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Published in:
Energy Policy

Link to article, DOI:
10.1016/j.enpol.2022.113395

Publication date:
2023

Document Version
Publisher's PDF, also known as Version of record

Energy Policy 173 (2023) 113395

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

A bigger bang for the buck: The impact of risk reduction on renewable energy support payments in Europe

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ARTICLE INFO

Keywords:
Cost of capital
Project financing
Renewable energy auctions
Remuneration schemes
Onshore wind
Solar PV

ABSTRACT

Decarbonizing Europe by 2050 requires significant capital investments in renewable energy (RE). The weighted average costs of capital (WACC) greatly impact RE production costs and influence the government support payments needed for the financial viability of RE projects. Reducing the risks for RE investors can decrease WACC and ensure that the EU meets its climate targets at the least cost. We investigate the potential for lowering support payments to RE projects by de-risking financing conditions through measures including revenue stabilization and low-risk auction designs for solar PV and onshore wind across 21 countries in Europe. We find that de-risking debt is almost twice as effective as de-risking equity. On average, support payments can be reduced by 3.3 EUR/MWh and 1.9 EUR/MWh, respectively, and in some cases, fall to zero. The effects differ across countries, higher-risk countries like Greece would experience more significant benefits from de-risking than lower-risk countries like Denmark and Germany, where support costs depend more on investment variables such as capacity factors. Overall, we show that WACC depends largely on country risk. Nonetheless, de-risking policies like revenue stabilization can improve the investment climate for RE, reduce the need for government support, and contribute to achieving decarbonization targets.

1. Introduction

Reducing greenhouse gas emissions in line with the Paris Agreement (UNFCCC, 2015) will require a substantial transformation of our energy systems. According to its Green New Deal, the European Union is committed to becoming carbon neutral by 2050 and reducing its emissions by 55% before 2030 compared to 1990 levels (European Commission, 2019). Renewable electricity will be one of the cornerstones of this transition, and it will also help to decarbonize other energy systems, including heating and transportation (European Commission, 2018). However, achieving these goals at the least cost to taxpayers will depend on the availability of low-cost financing.

Renewable energy (RE) projects are capital-intensive, and unlike fossil-fuel power plants, their capital expenditures make up 80%–90% of overall investment costs (Hirth and Steckel, 2016). The costs of capital are an expression of investors' perceptions of risk (Pratt and Grabowski, 2014): the higher the risk, the greater the required returns on the investment. Investors calculate the costs of capital by weighing the shares and costs of equity and debt financing and derive the weighted average costs of capital (WACC) (Steffen, 2020). When the WACC are high, they account for a significant part of RE production costs (Waissbein et al., 2013). In some EU member states, RE investors still require a considerable risk premium. While WACC for onshore wind in Germany averaged 1.9% in 2019, these costs amounted to 7.6% and 10% in Greece and Lithuania, respectively (Roth et al., 2021a). De-risking or reducing WACC through measures that decrease investor risks could significantly cut generation costs (Schmidt, 2014) and make Europe's energy transition more cost-effective. Such measures could include de-risking equity financing – typically employed during project development – and debt financing from banks in the form of non-recourse project financing loans (Steffen, 2018).

Alongside the inherent country risk, previous research has also highlighted the importance of policy design risks (Angelopoulos et al., 2017; Komendantova et al., 2019; Noothout et al., 2016; Schinko et al.,

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https://doi.org/10.1016/j.enpol.2022.113395
Received 4 April 2022; Received in revised form 8 December 2022; Accepted 11 December 2022
Available online 30 December 2022

2019; Schinko and Komendantova, 2016): in particular, that the choice of remuneration scheme influences the project's revenue volatility (May et al., 2017; May and Neuhoff, 2017; Neuhoff et al., 2018; Noothout et al., 2016). Sliding premiums and two-sided Contracts for Difference (CfD) remunerate producers when the reference electricity price is lower than the support price. While the two-sided CfDs require producers to return excess revenues occurring at high electricity prices, sliding premiums allow for their retention (Klobasa et al., 2013). In contrast, fixed premiums award producers a top-up on the wholesale electricity price (Held et al., 2014). Fixed and sliding premiums can increase the exposure of RE projects to electricity price risks compared to two-sided CfDs, with potential impact on financing conditions (Đukan et al., 2019). Apart from remuneration scheme designs, using auctions to allocate support for RE could aggravate revenue risks. Auctions reduce support levels (IRENA, 2019) and the share of secured project revenues (Đukan et al., 2019). In addition, they also induce new risks during project development, increasing the importance of low-risk auction designs (Amazo et al., 2021).

Within this context, this study examines how the de-risking of equity and debt financing through revenue stabilization and low-risk auction designs can help reduce government support payments to RE projects. To this end, we quantify support-cost savings from de-risking onshore wind in 22 and solar PV in 12 EU member states and the UK. We base our analysis on a recent survey of financing conditions for RE across the EU (Roth et al., 2021b), which makes available 187 project-specific and country estimates for project financing conditions.

Following Kitzing and Wendring's (2016) discounted cash-flow analysis of non-strategic auction bids, we first derive support-cost needs under the surveyed financing conditions. We then implicitly assume that policymakers adopt de-risking policies that alter RE projects' risk and return profiles (Dinica, 2006; Polzin et al., 2019), resulting in capital costs that equal the best country and technology-specific surveyed values. We quantify support-cost savings under such a de-risking scenario and individually examine the potential benefits of de-risking debt and equity financing. While this enabled us to obtain a bird's eye view of support-cost savings across EU member states and technologies, understanding the specifics of de-risking mechanisms requires a focus on individual cases. Following Waissbein et al.'s. (2013) analysis of de-risking potentials for several developing-country case studies, we derive more granular findings by examining the de-risking of onshore wind in Germany, Denmark, the UK, and Greece. We focus on these four cases due to their vastly different remuneration schemes and country risk levels. Finally, we compare the de-risking effects with changes in other investment variables, including capital expenditure (CAPEX), capacity factors, operations and maintenance costs (O&M), and electricity price projections.

The paper continues as follows. Section 2 presents an overview of the current research on de-risking, auction designs, and support payments and how we contribute to filling the research gaps, while in Section 3, we explain our methods and data. In Section 4, we reveal the results of our analysis, including levels of support costs under different de-risking sensitivity scenarios. Here, we also discuss de-risking measures and their potential effectiveness. Finally, Section 5 presents the main conclusions and policy implications.

2. Study background and contribution

Our study contributes to several streams of literature on risk for renewable energy and auctions for RE support. Due to the high impact of investment risk on WACC and project feasibility, a stream of literature developed investigating the drivers of RE investment risk and their effect on financing costs (Steffen and Waidelich, 2022; Egli, 2020; Angelopoulos et al., 2017; Noothout et al., 2016). RE investment risk consists of several evolving risk types. In the early stages of the energy transition, technology and policy risks were the main drivers of RE investment risk. In contrast, between 2015 and 2020, price and curtailment risks have grown into leading RE risk drivers in Europe (Egli, 2020).[1]

These sector-specific risks have an important impact on the cost of capital. However, other risk drivers outside the scope of individual projects, like country risks, also have a significant role. RE investments in countries with high country risk might still have high WACC, regardless of whether they implement low-risk policy designs (Steffen and Waidelich, 2022), such as remuneration schemes that guarantee revenue stability. Our study analyzes European countries with high and low country risks and remuneration schemes leading to different revenue volatility. Therefore, we contribute to understanding RE investment risks from a multi-country perspective, unlike previous studies that focused on single-country and policy design contexts (Angelopoulos et al., 2017; Egli et al., 2018; Estache and Steichen, 2015; Farooquee and Shrimali, 2016).

Second, we also contribute to research on de-risking renewables in Europe. The de-risking literature mainly focuses on providing policy solutions for decreasing WACC for RE investments in developing countries, where financing costs are at their highest. For instance, Waissbein et al. (2013) assess the impact of policy and financial de-risking instruments on decreasing the Levelized Cost of Electricity (LCOE) in Mongolia, Kenya, South Africa, and Panama. Several other studies focus mainly on de-risking concentrated solar power in North Africa (Komendantova et al., 2019; Schinko et al., 2019; Schinko and Komendantova, 2016), while Matthäus and Mehling (2020) investigate the savings in financing costs from implementing a global investment guarantee mechanism. Studies that specifically investigate de-risking in Europe are rare. May and Neuhoff (2017) estimate the cost savings from implementing feed-in-tariffs and sliding premiums instead of tradable green certificates by using surveyed financing conditions for 23 EU member states, while several other studies have assessed drivers of risk for RE in Europe through interviews and survey data (Angelopoulos et al., 2016; Egli, 2020). Our study enhances the knowledge base regarding the support cost savings potential of de-risking RE investments in Europe, and contributes to the debate on achieving EU climate goals cost-effectively (see e.g., Klessmann et al., 2013).

Unlike earlier studies that mainly view de-risking as a decrease in costs of equity and debt (Schinko and Komendantova, 2016; Waissbein et al., 2013), our third contribution involves expanding the methodology for estimating de-risking potentials by considering the improvement in project financing conditions. The debt service coverage ratio (DSCR) requirement – a bank restriction measuring the ability of the project company to repay its debt obligations (Gatti, 2013) – and loan duration directly impact debt size. Apart from costs of equity and debt, debt size also has a significant impact on WACC. Debt size is usually the output of a project-financing model (Bodmer, 2014). Lenders typically apply a sculpted debt-repayment schedule that adjusts periodic debt service to the project's cash-flow variability while considering the DSCR requirement (Mora et al., 2019; Stetter et al., 2020). In contrast to earlier de-risking studies that consider only the improvement in debt and equity costs, we integrate a sculpted debt-repayment schedule into our project finance modeling, thereby providing a more realistic representation of de-risking impacts and support-cost savings.

Our final contribution concerns analysis of the outcomes of auctions for allocating RE support. Previous research by Jansen et al. (2020) has harmonized and compare winning offshore wind-auction bids and support costs across leading European markets and show offshore wind projects being commercially viable without support payments.

[1] Egli (2020) divides risks into price risk – the risk from volatile electricity prices and unstable revenues, caused when selling electricity directly in power markets; curtailment risk – the risk of being forced to stop producing electricity due to grid congestion; resource risk – the risk of intermittent renewable resources including wind and solar irradiation; policy risk – the risk of policy designs and their unpredictable changes; technology risk – the risk of technical equipment failure.

Following this, Beiter et al. (2021) analyze offshore wind projects across different jurisdictions using a metric that enables a like-for-like comparison of their revenues and procurement prices and highlight the importance of subsidy regimes for de-risking projects, regardless of the zero-support bids in recent offshore wind auctions. Besides offshore wind, several other studies analyze record-low auction outcomes of solar PV auctions and their economic viability. Dobrotkova et al. (2018) examine the economic viability of solar PV bids in developing countries and reconstruct the 'projects' LCOEs from publicly available data and proprietary databases, while Apostoleris et al. (2018) reverse engineer record-low auction results for solar PV in the Middle East. Our study extends previous research on the analysis of auction outcomes by highlighting the effects of costs of capital and financing conditions and translating these into support costs needs in Europe.

3. Methods and data

Our research design consists of five steps (Fig. 1). The first three steps involved processing the data from a pre-existing survey of financing conditions (Roth et al., 2021b) and a review of past auction rounds (AURES II, 2020) to yield relevant data inputs for our model. Furthermore, we collected primary investment data from publicly available sources (see Table 10 Annex) to model the cash flows of representative projects in all EU member states. Step 4 developed and applied a cash-flow optimization model to estimate the expected bid levels and support costs. Finally, in step 5 we analyzed the results and evaluated the impacts of de-risking debt and equity financing through a sensitivity analysis.

3.1. Cash flow model

To estimate the expected bid levels and support costs, we developed a yearly discounted cash flow (DCF) model that minimizes the cost-based bid level while keeping the expected NPV at zero, assuming that bidders minimize their bids in competitive auctions. Using DCF, investors model expected cash flows and discount them to their present value (Brealey and Myers, 2003; Titman and Martin, 2008). Building upon Kitzing and Wendring (2016), we calculate the project's expected Net Present Value (NPVex) and consider three scenarios that reflect potential project costs within an auction-based support framework: [a] project realized in time, no penalties (90% probability); [b] project realized after realization period, incurs a penalty (5% probability); and [c] project not realized, incurs a penalty for non-realization (5% probability), as summed up in Eq. (1):

$$NPV_{ex} = \left(NPV_{pr\ realised} \times p_1\right) + \left(NPV_{pr\ delayed} \times p_2\right) + \left(NPV_{pr\ cancelled} \times p_3\right) \tag{1}$$

where $NPV_{ex} = 0$, p equals the probability of each scenario, and NPV is defined as shown in Eq. (2) (Brealey and Myers, 2003):

$$NPV = -I_0 + \sum_{t=1}^{T} \frac{Free\ Cash\ Flow}{(1 + WACC)^t} \tag{2}$$

Furthermore, we assume an after-tax WACC (Koller et al., 2005),

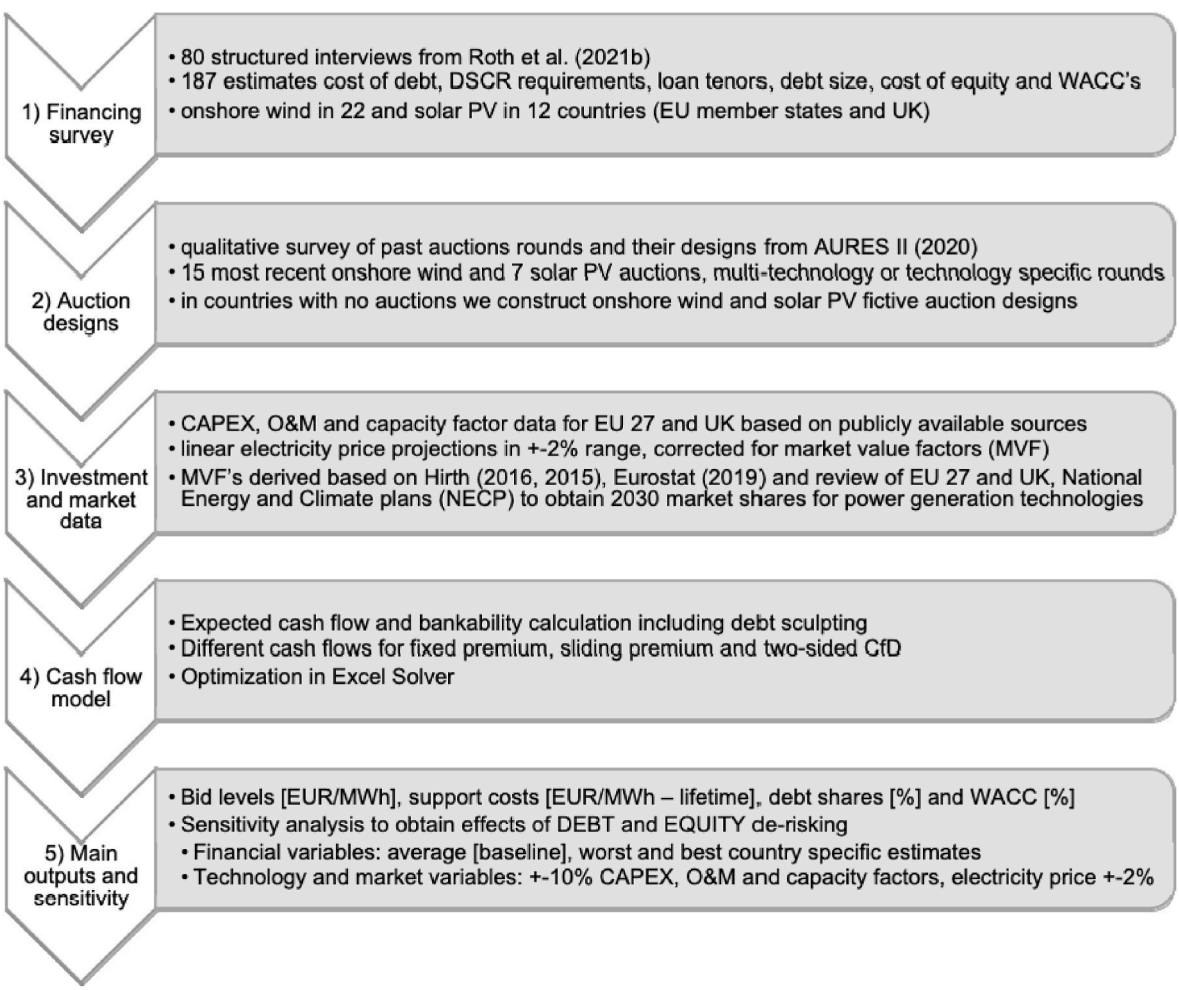

Fig. 1. Research methods.

defined as:

$$WACC = \frac{E}{D+E}(r_e) + \frac{D}{D+E}(r_d)\,(1-T) \tag{3}$$

where E is the market value of equity, D is the market value of debt, r_e is the cost of equity, r_d is the cost of debt, and T is the corporate tax rate.

Since investors are increasingly financing RE projects through non-recourse project financing (Steffen, 2018), we also consider the constraints on financing to estimate the minimum bid levels. Rather than using a constant annual debt service (as with simple annuity loans), we sculpt the debt-service schedule so that each debt repayment reflects periodic cash flows, fixing the debt-service coverage ratio at the DSCR-requirement level. The DSCR is the ratio between the cash flow available for debt service (CFADS) and the summed interest and principal payments per loan-repayment period. By requiring a constant DSCR, banks ensure a sufficient buffer between the project cash-flow available for debt service ($CFADS_t$) and debt repayments in each loan period (Gatti et al., 2012). Following Bodmer (2014), we size debt as follows:

$$DSCR_r = \frac{CFADS_t}{(R_t + I_t)} \tag{4}$$

$$R_t = \frac{CFADS_t}{DSCR_r} - I_t \tag{5}$$

$$I_t = (C_{t-1} - P_t) \bullet r \tag{6}$$

where $DSCR_r$ is the DSCR requirement, R_t is the principal repayment and I_t the interest in debt service period t, while C_{t-1} is the remaining loan amount from the previous debt-repayment period, and r is the interest rate. Lenders typically define the DSCR requirement together with a production scenario at a confidence interval (Raikar and Adamson, 2020). While P-50 represents the median of the modeled electricity generation, in a more conservative P-90 production scenario, projects generate at least this amount of electricity 90% of the time. We interpret the surveyed DSCR values as the DSCR requirement and assign P-90 to DSCR levels below or equal to 1.2, P-75 for DSCR values up to 1.3, and P-50 for DSCR values above this. In 2015, French onshore wind projects achieved a DSCR requirement of 1.2 for a P-90 scenario (Green Giraffe, 2016).

We derive bid levels that minimize the required bid while ensuring debt repayment at the end of the loan tenor or the balance at maturity. Our model solves the following optimization problem:

OBJECTIVE FUNCTION	DECISION VARIABLES	CONSTRAINTS
$f(x) = \min(x), x = B_l$	Bid level - B_l	Debt share - $i \in D_S : 0 \leq i \leq 100$
	Debt amount - D_a	Balance at maturity - $B_{m \in D_a} = 0$
	Debt amount - D_b	Balance at maturity - $B_{m \in D_b} = 0$
		Net Present Value - NPV ≥ 0

where D_a and D_b represent a calculated debt amount for our expected project cases [a] and [b] – explained in equation (1) – and where B_m represents the loan balance at maturity for each of the two cases. Since we restrict the model to generate a minimum bid level only when the project's balance at maturity equals zero, the model finds a debt size that satisfies this constraint, assuming a pre-determined DSCR requirement. From here, we derive the ' 'project's WACC using equation (3). According to Modigliani and Miller (1958), an increase in debt share should translate into a higher cost of equity, as greater leverage exposes equity investors to higher risk. However, we do not adjust the CoE for different debt sizes, as we assume our surveyed equity costs already account for this.

The derived bid level depends on project revenues, which are influenced by three main factors: 1) the remuneration scheme; 2) the assumed capacity factor and probabilistic production scenario; 3) and the assumed market electricity prices.

First, we calculate revenues under sliding premiums, two-sided CfD schemes, and fixed premiums, the three most frequently used remuneration schemes in Europe. Remuneration schemes define the project's payments depending on the support bid level and a reference price. For instance, the reference price in Germany is a monthly average of the hourly electricity spot prices adjusted to reflect a technology-specific market value (CEER, 2016). To simplify and make the analysis comparable across multiple EU countries, we model these remuneration schemes as follows:

REVENUES	if $E_t + I_t > B_l$	if $E_t + I_t < B_l$
Sliding premium	$[(E_t + I_t) \times V_t]$	$B_l \times V_t$
Two-sided CfD	$[(E_t + I_t) \times V_t)] - [(B_l - (E_t + I_t)] \times V_t]$	$B_l \times V_t$
Fixed premium	$(E_t + I_t) + B_l$	$(E_t + I_t) + B_l$

where E_t is the wind or solar PV market capture price in time t, V_t is the produced electricity volume in MWh, B_l is the bid level, and I_t an inflation price increase based on the ten-year average country-specific inflation rate (Eurostat, 2021). To correctly model the two-sided CfD in periods when $E_t + I_t > B_l$, we first calculate the revenues the producer would earn from selling in the market and then deduct the amount $[(B_l - (E_t + I_t)] \times V_t$ to account for the returned excess revenues. Moreover, we adjust B_l for inflation depending on the country's auction designs (see Table 13 in Annex). Our approach is a simplification of applications of remuneration schemes across Europe. Most importantly, within our framework, capture prices equal reference prices, whereas, in practice, reference prices are calculated separately over a pre-defined period (Beiter et al., 2021).

Second, we assume revenues at a P-50 production scenario for average country and technology capacity factors (Dalla-Longa et al., 2018; Pfenninger and Staffell, 2016). Third, since the surveyed financing data relates to project-level and market estimates until the end of 2019, we assume average wholesale baseload electricity prices for 2019 Q4 (DG Energy, 2019) and a nominal and linear electricity price increase of 1% per year thereafter as our baseline assumption. Electricity prices are stochastic, meaning they exhibit daily movements and change depending on the season (Keles et al., 2012) rather than behaving linearly, as we assume. Power valuation studies focusing on short-term and individual optimization, such as Thompson et al. (2004) and Lucia and Schwartz (2002), focus on complex price modeling. However, linear price assumptions are common among studies focusing on long-term overall business cases rather than short-term price volatility (e.g., Jansen et al. (2020)). In this long-term view, results are less dependent on spikes and jumps, which further supports our linear approach.

Unlike short-term price movements, long-term structural changes in energy systems are more critical for the projects' feasibility. To account for the increasing share of renewables and its long-term structural effect on energy systems (Clò et al., 2015; Sáenz de Miera et al., 2008; Sensfuß et al., 2008), we correct the assumed prices with market value factors (MVFs) for solar PV and onshore wind (taking into account the so-called cannibalization effect of RE project revenues) and derive the capture price E_t for individual time periods. To obtain MVFs, we first estimate the 2018 and 2030 market shares of onshore wind and solar PV in electricity consumption. For 2018 we use historical power market data

(Eurostat, 2019), while for 2030 we review the National Energy and Climate Plans (European Commission, 2020) of all EU member states and the UK. We then calculate the MVFs based on regression equations that represent the relationship between an increase in the onshore wind and solar PV market share and their effect on falling electricity prices (Hirth, 2016, 2015). We assume the MVFs change linearly between 2018 and 2030 and apply a constant MVF thereafter (see the Annex for more information).

After defining the project's revenue stream as described in steps 1) – 3), we quantify yearly support costs for the remuneration schemes as follows:

SUPPORT COSTS	if $E_t + I_t > B_l$	if $E_t + I_t < B_l$
Sliding premium	–	$[(B_l - (E_t + I_t)] \times V_t$
Contract for difference	$[(B_l - (E_t + I_t)] \times V_t$	$[(B_l - (E_t + I_t)] \times V_t$
Fixed premium	$V_t \times B_l$	$V_t \times B_l$

We then sum the yearly support costs and discount them at a social discount rate of either 5% for cohesion member states or 3% for other member states (European Commission, 2015). Our model generates results on an MW basis and expresses support costs as EUR/MWh over lifetime, accounting for the fact that solar PV projects have much lower capacity factors than onshore wind. A comparison in terms of EUR/MW would portray onshore wind as a more socially expensive technology.

3.2. Sensitivity analysis

A sensitivity analysis is conducted in two steps. First, to generalize our findings and differentiate the effects of single variables, we vary the financing inputs to their best and worst surveyed values for all 34 technology-country cases. The best financing inputs define the conditions that would apply in a scenario where policymakers de-risk RE investments. We define best financing conditions as a combination of the following inputs (and vice versa for the worst):

$$\begin{aligned} COD_{best} &= min_{COD} \\ COE_{best} &= min_{COE} \\ DSCR_{best} &= min_{DSCR} \\ loan\ tenor_{best} &= max_{loan\ tenor} \end{aligned} \tag{7}$$

To compare the magnitude of the impact with changes in other investment variables, we also vary CAPEX, O&M, and capacity factors, as shown in Table 1. We also consider a wider range of outcomes by varying the electricity price projections between + -2% per year. This approach generates nominal electricity prices (assuming an 10-year EU average inflation rate) of 59.43 EUR/MWh and 80.65 EUR/MWh for the 1% and 2% price increase scenarios in Germany in 2050, respectively (see Annex for more details).

Second, to produce more granular findings, we develop a waterfall model and show the de-risking impacts for onshore wind in Germany, Greece, Denmark, and the UK, similar to the analysis in Waissbein et al. (2013). Waterfall models help us understand the cumulative effects of changing input variables on a particular value, such as support costs, and illustrate the step changes that occur between multiple points (Rasiel, 1999). The four countries included represent both different remuneration schemes and a broad range of risk levels, including a calculated mean WACC of 1.88% in Germany, 2.86% in Denmark, 4.71% in the UK, and 5.56% in Greece. We change the average surveyed financing variables stepwise to their best and worst country values, as indicated in Fig. 2. In addition, we vary the CAPEX, capacity factors, and O&M costs by 10% (we display the assumed input values in Table 6).

Table 1
Sensitivity analysis scenarios. *The change in DSCR values causes an automatic change in the assumed probabilistic production scenarios: P-90 if DSCR 1.2, P-75 if DSCR is between 1.2 and 1.3, P-50 if DSCR is above 1.3

Best vs. worst scenario (country and technology-specific)	Description: varied variables (all others remain constant)
All financing conditions	Best: min COD, min COE, min DSCR, max LT Worst: max COD, max COE, max DSCR, min LT
All debt-financing	Best: min COD, min DSCR, max LT Worst: max COD, max DSCR, min LT
Cost of debt	Best: min COD Worst: max COD
Cost of equity	Best: min COE Worst: max COE
*DSCR**	Best: min DSCR Worst: max DSCR
Loan tenor	Best: max LT Worst: min LT
CAPEX ± 10%	Best: CAPEX Baseline x 0.9 Worst: CAPEX Baseline x 1.1
Capacity factor ± 10%	Best: Capacity factor x 1.1 Worst: Capacity factor x 0.9
O&M ± 10%	Best: O&M x 0.9 Worst: O&M x 1.1
Electricity price + -2%	Best: +2% yearly linear Worst: −2% yearly linear

3.3. Input data and assumptions

3.3.1. Financing and WACC data

We apply data from a financing survey performed between September 2019 and March 2020 across the EU 27 and UK (Roth et al., 2021b), which we present in more detail in Table 2. The survey recorded 187 financing and WACC estimates, of which 127 were related to onshore wind and the remaining to solar PV. Of these estimates, 51% were project-specific, and 49% were country estimates. Surveying financing data directly from market actors is suitable for initial estimates of WACC for a larger group of countries (Steffen, 2020), especially when data are lacking (Meyer and Booker, 2001), as is the case with project-financing deals. However, using this method risks obtaining data that are not representative and are subjective (Steffen, 2020). Fig. 3 indicates that the number of inputs per country and technology varies, often being below three. Therefore, we view this dataset as indicative rather than the actual state of financing and WACC in the individual countries. As a result, the actual bid levels and support costs might differ from the values we estimate.

In many instances, each estimate had a minimum and maximum range for one or more of the surveyed data inputs. Instead of averaging the inputs as single-country estimates and calculating the country-level support costs and bid levels, we disaggregated the data into best and worst sub-scenarios per country and technology, as shown in equation (7). Furthermore, we also derived an average estimate for each combination of country and technology from the best and worst scenarios, yielding 561 sub-scenarios or combinations of financing conditions, which we treat as individual in-country projects. This enabled us to reflect the full range of the financing inputs and their effects on bid levels and support costs. To execute each scenario, the model requires all of the inputs from equation (7). Since the survey did not record all of these inputs for some estimates, we filled the missing data with average values for the best and worst sub-scenarios, respective of the different technologies and countries.[2] Table 3 presents the extent of data adjustment for each financing indicator.

[2] In cases where the survey recorded no values for a single financing input in a country for a specific technology, we have used an average financing input of the other technologies for that country. In cases where the financing indicator was not available for any other technology in a country, we used regional values, averaging the best and worst financing indicators for all countries bordering the country lacking a specific financing indicator. The latter was only necessary in one case, for DSCR in Slovenia.

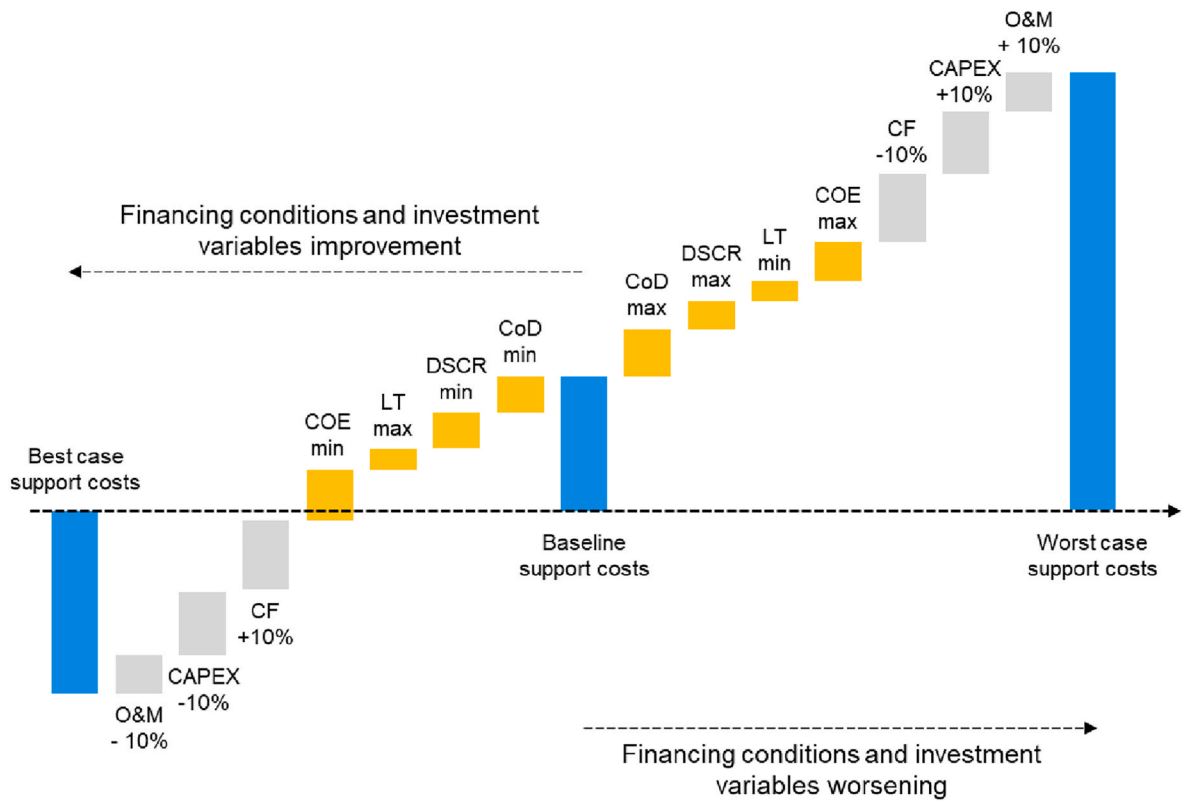

Fig. 2. Waterfall model steps. Since waterfall models enlarge the steps closer to the end values, we vary them before other investment variables to avoid over-estimating the effects of changing financing conditions.

Table 2
Financing survey aspects and main results.

Survey aspect	Description
Timing	September 2019 to March 2020
Geographical coverage	EU 27 and UK
Data collected	Cost of debt, cost of equity, DSCR requirement, loan tenor, debt size, and WACC (for project financed projects)
Number of respondents or structured interviews	80 interviewees from 78 organizations
Respondent types	37.43% project developers, 19.17% bankers, 8.56% energy companies, 6.95% investment funds, and 27.27% other
Years the data relate to	2018–39.57%, 2019–57.75%, other – 2.67%
Estimates recorded	187 estimates – for onshore wind in 22 and solar PV in 12 countries
Estimates by technology type	68% - onshore wind, 32% - solar PV
Types of estimates	51% - project-specific, 49% - country level

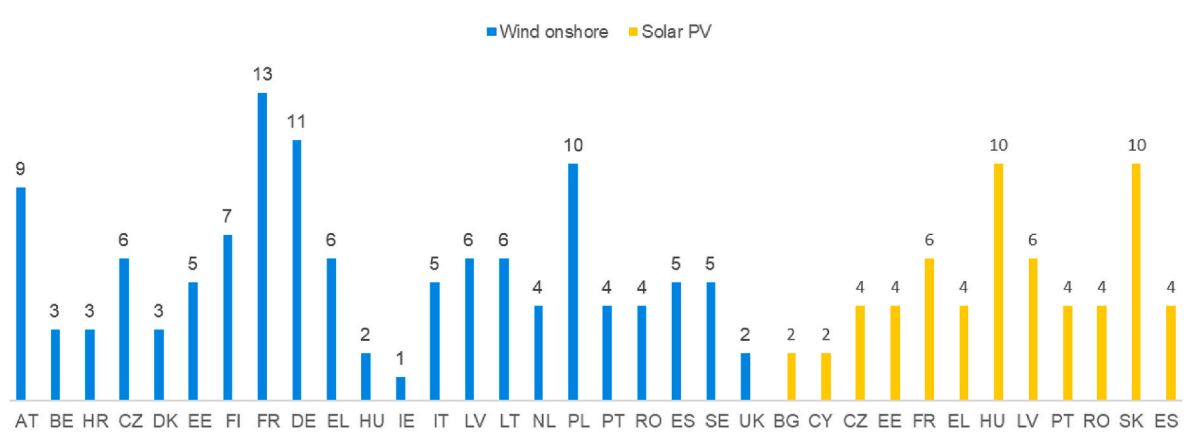

Fig. 3. Survey results: number of estimates per country and technology. List of abbreviations: AT Austria, BE - Belgium, BG – Bulgaria, CZ – Czech Republic, CY – Cyprus, DK – Denmark, EE – Estonia, FI – Finland, HR – Croatia, FR – France, DE – Germany, EL – Greece, HU – Hungary, IE – Ireland, IT – Italy, LV – Latvia, LT – Lithuania, NL – Netherlands, PL – Poland, PT – Portugal, RO – Romania, ES – Spain, SE – Sweden, SK – Slovakia, UK – United Kingdom.

Table 3
The extent of survey data adjustment.

	Cost of debt	Cost of equity	DSCR	Loan tenor
Adjusted	7	20	72	50
Share in total	3.74%	10.70%	38.50%	26.74%

3.3.2. Investment inputs and auction designs

We developed a country-level database with CAPEX, capacity factors, O&M costs, and other inputs. Table 4 presents the ranges of the investment data (for full country details, see Annex, Table 10).

Furthermore, we derived country and technology-specific auction designs for onshore wind and solar PV based on a review of auction rounds held before July 2020 (AURES II, 2020), as outlined in Fig. 1. This included eighteen multi-technology and four technology-specific auctions. Eight studied countries did not have an auction framework before July 2020, namely Austria, Belgium, Bulgaria, Cyprus, the Czech Republic, Latvia, Romania, and Sweden. To enable cross-country comparisons, we constructed fictive auction designs based on average bid bond levels, penalties, and realization periods of countries with an auction scheme. We assigned the countries mentioned earlier either a two-sided CfD, a sliding premium, or a fixed premium scheme, depending on the structure of their existing remuneration scheme and market-risk exposure. For instance, since Austria had a feed-in tariff when we conducted the analysis, we assigned it a two-sided CfD scheme. In contrast, Sweden has a quota obligation system, which we replace with a fixed premium. Table 5 presents the ranges of the main auction designs we use in the cash-flow model (see the Annex, Table 13).

3.3.3. Sensitivity analysis inputs

Finally, to perform the first step in the sensitivity analysis, which includes varying data inputs for all 34 country-technology cases, we use investment data in Table 10 (adjusted for a specific scenario, as shown in Table 1) and financing inputs in Table 11, as shown in the Annex. In the second step, we run the waterfall model using data inputs from Table 6.

4. Results and discussion

4.1. Bid levels, support costs, and calculated WACC

Figs. 4 and 5 show the bid levels and discounted support costs for all 561 scenarios, expressed in EUR/MWh over the project's lifetime and distributed across quartiles and outliers. We group the countries according to their remuneration schemes.

Fig. 5 a) indicates that, among the two-sided CfD countries, onshore wind in the UK would achieve the lowest mean support costs, equaling a mean of 3.55 EUR/MWh over the 'project's lifetime, while PV in Latvia rates the highest at 20.25 EUR/MWh. Among the sliding premium countries shown in Fig. 5 b), we observe the lowest support costs for

Table 4
Investment data ranges.

Min - max range	CAPEX	O&M	Capacity factor	Social discount rate	Operating time	Lead time
	[EUR/kW], 2019	[EUR/kW/y], 2019	%	%	[years]	[years]
Wind Onshore	1,200–1,697	40	20–45	3–5	25	3
PV	600–1,190	10	9.4–18.8	3–5	30	2

Table 5
Auction design ranges.

Min - max range	Amount of bid bond	Amount of performance bond	Project realization period	Penalty
	[EUR/kW]	[EUR/kW]	[months]	[EUR/kW]
Wind Onshore	2–75	38–77	12–48	0–110
PV	1–75	13–60	12–48	1–100

Table 6
Low, medium, and high surveyed financing conditions and technology-related inputs in Germany, Denmark, Greece, and the UK.

	Support-cost scenario	DE	DK	UK	EL
COD [%]	Low	0.76%	0.80%	1.50%	2.00%
	Average	1.31%	1.38%	3.40%	4.67%
	High	2.07%	2.00%	4.30%	7.50%
COE [%]	Low	2.80%	6.00%	7.00%	8.00%
	Average	4.74%	7.00%	8.75%	11.00%
	High	7.80%	8.00%	10.00%	14.00%
DSCR	Low	1.00	1.10	1.20	1.20
	Average	1.20	1.15	1.20	1.20
	High	1.58	1.20	1.20	1.20
LT [year]	Low	22	20	15	15
	Average	19	18	15	14
	High	18	10	15	12
CAPEX [EUR/KW], 2019	Low	1,526.79	1,415.89	1,327.24	1,523.57
	Average	1,696.43	1,573.21	1,474.71	1,692.86
	High	1,866.07	1,730.54	1,622.19	1,862.14
O&M [EUR/KW/year], 2019	Low	36.02	36.02	36.02	36.02
	Average	40.03	40.03	40.03	40.03
	High	44.03	44.03	44.03	44.03
Capacity factor [%]	Low	40.70%	26.40%	30.80%	37.40%
	Average	37.00%	24.00%	28.00%	34.00%
	High	33.30%	21.60%	25.20%	30.60%

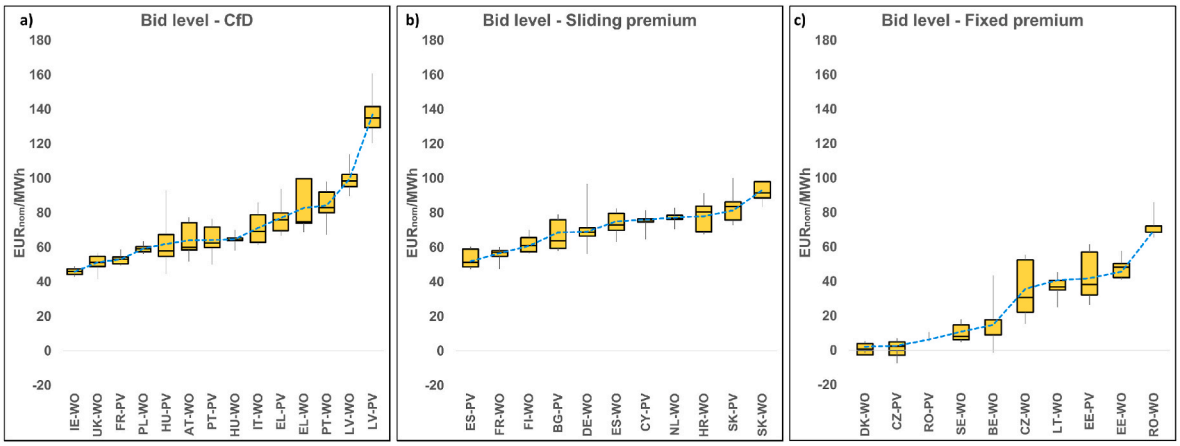

Fig. 4. Calculated bid levels. The whisker bars represent median, q25% and q75% values, while the whiskers represent minimum and maximum values or outliers. The dotted line represents the mean value for each country-technology combination. This explanation is also valid for Figs. 5 and 6.

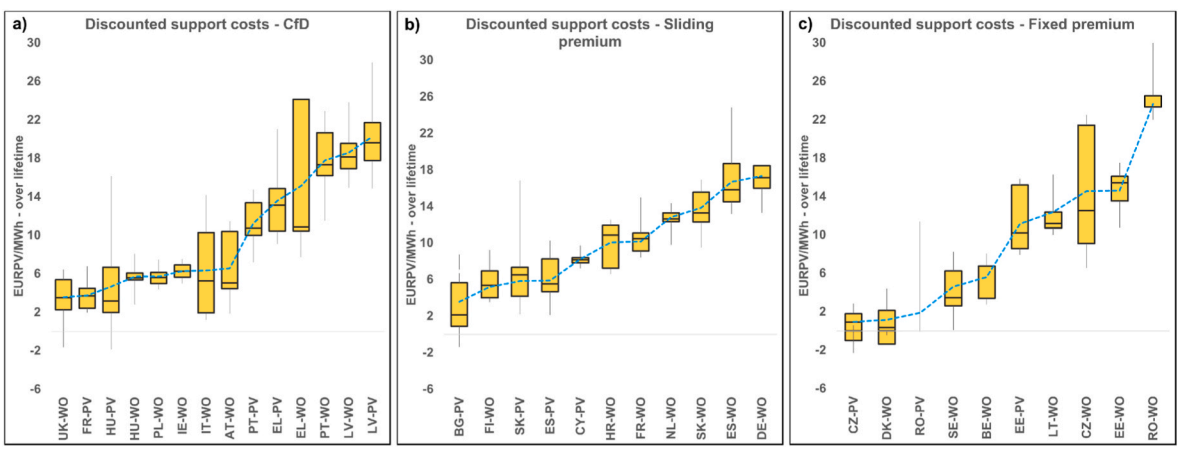

Fig. 5. Discounted support costs.

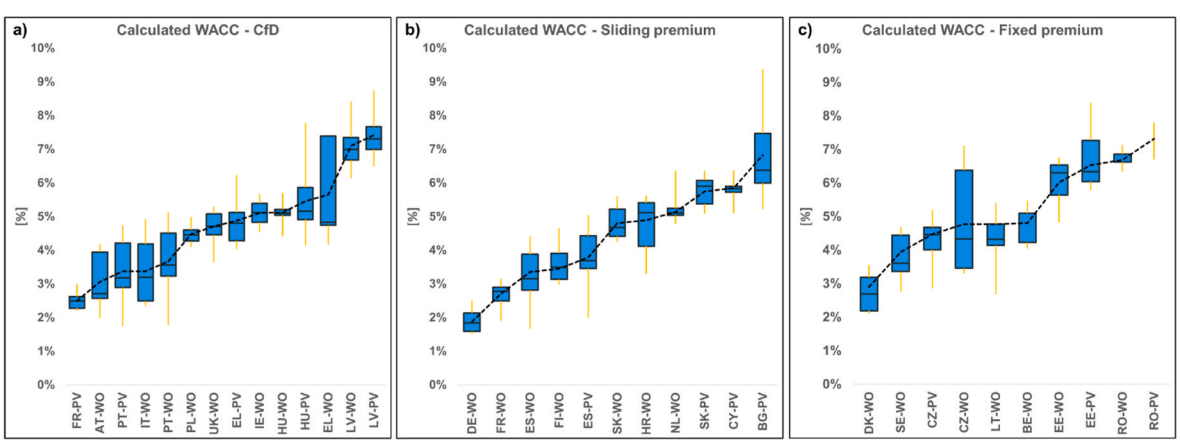

Fig. 6. Calculated post-tax WACC values.

solar PV in Bulgaria, equaling a mean of 3.56 EUR/MWh, while German taxpayers would pay the highest support costs at 17.33 EUR/MWh. As we explain later, this is because of the large spread between the required bid levels and the assumed market-capture prices for onshore wind in Germany. Finally, regarding fixed premiums, onshore wind in Denmark would achieve some of the lowest support costs, as presented in Fig. 5 c), equaling only 1.15 EUR/MWh. At the same time, Romanian taxpayers would pay more than twenty times higher support costs for electricity from onshore wind. Fig. 6 indicates that onshore wind in Germany has the lowest calculated WACC among the countries we investigate,

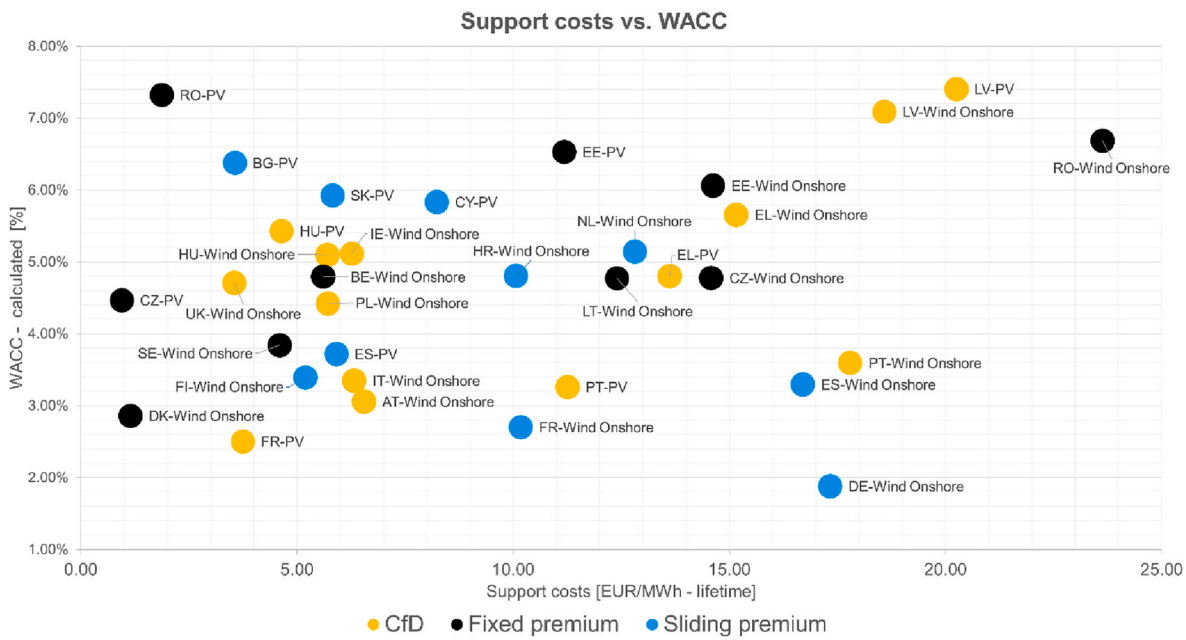

Fig. 7. Mean support costs vs. mean calculated WACC, divided per remuneration scheme.

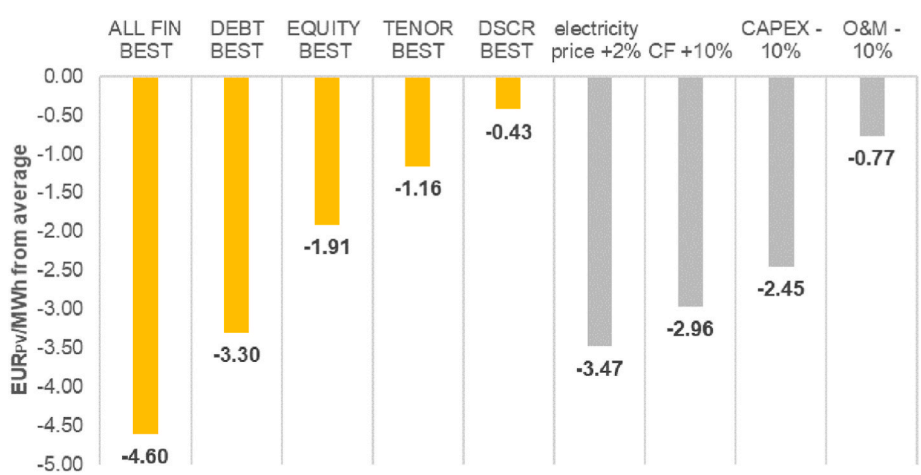

Fig. 8. Average reductions in support costs: comparison between the effects of financing variables vs. technical and market variables (capacity factor, CAPEX, O&M, and electricity price change).

equaling an average of 1.88%. In comparison, solar PV in Latvia has the highest WACC at 7.42%.

While higher WACC countries generally have higher support costs, such as solar PV and onshore wind in Latvia, or onshore wind in Greece, Fig. 7 reveals significant outliers, such as onshore wind in Germany. Despite having the lowest post-tax WACC in Europe, in our modeled framework, onshore wind in Germany would achieve support costs higher than those of onshore wind in Greece and much higher than in some lower-risk countries such as the UK and Denmark.

The reason for this result is based on how the remuneration scheme functions: with two-sided CfD and sliding premium schemes, support costs make up the difference between the assumed capture prices and bid levels, while fixed premiums top up the capture prices. Under our baseline scenario, onshore wind in Greece would achieve a mean bid level of 82.9 EUR/MWh, while in Germany, this would amount to 69.1 EUR/MWh. However, these two countries have very different underlying electricity market conditions. At the end of 2019, Germany's average wholesale electricity price amounted to 36.7 EUR/MWh and in Greece to 59.5 EUR/MWh (DG Energy, 2019). Consequently, the spread between the derived bid levels and the capture prices is higher in Germany, whose taxpayers would need to pay 1.5 EUR/MWh more than in Greece. However, as these results depend on applied MVFs that are subject to uncertainty, they should be treated with caution. Different wind conditions also increase the differences in support costs. While we assume a capacity factor of 28% for Greece, we apply a capacity factor of 24% for Germany (Dalla-Longa et al., 2018), which further reduces Greek support costs on an MWh basis. When compared in terms of EUR/MW, German taxpayers would pay 65.146 EUR/MW less under our baseline assumptions.

4.2. Impact of financing conditions and costs of capital on support costs

We highlight the following general findings as shown in Fig. 8 (for detailed country-level results, see Annex, Fig. 13).First, compared to country baseline values, de-risking debt financing would create the largest support-cost savings, equaling a 53.1% reduction on average or 3.3 EUR/MWh over the project's lifetime. Second and by comparison, de-risking equity financing would yield an average reduction in support

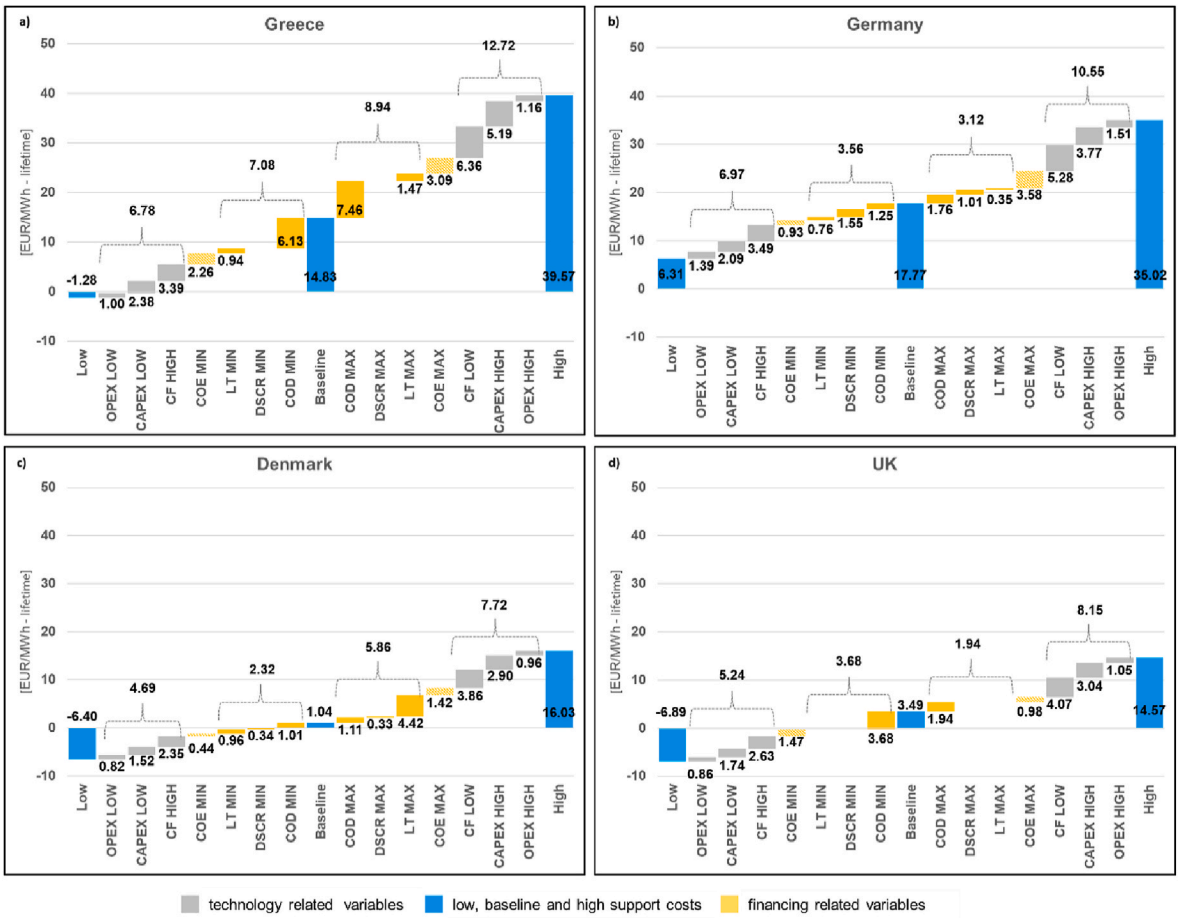

Fig. 9. Sensitivity of support costs to changes in financing conditions and technology-related input variables. The yellow columns show the effects of changing debt and equity financing, whereby we aggregate the effects of changing individual debt-financing conditions. The grey columns show the effects of changing technology-related inputs. The blue columns show from left to right support costs after improving all technology- and financing-related values, the baseline support costs, and the support costs after worsening all technology- and financing-related inputs.

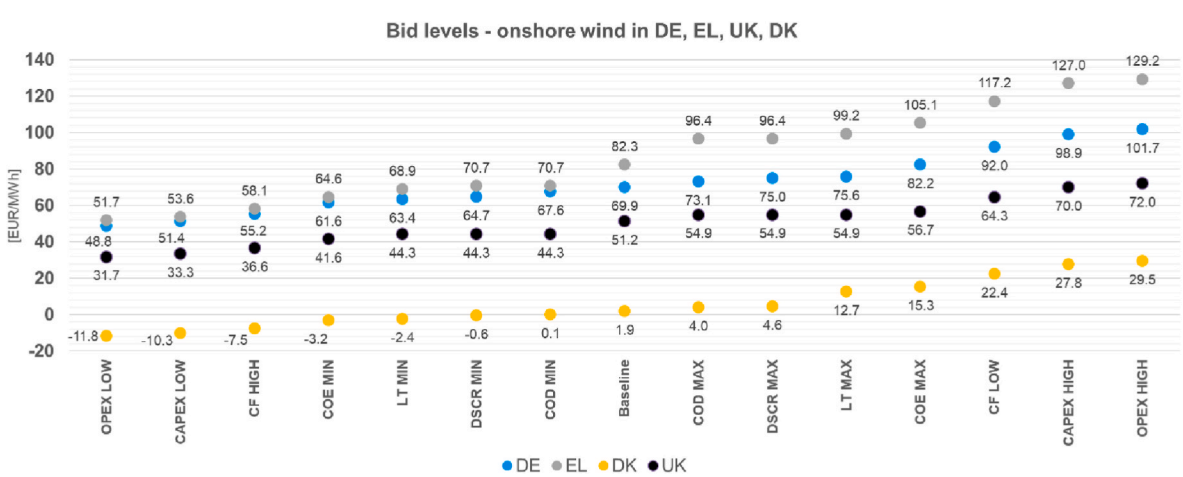

Fig. 10. Sensitivity of bid levels to changes in financing conditions and technology-related input variables. The figure shows the bid levels that correspond to the support-cost levels in the steps of the waterfall graph in Fig. 9.

costs of 33.6% or 1.9 EUR/MWh. Third, in terms of other debt-financing conditions, improving loan tenors would on average reduce support costs by 18% or 1.16 EUR/MWh and DSCR by only 8% or 0.43 EUR/MWh. Overall, de-risking financing conditions and WACC could lead to significant reductions in support costs.

Other investment variables also have significant impacts on support costs. Increasing capacity factors by 10% produces, on average, almost the same support-cost savings as improving all debt-financing conditions. In comparison, the effect of decreasing CAPEX values by 10% is slightly less, as shown in Fig. 8. Moreover, an increase in the electricity price of 2 percentage points per year instead of the 1 percentage point we assume in our baseline would have a greater average impact than de-

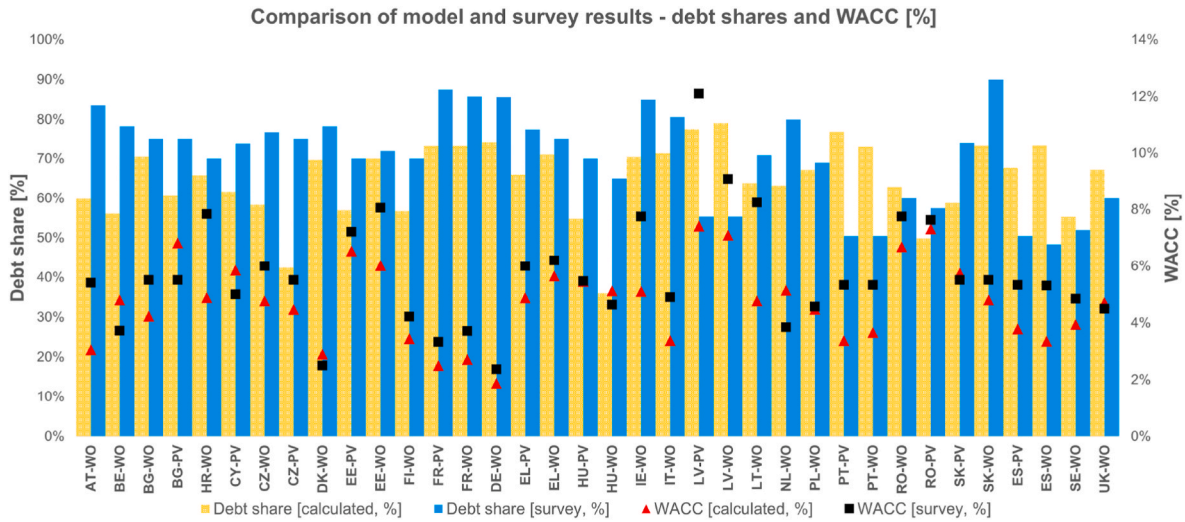

Fig. 11. Surveyed vs. calculated debt shares and WACC values.

Table 7
Comparison between modeled and actual bid levels.

	Adjusted average awarded price	Low - baseline	High - baseline	Low - waterfall	High - waterfall
	[EUR/MWh,2019]	[EUR/MWh]	[EUR/MWh]	[EUR/MWh]	[EUR/MWh]
HU-PV	65.00	44.51	92.99		
IT-Wind Onshore	63.43	61.57	86.21		
EL-Wind Onshore	53.53	68.83	99.92	51.73	129.23
EL-PV	49.31	66.70	93.87		
DK-Wind Onshore	2.00	−3.15	14.04	−11.78	29.53
DE-Wind Onshore	60.10	62.78	74.28	48.80	101.68

risking debt financing. On the other hand, changes in O&M levels seem to have a smaller and insignificant effect on support costs.

We now examine the effects of de-risking for the selected countries individually, which may reveal additional observations and insights. Fig. 9 presents the results of our waterfall model, in which we aggregate the effects of changing all debt-financing and technology-related inputs into separate values. Furthermore, Fig. 10 shows the bid levels that result from each step for the four selected countries.

What stands out in Fig. 9 is that Denmark and the UK would achieve negative support costs by only de-risking financing conditions, while Greece would also accomplish this, provided projects have lower CAPEX values and higher than average capacity factors. Fig. 9 also shows that Germany would reduce the support costs for onshore wind by a factor of three through a combination of de-risking, cost reductions, and allowing project developers to exploit sites with better wind conditions. Furthermore, de-risking debt in Greece could reduce support costs by 7.08 EUR/MWh, more than double the average of the 34 assessed country-technology cases shown in Fig. 8, emphasizing the importance of giving our results greater granularity. Furthermore, de-risking debt in Denmark would reduce support costs by only 2.32 EUR/MWh. These differences arise because the survey recorded a larger spread between the best and average CoD in Greece, equaling 2.67%, compared to only 0.6% in Denmark, as indicated in Table 6.

Our analysis found that varying the DSCR requirement would have a minimal impact on support cost savings. Within our waterfall model in Fig. 9, changing the DSCR requirements in Germany from an average of 1.2 to best and worst values equaling 1.0 and 1.58 triggers a change in debt share of between 8.3% and 6.5% points, respectively, inducing a change in WACC of only 0.36% and 0.22% points. The small changes in debt share and WACC result from our model set-up, where changing DSCR requirements trigger a change in assumed wind-probability production scenarios. This directly affects the CFADS and generates smaller changes in debt shares. However, changing debt shares by more than the debt shares resulting from varying the DSCR in our model could have a larger impact on support costs.

4.3. Model validation

Our baseline model calculates debt-share values that deviate from the surveyed debt shares, as shown in Fig. 11. For 25 country-technology combinations, we calculate debt shares that are, on average, 13.39 percentage points lower than the surveyed values. In nine cases, our calculated values are 16.69 percentage points higher on average. For example, while the survey recorded average debt shares of 85.6% for onshore wind in Germany and 87.5% for solar PV in France, in the average scenario, we calculate 74.16% and 73.26%, respectively. Despite this, the calculated WACC values are, on average, 0.97 percentage points lower than the surveyed values. As indicated in Fig. 11, there are some notable exceptions, including solar PV in Latvia and onshore wind in Lithuania, Croatia, and Ireland, where our resulting WACC levels are considerably lower than those surveyed.

These deviations in debt shares and WACC values could arise because: a) we do not model real-life financing arrangements, where multiple banks issue debt as loan syndicates. This often includes

concessional loans from state investment banks that de-risk financing deals (Geddes et al., 2018); b) we do not model real bidding behavior. While minimizing bid levels replicates situations where auction competition is high and average bid levels decrease, empirical research shows that this is often not the case. For example, in Germany, onshore wind auctions have been undersubscribed since May et al., 2018 (Sach et al., 2020), and the awarded projects maximized their bids by bidding at the ceiling price. In such circumstances, they would have higher CFADS and benefit from greater debt size; c) finally, 49% of the surveyed data are country estimates, meaning that the interviewees did not pair debt share and DSCR values for specific projects but treated them as general estimates which do not result in the surveyed WACC levels.

To further validate our model's performance, we cross-check our results with the outcomes of actual auction rounds, for which we have available data (AURES II, 2020). Table 7 compares achieved bid levels with the bids resulting from our baseline values in Fig. 4 and the bids we derive from the waterfall model in Fig. 10. The achieved bids fall within our baseline range for solar PV in Hungary and onshore wind in Italy and Denmark. However, our lower baseline estimate is slightly higher than actual auction outcomes for German onshore wind and significantly higher for solar PV and onshore wind in Greece, possibly because we use average CAPEX and capacity-factor values. In reality, such projects might not receive support. For instance, the lower range of our waterfall model corresponds to actual auction results in Greece, indicating that only projects with a combination of best financing conditions, lowest technology costs, and most favorable resource conditions win auction rounds.

4.4. De-risking measures and their effectiveness

Overall, our results indicate that de-risking financing conditions and WACC could lead to negative support costs in some countries, such as Denmark and the UK, mostly by de-risking debt financing. In contrast, de-risking equity would lead to lower support-cost savings. Hence, to improve project-financing conditions, reducing risks during the project's operating lifetime through revenue stabilization might be beneficial since cash-flow volatility largely impacts commercial banks' risk perceptions of RE projects. From a theoretical perspective, two-sided CfD schemes lead to the most significant revenue stabilization (May et al., 2018; Neuhoff et al., 2018). Their two-sided nature ensures higher shares of stabilized revenues and enables the bank to reduce uncertainty when determining the project's cash flow. However, assuming the bid levels that we calculated in our study, the one-sided structure of sliding premiums could potentially increase project revenues the most, especially when there is an increase in electricity prices, leading to the largest cash inflows and debt-sizing. Nonetheless, in combination with auctions, sliding premiums might incentivize bidders to submit lower bids in expectation of additional market revenues, leading to lower shares of stabilized revenues and potentially worse financing conditions (Đukan et al., 2019).

Besides the type of remuneration scheme, the duration of support also influences project risk, since it affects the length of the project's merchant tailor revenues after the support contract ends. Longer support durations could increase loan tenors, leading to less exposure to market risk and larger debt sizes. Although we demonstrate that loan tenors have a lower impact on support costs, changing them could significantly affect debt-sizing and WACC levels. Hence, we consider longer support durations to be an effective de-risking measure. Furthermore, despite the small impact of DSCR requirements on the support costs resulting from our model, maintaining low DSCR levels is critical to de-risking. Along with loan tenors, DSCR requirements directly impact debt size and overall capital costs (Rigby, 1999).

Although existing research expects that remuneration design, and especially CfD schemes, help improve financing conditions and should thus have a significant impact on cost reductions, we found no evidence of this in our cross-country analysis. First, we do not find that countries with two-sided CfD schemes have lower WACC levels than those with sliding and fixed premiums. Although Greece uses a two-sided CfD scheme, its average calculated WACC is 2.7% higher than Denmark's, with a fixed premium in our model, leading to larger market exposure and greater revenue volatility. Second, WACC depend more on the underlying country risk and country-specific financial markets than on individual support policies. The spread between Greece's worst and best CoD is 5.5%, significantly greater than the 1.2% in Denmark. According to Roth et al. (2021), Greece is an active market for international project developers with access to lower-cost project-financing loans from foreign banks and international bond markets. On the other hand, local project developers finance projects via domestic commercial banks that issue loans at higher interest rates, reflecting their risk-aversion to domestic macroeconomic conditions. In contrast, Denmark benefits from lower interest rates on commercial loans due to its more sophisticated financial market and greater access to low-cost capital (Roth et al., 2021).

Furthermore, the average risk premium markup on onshore wind[3] is similar among the four analyzed markets and varies from 4.55% in Germany to 7.42% in the UK. What makes the considerable difference between higher-risk Greece and the other lower-risk countries is the country risk, defined as the yield on 10-year government bonds, which at the end of 2018 amounted to 4.28% in Greece in comparison to an average of 0.58% in the other three markets (see Fig. 14 in Annex). Therefore, in addition to de-risking support policies, policymakers could induce further cost savings by improving the overall investment climate, for instance, by developing capital markets, ensuring the rule of law, and reducing the regulatory hurdles (United Nations, 2021).

Despite its relatively smaller impact on reducing support costs, policymakers could de-risk equity financing by reducing risks during project development, for instance, through low-risk auction designs such as smaller bid bond amounts, less stringent penalties, and demanding fewer material pre-qualifications like building permits. Risky auction designs involving high financial pre-qualifications or short realization periods could increase investors' required returns on equity by as much as 1.79 percentage points (Côté et al., 2022). However, these de-risking measures would most likely not alter the bidders' equity-return requirements and reduce support costs. Instead, such changes in auction design mainly affect the bidders' decision to participate in auctions (Đukan and Kitzing, 2021). Furthermore, as the German experience with special provisions for community energy organizations in onshore wind auctions in 2017 showed, such measures could also have unwanted consequences, such as low project-realization rates and misuse by commercial bidders (Grashof et al., 2020; Lundberg, 2019). Therefore, de-risking auction designs in the project development phase would not be cost-effective, and it could impact auction effectiveness.

Support-cost savings also depend on other investment factors besides financing. Projects located on sites with higher capacity factors will experience lower support costs. The higher revenues from greater electricity production suppress the bid level required to meet a bidder's hurdle rate. Capacity factors have a greater relative impact on support costs in lower-risk countries than in high-risk countries, where WACC have a higher impact on support costs and the project's profitability. As Fig. 9 shows, the impact of capacity factors is greater or almost equal to varying all financing conditions for onshore wind in Germany, Denmark, and the UK. Furthermore, other market conditions, such as changes in expected electricity prices (as shown in Fig. 8) or European Central Bank monetary policy (Roth et al., 2021), might dwarf the effects of de-risking

[3] Here defined as the difference between a 10-year government bond yield and the average surveyed cost of equity for the selected markets.

policies. While measures like revenue-stabilization schemes could improve the overall investment climate, future policy discussions on de-risking measures should acknowledge the significant impact of other exogenous factors on support costs.

5. Conclusions and policy implications

We quantify the potential impact of de-risking equity and debt financing on support costs in 22 onshore wind and 12 solar PV markets across the EU and the UK. Our study generates novel insights into the benefits of de-risking that can help guide future renewable energy support policies. We find that de-risking debt financing causes the greatest support-cost reductions on average. In contrast, de-risking equity financing would have a lesser effect by a factor of almost two. The combination of de-risking both sources of financing could lead to negative support costs in some cases, like Denmark and UK, effectively making producers pay the government for every generated kWh. In countries with less favorable financing conditions such as Greece, projects could also achieve negative support costs, but only if they have lower than average CAPEX values and are on sites with above-average wind conditions. Our results also imply that improving DSCR requirements and loan tenors individually would yield much smaller support-cost benefits than de-risking all debt-financing conditions and equity costs.

Second, our study shows that technology and market-investment variables have an equally large impact on support costs, as does de-risking financing conditions. Most notably, this includes the effects of greater capacity factors and higher assumed electricity prices. In our model, better site conditions increase project revenues, lowering the break-even bid level, while higher electricity prices suppress the needed support. These effects vary depending on individual country circumstances. Higher risk countries like Greece would experience greater support-cost savings from de-risking than their lower risk EU peers like Denmark. In contrast, in lower-risk countries, technology-related variables like capacity factors have a larger relative impact on reducing support costs than financing inputs.

Third, support policies are a less important driver of risk than country risk. Financing conditions depend primarily on wider macroeconomic conditions, especially in higher risk countries like Greece, which experienced more economic stress during the Eurozone debt crisis. For instance, although Greece has a two-sided CfD scheme that stabilizes project revenues, we calculate a WACC that averages 2.7% higher than Denmark's, where a remuneration scheme is applied that fully exposes projects to electricity price fluctuations under our model framework.

These findings have several policy implications. First, to achieve "a bigger bang for the buck", policymakers should mainly consider de-risking debt financing through revenue-stabilization mechanisms such as two-sided CfDs, as such measures could deliver the biggest support cost savings. However, policy de-risking has a limited impact in light of the overall country risk and macroeconomic conditions. Therefore, alongside de-risking support policies, policymakers can work on improving the overall investment climate by developing financial markets, reducing regulatory hurdle rates, and similar measures. Second, de-risking the costs of equity through measures that reduce auction-related risks for project developers, such as lower bid bonds and longer realization periods, might have a lesser impact on support-cost savings while reducing the effectiveness of auctions. Therefore, introducing such measures would have a limited impact on costs and potentially negatively affect auction outcomes. Third, since investment variables like capacity factors impact support costs as much as de-risking financing conditions, it is essential to enable project developers to develop projects on the windiest and sunniest sites. Alongside financial de-risking, this could also produce considerable cost savings to society.

Several questions still remain to be answered. For example, we did not find a link between two-sided CfD schemes and lower WACC, possibly because we examined cross-country differences where country risk may overlay the effect. Research in this direction could investigate the effects of revenue stabilization within individual countries, for instance, by comparing them with full exposure to merchant risk. Furthermore, additional research on the impacts of country risk and/or macroeconomic risk on costs of capital is needed. First efforts in this direction exist (e.g., see Schmidt et al. (2019)). Additional work is required to understand how country risk exactly factors into 'investors' equity return requirements and whether governments can use policies to effectively reduce this for specific investments like renewable energy projects.

In conclusion, as countries are moving slowly towards subsidy-free investment in renewable energy, lower shares of secured revenues may increase the WACC and 'projects' LCOEs. Political efforts to de-risk renewable-energy investments will therefore become increasingly relevant, as they could help shape future energy policy to accelerate the energy transition and contribute to more rapid reductions of support costs in Europe.

CRediT authorship contribution statement

Mak Đukan: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Software. **Lena Kitzing:** Conceptualization, Methodology, Investigation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements and Funding

The authors would like to thank Robert Brückmann, Moïra Jimeno and Agustin Roth from Eclareon for providing us with outputs from the financing survey and for conducting the survey itself. We would also like to thank other partners within the AURES II consortium for their constructive feedback, and especially for inputs and comments related to the early version of the results that underpin this paper. Finally, we are grateful for the feedback received at the 1st IAEE online conference and the WESC 2021 conference, especially Vasilios Anatolitis and Ann-Katrin Hanke, who hosted a session at which we presented this work. We are also grateful for the co-funding that made this research possible from the Horizon 2020 programme (grant agreement no. 817619) and the Technical University of Denmark.

Annex.

Electricity prices

Investors either make their own price forecasts using various methods (Weron, 2014), or more often rely on external projections like Baringa (2020), which are not freely available. Furthermore, the EU Reference Scenario (Capros et al., 2016) is publicly available and forecasts average annual power prices for every five years until 2050. However, its projected prices are significantly higher than current levels (Jansen et al., 2020), so using them would greatly affect the resulting bid levels. Price scenarios also rely on various views regarding the future energy system, such as developing power-to-gas and electric vehicles (Gea-Bermúdez et al., 2020), and while they provide an outlook on the future, in this study, we take a simplified approach. We assume 2019 Q4 average wholesale baseload electricity prices (DG Energy, 2019) for our starting values and a 1% yearly upward price trend as our (adjusted for inflation) as our baseline. To account for the cannibalization effect of the increasing share of zero marginal-cost renewables on wholesale electricity prices in European power markets, we correct the assumed prices with market value factors (MVF) for solar PV and onshore wind.

Unlike fossil-fuel power plants with long start-up times (IRENA, 2019a), hydro-generators are more flexible and can adjust their production to periods of the highest electricity prices. Therefore, compared to power systems like Germany, whose baseload relies mainly on inflexible thermal-power plants, power systems with large shares of hydroelectricity, like those in Sweden and Norway (and the well-interconnected power systems of countries like Denmark), experience lower reductions in market value. Hirth (2016) demonstrates this effect based on observed market data and defines the relationship between the share of onshore wind in a thermal and hydro-power system (x) and the wind-market value factors (y) as:

$$y = -0.3x + 1.0 \ (\textit{hydro system based on Sweden and Denmark}) \tag{8}$$

$$y = -1.0x + 1.0 \ (\textit{thermal system based on Germany}) \tag{9}$$

Using equations (8) and (9) requires defining two unknowns: a) current and projected market shares of onshore wind; and b) differentiating between thermal and hydro-based power systems. We address a) by deriving the market shares of onshore wind in gross electricity consumption for 2018 (Eurostat, 2019) and taking this as the current penetration rate. We derive the 2030 onshore wind shares for a future reference point by reviewing member 'states' National Energy and Climate Plans (NECP) (European Commission, 2020) and assuming constant MVF thereafter. To address b), we define a so-called Flex Ratio (FLR), i.e., the ratio of the share of hydroelectricity to shares of solar PV and onshore wind in a power system:

$$\textit{Flex Ratio} = \frac{\%\ \textit{hydro}}{(\%\ \textit{solar PV} + \%\ \textit{onshore wind})} \tag{10}$$

As our benchmark hydro-system, we take Sweden with an FLR of 4.03. Instead of classifying systems below this value as thermal, we introduce an intermediate system with a slope of −0.65, as indicated in Table 8. Furthermore, we define a power system as thermal if the share of hydroelectricity in overall electricity from renewables is less than 50%.

Table 8
Flex Ratio Ranges

FLR Range	Type of system	Market Value Factor equation
≥ 4.03	*Hydro systems – based on FLR in Sweden*	$y = -0.3x + 1.0$
$\geq 1.50 < 4.03$	*Intermediary system – at least 50% more hydro than VRE*	$y = -0.65x + 1.0$
$0.00 < 1.50$	*Thermal systems – less than 50% more hydro than VRE*	$y = -1.0x + 1.0$

As power systems evolve and change their hydro- and variable RE shares, they also reduce their FLRs. This is in line with Hirth (2016), who notes that the benefits of hydro-power seem to level off at around 20% wind-energy penetration. The upper graphs of Fig. 12 demonstrate the change in hydroelectricity and variable renewables between 2018 and 2030 according to the member 'states' NECPs. The lower two graphs show the effect of this change on the countries' FLRs. In all countries, the FLR declines significantly, indicating a loss of hydro-related flexibility.[4]

[4] We use this methodology for all countries except Denmark, which we regard throughout as a hydro-system due to its large interconnections with Norway and Sweden.

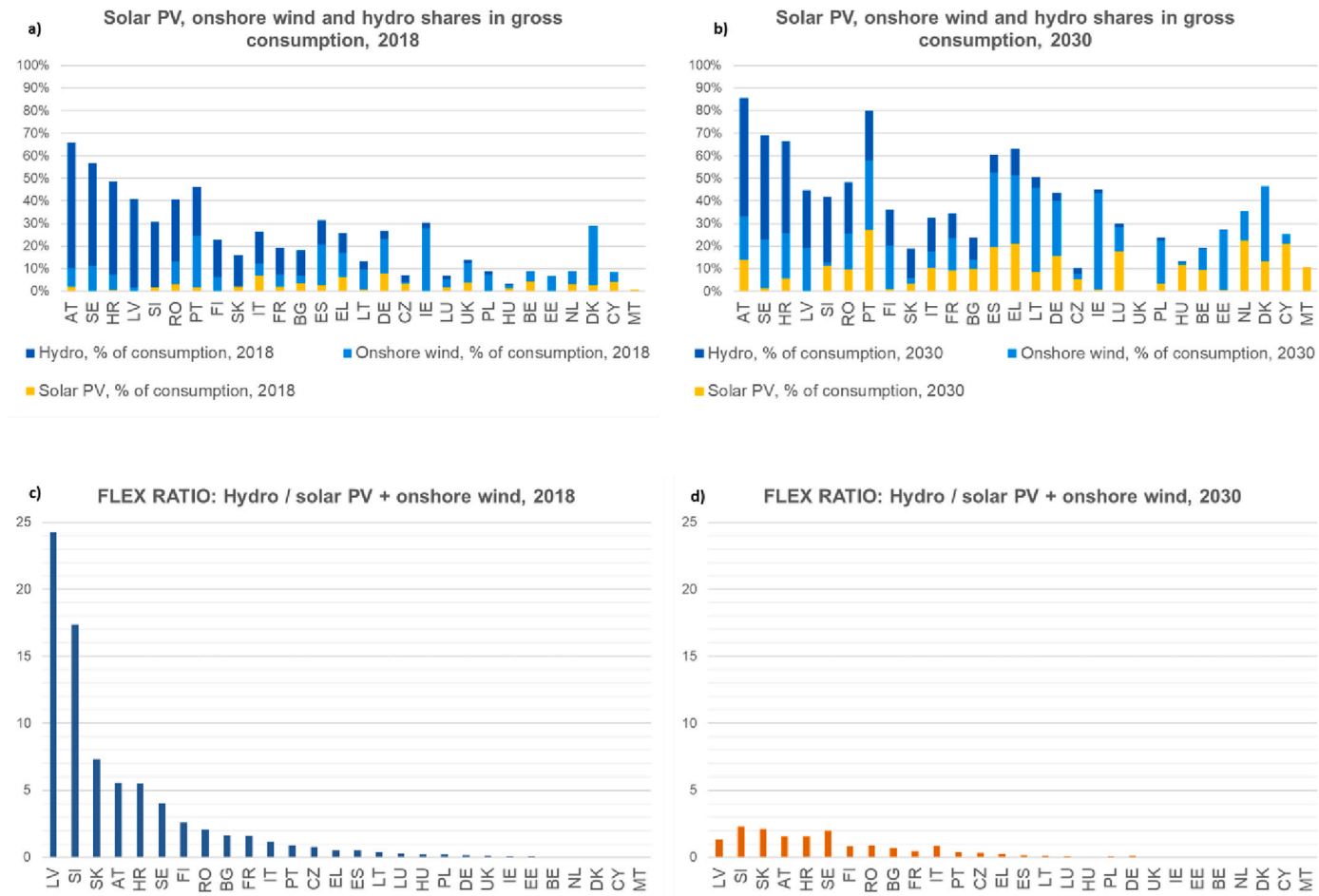

Fig. 12. a) share of solar PV and onshore wind in 2018 (Eurostat, 2019); b) share of solar PV and onshore wind in 2030 (European Commission, 2020); c) flex ratio for 2018; and d) flex ratio for 2030.

Concerning solar PV, we derive the MVF similarly as for onshore wind, though relying on equation (9), which takes into account a review of the market-value literature for California, Germany, Ontario, Australia, and Arizona (Hirth, 2015):

$$y = -3.6x + 1.3 \tag{11}$$

Although we do not differentiate between hydro- and thermal systems as we did for onshore wind, due to a lack of similar published studies, the above equation considers multiple markets, so we apply this to generalize roughly the drop in value of solar PV penetration in Europe. Only some studies estimated market-value factors for multiple European markets. At the same time, most studies focus on onshore wind in Germany. As shown in Table 9, our results deviate from these studies by small margins.[5]

Table 9
Calculated market-value factors vs. Market-value factors in the literature – values from 2010 to 2030 for European power markets for onshore wind and solar PV. Sources: [1] own calculations [2] Dalla Riva et al. - (Dalla Riva et al., 2017) – based on study that estimates the impact of system-friendly wind turbines [3] Hirth (2013) – modeled calculations [4] Hirth and Müller (2016) – based on observed market data [5] Dalla Riva et al. – (Dalla Riva, 2020) – preliminary results for IEA Task 26 [6] Ederer (2015) – projected value [7] Cludius et al. (2014).

	Onshore wind									Solar PV			
Market Value Factors	[3]	[4]	[7]	[1]	[6]	[5]	[2]	[1]	[2]	[3]	[7]	[1]	[1]
	[2010]	[2012]	[2016]	[2018]	[2019]	[2019]	[2020]	[2030]	[2030]	[2010]	[2016]	[2018]	[2030]
AT				0.98		0.98		0.87				1.23	0.81
BE				0.96		0.89		0.91				1.15	0.96
BG				0.98		0.90		0.96				1.18	0.94
HR				0.98				0.87				1.29	1.09
CY				0.96				0.96				1.16	0.54
CZ				0.99				0.98				1.18	1.11

(*continued on next page*)

[5] However, in some cases our results produce large decreases in value, for instance, for solar PV in Portugal, where the market value factor declines from 1.24 in 2018/2019 to 0.33 in 2030. However, in the same period Portugal plans on increasing its share of solar PV from the current level of 1.8%–27% in 2030, or a factor 15 increase.

Table 9 (*continued*)

	Onshore wind									Solar PV			
Market Value Factors	[3]	[4]	[7]	[1]	[6]	[5]	[2]	[1]	[2]	[3]	[7]	[1]	[1]
	[2010]	[2012]	[2016]	[2018]	[2019]	[2019]	[2020]	[2030]	[2030]	[2010]	[2016]	[2018]	[2030]
DK				0.92		0.89	0.9	0.90	0.87			1.20	0.82
EE				0.94				0.73				1.29	1.28
FI				0.96				0.81				1.30	1.26
FR				0.97		0.95	1.04	0.86	1.02			1.23	0.96
DE	0.94	0.88	0.83	0.85	0.75	0.84	0.83	0.75	0.85	0.98	0.91	1.02	0.74
EL				0.89		0.96		0.70				1.07	0.55
HU				0.99				0.99				1.25	0.88
IE				0.72		0.86		0.58				1.30	1.27
IT				0.95		0.98		0.93				1.05	0.93
LV				1.00				0.81				1.30	1.30
LT				0.91				0.63				1.28	1.00
LU				0.96				0.89				1.24	0.67
MT				1.00				1.00				1.28	0.91
NL				0.94		1.03		0.87				1.19	0.49
PL				0.93		0.92		0.81				1.29	1.18
PT				0.77		0.95		0.69				1.24	0.33
RO				0.93		0.94		0.84				1.20	0.95
SK				1.00				0.98				1.23	1.18
SI				1.00				0.99				1.24	0.89
ES				0.82		0.97		0.67				1.20	0.60
SE				0.97		0.96	1.03	0.86	0.96			1.29	1.25
UK				0.91		0.98	0.98	0.84	0.92			1.17	0.92

Investment data

We used investment and financing inputs in our sensitivity analysis, as shown in Tables 10 and 11.

Table 10
Main investment values. Sources: [1] IRENA (IRENA, 2019b) – average for commercial utility scale for solar PV [2] Wind Europe internal unpublished values [3] IRENA (IRENA, 2017) and adjusted with a quoted technology learning rate of 3% p.a. [4] Average values of other countries [5] Derived from Solar Power Europe (Solar Power Europe, 2019) shares of utility and commercial-scale PV and multiplied by a weighted average of utility and commercial-scale PV from IRENA (IRENA, 2019b) [6] HEP (HEP, 2020) – average of planned projects [7] IRENA (IRENA, 2015) [8] Average of IRENA (IRENA, 2019b) utility-scale and IRENA (IRENA, 2020) average for other EU commercial scale [9] Dalla Longa et al. (Dalla-Longa et al., 2018) [10] Pfenninger and Staffell (2016) [11] KPMG (KPMG, 2019) and Eurostat (2021).

	CAPEX				Capacity Factor					
Country	Onshore wind		Solar PV		Onshore wind		Solar PV		Corporate Tax [11]	Inflation [12]
	[EUR/kW], 2019		[EUR/kW], 2019		[%]		[%]		[%,2019]	[%, 2019]
AT	1,498	[2]	1,155	[5]	28.0	[9]	13.9	[10]	25.0	1.5
BE	1,294	[2]	1,165	[5]	32.0	[9]	12.3	[10]	29.0	1.2
BG	1,351	[3]	853	[5]	23.0	[9]	15.2	[10]	10.0	2.5
HR	1,289	[2]	1,059	[6]	24.0	[9]	14.0	[10]	18.0	0.8
CY	1,487	[4]	1,156	[7]	20.0	[9]	18.5	[10]	12.5	0.5
CZ	1,487	[4]	878	[5]	24.0	[9]	13.2	[10]	19.0	2.6
DK	1,696	[1]	952	[5]	37.0	[9]	11.2	[10]	22.0	0.7
EE	1,487	[4]	1,008	[4]	27.0	[9]	10.6	[10]	20.0	2.3
FI	1,427	[2]			29.0	[9]	9.4	[10]	20.0	1.1
FR	1,576	[1]	1,173	[1]	27.0	[9]	13.9	[10]	28.0	1.3
DE	1,573	[1]	906	[1]	24.0	[9]	12.4	[10]	30.0	1.4
EL	1,475	[2]	1,061	[5]	28.0	[9]	16.0	[10]	24.0	0.5
HU	1,427	[2]	1,092	[5]	23.0	[9]	13.9	[10]	9.0	3.4
IE	1,518	[2]			45.0	[9]	10.8	[10]	12.5	0.9
IT	1,491	[1]	880	[1]	25.0	[9]	15.4	[10]	24.0	0.6
LV	1,487	[4]	1,008	[4]	28.0	[9]	10.8	[10]	20.0	2.7
LT	1,487	[4]	1,008	[4]	29.0	[9]	11.4	[10]	15.0	2.2
LU	1,697	[2]	1,008	[4]	0.0	[9]	13.0	[10]	24.9	1.6
MT			1,008	[4]	27.0	[9]	18.8	[10]	35.0	1.5
NL	1,516	[2]	1,094	[1,8]	32.0	[9]	12.1	[10]	25.0	2.7
PL	1,332	[2]	1,037	[5]	26.0	[9]	12.0	[10]	19.0	2.1
PT	1,386	[4]	891	[5]	23.0	[9]	16.5	[10]	21.0	0.3
RO	1,672	[2]	839	[5]	23.0	[9]	14.1	[10]	16.0	3.9
SK	1,487	[4]	950*	[5]	24.0	[9]	13.4	[10]	21.0	2.8
SI	1,224	[3]	1,174	[5]	20.0	[9]	14.1	[10]	19.0	1.7
ES	1,386	[1]	824	[1]	26.0	[9]	16.7	[10]	25.0	0.8
SE	1,200	[1]	1,008	[4]	30.0	[9]	9.7	[10]	21.4	1.7
UK	1,693	[1]	1,190	[1]	34.0	[9]	10.7	[10]	19.0	1.8

*For solar PV in Slovakia, we assume a CAPEX of 950, as deriving the CAPEX values from the current shares of solar PV project types yields a very high CAPEX value that is not in line with other countries in the region.

Table 11
Surveyed minimum, maximum and average project-financing inputs per country and technology – values used in the sensitivity analysis. Due to data confidentiality, the table excludes some countries for which the survey recorded fewer than three data inputs and which are still part of the analysis. This affects onshore wind in Hungary, Ireland and the UK, and solar PV in Bulgaria and Cyprus. Data derived based on Roth et al. (2021b).

Country-Technology	COD - MIN	COD - MAX	COD - av	COE - MIN	COE - MAX	COE - av	DSCR - MIN	DSCR -MAX	DSCR - av	LT - MIN	LT - MAX	LT - av
AT-Wind Onshore	1.00%	3.50%	1.93%	2.20%	10.00%	6.13%	1.05	1.40	1.18	12	15	13.2
BE-Wind Onshore	1.50%	3.00%	2.33%	7.00%	10.00%	8.83%	2.00	3.00	2.28	18	20	18.8
HR-Wind Onshore	3.00%	5.00%	3.67%	6.00%	12.00%	9.17%	1.25	1.30	1.28	10	15	11.8
CZ-Wind Onshore	2.10%	4.00%	3.10%	5.00%	12.00%	8.10%	1.20	1.70	1.43	12	15	13.0
DK-Wind Onshore	0.80%	2.00%	1.38%	6.00%	8.00%	7.00%	1.10	1.20	1.15	10	20	18.3
EE-Wind Onshore	2.50%	6.00%	3.80%	8.00%	20.00%	13.33%	1.20	1.40	1.30	11	12	11.7
FI-Wind Onshore	1.00%	2.50%	1.67%	6.00%	8.00%	6.83%	1.05	1.50	1.29	10	19	12.6
FR-Wind Onshore	1.00%	2.50%	1.72%	4.00%	9.00%	6.92%	1.15	1.20	1.17	14	19	17.8
DE-Wind Onshore	0.76%	2.07%	1.31%	2.80%	7.80%	4.74%	1.00	1.58	1.20	18	22	19.4
EL-Wind Onshore	2.00%	7.50%	4.67%	8.00%	14.00%	11.00%	1.20	1.25	1.22	12	15	13.7
IT-Wind Onshore	1.60%	4.50%	2.44%	5.50%	10.00%	7.15%	1.05	1.37	1.18	12	19	17.0
LV-Wind Onshore	4.00%	6.00%	4.92%	17.00%	25.00%	19.17%	1.10	1.10	1.10	10	12	11.0
LT-Wind Onshore	1.60%	3.70%	2.38%	8.00%	15.00%	9.40%	1.10	1.40	1.18	5	12	10.7
NL-Wind Onshore	1.50%	2.50%	1.94%	10.00%	12.00%	11.50%	2.00	2.00	2.00	15	15	15.0
PL-Wind Onshore	2.50%	3.00%	2.76%	8.00%	10.00%	9.10%	1.20	1.50	1.44	14	15	14.7
PT-Wind Onshore	0.75%	4.27%	2.56%	5.00%	12.00%	8.01%	1.05	1.30	1.23	10	17	14.0
RO-Wind Onshore	5.00%	6.00%	5.63%	10.00%	10.00%	10.00%	1.25	1.25	1.25	10	10	10.0
ES-Wind Onshore	0.75%	4.27%	2.50%	4.00%	12.00%	7.41%	1.05	1.45	1.24	10	18	15.0
SE-Wind Onshore	1.00%	2.00%	1.70%	6.00%	8.00%	7.10%	1.15	1.40	1.24	5	18	12.1
CZ-PV	2.00%	4.00%	3.00%	5.00%	7.00%	6.00%				10	13	11.8
EE-PV	2.50%	6.00%	3.56%	7.50%	20.00%	12.19%	1.20	1.40	1.30	7	12	10.8
FR-PV	1.15%	2.00%	1.71%	5.00%	8.00%	6.00%	1.10	1.20	1.14	20	20	20.0
EL-PV	2.00%	4.00%	3.25%	8.00%	12.00%	9.50%	1.20	1.25	1.21	10	15	12.3
HU-PV	3.20%	6.00%	4.61%	5.00%	12.00%	7.15%	1.05	1.50	1.23	10	15	12.7
LV-PV	4.00%	6.00%	4.79%	17.00%	25.00%	19.89%	1.10	1.10	1.10	10	12	11.0
PT-PV	0.75%	4.27%	2.56%	5.00%	12.00%	7.76%	1.05	1.30	1.23	10	17	14.0
RO-PV	5.00%	6.00%	5.50%	10.00%	10.00%	10.00%	1.25	1.25	1.25	10	10	10.0
SK-PV	2.00%	5.00%	3.70%	10.00%	10.00%	10.00%	1.10	1.35	1.21	8	12	10.3
ES-PV	0.75%	4.27%	2.56%	5.00%	12.00%	7.76%	1.05	1.30	1.23	10	17	14.0

*In the sensitivity analysis, we round up the average loan-period values to either a lower or higher number of years, depending on the first decimal point.

Further, as shown in Table 12, we assumed EU-wide inputs for operational expenditure (O&M), mainly because of a lack of available country-level data. For onshore wind, IRENA (IRENA, 2019b) provides O&M inputs for Sweden, Germany, Denmark, and Ireland. After adjusting for inflation and currency, we average these values to obtain an OPEX of 40.03 EUR/kW/year. Regarding solar PV, we assume 10 EUR/kW/year based on IRENA (IRENA, 2019b) estimates for Germany. Our OPEX values might over- or underestimate actual country-level data. For instance, for onshore wind, IRENA (IRENA, 2019b) assumes 55.72 EUR/kW/year for 2019, while Steffen et al. (2020) derive 1.32 EURc/kWh for 2017. After converting from kWh to kW with a capacity factor of 24% and accounting for inflation, this amounts to 27.75 EUR/kW/year.

Table 12
Other investment values. Sources: [1] IRENA (IRENA, 2019b) [2] Danish Energy Agency and Energinet (Danish Energy Agency, 2020) [3] own estimate [4] Straight-line depreciation, own estimate

	OPEX	Operating time	Lead time	Depreciation
	[EUR/kW/year)	[years]	[years]	[years]
Onshore wind	40.03	25	3	20
Solar PV	10.00	30	1	20
Sources	[1]	[2]	[3]	[4]

Auction designs data

Finally, we apply auction designs to model an auction-based support framework as presented in Table 13. We derive these from an auction database that was compiled for the AURES II project (AURES II, 2020).

Table 13
Main auction designs considered in the cash flow model. Includes designs for onshore wind and solar PV. These designs reflect the most recent auction rounds until July 2020.

	Active auction framework	*Year of auction round*	*Rem. scheme*	*Support duration*	*Project realization period*	*Inflation indexation*	*Amount of bid bond*	*Amount of performance bond*
				[years]	[months]	[1 = yes, 0 = no]	[EUR/kW]	[EUR/kW]
AT-Wind Onshore	no		CfD	13	33	0	29.98	52.46
BE-Wind Onshore	no		Fix P	13	33	0	29.98	52.46
BG-Wind Onshore	no		Slid P	15	33	0	29.98	52.46

(*continued on next page*)

Table 13 (*continued*)

	Active auction framework	*Year of auction round*	*Rem. scheme*	*Support duration*	*Project realization period*	*Inflation indexation*	*Amount of bid bond*	*Amount of performance bond*
				[years]	[months]	[1 = yes, 0 = no]	[EUR/kW]	[EUR/kW]
BG-PV	no		Slid P	15	28	0	25.85	42.34
CY-Wind Onshore	no		Slid P	15	33	0	29.98	52.46
CY-PV	no		Slid P	15	28	0	25.85	42.34
HR-PV	yes	2020	Slid P	12	36	1	6.63	39.77
HR-Wind Onshore	yes	2020	Slid P	12	48	1	6.63	39.77
CZ-Wind Onshore	no		Fix P	20	33	0	29.98	52.46
CZ-PV	no		Fix P	20	28	0	25.85	42.34
DK-PV	yes	2019	Fix P	20	24	0		26.31
DK-Wind Onshore	yes	2019	Fix P	20	24	0		77.45
EE-PV	yes	2020	Fix P	12	12	0	0.93	
EE-Wind Onshore	yes	2020	Fix P	12	12	0	2.37	
FI-PV	yes	2018	Slid P	12	36	0	1.65	13.18
FI-Wind Onshore	yes	2018	Slid P	12	36	0	5.08	40.65
FR-PV	yes	2019	CfD	20	20	1		30.00
FR-Wind Onshore	yes	2020	Slid P	20	36	1	30.00	
DE-Wind Onshore	yes	2020	Slid P	20	24	0	30.00	
DE-PV	yes	2020	Slid P	20	18	0	5.00	45.00
EL-PV	yes	2020	CfD	20	36	0	10.00	30.00
EL-Wind Onshore	yes	2020	CfD	20	36	0	12.50	37.50
HU-PV	yes	2019	CfD	15	36	1	16.39	38.23
HU-Wind Onshore	yes	2019	CfD	15	36	1	21.41	49.96
IE-PV	yes	2020	CfD	15	23	0	2.00	
IE-Wind Onshore	yes	2020	CfD	15	23	0	2.00	
IT-PV	yes	2020	CfD	20	24	0	50.00	50.00
IT-Wind Onshore	yes	2020	CfD	20	31	0	55.13	55.13
LV-PV	no		CfD	17	28	0	25.85	42.34
LV-Wind Onshore	no		CfD	17	33	0	29.98	52.46
LT-Wind Onshore	yes	2019	Fix P	12	22	0	14.48	
LU-PV	yes	2020	Slid P	15	18	0		50.00
MT-PV	yes	2018	Slid P	20	18	0		50.00
NL-PV	yes	2020	Slid P	15	48	0		
NL-Wind Onshore	yes	2020	Slid P	15	48	0		
PL-Wind Onshore	yes	2018	CfD	15	30	1	14.04	
PL-PV	yes	2018	CfD	15	18	1	14.04	
PT-PV	yes	2019	CfD	15	36	0	10.00	60.00
PT-Wind Onshore	no		CfD	17	33	0	29.98	52.46
RO-Wind Onshore	no		Fix P	15	33	0	29.98	52.46
RO-PV	no		Fix P	15	28	0	25.85	42.34
SK-PV	yes	2019	Slid P	15	21	0	75.00	
SK-Wind Onshore	yes	2019	Slid P	15	39	0	75.00	
SI-PV	yes	2020	Slid P	15	36	0		
SI-Wind Onshore	yes	2020	Slid P	15	36	0		
ES-PV	yes	2017	Slid P	15	36	0	60.00	
ES-Wind Onshore	yes	2017	Slid P	15	36	0	60.00	
SE-Wind Onshore	no		Fix P	15	33	0	29.98	52.46
UK-PV	yes	2015	CfD	15	43	1		
UK-Wind Onshore	yes	2015	CfD	15	43	1		

Since we incorporate these designs into the cash-flow model in yearly time steps, we do not differentiate between multi-stage penalties and monthly differences in realization periods. Instead, we assume that all bid-bond retention penalties occur after the final realization period elapses. Furthermore, not all countries have bid bonds and penalties in the form of a fixed amount of EUR per kW. Estonia and Finland express their bid bonds in EUR/kWh, Hungary in the form of CAPEX percentages. By using country- and technology-specific CAPEX levels and capacity factors, we convert these into EUR/kW. Finally, only a few countries express their penalties in forms other than the retention of the submitted bid bond and performance bond. France applies a two-stage support-level reduction for its solar PV auction (0.00025 EUR/kWh in the first stage and 0.005 EUR/kWh in the second stage), while Germany applies a one-stage reduction for solar PV of 0.005 EUR/kWh. Ireland is the only country that applies a support-duration penalty, equal to a one-year reduction. While most countries apply their bid-bond retention penalties after the final realization period elapses in a single blow, Germany imposes a three-stage bond-retention penalty in the case of onshore wind, while Hungary and Slovakia apply this type of penalty in two stages for both onshore wind and solar PV.

Detailed country results

Fig. 13 gives the results of our sensitivity analysis for all 34 country-technology cases in the scenarios we presented in Table 1.

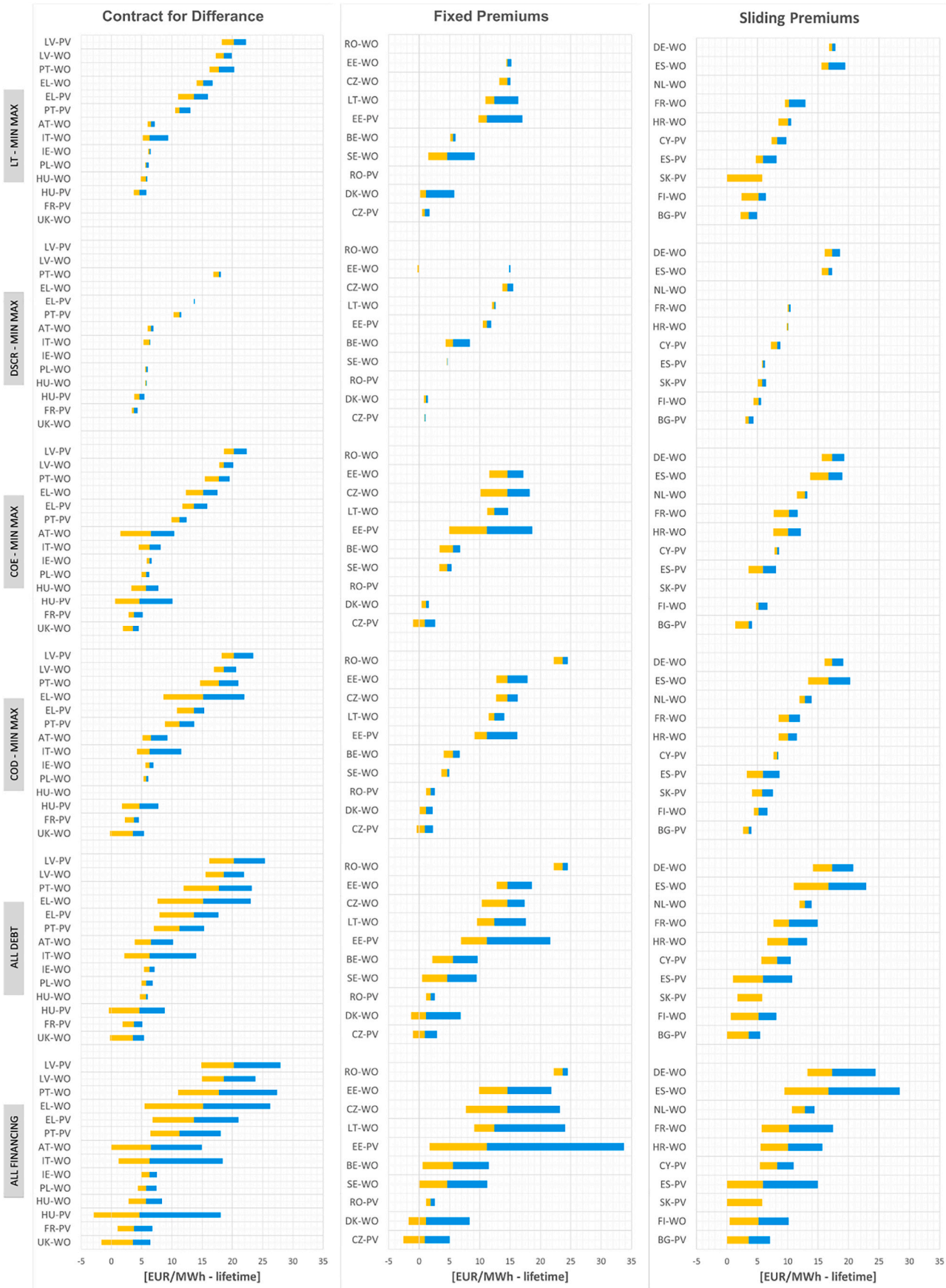

Fig. 13. Detailed country-level results from changing individual financing and technology variables in all countries and for all technologies.

Impact of country risk on costs of equity

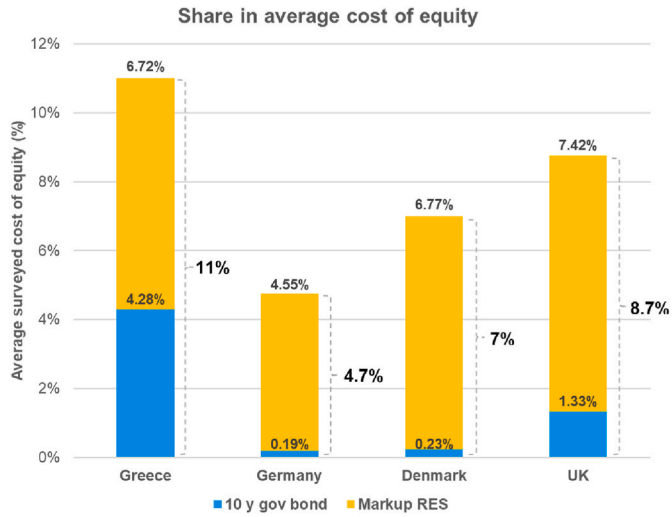

Fig. 14. Impact of country risk on the costs of equity for onshore wind projects in selected markets.

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