect of policy risk on risk-return profiles is the spot market price for electricity. An increasing spot market price that reduces the difference to the guaranteed FIT dampens the impact of policy risk. Furthermore, a lower FIT level has a considerable impact on the expected present value and the value at risk, while an increasing policy risk decreases the value at risk and has only a minor impact on the expected present value. Depending on the investors' risk preferences, this can result in a tradeoff between policy risk and the FIT level.

These implications of policy risk on investors lead to the following policy implications. As policy risk is driven by several risk factors, such as the economic situation, national targets or political uncertainty, politics should be careful with actions which can worsen one or more of these risk factors. This could either decrease the investments in renewable energy and could cause the failure 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 linked to renewable energy in order not to 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.

In contrast to high-risk countries, countries with a low level of policy risk are relatively free with the configuration of the support scheme. Countries with a higher policy risk might need to offer a higher FIT with a shorter support period, since a longer support period will increase the impact of policy risk and therefore the corresponding costs due to the additional risk premium required by the investors.

In regard to the cross-country diversification effect, 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. In addition, including an analysis of dependencies between policy risks in different countries would be of interest, especially regarding the diversification effects.

REFERENCES

Abdelgawad, M., Fayek, A. R. (2011): Fuzzy Reliability Analyzer: Quantitative Assessment of Risk Events in the Construction Industry Using Fuzzy Fault-Tree Analysis. *Journal of Construction Engineering and Management* 137(4), 294-302.

Abadie, L. M., Chamorro, J. M. (2014): Valuation of Wind Energy Projects: A Real Options Approach. *Energies* 7, 3218-3255.

Ahlgrim, K. C., D'Arcy, S. P. (2012): A User's Guide to the Inflation Generator. Working Paper, Illinois State University, University of Illinois at Urbana-Champaign.

Alesina, A., Perotti, R. (1996): Income Distribution, Political Instability, and Investment. *European Economic Review* 40, 1203-1228.

Alessandri, P., Drehmann, M. (2010): An Economic Capital Model Integrating Credit and Interest Rate Risk in the Banking Book. *Journal of Banking and Finance* 34(4), 730-742.

Barradale, M. J. (2010): Impact of Public Policy Uncertainty on Renewable Energy Investment: Wind Power and the Production Tax Credit. *Energy Policy* 38(12), 7698-7709.

Bollino, C. A., Ciferri, D., Polinori, P. (2013): Integration and Convergence in European Electricity Markets. Working paper. Available at SSRN 2227541.

Bond, G., Carter, L. (1995): Financing Energy Projects: Experience of the International Finance Corporation. *Energy Policy* 23(11), 967-975.

Boomsma, T. K., Meade, N., Fleten, S. (2012): Renewable Energy Investments under Different Support Schemes: A Real Options Approach. *European Journal of Operational Research* 220(1), 225-237.

Brandstätt, C., Brunekreeft, G., Jahnke, K. (2011): How to Deal with Negative Power Price Spikes? - Flexible Voluntary Curtailment Agreements for Large-Scale Integration of Wind. *Energy Policy* 39, 3732-3740.

Brink, C. H. (2004): Measuring Political Risk. Ashgate, Aldershot.

Bürer, M. J., Wüstenhagen, R. (2008): Cleantech Venture Investors and Energy Policy Risk: an Exploratory Analysis of Regulatory Risk Management Strategies. In: Wüstenhagen et al. (Ed.), Sustainable Innovation and Entrepreneurship, Edward Elgar Publishing, 290-309.

Campoccia, A., Dusonchet, L., Telaretti, E., Zizzo, G. (2009): Comparative Analysis of Different Supporting Measures for the Production of Electrical Energy by Solar PV and Wind Systems: Four Representative European Cases. *Solar Energy* 83, 287-297.

Cheng, C., Lin, Y. (2002): Evaluating the Best Main Battle Tank using Fuzzy Decision Theory with Linguistic Criteria Evaluation. *European Journal of Operational Research* 142, 174-186.

Choobineh, F., Behrens, A. (1992): Use of Intervals and Possibility Distributions in Economic Analysis. *The Journal of the Operational Research Society* 43(9), 907-918.

Crouhy, M., Galai, D., Mark, R. (2000): A Comparative Analysis of Current Credit Risk Models. *Journal of Banking and Finance* 24(1-2). 59-117.

Deng, S. J., Oren, S. S. (2006): Electricity Derivatives and Risk Management. *Energy* 31(6-7), 940-953.

Fagiani, R., Hakvoort, R. (2014): The Role of Regulatory Uncertainty in Certificate Markets: A Case Study of the Swedish/Norwegian Market. *Energy Policy* 65, 608-618.

Falbo, P., Paris, F. M., Pelizzari, C. (2010): Pricing Inflation-Linked Bonds. *Quantitative Finance* 10(3), 279-293.

Garthwaite, P. H., Kadane, J. B., O'Hagan, A. (2005): Statistical Methods for Eliciting Probability Distributions. *Journal of the American Statistical Association* 100(470), 680-699.

Gatzert, N., Kosub, T. (2015): Determinants of Policy Risks of Renewable Energy Investments. Working Paper, Friedrich-Alexander University Erlangen-Nürnberg.

Gatzert, N., Kosub, T. (2016): Risks and Risk Management of Renewable Energy Projects: The Case of Onshore and Offshore Wind Parks, in: *Renewable and Sustainable Energy Reviews* Vol. 60 (July 2016), pp. 982–998.

Grothe, O., Müsgens, F. (2013): The Influence of Spatial Effects on Wind Power Revenues under Direct Marketing Rules. *Energy Policy* 58, 237-247.

Guyonnet, D., Bourgine, B., Dubois, D., Fargier, H., Côme, B., Chilès, J. (2003): Hybrid Approach for Addressing Uncertainty in Risk Assessments. *Journal of Environmental Engineering* 129(1), 68–78.

Haslett, J., Raftery, A. E. (1989): Space-Time Modelling with Long-Memory Dependence: Assessing Ireland's Wind Power Resource. *Journal of Applied Statistics* 38, 1-50.

Hitzeroth, M., Megerle, A. (2013): Renewable Energy Projects: Acceptance Risks and Their Management. *Renewable and Sustainable Energy Reviews* 27, 576-584.

Holburn, G. L. F. (2012): Assessing and managing regulatory risk in renewable energy: Contrasts between Canada and the United States. *Energy Policy* 45, 654-665.

Hsu, C., Sandford, B. A. (2007): The Delphi Technique: Making Sense of Consensus. *Practical Assessment Research & Evaluation* 12.

Jacobsen, H. K., Schröder, S. T. (2012): Curtailment of Renewable Generation: Economic Optimality and Incentives. *Energy Policy* 49, 663-675.

Jin, X., Zhang, Z., Shi, X., Ju, W. (2014): A Review on Wind Power Industry and Corresponding Insurance Market in China: Current Status and Challenges. *Renewable and Sustainable Energy Reviews* 38, 1069-1082.

Kafka, P. (2008): Probabilistic Risk Assessment for Nuclear Power Plants. In: Misra, K. B. (Ed.): Handbook of Performability Engineering, Springer, 1179-1192.

Kaufmann, A., Gupta, M. M. (1988): Fuzzy Mathematical Models in Engineering and Management Science. Elsevier.

Kitzing, L. (2014): Risk Implications of Renewable Support Instruments: Comparative Analysis of Feed-In Tariffs and Premiums Using a Mean-Variance Approach. *Energy* 64, 495-505.

Klir, G., Yuan, B. (1995): Fuzzy Sets and Fuzzy Logic. Prentice Hall.

Kuo, R. J., Xue, K. C. (1998): A Decision Support System for Sales Forecasting through Fuzzy Neural Networks with Asymmetric Fuzzy Weights. *Decision Support Systems* 24, 105-126.

Liu, H., Erdem, E., Shi, J. (2011): Comprehensive Evaluation of ARMA–GARCH(-M) Approaches for Modeling the Mean and Volatility of Wind Speed. *Applied Energy* 88, 724-732.

Lüthi, S., Prässler, T. (2011): Analyzing Policy Support Instruments and Regulatory Risk Factors for Wind Energy Deployment—A Developers' Perspective. *Energy Policy* 39(9), 4876-4892.

Lüthi, S., Wüstenhagen, R. (2012): The Price of Policy Risk - Empirical Insights from Choice Experiments with European Photovoltaic Project Developers. *Energy Economics* 34(4), 1001-1011.

Meyer, N. I. (2003): European Schemes for Promoting Renewables in Liberalised Markets. *Energy Policy* 31, 665-676.

Micale, V., Frisari, G., Hervé-Mignucci, M., Mazza, F. (2013): Risk Gaps: Policy Risk Instruments. Climate Policy Initiative.

Monjas-Barroso, M., Balibrea-Iniesta, J. (2013): Valuation of Projects for Power Generation with Renewable Energy: A Comparative Study based on Real Regulatory Options. *Energy Policy* 55, 335-352.

O'Hagan, A., Buck, C. E., Daneshkhah, A., Eiser, J. R., Garthwaite, P. H., Jenkinson, D. J., Oakley, J. E., Rakow, T. (2006): Uncertain Judgements: Elicting Experts' Probabilities. John Wiley & Sons.

Production Hochfeld (2015): Produktionsdaten Windpark Hochfeld. Available at http://www.energie-expertise.de/fileadmin/user_upload/ertraege/Ertrag_Hochfeld.pdf, access 02/16/2014.

Reuter, W. H., Szolgayová, J., Fuss, S., Obersteiner, M. (2012): Renewable Energy Investment: Policy and Market Impacts. *Applied Energy* 97, 249-254

Sachs, T., Bellinger, C., Tiong, R. L. K. (2008a): Risk Exposure and Recovery Assessment under a Guarantee in a Water Project. *The Journal of Structured Finance* 14(1), 50-64.

Sachs, T., Tiong, R. L. K. (2009): Quantifying Qualitative Information on Risks: Development of the QQIR Method. *Journal of Construction Engineering and Management* 135(1), 56-71.

Sachs, T., Tiong, R. L. K., Wagner, D. (2008b): The Quantification and Financial Impact of Political Risk Perceptions on Infrastructure Projects in Asia. *The Journal of Structured Finance* 13(4), 80-104.

Sadeghi, N., Fayek, A. R., Pedrycz, W. (2010): Fuzzy Monte Carlo Simulation and Risk Assessment in Construction. *Computer-Aided Civil and Infrastructure Engineering* 25, 238-252.

Smith, W. (1997): Covering Political and Regulatory Risks: Issues and Options for Private Infrastructure Arrangements. In: Irwin, T. et al. (Ed.), Dealing with Public Risk in Private Infrastructure, World Bank, 81-97.

Thomas, A. V., Kalidindi, S. N., Ganesh, L. S. (2006): Modelling and Assessment of Critical Risks in BOT Road Projects. *Construction Management and Economics* 24, 407-424.

Turner, G., Roots, S., Wiltshire, M., Trueb, J., Brown, S., Benz, G., Hegelbach, M. (2013): Profiling the Risks in Solar and Wind. Bloomberg and Swiss Re. Available at http://about.bnef.com/, access 06/30/2014.

Vasicek, O. (1977): An Equilibrium Characterization of the Term Structure. *Journal of Financial Economics* 5(2), 177-188.

Van de Wekken, T. (2007): Distribution Generation and Renewables – Wind Farm Case Study. Available at http://www.energycentral.com/download/products/851-wind-farm-case-study.pdf, access 01/19/2015.

Wonneberger, S., Kistinger, S., Deckert A. (1995): Nuclear Science and Technology. Unbiassed Guess, a Concept to Cope with Fuzzy and Random Parameters? European Commission, Luxembourg.

Yang, M., Nguyen, F., De T'Serclaes, P., Buchner, B. (2010): Wind Farm Investment Risks under Uncertain CDM Benefit in China. *Energy Policy* 38, 1436-1447.

Yoshida, N. (1992): Estimation for Diffusion Processes from Discrete Observations. *Journal of Multivariate Analysis* 41, 220-242.

APPENDIX

Table A.1: Information regarding the experts participating in the survey to determine the likelihood of the policy risk events

	Expert 1	Expert 2	Expert 3	Expert 4
Role in industry	Associate at an investment company	CEO of a renewable energy investment fund	Managing Director at an investment company	Director at an investment company
Relevant working experience in years with respect to renewable energy investments in Europe	4 years	14 years	14 years	13 years
Return round 1 (sent 06/30/2015)	07/03/2015	07/21/2015	07/28/2015	07/28/2015
Return round 2 (sent 08/07/2015)	08/25/2015	08/13/2015	08/11/2015	08/07/2015

Table A.2: Survey questions to determine the risk factors driving the policy risk event RE (see Figure 4 for the corresponding fault tree) during a time period of five or twenty years; the survey contains the same questions for France with country-adjusted information which were asked after the German case; all experts answered all questions

No.	*Risk factors*	*Questions in survey*
1	Likelihood of "economic stress situation"	What is the likelihood of an economic stress situation in Germany caused by economic uncertainty (e.g., severe budget constraints, high unemployment rates, strong decrease in GDP) during the next five/twenty years? (Examples for economic indicators: Government debt to GDP ratio: 74.7% (01/2015); S&P Rating: AAA (03/2015))
2	Likelihood of RE given "economic stress situation"	Given the occurrence of an economic stress situation in Germany as described in Question 1, what is the likelihood of a retrospective reduction of the FIT?
3	Likelihood of "national targets reached"	What is the likelihood that Germany reaches the national targets for wind energy during the next five/twenty years? (The German EEG (renewable energy law) aims to increase the share of renewable energy to 40%-45% in 2025, 55%-60% in 2035 and 80% in 2050. Currently: 25.8% (12/2014))
4	Likelihood of RE given "national targets reached"	Given that national targets for wind energy are reached in Germany as described in Question 3, what is the likelihood of a retrospective reduction of the FIT?
5	Likelihood of "uncontrolled growth"	What is the likelihood of uncontrolled growth of wind energy in Germany (e.g., caused by a cap on additional capacity per year that is too high) during the next five/twenty years? (Note: The corridor for the annual net expansion of installed capacity for onshore wind is 2,400-2,600 MW. If the annual net expansion exceeds 2,600 MW, the FIT for new wind farms is reduced. In 2014, the annual net expansion was 4,386 MW)
6	Likelihood of CE (very high subsidy payments) given "uncontrolled growth"	Given the occurrence of an uncontrolled growth of wind energy in Germany as described in Question 5 (assuming that this is the case), what is the likelihood of very high subsidy payments to be paid by the state or by consumers (e.g., very high additional costs per kWh, which may exacerbate the political pressure to reduce the FIT)? (Subsidy payments: Surcharge ("EEG-Umlage") to support green energy: 6.17 ct./kWh (2015))
7	Likelihood of "decrease in production costs"	What is the likelihood of a considerable decrease in production costs of wind energy in Germany (e.g., similar to the considerable decrease in case of photovoltaic) during the next five/twenty years?
8	Likelihood of CE (very high subsidy payments) given "decrease in production costs"	Given a considerable decrease in production costs of wind energy in Germany as described in Question 7, what is the likelihood of very high subsidy payments to be paid by the state or by consumers (e.g., very high additional costs per kWh, which may exacerbate the political pressure to reduce the FIT)? (Subsidy payments: Surcharge ("EEG-Umlage") to support green energy: 6.17 ct./kWh (2015))
9	Likelihood of RE given CE ("very high subsidy payments")	Given the occurrence of very high subsidy payments in Germany by the state or by consumers as described in Question 6 and Question 8, what is the likelihood of a retrospective reduction of the FIT?
10	Likelihood of "political uncertainty"	What is the likelihood of political uncertainty in Germany (e.g., a new government after an election, which may intend to reduce subsidy payments for wind energy) during the next five/twenty years?
11	Likelihood of RE given "political uncertainty"	Given the occurrence of a political change in Germany as described in Question 10, what is the likelihood of a retrospective reduction of the FIT?
12	Impact evaluation	What is the possible seize (in percent) of a retrospective FIT reduction in Germany? Please provide an optimistic, a most plausible, and a pessimistic value. (FIT for onshore wind in Germany is 89.3 €/MWh (for onshore wind farms starting to operate after 01/2014))

Table A.3: Results from the survey with expert assessments (RE occurs within five years)

	Risk factors	Expert 1 (France / Germany)	Expert 2 (France / Germany)	Expert 3 (France / Germany)	Expert 4 (France / Germany)
No.	**Round 1**				
1	Likelihood of "economic stress situation"	L / VL	VL / EL	M / EL	VL / EL
2	Likelihood of RE given "economic stress situation"	M / L	L / VL	M / L	L / VL
3	Likelihood of "national targets reached"	M / EH	EL / EL	L / H	L / H
4	Likelihood of RE given "national targets reached"	L / VL	VL / EL	M / VL	L / VL
5	Likelihood of "uncontrolled growth"	EL / M	VL / VL	VL / VL	VL / M
6	Likelihood of CE (very high subsidy payments) given "uncontrolled growth"	M / H	M / H	M / M	M / M
7	Likelihood of "decrease in production costs"	L / L	VL / VL	L / L	VL / VL
8	Likelihood of CE (very high subsidy payments) given "decrease in production costs"	M / M	M / L	M / M	M / M
9	Likelihood of RE given CE ("very high subsidy payments")	M / L	VL / VL	M / L	L / L
10	Likelihood of "political uncertainty"	M / L	VL / L	M / M	L / VL
11	Likelihood of RE given "political uncertainty"	M / M	VL / VL	M / L	L / L
12	Impact evaluation in % (optimistic medium pessimistic)	(5 10 15) / (1.5 5 10)	(0 10 30) / (0 10 30)	(10 30 40) / (10 30 40)	(0 0 25) / (0 0 30)
	Probability of occurrence (5 years) (aggregated values: 8.658% / 4.855%)	15.623% / 10.111%	1.140% / 0.910%	19.845% / 6.537%	4.290% / 4.193%
No.	**Round 2**				
1	Likelihood of "economic stress situation"	L / VL	VL / EL	M / EL	VL / EL
2	Likelihood of RE given "economic stress situation"	L / L	L / VL	M / L	L / VL
3	Likelihood of "national targets reached"	M / EH	EL / EL	L / H	L / H
4	Likelihood of RE given "national targets reached"	L / VL	VL / EL	M / VL	L / VL
5	Likelihood of "uncontrolled growth"	EL / M	VL / VL	VL / VL	VL / M
6	Likelihood of CE (very high subsidy payments) given "uncontrolled growth"	M / H	M / H	M / M	M / M
7	Likelihood of "decrease in production costs"	L / L	VL / VL	L / L	VL / VL
8	Likelihood of CE (very high subsidy payments) given "decrease in production costs"	M / M	M / L	M / M	M / M
9	Likelihood of RE given CE ("very high subsidy payments")	M / L	VL / VL	M / L	L / L
10	Likelihood of "political uncertainty"	M / L	VL / L	M / M	L / VL
11	Likelihood of RE given "political uncertainty"	L / L	VL / VL	M / L	L / L
12	Impact evaluation in % (optimistic medium pessimistic)	(2.5 5 10) / (0 1.5 5)	(0 10 30) / (0 10 30)	(10 30 40) / (10 30 40)	(0 0 25) / (0 0 30)
	Probability of occurrence (5 years) (aggregated values: 7.480% / 4.455%)	9.679% / 8.327%	1.140% / 0.910%	19.845% / 6.537%	4.290% / 4.193%

Notes: EL = extremely low; VL = very low; L = low; M = medium; H = high; VH = very high; EH = extremely high.