Discount and hurdle rates: the dark horses of capacity expansion planning

Smaranda Sgarciu[1] Author, Iegor Riepin, Felix Müsgens Co-Authors

Siemens-Halske-Ring 13, +49 (0) 355 69 4513, smaranda.sgarciu@b-tu.de,

https://www.b-tu.de/fg-energiewirtschaft/team/mitarbeiter/smaranda-sgarciu

Abstract:

Discount and hurdle rates are part of the input data in each state-of-the-art capacity expansion model, but these parameters do not receive adequate attention compared to the impact they have on model outputs. In this paper, our contribution is threefold. First, we analyse the impact of hurdle rates in a state-of-the-art bottom-up optimization model for the European electricity market. Second, we quantify the impacts caused by the choice of social discount rates on the investment mix. Finally, we illustrate a range of energy system development pathways resulting from assumptions on hurdle rates, social discount rates and three settings of demand, fuel price and CO_2 price development.

We show that hurdle rates significantly impact technology pathways. In particular, lower hurdle rates favour investment in renewable sources, hence leading to a system with lower carbon emissions intensity. Regarding the second objective, we highlight that technologies such as wind onshore experience a prominent decline in investments with increasing discount rate. The impacts caused by the choice of the discount and hurdle rates are illustratively compared with those caused by the choice of other uncertain input parameters, such as electricity demand, fuel and CO_2 prices.

Our findings indicate that careful consideration of these factors and understanding how they affect model outputs is of paramount importance for modelling exercises that aim for long-term policy planning. A key policy result of our study is that low discount rates fostered by the European Central Bank help to achieve current climate and energy targets. Our illustrative modelling example and conclusions are relevant for both energy modellers and policy makers with an interest in European energy markets.

Keywords: Capacity Planning, Electricity Market, Discounting, Uncertainty

[1] Young author

1 Introduction

Nowadays, energy research and policy consulting often rely on optimization models for energy markets. One of the pillars of energy systems optimization—capacity expansion models—aim to find the optimal energy infrastructure investments under a certain set of system parameters, e.g., electricity load, renewable energy sources (RES) infeed, carbon and fuel price developments, and policy regulation. Driven by the wide use of optimization for modern world energy- and climate challenges, academic literature has extensively investigated the effects of these parameters on energy models (Weber and Swider, 2004; Nagl *et al.*, 2012; Schröder, 2014; Steffen, 2020).

However, *discount rates* and *hurdle rates* are two factors which do not receive adequate attention in the literature given their undeniable impact on model outputs and resulting policy takeaways.

The existing literature on discount and hurdle rates focuses primarily on two aspects: the possible values that both parameters can take and the impact of varying these parameters at regional level.

(Simoes *et al.*, 2013) describe the JRC-EU-TIMES bottom-up linear optimization model. The authors outline that technology-specific values used for the hurdle rate are classified by sector or technology groups, while discount rates values are employed globally. (Hermelink and de Jager, 2015) discuss discrepancies in the discount rates in the context of PRIMES model, when modellers take into account the Energy Efficiency Directive. They set out to determine that countries preferring a “social” point of view on the discount rate choose a value of 3.3%, while member states with a “financial” point of view on the metric elect a value of 5.7%.

(Kannan and Turton, 2012) use the TIMES model to assess Swiss nuclear policy. The authors implement two estimations for hurdle rates, while they vary the global discount rate across three estimations. In the assessment of the Indian electricity market, (Mallah and Bansal, 2011) conduct a sensitivity analysis on both parameters. They conclude that a higher hurdle rate changes the technology mix, as it becomes more complicated for efficient technologies to penetrate the market and lower discount rates favour hydro power technologies, while coal technologies are preferred with higher discount rates. A recent study by (García-Gusano *et al.*, 2016) investigated the European electricity generation mix and total system costs using different discount rates and two types of hurdle rate estimations. The authors also look into the Norwegian generation and electricity trade and find that lower social discount rates increase the contribution of renewable energy sources, while a higher discount rate leads to a system dominated by fossil plants.

The literature discussed above is based on various parametrizations of DR and HR. We systematize the effect on energy system models caused by the choice in discount and hurdle rates, which are later reflected in policy takeaways.

1.1 Discount and hurdle rates

As the concepts of discounts and hurdle rates are central for this paper, it is worth making an exact definition for each concept.

The *Hurdle Rate* (HR) refers to the lowest expected rate of return for investing into a technology, which is completed during the economic lifetime of the facility (Mellichamp, 2017).

Therefore, the change in this parameter is impacting the annuity calculation and has a stronger effect on capital intensive technologies such as nuclear and the vast majority of renewable technologies. As this parameter reflects the investor's view of how assets are discounted in the future, the associated risk influences the value of the HR.

According to Boudt (2021), a higher hurdle rate can be directly correlated to the willingness of banks to offer debt financing, which depends on the technology type considered in the investment. Change in producer and consumer preferences, as well as policy and market design can also alter the valuation of hurdle rate. Policy alterations such as support schemes for RES generation, limitations on carbon intensive facilities and requirements for shares of gas-fired power plants can lead to shifts in the profitability of such technologies and implicitly their risk evaluation. Other market design and temporal characteristics are generally seen as important driving factors in the evaluation of hurdle rate. Provided that the investment project has a time horizon of less than three years or it benefits from a capacity remuneration mechanism, investors should perceive a very low hurdle rate. In contrast, increasing the investment time horizon would expand the scale for the hurdle rate.

Figure 1 depicts the main influencing factors of hurdle rates based on the risk type. It reveals that both systematic risk agents, which are intrinsic to the market and influence the cost of equity, as well as non-systematic risks i.e. the one which is associated to the type of technology are accounted in the computation of this metric. However, the resulting valuation can differ from the investor's choice, since the latter depends on the implied risk attitude and financial constraints.

The social *Discount Rate* (DR) indicates the time dependent decrease in the future cash flows of a social planner reported to the present time[2] (Karp and Traeger, 2013). It reflects the willingness to trade-off the future economic benefits to the current time. From the modelling perspective, DR affects both the investments and the operational costs.

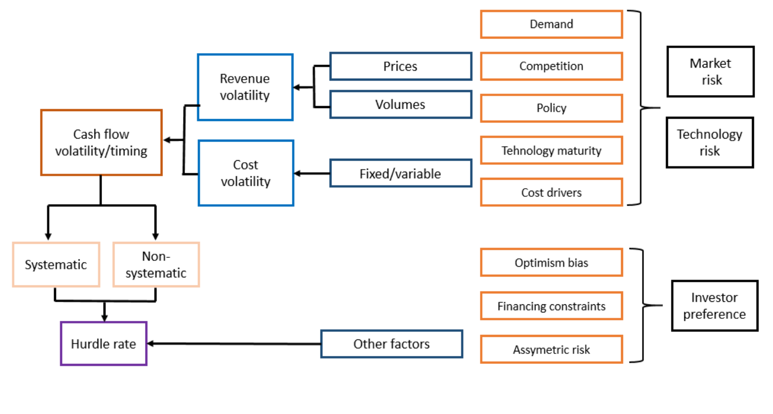

Figure 1: Determinants of investor hurdle rates. Adapted after: (Oxera Consulting Ltd, 2011)

A number of factors are known to affect the valuation of the discount rate. Policy related constituents, such as monetary policy conducted by central banks and tax policy related elements e.g. loans. Other macroeconomic components, such as gross domestic product, inflation, exchange rate may also modify under the course of project completion (Grzech, 2015). Considering the previously mentioned factors, it is likely that the discount factor might vary over the project

[2] Discount rates can be clustered into behavioural, social and real market-based discount rates. In this paper, we focus on the social discount rate as we look at the benefits on the energy market from a social standpoint.

planning and realization time and its fluctuation should be taken into account. To determine how various firms undergo their investment decisions, (Meier and Tarhan, 2011) conduct a study on how the asset related cash flows are estimated. The presented evidence suggests that hurdle rates estimated by investors surpass their weighted average cost of capital most of the time and firms usually do not update their HRs periodically, which can cause underinvestment or overinvestment. Authors also point out that investors are not successfully determining discount rates.

1.2 Contribution

Whereas the previous listed studies exercise different evaluations of these metrics, not enough attention is brought to the effects that discount and hurdle rates have on model outputs in combination with other uncertain parameters.

In this paper, our contribution is three-fold. First, we analyze the impact of disregarding technology-specific hurdle rates in a state-of-the-art bottom-up optimization model for the European electricity market. This exercise accounts for the fact that hurdle rates for power generation capacity are *different* among technologies, as investment projects face different types of risks. Previous studies have not dealt with three risk-based estimates of whole project hurdle rates, even though certain technologies are either affected by shifts driven by market price volatility or by key factors such as project success rates. Secondly, we quantify the impacts caused by the choice of social discount rates on the shift in investment capacity. This exercise accounts for the fact the evaluation of the social discount rate and its consequences on technological preferences and policy goals is a challenging issue that is often left to the modeler. Finally, we illustrate a range of energy system development pathways resulting from assumptions on both the hurdle rates and social discount rates.

We contribute to the policy discussion on the evaluation of these input parameters as instruments for reducing CO_2 emissions. A number of factors related to both the capital costs and the marginal running costs are known to affect the investment volumes and type of technology to be invested in.

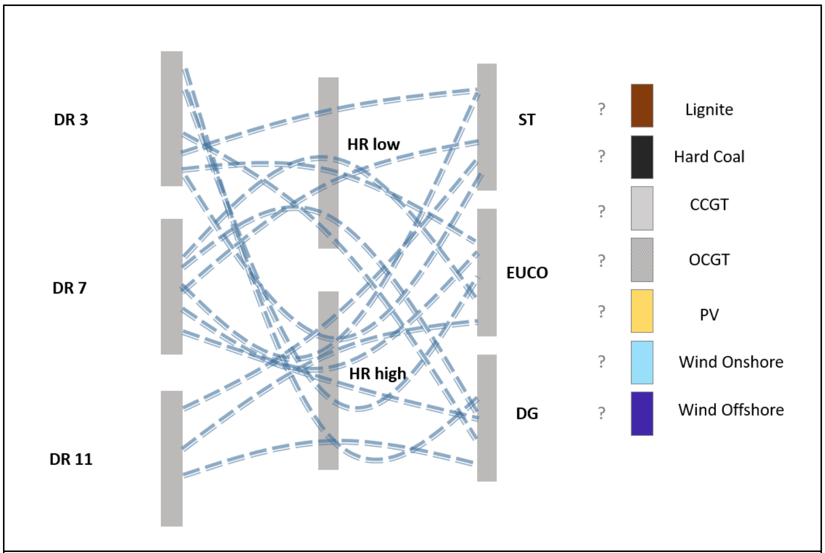

Figure 2: Using Sankey diagram to accentuate which parameter combination will lead to certain investments

We designate the main stream combinations, which lead to investments into low carbon intensive facilities, therefore contributing to a more decarbonized energy system. We perform this by means of a Sankey diagram as depicted in ***Figure 2***, which establishes the volume of each technology based on the possible links between the nodes. In the first level, three viable discount rates are interlinked to two nodes i.e. represented by the low and high risk technology-based hurdle rate. They in turn are connected to the three energy future scenarios, with distinct marginal costs.

1.3 Broad Structure

The remaining part of our paper proceeds as follows: chapter 2 describes the composition of our dynamic investment model along with the data and model equations; chapter 3 analyses the investment results for our different discount rates, hurdle rates and energy futures scenarios and at last the chapter 4 lays out the corresponding conclusions.

2 Methodology

2.1 The Investment Model

The bottom-up investment optimization models is a well-established methodology in research focusing on the electricity markets (Nguyen, 2008; Weijde and Hobbs, 2012; Georgiou, 2016; Riepin, Möbius and Müsgens, 2021). The objective functions of these models are based on discounted cash-flows, making the choice of input parameters an essential one. We initiate our analysis with the computation of annuity, which encompasses the overnight construction costs i.e. the costs captured as if the entire payment would be spent by the vendor overnight.

We optimize a greenfield cost-minimization model[3] which determines investments into conventional and renewable technologies endogenously. The model is formulated as a linear program (LP) which minimizes the total system costs in partial equilibrium for the European electricity sector. For computing this problem, we use the General Algebraic Modeling System (GAMS) and the CPLEX solver. Starting from the basis year 2020, the model optimizes the investments in a dynamic manner with a five-year step until 2030.

The hurdle rate accounts for the risk-based factor attributed to each technology, which is raised to the power of the technical lifetime t.

$$Annuity\ = HR \cdot \frac{Costs_{overnight}}{(1+HR)^t} \tag{1}$$

To discount the cash flows for 2025 and 2030 to the net present value of the reference year, the discount factor is calculated as in equation (2)[4].

$$DF = \frac{1}{\left(1+DR_y\right)^{(y-1)*n}} \tag{2}$$

The geographical resolution consists of nineteen nodes, as the Balkan, Baltic and Iberian countries are integrated into a single node. The resulting investment model is complex and we run many scenarios for discount, hurdle rates and energy futures, so we have to tackle the computational complexity by temporal sampling.

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[3] Storage and hydropower technologies are implemented exogenously using the existing capacity from our established energy future estimations.

[4] Where y signifies the current year and n the time step between years.

The methodology used for our representative hours' series is presented in Annex A: Reducing computational complexity.

2.2 Mathematical formulation

Nomenclature

Abbreviation	*Dimension*	*Description*
Model sets		
i		*Technology*
n		*Node*
nn	*Alias of n*	*Node*
s		*Scenarios for energy futures*
t		*(Representative) hours*
y		*Year*
conv(i)	*Subset of i*	*Conventional technology*
psp(i)	*Subset of i*	*Pump storage*
res(i)	*Subset of i*	*RES technology*
$reservoir(i)$	*Subset of i*	Water reservoir
Model parameters		
AF	*%*	*Availability factor*
$CAP_{i,n,y,s}^{existing}$	*MW_{el}*	*Existing capacity for pump storage and reservoir*
$CAP_{i,n}^{max}$	*MW_{el}*	*Maximum attainable capacity*
CC	*tCO_2/MWh_{th}*	*CO_2 emission factor per fuel consumption*
CHP	*MWh_{el}/h*	*Minimum electricity generation by combined heat and power (CHP) plants to fulfil heat supply requirements*
CPF	*h*	*Storage capacity-power factor*
$DEMAND$	*MWh_{el}/h*	*Electricity demand*
DF		*Discount factor*
HR		*Hurdle rates*
IC	*€/MW_{el}*	*Annual investment costs*
NTC	*MW_{el}*	*Net transfer capacity*
P^{CO2}	*€/ t CO_2*	*CO_2 price*
PF	*%*	*Hourly production factor for RES*
$SHED^{max}$	*%*	*Maximum shedding factor*
VC	*€/MWh_{el}*	*Variable generation costs for electricity*

$VOLA$	€/MWh$_{el}$	*Value of lost adequacy (the cost for load shedding)*
η	%	*Efficiency of generation or storage technology*
Model variables		
cap	MW$_{el}$	*Investments in electricity generation capacity*
$charge$	MWh$_{el}$/h	*Pumping water into the pumped-storage plants (PSP) reservoir*
$flow$	MWh$_{el}$/h	*Electricity flow between nodes*
g	MWh$_{el}$/h	*Electricity generation*
oc	MW$_{el}$	*Operational costs*
$shed$	MWh$_{el}$/h	*Load shedding for electricity*
sl	MWh$_{el}$	*Storage level of PSP*
su	MW$_{el}$	*Start-up decision*
tc	€	*Total system costs*

Objective function

Objective function **(3)** minimizes the total expected discounted capital and operating costs for the electricity sector:

$$\min \mathrm{TC} = \sum_{\mathrm{s}} \mathrm{OC_s} + \sum_{\mathrm{i,n,y,s}} \mathrm{DF_y} \cdot \mathrm{cap_{i,n,y,s}} \cdot \mathrm{IC_i} \tag{3}$$

$$OC_s = \sum_{s,y} \cdot DF_y \cdot \left(\begin{array}{c} \sum_{i,n,t} \left(g_{i,n,t,y,s} \cdot VC_{i,n,t,y}\right) \\ + \sum_{n,t} \left(shed_{n,t,y,s} \cdot VOLA_n\right) \end{array} \right) \tag{4}$$

Corresponding system constraints

Equation	Domain	Eq.
As primary restriction, **Eq. (5)** establishes the market clearing under the condition that electricity demand in every node is met at each point in time: $DEMAND_{n,t,y,s} = \sum_{conv} g_{conv,n,t,y,s} + \sum_{res} g_{res,n,t,y,s} + shed_{n,t,y,s} + \sum_{nn}\left(flow_{nn,n,t,y,s} - flow_{n,nn,t,y,s}\right)$	$\forall n,t,y,s$	(5)
Eq. (6) ensures that the hourly load shedding is restricted for the specific demand: $shed_{n,t,y,s} \leq DEMAND_{n,t,y,s} \cdot SHED^{max}$	$\forall n,t,y,s$	(6)
Eq. (7)-(11) define the availability limitations for both the conventional and the renewable capacities. Since the model is designed on a time frame of 10 years, a yearly interdependency is required. **Eq. (7)** guarantees that the new generation capacity from the previous year is present in the subsequent year. Since our approach is a greenfield one, **Eq. (8)** restricts the conventional generation only to the newly invested capacity and the availability factor. **Eq. (10)** does the same for the		

reservoir generation. The restriction **(9)** - analogous to the latter, but for RES technologies determines the periodical infeed, while taking into account the hourly production factor. **Eq. (11)** considers political or technical restrictions on investments in specific technologies (e.g. nuclear or coal phase-out):

$$cap_{i,n,y-1} \leq cap_{i,n,y} \qquad \forall\, i,n,y \tag{7}$$

$$g_{conv,n,t,y,s} \leq cap_{conv,n,y,s} \cdot AF_{i,n} \qquad \forall\, n,t,y,s \tag{8}$$

$$g_{res,n,t,y,s} \leq cap_{res,n,y,s} \cdot PF_{res,t,n} \qquad \forall\, res \in i,\; n,t,y,s \tag{9}$$

$$g_{reservoir,n,t,y,s} \leq CAP^{existing}_{reservoir,n,y,s} \cdot AF_{reservoir,n} \qquad \forall\, reservoir \in i,n,t,y,s \tag{10}$$

$$cap_{i,n,y,s} \leq CAP^{max}_{i,n} \qquad \forall i,n,y \tag{11}$$

Eq. (12)–(14) outline the implementation of the storage systems**.** Eq. (12) delimitates the maximum storage level**.** Eq. (13) declares in which state the storage level is at the end of hour ***t*.** Eq. (14) defines the maximum charging capacity:

$$sl_{psp,n,t,y,s} \leq \left(CAP^{existing}_{psp,n,y,s} + cap_{psp,n,y,s}\right) \cdot CPF \qquad \forall n,t,y,s \tag{12}$$

$$sl_{psp,n,t,y,s} = sl_{psp,n,t-1,y,s} - g_{psp,n,t,y,s} + charge_{psp,n,t,y,s} \qquad \forall n,t,y,s \tag{13}$$

$$charge_{psp,n,t,y,s} \leq CAP^{existing}_{psp,n,y,s} + cap_{psp,n,y,s} \cdot AF_{psp,n} \qquad \forall n,t,y,s \tag{14}$$

Eq. (15) defines an annual boundary for generation produced by **reservoirs:**

$$\sum_t g_{reservoir,n,t,y,s} \leq CAP^{existing}_{reservoir,n,y,s} \cdot FLH \qquad \forall n,y,s \tag{15}$$

Eq. (16) states that gas-fired power plants are restricted to produce a certain amount due to country-specific CHP requirements:

$$CHP_{n,t,y} \leq \sum_{gas} g_{gas,n,t,y,s} \qquad \forall n,t,y,s \tag{16}$$

Eq. (17) constrains cross-border electricity trading:

$$flow_{n,nn,t,y,s} \leq NTC_{n,nn,y} \qquad \forall n,nn,t,y,s \tag{17}$$

2.3 Data

Hurdle rates

Data about technology-specific hurdle rates is limited. We opt for a risk-based analysis provided by (NERA, 2015), which lists projections for 2030. In this study, sub-categorical technologies, such as Open Cycle Gas Turbines (OCGT) and Combined Cycle Gas Turbines (CCGT) are assumed to face the same hurdle rate values, due to scarcity on corresponding data.

Most studies of technology-specific hurdle rates have only been carried out for a technological niche or certain technology classes i.e. conventional, dispatchable or non-dispatchable renewable plants. (Oxera Consulting Ltd, 2011) undergoes a survey on low carbon generation technologies and identify that hurdle rates are extensively different between individual renewable utilities. (Simoes *et al.*, 2013) provide hurdle rate estimates for coal and oil technologies used in the TIMES Model and the templates EFDA-TIMES and ETSAP-TIAM contain a different hurdle rate estimate depending on the technology scale (Grohnheit, 2013).

According to (BEIS, 2018), hurdle rates estimates for 2018 experience a major drop compared to 2015 values, when it is assumed that contracts for difference are available for most considered technologies, but it is not the case when technologies are employed on a merchant basis.

The choice of our hurdle rate scenarios is based on (NERA, 2015), which incorporates systematic and idiosyncratic risk-based projections for 2030, either inherent to the investor or determined by market and policy, contingent on technology type. All projects face allocation risk, but features such as market price volatility constitutes a risk factor for conventional technologies. Policy risks might affect mostly carbon intensive utilities which are expected to phase-out i.e. generation fuelled by uranium and coal, or renewable technologies through change in subsidy scheme. Supply and demand circumstances as well as governmental actions can lead to jumps in both the carbon and fuel price, which attributes another risk for coal fired plants.

Table 1: Input parameters for the hurdle rate scenarios

Technology-specific hurdle rates	Low risk	Medium risk	High risk
Nuclear	10.5%	12.4%	17.4%
Lignite	8.9%	10.2%	19.4%
Hard Coal	8.9%	10.2%	19.4%
Combined cycle gas turbine	8.0%	12.2%	15.3%
Open cycle gas turbine	8.0%	12.2%	15.3%
Pump storage hydro power plant	8.4%	10.2%	12.0%
Reservoir	8.4%	10.2%	12.0%
Solar photovoltaic	6.9%	8.5%	13.4%
Wind onshore	7.5%	8.7%	13.3%
Wind offshore	9.3%	10.9%	14.2%
Biomass	11.0%	11.9%	19.4%

Discount rates

A number of studies have postulated a range for discount rates. (Burgess and Zerbe, 2013) recommend of discount rate in the range of 6 to 8% for governmental projects, while (Kannan and Strachan, 2009) implement a value of 3% for their residential sector model. (Mallah and Bansal, 2011) vary the metric from 6.5% to 15% and (Simoes *et al.*, 2013) consider the public sector system and imply an overall rate of 5% for their model.

Our range of discount rates has been broadened for the purpose of capturing the repercussions on the investment mix. We use uniform values across all technologies ranging from 3 to 15 %, as shown in *Table 2*.

Table 2: Input parameters for the discount rate scenarios

Discount rates	3%	5%	7%	9%	11%	13%	15%

Energy future scenarios

The other input data in our model, such as the fuel costs, the carbon price and the electricity demand, are parametrized according to the scenarios developed by the European Transmission System Operator in the Ten Year Network Development Plan (TYNDP) report (ENTSO-E and ENTSOG, 2018).

We include the European Commission core policy scenario (EUCO), the sustainable transition (ST) and the distributed generation scenario (DG) for 2030. For 2020 and 2025, the best estimate (BE) scenario is used.

The EUCO scenario uses as basis the European Union reference scenario in the PRIMES model and is focuses on the realisation of climate and energy targets, as well as accomplishing a 30% energy efficiency aim by 2030. To sustain the implicit targets, high fuel prices are implemented for the carbon intensive technologies, 8.27 €$_{2030}$/MWh$_{th}$ for brown coal and 15.47 €$_{2030}$/MWh$_{th}$ for hard coal, but the lowest carbon price out of the three scenarios, namely 27.0 €$_{2030}$/t CO_2.

A decentralised evolution of the energy system is envisioned for the DG scenario, which is concentrated on the end-user utilities. The storyline presumes that consumers will switch their appliances according to the smart time of use electricity tariffs along with using smart devices and dual fuel appliances. Moreover, the building sector benefits from a high share of renewables, especially photovoltaics (PV) and storage systems[5]. Overall, the scenario has the highest renewable systems penetration accompanied by the highest demand and a medium level carbon price of 50 €$_{2030}$/t CO_2.

In the electricity sector of the ST scenario, hard coal and lignite capacities are shifted down by gas installations, as a means to reduce CO_2 emissions. For the transportation sector, gas replaces some oil consumption for conventional fuels. These replacements cause the highest peak and total demand for natural gas utilities along with very high 84.3 €$_{2030}$/t CO_2.

Other data

To parametrize the greenfield pan European investment model for both the conventional and the renewable power plants, we use assumptions for two key inputs used in the calculation of annuity: overnight cost projections are taken from (Held *et al.*, 2014) and the development of technical lifetime extension for RES facilities as projected by (Wirth, 2017; IRENA, 2019a) for solar PV, (Müsgens and Riepin, 2018) for wind offshore and (Ziegler *et al.*, 2018; IRENA, 2019b) for onshore wind assets.

[5] From the storage technologies portfolio, batteries have the highest share in the system.

Scenario correlation

As considered in the introduction, the discount rate regards the preference of society and how costs and cash flows are discounted in the future. The outlook on hurdle rate is similar, but with respect to the investor i.e. investors have the same preference as society in general. In spite of this supposition, investors face risks which are directly correlated to the type of facility they are willing to invest in, therefore there is a mark-up between the risk-based hurdle rate and the social discount rate. It is important to note that our results will only depict the correlation of discount rates which are lower or equal with the scenario based hurdle rates.

3 Results and discussion

The modelling exercise conducted for this paper includes three degrees of freedom: a choice of the hurdle rate, a choice of the discount rate, and a certain way how other system parameters develop (energy future). To isolate the effects of both factors, we structure our results section into the following three headings. First, we illustrate how the choice of the technology-specific hurdle rates affects the key outputs of investment optimization model for electricity market; while fixing the value of a discount rate. Second, we illustrate how the choice of the discount rates affects the same model outputs; similarly fixing the value of a hurdle rate. Finally, we analyse the range of energy system development pathways that arise from possible combinations of the two factors. All three analyses are performed considering three energy futures, i.e., future developments of electricity demand, fuel and carbon prices, which are parametrized based on the three TYNDP scenarios for 2030. The investigation focuses on the European electricity generation mix and emission intensity only.

3.1 The impact of hurdle rate

In this section, we show how the choice of the technology-specific hurdle rates affects the key outputs of investment optimization model for electricity market. The key outputs include (i) investments in generation capacity, and (ii) carbon emission intensity of the investment mix. To isolate this effect, we fix the value of the discount rate to 5%.

Figure 3 presents the model results for investments in generation capacity. The results show that increasing hurdle rates substantially penalizes the capital-intensive technologies. The shift of investments is more remarkable for renewable energy sources than conventional technologies when a higher risk-based hurdle rate is applied. Thus, wind offshore

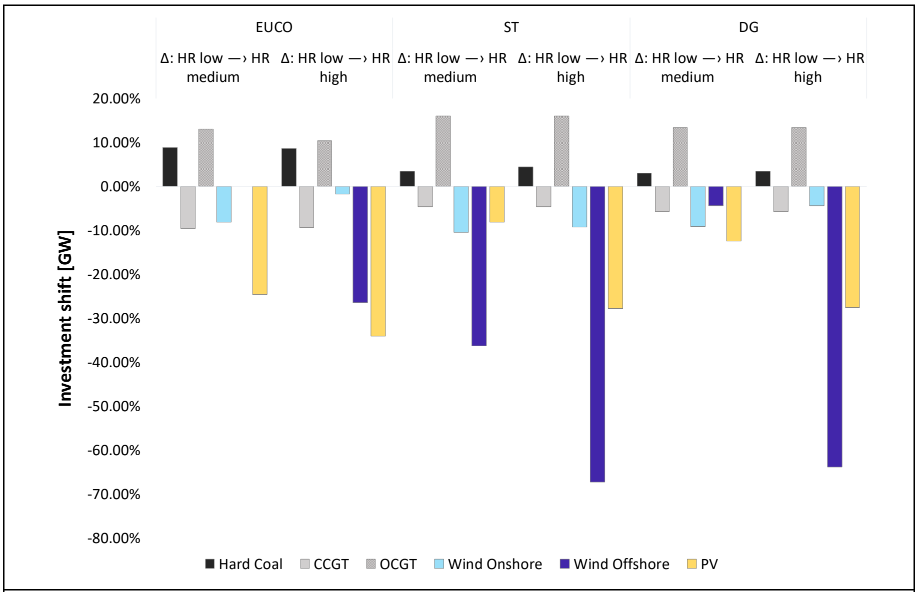

Figure 3: Shifts of investment mix relative to low risk HR scenario, keeping DR constant at 5%.

undergoes the most prominent reduction of its share in the optimal investment mix – 26% in the EUCO, and up to 64% and 67% in the DG and ST energy futures, respectively. Solar PV experiences a drop up to 35% in the EUCO setting, with a smaller change in the other two energy futures. Increasing the hurdle rate also unambiguously reduces investment in wind onshore technology, but the effect is smaller than for wind offshore and photovoltaics.

Investment in hard coal technology, on the contrary, increases with higher hurdle rates. The effect is of similar magnitude whether a medium risk or a high risk value is chosen – the investment raise by 9% in the EUCO scenario, and by 5% and 4% in the ST and DG, respectively.

For gas-fired power plants, the effect is twofold. Investment in OCGT plants increases higher values of the HRs. The effect is the most notable in the ST setting, in which the investment capacity raises by 16%. The CCGT plants experience very little change in the investment mix though. Lignite fired power plants appear to be unaffected by the change in hurdle rate for these three settings.

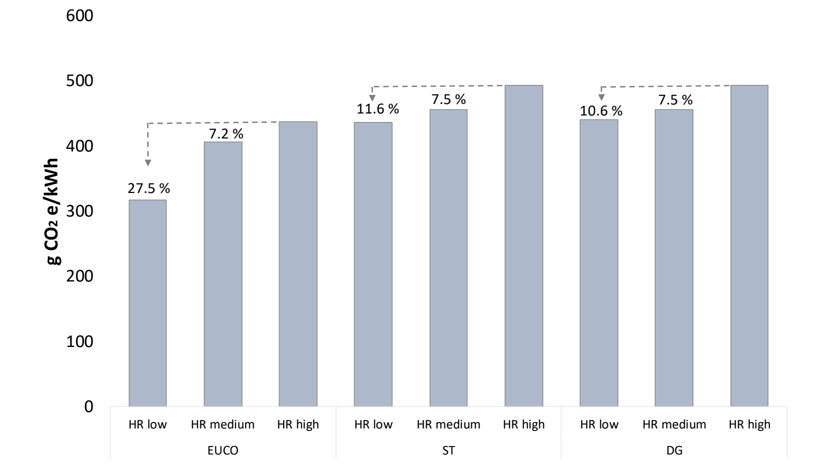

Figure 4: Carbon emission intensity of the investment mix.

In ***Figure 4*** we present the carbon emission intensity of the previously depicted investment mix.

For all of TYNDP energy future projections, a lower hurdle rate results in a system with lower emission intensity. We use the carbon emission intensity of the HR high scenario as a reference level. Both ST and DG exhibit a similar emission reduction path with lower hurdle rate (ca. 10%-11%). This effect originates from the optimal technology mix for both scenarios, which include a high share of zero-emitting renewables. In the EUCO setting, a low hurdle rate causes a remarkable fall of the carbon emission intensity at ca. 27%. This is explained by the large RES shares in the system, but also the low amount of coal-fired power plants present in EUCO, as this setting has the highest fuel price for coal technologies.

3.2 The impact of discount rate

In this section, we show how the choice of the discount rates affects the key outputs of investment optimization model for electricity market. Similar to previous section, we narrow down our focus on investments in generation capacity and carbon emission intensity of the investment mix. To isolate the effect of discount rate, we fix the value of the hurdle rate to high risk technology-specific hurdle rate (see *Table 1*).

Figure 5-***Figure 7*** depict the model results for investments in generation capacity for six discount rate values, in a range from 3% to 15%. The results show that the effect of discount rate on investment mix is highly heterogeneous across energy futures.

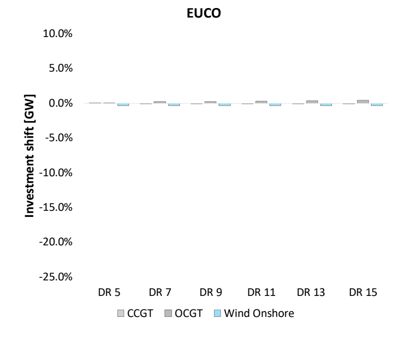

Figure 5: Shifts of investment mix in relative terms based on [DR = 3%] scenario in EUCO setting.

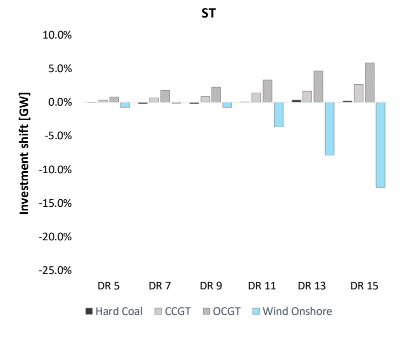

Figure 6: Shifts of investment mix in relative terms based on [DR = 3%] scenario in ST setting.

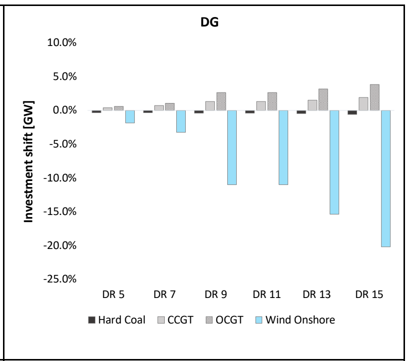

Figure 7: Shifts of investment mix in relative terms based on [DR = 3%] scenario in DG setting.

In the EUCO energy future the choice of the discount rate has a negligible effect on the investments.

In the ST setting, the results show a prominent decline of wind onshore investments with increasing DR, up to 13% when DR=15%. The gas fired plants experience the opposite effect, with an increase in investment up to 3% for CCGT and 6% for OCGT.

The DG setting exerts a similar pattern. Wind onshore investments drop by 20%, while CCGT and OCGT investments increase just 2% and 4%, respectively.

Note that these results are obtained in the modelling exercise that aims to illustrate sensitivity of an investment mix to different DR inputs, while keeping HR fixed to high risk technology-specific value. Thus, the modelling exercise illustrates the general trend of our results; however, it is just a snapshot of possible investment mixes, e.g., Solar PV are not invested in this scenario at all.

3.3 Discount rates, hurdle rates and energy futures: possible energy system development pathways

In this section, we analyse the overlapping effects of the three degrees of freedom discussed above: a choice of the hurdle rate, a choice of the discount rate, and a certain way how other system parameters develop (energy futures). For that we make 18 model runs for combinations of three (selected) discount rates, two (selected) hurdle rates and three TYNDP's energy futures.

Each line in ***Figure 8*** represents an investment decision in GW made into one of the seven endogenously optimized technologies within the 18 model runs. Overall, such visualisation is helpful to track down how a certain combination of these parameters leads to different investments mixes. ***Figure 8*** generalizes the trends discussed in chapters 3.1 and 3.2, which presented only the selected combinations of discount and hurdle rates.

Discount rates below 7% in combination with low hurdle rates drive most of the investment in RES. Especially the ST scenario sees significant capacity additions of wind onshore, offshore and PV. However, both EUCO and DG also show significant investment in wind onshore and PV for such levels of the hurdle rate.

Gas-fired power plants are predominantly invested in the ST and in the EUCO scenario, as these present the lowest gas prices from the entire setting. In ST, they overshadow other technologies when the hurdle rate is low and the DR is 7% and more so in the EUCO scenario with high hurdle rate and high discount rate, namely 11%.

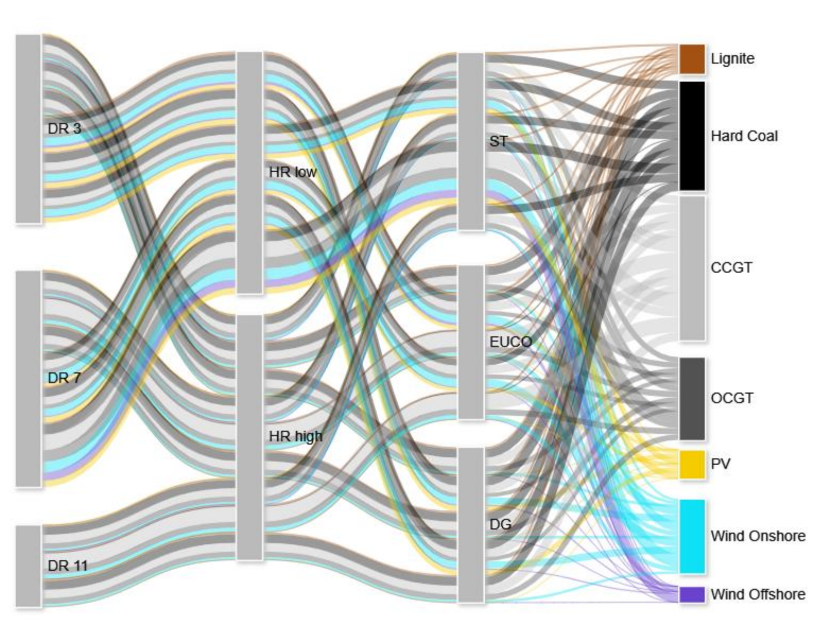

Figure 8: Sankey diagram depicting the distribution of the investment flows for each technology

Investments into hard coal are strongly related to a low hurdle rate and medium ranged discount rate in ST, but they also benefit from the lowest fuel prices in this setting. Lignite is the only technology which is not predominantly preferred in by any of the three-levelled parametrization.

4 Conclusions

This paper focuses on the particularly important assumptions for every investment optimization model for electricity markets—the social discount factors and the hurdle rates. We assess how the choice of these factors impacts the energy system development pathways. The modelling exercise is conducted for the generation capacity expansion model for Europe and considers the three possible energy futures based on TYNDP parametrization.

Our results show that renewables are the most affected generation technology by the risk component of the hurdle rate. This effect is especially prominent for offshore wind and solar photovoltaic, which decrease up to 67% and 35%, respectively, if the high hurdle rate scenario is benchmarked with the low risk. The findings of this study suggest that lower hurdle rates facilitate larger shares of renewable technologies in the optimal investment mix. Conversely, higher hurdle rates increase the conventional technology quota in the system. These results add to the rapidly expanding field of energy system decarbonisation, as lower hurdle rates also facilitate lower carbon emissions intensity.

A policy takeaway is that low discount rates fostered by the European Central Bank[6] make climate and energy targets attainable.

[6] The institution responsible for the monetary policy of the European Union member states.

A modelling takeaway is that a choice of risk-based hurdle rate exerts substantial influence on the key outputs of the investment optimization models, such as the investment mix and the system's carbon emission intensity. Our results illustrate that selecting a certain combination of discount and hurdle rate might lead to a system configuration which favours RES installations or to one that is mainly dominated by gas- and coal-fired technologies.

Overall, our findings indicate that assumptions for discount and hurdle rates should be carefully considered for any modelling with empirical interest. Understanding how these parameters affect model outputs is of paramount importance for any modelling exercises that aim for long-term policy planning. As most capacity expansion models introduce discount and hurdle rates exogenously, we advise that valuations of both metrics are taken under careful and justified consideration followed by sensitivity analysis.

The study is limited by the lack of information on the behaviour of storage technologies and hydroelectric generators with regard to discount and hurdle rates, as these technologies were implemented exogenously. In spite of its limitations, the investigation certainly adds to our understanding of the effects that hurdle and discount rates have on the investments in conventional and renewable generating technologies. The issue of discount and hurdle rates is an intriguing one which could be usefully explored to assess multiple model outputs such as total system costs and trade in further research.

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Annex A: Reducing computational complexity

The resulting investment model is complex and we run many scenarios for discount and hurdle rates, therefore we tackle the computational complexity by temporal sampling. we use a reduced time series of 351 hours, by sampling the full time set every 25th hour. The key factor is capturing seasonal fluctuations and the daily variations of the residual load. We analyse the difference in the minimum, maximum and standard deviation of the residual load between the full time series (8760 hours) and the reduced set. The hour with the minimum difference for the three metrics is chosen as the optimum series of representative hours. ***Figure 9*** depicts the residual load in Germany for the first 500 hours of the year. The full time series is compared to the reduced time sets starting with hour 1, 11, 12 and 13.

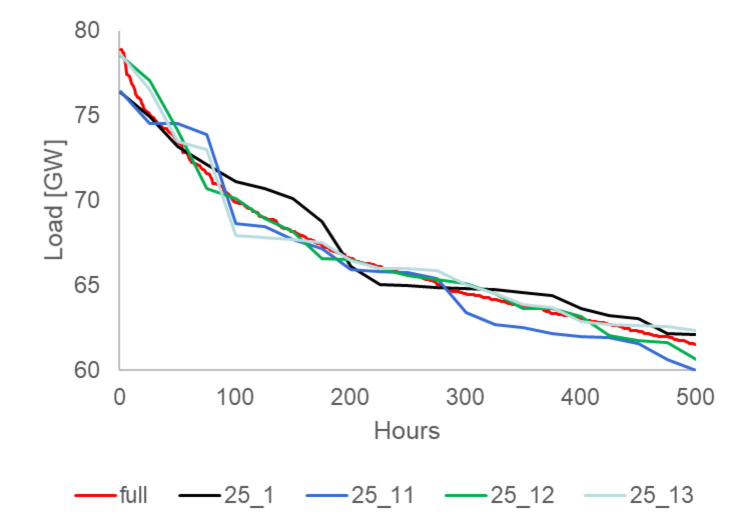

Figure 9: Residual load duration curve for the full time series and the selected reduced time series