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Support Mechanisms for Renewables: How Risk Exposure Influences Investment Incentives

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ABSTRACT

We analyse quantitatively how risk exposure from different support mechanisms, such as feed-in tariffs and premiums, can influence the investment incentives for private investors. We develop a net cash flow approach that takes systematic and unsystematic risks into account through cost of capital and the Capital Asset Pricing Model as well as through active liquidity management. Applying the model to a specific case, a German offshore wind park, we find that the support levels required to give adequate investment incentives are for a feed-in tariff scheme approximately 4-10% lower than for a feed-in premium scheme. The effect of differences in risk exposure from the support schemes is significant and cannot be neglected in policy making, especially when deciding between support instruments or when determining adequate support levels.

Keywords:

Investment risk;
Unsystematic risk;
Liquidity management;
Offshore wind; Feed-in tariffs.
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1. INTRODUCTION

Electricity generation from renewable energy sources (RES-E) is supported in many countries around the world. In the European Union, every Member State has established a dedicated policy programme for financial support of RES-E [1]. Ever since the first support schemes were designed by policy makers some decades ago, there is an ongoing debate about which policy instruments and which design options are most suitable for reaching the targeted deployment of renewable energies.

This paper contributes to this debate by exploring risk implications of policy instruments and by analysing the impact of policy choices on incentives for private investors. This perspective is especially relevant in liberalised markets. Here, policy making must ensure that adequate incentives are given to private investors if specific RES-E targets are to be achieved. To design policies that are effective (in terms of target achievement) and efficient (in terms of ensuring the highest social welfare), policy makers must look beyond costs and (amongst other things) consider all aspects of profitability that are of concern for private investors, including risk aspects and other effects on cost of capital (see also [2]). Such a focus on profitability and risk rather than on costs is crucial for designing policies that create adequate investment incentives. Therefore, this paper uses a stochastic discounted cash flow approach to model average profitability (i.e. net present values) as well as risks (i.e. probability distributions of net present values). Using an extended financing and investment decision model we identify the impact of increased risks on renewable investments and thus on the required renewable support. Thereby we go beyond standard

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finance models which focus exclusively on systematic risk, i.e. risks that are correlated with overall market returns. Such standard approach would provide adequate results for perfectly diversified investors. Yet renewable investors frequently do not have a perfectly diversified portfolio. We therefore acknowledge the relevance of non-systematic risk (sometimes called idiosyncratic risk) by explicitly modelling liquidity management. Liquidity management should be a key concern for companies in the presence of systematic and unsystematic financial risk if financial illiquidity is costly. Thus we develop a more realistic model of investor behaviour which allows assessing the impact of support scheme design on investment decisions. With such insight, policy makers are able to make more informed decisions about required support levels and to evaluate the consequences of e.g. switching from one policy instrument to another.

In Europe, fixed feed-in tariffs (FIT) are the dominant policy instrument applied for the support of RES-E [1]. With an increasing share of variable RES-E in the system and an increasing pressure to improve market integration of RES-E, many countries have now started to re-evaluate the use of traditional FIT schemes. Some have already implemented alternatives, mostly in form of feed-in premiums (FIP) [1]. A counter-argument frequently put forward against FIP is that this instrument exposes RES-E investors to higher risk (see [3]). In this paper, we do not investigate which policy instrument is to be preferred. Instead, we take the ongoing policy trend in Europe as a starting point and develop a general approach to analyse the implications of exposing investors to higher market risk. We then use the developed approach to analyse the switching from a FIT to a FIP scheme and quantify the consequences regarding investment attractiveness and required support payments for the case of an offshore wind investment in Germany.

The developed model aims at a theoretically consistent approach, drawing from different aspects of financial theory, along with an empirically sound parametrisation. The standard model for dealing with risk in investment analysis is the Capital Asset Pricing Model (CAPM), developed by Sharpe, Lintner, and Mossin ([4-6]), which determines systematic risk and cost of capital based on the correlation of asset return with the market. We consider systematic risk based on the CAPM approach. In addition to that, we also consider unsystematic risk. We diverge from the standard approach here by assuming that investors may accrue cost from avoiding financial distress. In this, we draw from the approach developed by Schober *et al*. [7].

The contributions of this paper are threefold: 1) We expand the framework of Schober *et al*. [7], who assessed the impact of unsystematic risk via liquidity management for a single year, by developing a multi-year approach; 2) We apply the framework to a new area, namely investments in renewable energy projects under different support schemes; 3) We quantify the consequences of different risk exposures for a concrete case, an offshore wind park in Germany.

The remainder of the paper is structured as follows. In Section 2, we describe the background for our analysis, including the relation to financial theory, the general DCF approach and the relevant support instruments. In Section 3, we introduce our methodology, including the model structure, the modelling of stochastic processes, the modelling of liquidity management, and the beta analysis for the CAPM. In Section 4, we apply the model to a specific case, namely a German offshore wind park in the Baltic Sea. We discuss the results in Section 5 and conclude with Section 6.

2. GENERAL CONSIDERATIONS: INVESTMENT RISK

2.1. Standard financial theory and systematic vs. unsystematic risk

A basic assumption of standard financial theory and portfolio selection theory, as formulated by Markowitz in 1952, is that risk and return are the only - and equally important - factors to consider in investment appraisal [8]. Later, Sharpe and Lintner [4,5] showed that firms should only be concerned with systematic risks when considering investment in new assets. This is, because it is assumed that perfect portfolio diversification can be obtained at shareholder level without transaction costs. This also implies that a firm should not undertake costly measures to avoid bankruptcy as, in perfect markets without transaction costs, old firms can go bankrupt and new firms can be established immediately at no loss. In reality, however, costs of bankruptcy can be substantial and irreversible [9]: They can include loss of market share, inefficient asset sales, foregone investment opportunities, and more. In the presence of transaction costs, the generally agreed assumption of financial theory that investors are risk-averse (see [10]) predicts that investors are willing to take action against risk exposure, by implementing safety measures. Firms are thus often willing to undertake costly measures to avoid economic and financial distress [11].

In newer developments of financial analysis, risks other than systematic market risk are being acknowledged. Further risk factors are incorporated, e.g. in the three-factor model by Fama and French [12], with the argument that market imperfections (and consequential diversification constraints) as well as transaction costs make more types of risk costly. The choice of model can have significant implications on the valuation of investment projects. Empirical studies have found that required returns on equity may differ by 2% and more between the CAPM and the Fama-French-Model [13,14].

Also for renewable assets, we expect that both systematic and unsystematic risks are relevant for investment decisions, because of transaction costs and irreversibility effects. We thus acknowledge that failures (e.g. bankruptcy) are costly to investors, and incorporate them into the analysis. Our model is therefore based on a net cash flow approach with risk modelling at two levels: 1) systematic risk, which stems from market risks and influences the cost of capital; and 2) unsystematic risk, which affects the required capital basis for an investment. More specifically, we assume that firms use liquidity reserves to mitigate their exposure to risk of financial distress. A greater variation in profit will generally require higher liquidity reserves. We thus expect that a support mechanism which mitigates variation in profits the most leads to the lowest required liquidity reserves and thus highest expected returns or lowest required support levels.

A challenge with unsystematic risks is, however, that they are mostly in-transparent and specific for an individual firm. We therefore revert to an application case showing the concrete effects in a specific setting.

2.2. Discounted cash flow evaluation of an investment

The standard method for evaluating investments is the discounted cash flow (DCF) approach (see e.g. [15]). In this approach, all positive and negative cash flows related to the respective investment project are simulated, discounted with the applicable rate for the cost of capital, and summed up, as shown in Eq. (1):

$$NPV = -I_0 + \sum_{t=1}^{T} \frac{R_t - C_t}{(1+r)^t}, \tag{1}$$

where I_0 are the investment costs, R_t are the revenues, C_t are the operational costs, r is the discount rate (cost of capital), and T is the project lifetime.

If the resulting net present value (NPV) of a project is positive, then the investment should be undertaken. Since many of the different elements contained in the future cash flows are not known with exactitude, they have to be simulated. To account for the uncertainty, many investors include probability distributions of underlying elements in their assessment. This is done by e.g. creating different scenarios or making Monte Carlo simulations.

In principle, all three basic cash flows, namely revenues R_t, operational cost C_t, and investment cost I_0, can contain uncertainties. We simplify subsequently by assuming that at the time of investment decision, I_0 and C_t are known and fixed. This may e.g. be achieved through fixed price contracts. Future revenue streams R_t are, however, uncertain and can cause variations in the returns from the project, which induces risk.

Traditional DCF analysis is based solely on standard financial theory and the assumptions underlying the CAPM in which only systematic risk is relevant. Systematic risks are exclusively dealt with through the cost of capital r. We have argued above that also unsystematic risks should be accounted for in our type of analysis. We do this by considering the prevention of bankruptcy through liquidity management.

Some may argue that a real option approach would be most appropriate to dealing with risks. This is especially the case for irreversible decisions (such as investments with sunk costs) and evaluation of different decision options (such as operational choices). In this paper, we, however, deal with a somewhat different kind of risk exposure: First, our starting point is the assumption that the investment is politically desired and thus shall be undertaken - we are merely investigating the effects of different support schemes on that investment; Second, the profitability is in our setting mostly unrelated to operational decisions. We therefore argue that these kinds of risk are sufficiently addressed by a stochastic approach as used here, in which we use a DCF analysis with added risk elements, i.e. liquidity management and related Monte Carlo simulation.

2.3. Liquidity management: cash reserves in firms

When considering unsystematic risks in form of risk of default or bankruptcy in a firm, one should distinguish between economic and financial distress. Economic distress occurs at low market asset values relative to debt and causes insolvency. Financial distress occurs at low cash reserves relative to current liabilities and leads to illiquidity. Usually, a firm defaults because of both factors, but this has not necessarily to be the case.

Davydenko [11] shows that 13% of defaulting firms in his sample were insolvent but still liquid, and 10% of defaulting firms were illiquid but still solvent. In our theoretical model, we focus on the indicator of financial distress (and firms avoiding illiquidity), acknowledging the simplification made. Moreover, we simplify by assuming that risk of financial distress represents all unsystematic risks in a firm. Knowing that there might be additional sources of costly unsystematic risk, our results can only establish the lower boundary for such costs. This approach corresponds to the one taken by Schober *et al*. [7].

One way of dealing with risk of financial distress is liquidity management. Liquidity management can take the form of either expenses for costly hedging (in order to reduce the risk of low revenues for the firm) or provision of an additional capital buffer in the firm [7]. We understand liquidity management as the decision to upholding an optimised level of capital buffer within the firm to prevent defaulting, i.e. the going concern in possible illiquid states. A firm has several options to create a capital buffer: 1) secure bank lines of credit; 2) establish sufficient cash reserve in the beginning of a risky project; 3) raise required capital in the short term from shareholders (through retained earnings or equity injections).

As discussed by Flannery and Lockhart [16], uncertainty about access to funds in the future (including from banks) might lead to excess cash holdings in a firm. Bates *et al*. [17] give an overview of the literature's theories of holding excess cash in firms and show empirically that excess cash holdings in firms are common. Thus, we focus on cash reserves and capital from shareholders in this analysis (and not bank lines of credit). Because of the time-value of money and tax effects of cash holdings, a firm will however consider it optimal to build up cash reserves as late as possible. This corresponds to the conclusions of Acharya *et al*. [18], who find that constrained firms are more likely to save cash out of cash flows. Therefore, we focus on the third of the above mentioned options, in which firms raise capital as late as possible either through retained earnings (i.e. by saving of incoming cash flows during operations) or, whenever necessary, by additional equity injections. This implies that a firm will strive to keep the liquidity reserve in any year as low as possible - just at the level needed to avoid financial distress in the next period with sufficient probability. It should be noted that liquidity management through cash reserves in the firm can at best decrease the risk of financial distress to a desired level, but can never eliminate it completely.

2.4. Support schemes and investment risk

Several different policy instruments can be used to provide financial support for renewable energy projects. These span from investment grants over tax breaks to generation-based support. The latter type is dominant in Europe [1]. Here, one can distinguish between instruments that expose renewable producers to market price risks and those that eliminate or at least reduce market price risks. During the early implementations of renewable support, mostly those instruments were applied that shield renewable producers from market price signals and thus also market risks [1]. These are for example fixed feed-in tariffs, where renewable producers are guaranteed a fixed price for a certain period (e.g. 20 years).

Eq. (2) illustrates the revenue flows under a feed-in tariff scheme:

$$R_t^{FIT} = q_t FIT, \tag{2}$$

where q_t is the renewable energy production volume per time period and FIT is the long-term guaranteed tariff level. Uncertainty stems here solely from the unknown production volume, which depends on the available renewable resources in time period t.

More recently, other instruments like quota systems with tradable green certificates or feed-in premiums are increasingly applied in Europe [1]. In these schemes, support is paid out as market add-on. This means that renewable producers need to sell their production on the power market and are exposed to its risks. We focus here on feed-in premiums, under which revenues are determined as in Eq. (3):

$$R_t^{FIT} = q_t(g_t S_t + FIP), \tag{3}$$

where q_t is the renewable energy production volume in period t, S_t is the power price and FIP is the long-term guaranteed premium level. g_t is a weighting factor (sometimes labelled "market-value factor") describing the fact that the average revenue by renewable producers might be below (or above) the average spot price level. This thus allows taking into account systematic correlation between the supported production and the market price [cf. 19]. Revenue risk stems in this support setting from both the unknown production volume and the unknown market price.

3. METHODOLOGY

3.1. Model structure

We develop a multi-year cash flow model that estimates the investment incentives for a wind energy investor under different risk exposures, and that incorporates dynamic liquidity management. It is dynamic in the sense that the liquidity reserve is recalculated each year depending on the current cash flow situation. However, it is static in the sense that the cost of capital used for the liquidity reserve is fixed and does not depend on previous utilisation.

The purpose of the model is to determine a Shareholder Value (SHV) after liquidity management which then can be used to compare the attractiveness of investment under different scenarios. For transparency reasons we model a firm that has a single activity: the investment project throughout the lifetime of the project. This is also similar to creating a special purpose vehicle for a project. We thus assume that the SHV of this project/firm is the key determinant for the investment decision. Using the SHV we can also derive the minimum required support level for the specific project by assuming that the investment threshold is given by an ex-ante expected SHV of at least zero. Based on these two indicators (SHV and required support levels), comparisons between different support scheme designs can be made.

Figure 1 illustrates the model structure. The model consists of several parts: a power price model, a wind production model, the beta analysis (estimating cost of capital), and the cash flow model (divided into cash flows before liquidity management and after). All parts of the model are necessary to be able to adequately dealing with risk: Power price and wind production model generate inputs to the cash flow model, which calculates the cash flows required to determine the shareholder values. Since the cash flows to shareholder depend on the liquidity reserve, which in turn depends on the probability of financial distress, a nested Monte Carlo simulation approach is required. Probability distributions and expected values of shareholder values and support payments are the result of our cash flow analysis. At the step of discounting the cash flows for the Shareholder Value, the beta analysis is required to determine the cost of capital for the shareholders.

In the following sections, the different components of the model are explained in detail. Since we aim at deriving a multi-year investment assessment, we focus on the stochastic characteristics of annual quantities and prices, which in turn represent aggregates of shorter-term (e.g. hourly) values.

3.2. Power price model

For modelling the annual average power prices, we use the two-factor model developed by Schwartz and Smith [20]. This two-factor model consists of a long term process reflecting the uncertainty in the equilibrium

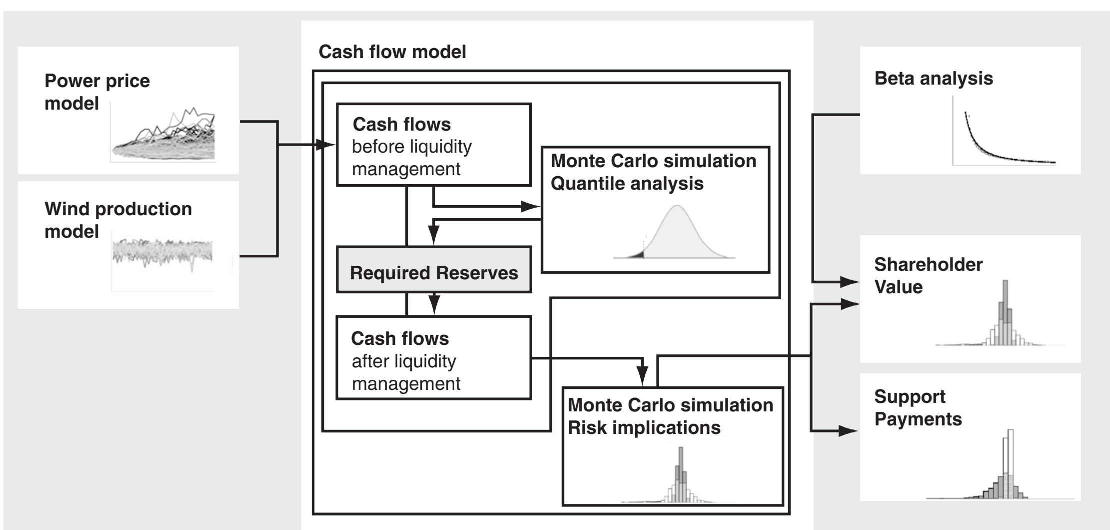

Figure 1: Model structure

price and a short term process reflecting stochastic shorter term deviations from the equilibrium price. The logarithm of the overall power price S_t is obtained as the sum of the two stochastic components:

$$\ln(S_t) = \xi_t + \chi_t. \tag{4}$$

The long term process ξ_t expresses fundamental changes in the equilibrium level that are expected to persist, and reflects the natural logarithm of the long-run equilibrium level $\overline{S_t}$. Changes in this long-run equilibrium level may e.g. be related to changing fuel prices or modifications in the CO_2 regime. The developments over the last decade suggest that these changes are hardly predictable and that also in the future, substantial uncertainty will persist. The long term process then follows an arithmetic Brownian motion:

$$d\xi_t = \mu_\xi\, dt + \sigma_\xi dz_\xi, \tag{5}$$

where ξ_t has drift μ_ξ and volatility σ_ξ. This corresponds, according to Itô's Lemma, to

$$d\overline{S_t} = \overline{S_t}\left(\mu_\xi + \frac{1}{2}\sigma_\xi^2\right)dt + \overline{S_t}\sigma_\xi dz_\xi. \tag{6}$$

The long term process can be exactly discretised using an Euler scheme [21], to:

$$\xi_{t+\Delta t} = \xi_t + \mu_\xi \Delta t + \sigma_\xi \sqrt{\Delta t}\varepsilon_t, \tag{7}$$

where ε_t is a random element with $\varepsilon_t \sim N(0,1)$.

The short term process χ_t expresses the mean reverting relation between the current price and the currently expected long term equilibrium:

$$\chi_t = \ln\left(\frac{S_t}{\overline{S_t}}\right) = \ln(S_t) - \xi_t. \tag{8}$$

Its deviations are assumed to revert to zero following an Ornstein-Uhlenbeck process:

$$d\chi_t = -\kappa\chi_t dt + \sigma_\chi dz_\chi, \tag{9}$$

where χ_t has volatility σ_χ and mean reversion coefficient κ.

The discretisation necessary for simulation is according to Phillips [22] :

$$\chi_{t+\Delta t} = \chi_t e^{-\kappa\Delta t} + \sigma_\chi \sqrt{\frac{1-e^{-2\kappa\Delta t}}{2\kappa}}\bar{\omega}_t, \tag{10}$$

where $\bar{\omega}_t$ is a random element with $\bar{\omega}_t \sim N(\rho_{\chi\xi}\varepsilon_t, 1-\rho_{\chi\xi}^2)$, and $\rho_{\chi\xi}\varepsilon_t$ e [–1,1] represents the correlation of dz_ξ and dz_χ.

For sake of simplicity we set the market value factor g_t to 1. This is also justified by the fact that the market value factor for offshore wind in Germany has been so far rather close to 1 and is expected to remain so at least in the near future [cf. 23].

3.3. Wind power production model

Wind production is modelled in a somewhat simplified setting by assuming that the wind production of one period is unrelated to previous or subsequent periods. We deem this approach appropriate when the model calculations are based on relatively large time steps t, such as monthly or yearly periods. Thus focusing on time-uncorrelated distributions, several studies emphasise the appropriateness of Weibull distributions. These are deemed most appropriate for estimating wind speeds and also wind energy production (see e.g. [24] or [25]). We thus use a Weibull distribution, directly on the wind energy production. For the implementation in simulation, we use the quantile inverse cumulative distribution function:

$$q_t = P\lambda(-\ln(1-\varepsilon_t))^{\frac{1}{k}}, \tag{11}$$

where q_t is the stochastic wind power production in period t, P is the average expected wind power production from the project, λ is the scale parameter of the Weibull distribution, k is the shape parameter of the Weibull distribution, and $0 < \varepsilon_t < 1$ is a uniformly distributed random variable, corresponding to the quantile of the production distribution function.

3.4. Cash flow model: before and after liquidity management

As mentioned above, we focus on the shareholder values and thus use the free cash flow available for shareholders $FCFE_t$ as basis of the evaluation. We denote the sum of all discounted $FCFE$ after liquidity management as the Shareholder Value (SHV). This indicator serves as the basis for comparing the investment incentives between different cases.

At time of investment ($t = 0$), $FCFE_0$ consists of cash flows from investment and financing activities. Total capital required at project investment is: $\Omega_0 = I_0 + L_0$, where I_0 is the direct investment cost and L_0 is the liquidity reserve that the firm has chosen to establish from the beginning of the project (if any).

We calculate the free cash flow available for shareholders before liquidity management for each year $t=1...T$ as:

$$FCFE_t = R_t - C_t - \theta_t - T_t + D_t, \quad (12)$$

where R_t are the revenues, C_t are the operation and maintenance cost, θ_t are the interests paid for interest-bearing debt, T_t are the payable taxes (based on revenues, operational costs depreciation and interests), and D_t are the debt injections (if positive) or the debt repayments (if negative).

The revenues R_t depend on the production volume, on the achieved market price, and on the payments from the support scheme. The revenues under the two analysed support schemes are defined as in Eq. (2) and (3). The operation and maintenance cost C_t are in our model deterministic and fixed costs, but in principle they can also be modelled as stochastic, if necessary. The interest bearing debt is calculated as follows: In the year of investment, a loan corresponding to a certain percentage of total investment Ω_0 is taken, which is then repaid on an annuity basis over a predefined amount of years.

The liquidity management is addressed through creating a cash reserve, here denoted the liquidity reserve L_t, which changes with $\Delta L_t = L_t - L_{t-1}$. The liquidity reserve must not become negative at any point in time during the project lifetime. As soon as $L_t < 0$, there is insufficient cash available and the firm experiences financial distress.

We calculate the free cash flow available for shareholders after liquidity management as:

$$FCFE_t^{LM} = FCFE_t + \Delta L_t, \quad (13)$$

The change in liquidity reserve ΔL_t depends on the liquidity reserve still available in the ongoing year L_t, the expectation of $FCFE_{t+1}$ and the risk appetite of a firm. In order to determine the required level of liquidity reserve L_t to avoid financial distress in the following year with sufficient probability, we apply a quantile computation analogous to the Value-at-Risk (VaR) calculation:

$$\eta = Q_{q-\alpha}(FCFE_{t+1}) = sup\{1-\alpha : P(FCFE_{t+1} < 1-\alpha)\}, \quad (14)$$

where η is the level exceeded by $FCFE_{t+1}$ at confidence level $\alpha \in [0,1]$. We define $L_t = max\{0,-\eta\}$. If η is positive, no liquidity reserve is required since the free cash flow is almost certainly positive and thus sufficient to satisfy all payment obligations. In contrast, a negative η implies that liquidity reserves are necessary to prevent financial distress.

We determine η by Monte Carlo simulations on $FCFE_t$. Assuming for example that the firm strives to avoid financial distress with a probability of $a = 99.73\%$ (the three-sigma rule), financial distress may only occur in 0.27% of the simulation paths in any year. From the simulation results, we determine η as the 0.27%-quantile of $FCFE_{t+1}$, from which we then derive the required liquidity reserve L_t. Depending on the level of the liquidity reserve in the previous year L_{t-1}, we subsequently determine the required change in reserve ΔL_t. We also undertake a sensitivity analysis for a financial distress probability of $a = 95.45\%$ (two-sigma).

After having determined the necessary liquidity reserve for each year, an additional set of Monte Carlo simulations must be undertaken for $FCFE_t^{LM}$. In outcomes where $FCFE_{t+1}$ realises as $FCFE_{t+1} > \eta$, the excess reserve is paid out to the shareholders in each year, so that no cash is held in the firm other than the reserve required for the subsequent year. In outcomes where the liquidity reserve was not sufficient in a year, i.e. where $FCFE_{t+1}$ realises as $FCFE_{t+1} < \eta$, the firm is assumed to immediately default. As a simplification we model this as if from this year onwards, all future cash flows in the defaulting simulation path become zero. This implies that we do not consider any final financial settlements and consider neither additional equity obligations nor pay-outs after bankruptcy of the firm.

3.5. Model outputs: Shareholder Value and Support payments

The Shareholder Value is then determined as:

$$SHV = \sum_{t=0}^{T} \frac{FCFE_t^{LM}}{(1+r_e)^t}, \quad (15)$$

The free cash flows available for shareholders after liquidity management $FCFE_t^{LM}$ are discounted with the cost of equity r_e, which is described in Section 3.6.

The support payments are determined from a socio-economic perspective, as they are borne by all electricity consumers or tax payers. They are calculated differently for each support scheme:

For FIP schemes with a fixed market add-on, the support level is straightforward: It directly corresponds to the guaranteed premium. The net present value of support payments (NSP) is for each simulation path calculated as the sum of the discounted yearly support payments, which corresponds directly to the project revenues from support:

$$NSP_{FIP} = \sum_{t=1}^{T} \frac{q_t FIP}{\left(1+r_f\right)^t}, \tag{16}$$

where we use the risk-free rate r_f to reflect the social time preference rate[ii] . This ensures also a consistent comparison of the different cases.

For FIT schemes, the support payments have to be determined as difference between the guaranteed tariff and the market price:

$$NSP_{FIP} = \sum_{t=1}^{T} \frac{q_t \left(FIP - S_t\right)}{\left(1+r_f\right)^t}, \tag{17}$$

This relies on the following assumptions: (1) the market value of the electricity produced under the FIT corresponds to the current market price S_t, (2) this value is fully realised by the off-taking entity, and (3) the revenue from its market sales is entirely used to counterbalance the cost of support. Otherwise, the total support costs would depend on further factors and could not be calculated based on the market prices only. Note that potentially, in years where the market price lies above the guaranteed price level, the FIT support costs can be below zero.

To obtain the equivalent FIT support level in real terms that is directly comparable with the FIP support level, the total support payments NSP_{FIT} are then divided by the total production and an equivalent real per unit price is computed using an annuity factor.

3.6. Estimating beta and the support scheme-specific cost of capital

As mentioned above, we use the CAPM to describe the impact of systematic risk on the required return on equity. The expected rate of return on equity r_e is estimated by the CAPM as [15]:

$$E\left[r_e\right] = r_f + \beta_e \left(r_m - r_f\right), \tag{18}$$

where r_f is the risk-free rate, r_m is the market return, and β_e is the equity beta.

Risk-free rate r_f and market return r_m are general (not firm-specific) indicators and can be estimated by adequate long term government bonds and market indices (such as the S&P500, Eurostoxx or DAX). Equity beta β_e describes to what extent the risks of a firm (in occurrence a project) are correlated with general market risks.

Generally, β_e is derived from historical observations using a two-step procedure: First, an asset beta β_a is determined from historical returns (on shares) using Eq. (19):

$$\beta_a = \frac{Cov(r_a, r_m)}{Var(r_m)}. \tag{19}$$

This procedure can easily be applied for firms with publicly quoted stocks, using historical time series of their stock prices. However, we are not dealing with a stock-listed company but a specific investment project. We thus have to derive historical equivalent returns by creating a time series of profits for each support type. Since the price for FIT consists of a fixed tariff, there is no variation in market prices. For FIP schemes, we create a time series from historical power prices, the fixed premium and a fixed level of operation and maintenance cost and depreciation. This reflects typical FIP 'profits', from which the returns can be derived. Using Eq. (19), asset beta β_a can be derived, comparing the obtained time series to the market index. Since the FIP time series becomes more or less volatile depending on the level of the fixed premium, the asset beta changes with the support level granted. This should be accounted for in any model application.

Second, β_a needs to be re-leveraged to β_e based on specific firm characteristics, i.e. debt/equity-ratio $\frac{D}{E}$ and tax rate r_T, using Eq. (20) [26, p.713]:

$$\beta_e = \beta_a \left(1 + \frac{(1-r_T)D}{E}\right). \tag{20}$$

The resulting 'geared' beta β_e can be used to calculate the cost of equity using Eq. (18).

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i and not - as often done - using an Euler scheme, see [21]

ii How societal risk preferences should be reflected in the used discounting factor requires further investigation. As the NSP serves subsequently only as a relative measure for comparing different support schemes, we leave this question for further research.

For the data analysis, we use the closing price of each trading day from a (stock) market index and compare it to a closing price of forward electricity prices, which are then adjusted according to the support scheme. Here, closing prices of short term electricity forwards (e.g. one-year ahead) are used as basis, acknowledging that the life-time value of a project does not only depend on short term electricity forwards, but on the longer term electricity price evolution. Yet data and our empirical estimation of the power price model suggest that one-year ahead power futures already strongly correlate with the long-term price expectations. Therefore, changes in forward prices reflect changes in project value and can be compared to asset prices from stock markets.

4. CASE APPLICATION: OFFSHORE WIND PROJECT

Applying the developed model to a specific case, we chose a typical offshore wind project in the German Baltic Sea. We first introduce the assumptions taken for the cash flow analysis, then proceed to the beta analysis, and finally present the case results.

4.1. Cash flow analysis

As basis for the cash flow analysis, we make a number of assumptions related to the design choices of the support schemes, the stochastic processes, and project specific characteristics.

4.1.1. Support schemes

As mentioned in Section 1, feed-in tariffs and premiums are the two support schemes that are highly relevant in the current European discussion of energy policy development. We thus compare the two in our case.

We assume the FIT scheme to be a traditional price guarantee. This means that an operator of a renewable project receives a pre-determined, fixed price for each unit of electricity generated, independent of the market price. We do not allow temporary or permanent opting-out of the FIT scheme. We see this as simplification, as in some circumstances an opting-out might be attractive, e.g. when the market price becomes structurally higher than the guaranteed tariff. Such analysis is not in focus of our study, but it might be relevant for future investigation.

We assume the FIP scheme to be a pre-determined, fixed add-on to the market price for each unit of electricity generated. Neither the FIT nor the FIP prices are assumed to be index-regulated, i.e. they do not increase with inflation but remain constant in nominal terms. In order to increase the transparency of results we assume that the support in both cases is granted throughout the project lifetime. We do not *ex ante* assume a support level. We rather determine the minimum required support levels in each scheme through simulation.

4.1.2. Calibration of the price processes

The two-factor Schwartz and Smith model is calibrated to the German power market. As basis for the calibration we use German power forwards (Phelix Futures), more specifically the closing price on each trading day between October 2003 and September 2013 [27]. The relevant prices of the 1-year Forwards and 5-year Forwards are shown in Figure 2. Since the focus of the paper is not on advanced econometric estimation, we use rather straightforward calibration techniques for deriving the parameter values.

For the long term process the drift and volatility parameters μ_ξ and α_ξ have to be estimated. We use

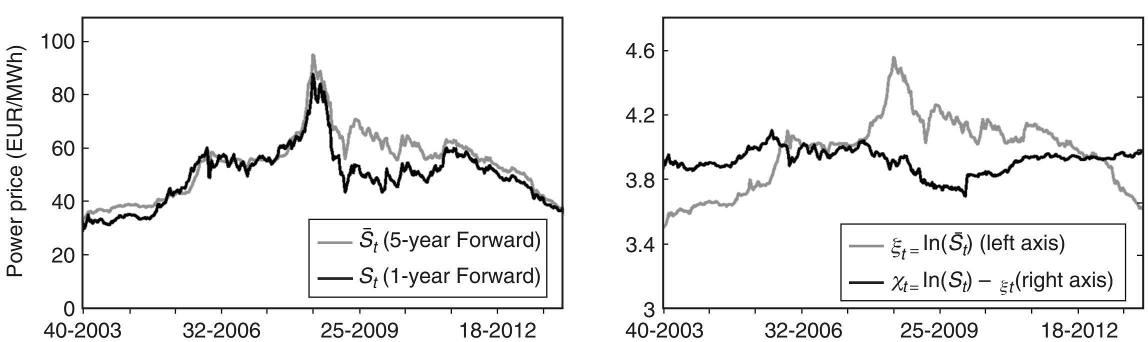

Figure 2: Historical power prices, weekly, 1-year and 5-year Forwards from the German market (EEX), and the corresponding short-term and long term model processes, [27] and own calculations

5-year Forwards as proxy, since these represent the longest time horizon on the German power market with at least some trading volume on a continuous basis. α_ξ is estimated as the standard deviation of price differences $\Delta\xi_t = \ln(\bar{S}_t) - \ln(\bar{S}_{t-1})$ where $\bar{S}_t$ is represented by the weekly time series of the 5-year Forward over ten years (from mid-2003 to mid-2013). The drift $\left(\mu_\xi + \frac{1}{2}\sigma^2\right)$ is estimated by taking the average of, $\Delta\xi_t = \ln(\bar{S}_t) - \ln(\bar{S}_{t-1})$ and hence μ_ξ can be analytically derived from the formula. In a last step, the parameters must be annualised from weekly values using a factor of $\sqrt{\Delta t}$, whereby $\Delta t = 1/52$. We arrive at an annual drift of $\mu_\xi = 0.00148$ and volatility of $\sigma_\xi = 0.11402$. As starting value $\bar{S}_0$ for the simulation, we take the closing price of the last traded 5-year Forward of our time series, i.e. from week 36 in 2013, and obtain $\bar{S}_0 = 37.65$ EUR/MWh.

For the short term process mean reversion coefficient κ, volatility parameter σ_χ, and correlation parameter $\rho_{\chi\xi}$ have to be estimated. We estimate κ from an ordinary least squares regression analysis of the time series $\Delta\chi_t = \chi_t - \chi_{t-1}$ with $\chi_{t-1} = \ln(\bar{S}_{t-1})$. From the resulting weekly coefficient α, the annualised mean reversion rate is derived using the relation $-\frac{ln(1+a)}{\Delta t}$ (cf. Eq. (10)). We obtain $\kappa = 0.5377$. In an alternative approach based on Skorodumov [28] that uses the property of 1/2 be made with a diagonal line mean-reverting process $t_{\frac{1}{2}} = \frac{ln(2)}{a}$ for estimating the mean reversion and a graphical analysis of the price process, we would arrive at a similar level of $\kappa = 0.4806$. We derive σ_χ by making use of the closed-form solution of the process, as described by Davis [21]:

$$Var\left[\chi_{t+\Delta t}\right] = \left(1 - e^{-2\kappa(t+\Delta t)}\right)\frac{\sigma_\chi^2}{2\kappa}, \qquad (21)$$

We estimate $Var\,[\chi_{t+\Delta t}]$ from our time series through least squares linear regression. Inserting all parameters into Eq. (21), we find $\sigma_\chi = 0.0976$. To estimate $\rho_{\chi\xi}$, we apply the standard statistical approach, using $\rho_{\chi\xi} = \sum_{i=1}^{n} \frac{(\Delta\bar{\xi}_i - \Delta(\bar{\xi}))(\Delta\chi_i - \Delta\bar{\chi})}{(n-1)\sigma_\xi\sigma_\chi}$, where we have $n = 520$ observations. The correlation is estimated to be $\rho_{\chi\xi} = 0.1073$. As starting value S_0 for the simulation, we take the closing price of the last traded 1-year Forward of our time series, and obtain $S_0 = 37.28$ EUR/MWh.

4.1.3. Calibration of the wind distribution

The wind model is calibrated to a historical wind index. The most comprehensive set of data available is from Denmark [29], which is a set of monthly values from 1979 to 2013. Since our model is based on annual considerations, we aggregate the data into yearly values. We assume that this data set is also applicable for a location in the German Baltic Sea.

As described in Section 3.3, the Weibull distribution is determined by scale parameter λ and shape parameter k. We use the maximum likelihood method for estimating the parameters, and obtain $\lambda = 103.6$ and $k = 12.05$. The wind index obtained from the Weibull distribution is then multiplied with the expected annual wind production. We estimate the expected annual wind production to be 4,040 MWh/MW at 100% availability, which is the expected average for a typical new large offshore wind park in the Baltic Sea, such as Kriegers Flak [30]. At 96% availability, the expected electricity exported to the grid is estimated at 3,878 MWh/MW per year.

4.1.4. Project specific cost assumptions

The required project specific assumptions are investment cost, operational cost, project lifetime, depreciation rules, and income tax rate. Table 1 summarises all estimates.

We estimate investment costs based on an average of the historical investment cost of all 45 commercial offshore wind parks in Europe (data collected from [31]). Furthermore, we expect additional project financing cost, which we estimate based on information given in [32]. Total upfront capital expenditures are thus estimated to be 3.87 million EUR/MW.

Table 1: Project specific cost assumptions, based on [30-33] and own calculations

Investment cost	3.01 mEUR/MW
Additional financing cost	0.86 mEUR/MW
Operational cost	106.8 kEUR/MW/y
Lifetime	20 years
Depreciation	straight line, 20 years
Income tax rate	28.1%

Empirical values for operational costs of offshore wind parks in Europe range from 20.2 EUR/MWh to 36.7 EUR/MWh (2010 prices) [31, p.80]. In reality, the operational costs are partially fixed and partially dependent on the production volume. We simplify by assuming fixed annual cost. We use the average value of source [33] transferred to 2014-prices and a per-MW-value, arriving at a fixed annual cost of 106.8 kEUR/MW.

The income tax rate in Germany comprises 15% corporate tax, 0.825% solidarity levy, and a local trade tax, which depends on the municipality the offshore wind park is assigned to. The federal State of Schleswig-Holstein e.g. suggests that local trade tax from offshore wind parks is to be paid out to the municipality of Helgoland [34], with a local tax rate of 12.25%. In total, we arrive at an income tax rate of 28.1%.

4.1.5. Assumptions on debt financing cost

Valuable information on financing of existing offshore wind parks in Europe can be found in [32] and [33]. In Table 2, we present some relevant data for the (rather limited) experiences in Germany.

From the data of existing German projects, we can expect a debt share between 60% and 70%. Since this is such a decisive assumption for the case, we analyse different debt shares, while focussing most on the results within this range.

We assume that the project can obtain a 15-year loan. The total interest rate consists of a bank margin (2.5% to >3%), added to a (risk-free) reference rate. As reference rate, the interest rates for 10-year German government bonds can be used[iii]. The 'Bund 14' was at 1.66% in January 2014 [35]. Often, a swap premium is also added (typically 0.2% to 0.5%) [32]. We hence estimate the total interest rate to be 5.21%, consisting of 1.66% reference rate, 3.25% margin and 0.3% swap premium.

4.2. Beta analysis and cost of equity

As described in Section 3.6, we start the beta analysis by determining the asset beta. We undertake the analysis based on historical developments of the DAX index [36], as compared to returns composed of support payments and German one-year power forwards (Phelix Futures) on a daily level [27]. Annual costs are deducted from the returns, as described above. We have ten years of consistent data, from October 2003 to September 2013, with data on each trading day. Power price data before 2003 are not considered as being sufficiently reliable because of limited market liquidity in the first years after liberalisation.

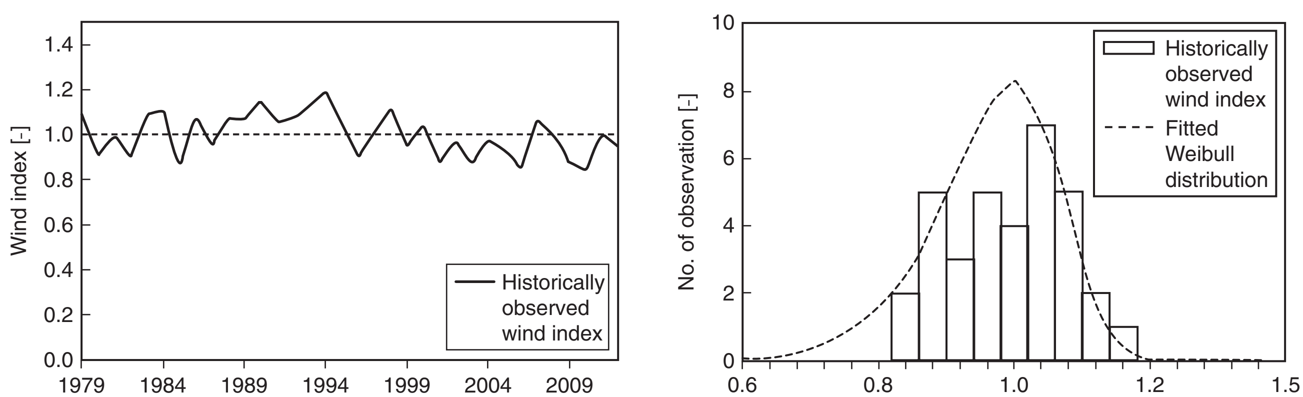

Figure 3: Historical wind production index, annual, 1979-2013 [29], and the fitted Weibull distribution

Table 2: Financial data of real offshore wind parks in Germany [32, p.73]

Financial Close	Project	Capacity (MW)	Cost (mEUR)	Gearing (Debt share)	Tenor (Loan maturity) (years)	Margin
2011	Globaltech 1	400	1850	58%	15	3%
2011	Meerwind	288	1200	69%	15	2.5-3%
2010	Borkum West	200	780	59%	2+15	>3%

iii German government bonds with 15 year duration are rather exceptional. Therefore 10-year bonds are used as best available approximation.

From time series analysis, we find a positive correlation of the market index and the power prices. A FIT scheme, which eliminates this positive correlation through a fixed price guarantee, is expected to have an asset beta of zero. This can certainly be seen as a simplification, but is theoretically consistent in our approach. A FIP scheme partially decreases the positive correlation, to an amount depending on the support level: The higher the support level, and thus the fixed part of the income, the lower the correlation of return with the market. Figure 4 shows the results of our analysis.

Depending on the support level, we are now able to determine the beta, using the relationship depicted in Figure 4. In order to estimate the equity beta β_e, we re-leverage the betas using Eq. (20), specifically for each support level. For example, a FIP of 50 EUR/MWh corresponds to approximately 150% of the long-term average market price. The asset beta amounts to $\beta_a = 0.11$ and the corresponding equity beta is then $\beta_e = 0.24$, with 28.1% tax rate and 60% debt share.

The results of our analysis correspond roughly to the findings of [32], who estimate that the introduction of a FIT mechanism in the UK will result in a 0.1 reduction of the asset beta.

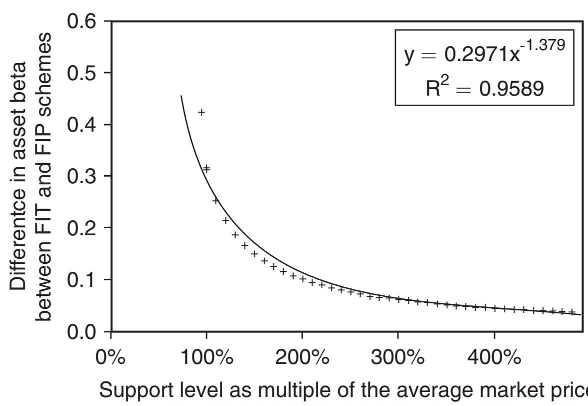

Figure 4: Difference in asset beta of a FIP scheme as compared to a FIT scheme

We obtain the overall cost of equity by applying Eq. (18). Here, we make a restriction: We assume that the cost of equity applied in the project appraisal cannot be lower than the total interest rate of the loan obtained for the project plus a margin. This reflects rational decision making by shareholders who would not accept a lower expected rate of return for their equity than the cost of debt. In fact, as the equity in a project involves greater risks than the debt, there should be a positive margin between the cost of equity and the cost of debt. We estimate this margin to be 2%, which is a conservative assumption when compared to Wallasch et al. [37, p.99] and to [32] where differences between cost of equity and cost debt amount 4–7%.

4.3. Results of the case application

We apply all above described assumptions and run the model with 5000 Monte Carlo simulations. In the presentation of results, we focus on the required support levels (in EUR/MWh), as introduced in Section 3.5. The support levels are set so that in each case, an expected Shareholder Value of zero is reached, which is assumed to be the threshold of investment. For illustration, we also show the probability distributions of total support payments (kEUR/MW) over the project lifetime and corresponding Shareholder Values (kEUR/MW).

4.3.1. Results for different debt shares

Because the debt shares are a crucial assumption with significant impact on the results, we present the results over the whole range of gearing, i.e. debt shares between 0% and 100%, in Figure 5. For comparison, debt shares between 58-69% have been achieved for offshore wind parks in the past (see Section 4.1.5). One could expect

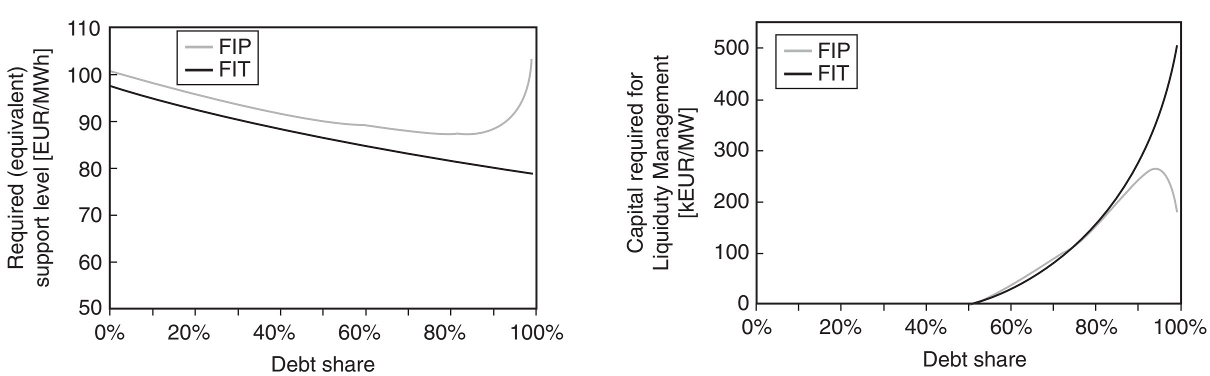

Figure 5: Case results for the whole range of debt shares, required support levels in EUR/MWh (left) and capital required for liquidity management in kEUR/MW (right)

that the FIT can achieve higher debt shares than a FIP, because of the more stable cash flows.

In our results, the FIT scheme requires support levels between 97.3 EUR/MWh and 78.8 EUR/MWh, constantly decreasing with increasing debt shares. At very high debt shares, the liquidity reserves have to become extremely high to prevent financial distress. This is, because the debt service is becoming higher while the fixed part of the revenues becomes lower with decreasing support levels. We would have expected to find an optimum gearing of below 100% debt share - this is not the case in our settings, most likely due to several risk factors which we do not model in the cash flows (such as e.g. risk of technical failures, which would always lead to some safety margin in the loan structure).

The FIP scheme requires support levels between 100.6 EUR/MWh and 87.4 EUR/MWh, decreasing first with higher debt shares and then increasing again, so that we find an optimum gearing at approximately 82.5% debt. The increase in required support level is due to the higher cost of liquidity management, which affects the FIP much more than the FIT scheme, because of the additional revenue uncertainty due to fluctuating prices.

Taking the range of debt shares between 20% and 90% into account (which is more realistic than the whole range), the difference in support levels required by the schemes are between 3.5 EUR/MWh and 8.3 EUR/MWh, corresponding to 4-10% of total support paid. As expected, the FIP scheme requires higher support levels than the FIT scheme, due to the higher risk exposure and consequently higher variation in shareholder values. Figure 6 illustrates this on the left hand side. On the other hand, the support payments show higher variations under a FIT scheme. Note that the evaluation of the variability of support payments is not within the scope of our analysis.

Comparing these results to the literature, we find that they are comparable to previous analyses. For example Kitzing [38] arrived for a Danish offshore case at a difference in required support levels of 5-10 EUR/MWh between FIT and FIP, however using a different approach, which is based on a mean-variance analysis and thus not fully comparable to this liquidity management approach.

For debt shares lower than 82.5%, the FIT scheme requires (as expected) fewer liquidity reserves than the FIP scheme. For example at 70% debt share, the cost of holding the reserve has a present value of 88 kEUR/MW under the FIP scheme, which corresponds to 53 million EUR for a wind park of 600 MW. Here, the FIT scheme would require 4 million EUR fewer liquidity reserves. The difference is, however, surprisingly small. We thus investigate the significance of the liquidity management further in Section 4.3.2.

4.3.2. The effect of liquidity management

In order to test the significance of liquidity management for the results, we analyse the results of a case with liquidity management as compared to a case in which no liquidity management is undertaken. For the latter we assume that the firm can tolerate negative cash holdings, e.g. through a bank agreement with short term loans or through a mother company guarantee. We investigate the effect based on the example of 70% debt share. Table 3 compares all relevant results for this case.

It becomes apparent that the required support levels increase through liquidity management, e.g. for FIP from 85.4 EUR/MWh to 88.0 EUR/MWh. This is due to

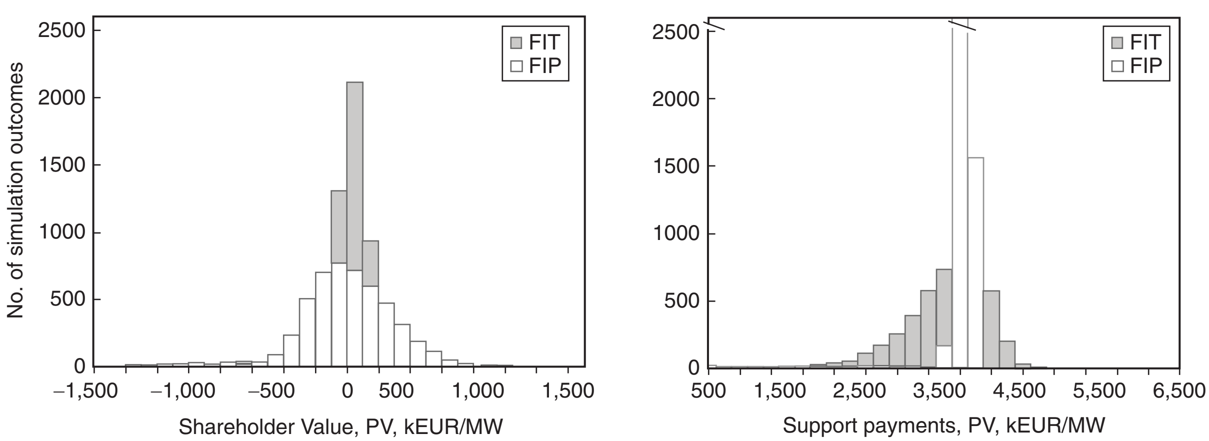

Figure 6: Distribution of simulation outcomes for shareholder value and support payments, for a debt share of 70%

Table 3: Required support levels and their differences with and without liquidity management, for 70% debt share, in EUR/MWh

				Without Liquidity Management	With Liquidity Management
Support instrument	FIT		FIP	FIT	FIP
Required equiv. support level	80.7		85.4	83.2	88.0
Difference in support level		4.7		4.8	

the cost related to holding the liquidity reserves. The difference in required support increases though only by 0.1 EUR/MWh, corresponding to approximately 2% of the effect. A factor that makes the liquidity management seem less significant is the opposing effects of liquidity management and beta: Because support levels are increased through liquidity management and thus the share of fixed income increases, the beta is reduced for FIP, in the case of 70% debt share from 0.217 to 0.208 (see the relationship depicted in Figure 4). Therefore, the difference in cost of capital between the two schemes decreases, which works in favour of the FIP scheme. Without this decrease in beta the difference in support levels between the FIT and the FIP scheme would have increased to 5.0 EUR/MWh. This was, however, overshadowed by the effect from the beta reduction before.

Taking all of this into account we conclude that in our investigated cases most of the difference in support level stems from systematic risk, modelled through the beta differences. There is, however, also a small and continuous effect from liquidity management throughout the whole range of debt shares. The liquidity management counterbalances some reduction effects from changes in beta that could otherwise have led to an underestimation of the differences in required support level. Therefore, it is crucial to consider both elements in the analysis.

Note that we determine the cost of capital only once in the calculation, i.e. we use a constant debt share for each scenario. This implies that additional capital injections through liquidity management do not affect the discount rate, which is a simplification. In our cases, the additionally required capital makes on average 3-7% of the injected equity[iv]. Within this range, we find it acceptable as an approximation to operate with constant cost of capital. Since the FIP scheme generally requires higher additional capital, it would also be affected more by a dynamic determination of the cost of capital. The difference between the two instruments would then increase somewhat.

4.3.3. Sensitivity analysis

Because the debt shares are a crucial assumption with significant impact on the results, we have shown results for the whole range of debt shares above.

Another factor especially important for the liquidity management is the assumption what probability threshold a firm applies when it comes to avoidance of financial distress. In the above analysis, we have assumed a rather strong avoidance probability of 99.73% (the three-sigma rule). When relaxing this assumption to two sigma, i.e. allowing financial distress with a probability of 95.45%, the capital required for liquidity reserves decreases substantially. Taking a debt share of 60% as example, the present value of liquidity reserves decreases from 39 kEUR/MW to 2 kEUR/MW, on average over all Monte Carlo simulations.

5. DISCUSSION

5.1. Comparison to the actual EEG tariffs

The German Renewable Energies Act (EEG) provides two different options of feed-in tariffs for offshore wind parks starting operation before January 2018:

1. An initial tariff of 150 EUR/MWh for 12 years plus a tariff of 35 EUR/MWh for the remaining 8 years;
2. An initial tariff of 190 EUR/MWh for 8 years ('optional acceleration model') plus a tariff of 35 EUR/MWh for the remaining 12 years.

The period for the initial tariff of 150 EUR/MWh is extended by 0.5 months for every nautical mile of distance to shore outside the 12-mile zone, and by 1.7 months for each metre of water depth exceeding 20 metres. We estimate that a park with a distance to shore and water depth typical for German offshore wind parks currently under development could realistically achieve 14 years of the higher initial tariff of 150 EUR/MWh, and then 6 years at 35 EUR/MWh.

Applying these tariff levels in our model, we obtain an internal rate of return for the project of 6.4%, which

[iv] The most extreme case in the Monte Carlo simulation resulted in 19.1% increased equity.

is in line with the rates of return of 7-9% that the German government assumes reasonable for wind parks (at somewhat higher assumptions on cost of debt) (see [37]). Hence, our model overall aligns with what is underlying official government policy in Germany.

In a next validation step, we compare the EEG tariff levels to our calculated ones, using the indicator of discounted net support payments over the whole lifetime of the project. These amount to 3.7 million EUR/MW for the EEG tariffs as compared to 3.4 to 3.5 million EUR/MW in our cases. We thus arrive at support payments that are equivalent to 92-95% of the actual EEG levels. Hence, our modelled tariffs of 121.2 to 125.3 EUR/MWh (that are assumed constant over 20 years) are comparable to the actual EEG tariffs (that are stepping down from 150 to 35 EUR/MWh after the initial period).

5.2. Model assumptions and their consequences

We have made several crucial assumptions and simplifications. We have focussed on financial distress and related issues and have not treated other risks more than by introducing an add-on to the cost of equity reflecting some of these risks. We have focussed on a single investment and do not consider portfolio effects. If portfolios would be considered, one can expect that required support costs would be decreased - in that sense we have calculated a maximum range of required support levels. On the other hand, portfolios could also change the risk exposure of investors and thus the risk implications between FIT and FIP. Our approach cannot capture these effects. Investigating this remains to further research.

We assume for transparency reasons and comparability of results that there is no opt-out option of the feed-in tariff scheme. However, we can see from our case simulations that in 4.7% of the price scenarios, a price occurs exceeding the lowest FIT level (of 121.2 EUR/MWh). In these situations, a RES-E producer would opt-out of the FIT scheme and transfer into normal market operation had he the opportunity to do so. This has some consequences on our estimation of support payments because they are estimated as the difference between guaranteed tariff and market price and can become negative. Had the FIT producer the option to leave the FIT scheme whenever the market price exceeds the tariff (and maybe even return to the FIT at a later point in time), no instances of negative support payments could occur. In this case, the netting approach adopted here would underestimate the overall support payments related to a FIT.

Assumptions regarding project-specific costs are also decisive for the results. We have used average values for all estimations. Specific parks can lie significantly higher or lower than that. This will have an effect on the required support levels and also on the absolute differences. However, since support schemes are usually not designed for single projects but a whole sector, our approach of taking an average wind park seems reasonable. Additionally, it could also be beneficial to test the consequences for a marginal park, i.e. the most expensive wind energy investment necessary to reach deployment targets.

The choice of power price process and its calibration also affects the results. Especially seasonal variations and jumps could have been modelled. However, we do not expect that incorporating these into the model would lead to significant changes in the comparative conclusions, because of the long time horizon of the analysis. We have confirmed that moderate changes in parameters of the short term process do not have any significant effect on the conclusions.

An issue still to be analysed is the consequences of having two different distribution types. The wind production model uses a Weibull distribution whereas the power prices are assumed lognormal. Since the cash flows under the FIT scheme only depend on the wind production and not the power prices, the results under the two support schemes FIT and FIP are affected differently by the two distribution types. Especially the skewness factor differs between the two schemes. Whether this affects the comparison of the support schemes depends on the risk preferences of the decision makers. Here, further investigations are needed.

5.3. Implications for policy makers

The model and insights generated in this study can help policy makers to determine appropriate support levels for renewable support schemes. While we do not assume that support instruments are designed for individual investors, we use the case of a single investment as case to demonstrate the impacts that different support scheme designs have on required support levels. We have shown that similar differences occur over the whole range of gearing (i.e. debt shares), so we can assume that most investors would be affected in a similar way.

The insight about impacts on required support levels is especially relevant when switching from a certain support scheme to another, e.g. from a FIT to a FIP scheme. Then, the net support levels of the FIT cannot be directly transferred to the new scheme - they must be adjusted upwards to ensure continued adequacy of investment incentives.

In the recent past, policy makers in Europe are becoming more and more concerned with the burden of support schemes on consumers [39]. Policy making strives to limit total support costs to a minimum that can still provide the desired deployment of new renewable projects. In this, policy makers should be aware of the connection between required support level and risk exposure: The higher the risk exposure, the higher the required support level. As this analysis illustrates with a quantitative case, the effect of both systematic risk and unsystematic risk should not be neglected in policy making.

5.4. Further development of the approach

In a first step, it could be beneficial to test the significance of several assumptions made. First, the loan maturity could influence the results significantly. We expect that the shorter the duration of the loan, the smaller the difference between the support schemes. Second, with technology development and further decreases in overall cost of offshore wind, also the support levels are expected to decrease. It could thus be beneficial to make a similar analysis with reduced support levels. We expect that the lower the support levels are, the larger the difference between the FIT and FIP scheme becomes, as volatile market prices become more dominant in the FIP case.

As the results are very sensitive to the assumed debt share, it would be of great advantage if these were not set exogenously, but could be determined endogenously. This could be e.g. done on the basis of probabilistic analysis of deficits in debt service, and limiting them to a certain level. We expect that here, the FIT could achieve higher debt shares, due to the more stable income flows.

Additionally, the model could be further expanded to cover other support instruments, such as tradable green certificate systems with quotas.

6. CONCLUSION

This study contributes to the analysis of risk implications from policy instruments in several ways: First, we developed a multi-year approach to liquidity management in a firm in order to capture effects of exposure to unsystematic risks. Second, we adapted the framework to wind energy investment projects. Third, we quantified the policy consequences of choosing between feed-in tariffs and premiums for a specific case.

In an application case for a German offshore wind park in the Baltic Sea, we estimated that a FIP scheme would require a 3.5 to 8.3 EUR/MWh higher support level in order to give the same investment incentive as a comparable FIT. This corresponds to about 4-10% of the total support payments. As for most case specific analysis, these values are very much dependent on the assumptions taken. We find, however, that they show very illustratively that there is a systematic difference between support levels required for FIT and FIP, respectively, and that the difference can be significant.

While the focus of the analysis in this paper is only on certain risk aspects and does not evaluate the general benefits or disadvantages of different policy instruments, it does provide additional insights for policy makers about how to determine support levels. We find that risk implications have a significant influence on required support levels and thus should be taken into consideration when support policies are chosen and the respective support levels are determined. Otherwise, support levels might not be set at an adequate level, and the investment incentives experienced on the market could be quite different than what was intended by policy makers. This could lead to under-investment on the one hand, so that RES-E targets may not be achieved, or to over-investment on the other, so that total support cost are not easily predicted or controlled.

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