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Renewable Electricity Support in Perfect Markets: Economic Incentives Under Diverse Subsidy Instruments

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Abstract

We aim to provide an overview of renewable subsidy schemes, thereby focusing on renewable investment incentives and cost effects in a uniformly-priced market zone. Specifically, we develop a deterministic short-term market equilibrium model that allows to investigate both siting and technological distortions in onshore wind turbine deployment. This paper includes five support instruments: the feed-in tariff, sliding feed-in premium, fixed feed-in premium, investment-based subsidies and capacity-based subsidies. Investment decisions under these instruments are analyzed using an extensive German case study. Apart from providing a general overview, our contribution is threefold. First, we show that investment- and capacity-based subsidies generally are not equivalent, despite being used interchangeably in literature. Generators granted investment offsets opt for the most system-friendly technologies, whilst those granted capacity-based subsidies tend to select the least system-friendly ones. As these two generation-independent subsidy instruments promote very different technologies, we question the prevailing belief that learning-by-doing externalities must be related to capacity. Second, sliding feed-in premiums yield very similar outcomes as fixed feed-in premiums for both investment and cost effects, and can substitute fixed premiums to mitigate investment risks. This conclusion holds for technology-specific support within a uniformly-priced market zone, but might not hold over multiple pricing zones or for technology-neutral support. Finally, we show that most of these effects arise from technological distortions, whilst locational incentives are roughly the same under all instruments.

Keywords: Energy policy, Renewable electricity, System-friendly renewables, Renewable promotion instruments

1. Introduction

The European Union has steadily been expanding its renewable energy (RES) portfolio and is committed to reach a 32 % share for renewables in final energy consumption by 2030 (EU, 2018a). To that end, the European Commission established the Energy Governance Regulation through which they aim to reach a set of voluntary national contributions which collectively satisfy the EU-wide quota (EU, 2018b). As these national goals also are defined by RES quotas, the EU artificially imposes positive generation-based (per-MWh) externalities. Indeed, RES generation has a value outside the energy markets, i.e. the contribution towards achieving the national quota (Aune et al., 2012). Member States are thus strongly incentivized to design their subsidy instruments such that these correct for per-MWh externalities.

Several authors argue against such RES quotas by observing that renewable electricity (RES-E) is not accompanied by generation-based externalities. There essentially exist two convincing arguments for promoting renewable energy: carbon mitigation and learning externalities[1]. The former does not hold for

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[1]Other motivations, such as security of supply, green jobs, etc. are controversial and will not be considered in this paper. Interested readers are referred to the work of Lehmann et al. (2019), which reviews the rationales to promote renewables.

RES-E because the electricity sector is covered by the EU emissions trading system (ETS). Renewable electricity does drive out thermal generation, but the accompanying emissions are shifted rather than cancelled[2]. Learning-by-doing (LbD) spillovers, in contrast, might be a valid rationale for subsidizing renewable electricity[3]. Then again, these externalities are presumably not related to generation. Newbery et al. (2018) argue in favor of capacity-subsidies because learning-by-doing benefits are mainly derived from the manufacturing, siting and construction, rather than the subsequent operation of RES-E installations. The prevailing idea therefore is that renewable electricity should ideally be subsidized based on capacity, while the EU pushes its Member States to subsidize generation.

Andor and Voss (2016) and Özdemir et al. (2019) concluded that significant welfare losses arise from subsidizing RES-E generation (in MWh) when actually subject to capacity-based externalities (in MW) and argue in favor of capacity-subsidies to address LbD spillovers. On the other hand, capacity-based subsidies have been heavily criticized for exhibiting the so-called steel-in-the-ground phenomenon (Boute, 2012). Remunerating investors based on capacity makes them focus on installed capacity rather than energy generation. Past experiences with capacity-based subsidies, such as in the Netherlands and India, have indeed led to a portfolio of low-performing generators (Kamp, 2002; Arora et al., 2010). In the Netherlands, investors typically selected turbines with high nominal powers but low rotor diameters, both of these reducing the capacity-factor (Kamp, 2002). It thus seems that we have to promote poorly performing generators to optimally advance technological innovation, which of course is highly paradoxical.

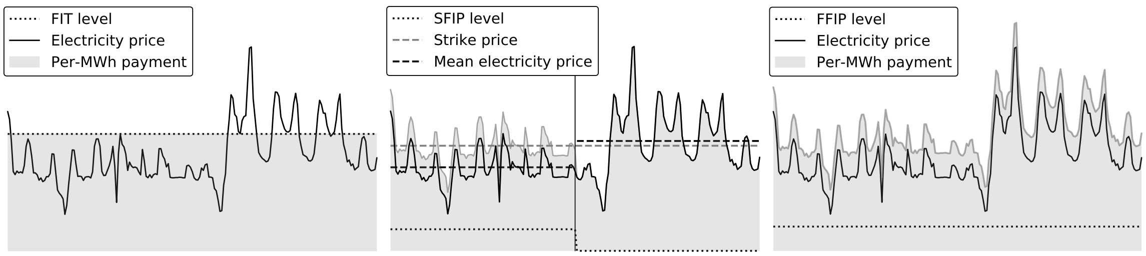
Following Newbery et al. (2018), it is indeed likely that LbD benefits are not derived from electricity generation. We, however, do challenge the belief that these are directly linked to capacity and illustrate this by modelling technology selection under investment-based and capacity-based subsidies. Although both instruments have been used interchangeably in academic literature, it will be shown that the equivalence between both instruments does not generally hold and that investment-based subsidies can provide fundamentally different incentives than capacity-based subsidies. We do not claim to exactly identify the drivers of LbD benefits, which could be investment-based, capacity-based, or something entirely different. Instead, we basically aim to argue that one can conceive a myriad of generation independent (not per-MWh) subsidy schemes, each promoting different technologies and thus also variously affecting LbD benefits. This paper therefore aims to stimulate additional research on the actual drivers of LbD benefits, such that RES-E support instruments can be designed accordingly.

The literature on RES-E investment incentives under various subsidy instruments is very much fragmented and we therefore include three generation-based instruments in our analysis: the feed-in tariff, sliding feed-in premium and fixed feed-in premium. Apart from uncovering the discrepancy between capacity- and investment-based subsidies, we specifically focus on evaluating the cost-effects of sliding feed-in premiums. To the authors' knowledge, the efficiency of sliding premium systems has never been thoroughly assessed, despite the many Member States implementing these systems (Benja et al., 2017).

Our main contribution is to provide an overview of both siting and technological distortions for technology-specific support. To this end, a market equilibrium model is developed to examine investor incentives and the accompanying impact on total system costs. The model is applied to a large-scale German case study that examines technology-specific support for onshore wind energy and allows investors to select from a set of turbine technologies and a set of locations. As investment incentives depend on the support instrument, this framework allows to reveal distortions in siting- and technology choices (including the steel-in-the-ground phenomenon). The main goal of the paper is to present a clear-cut overview on how support instruments drive investment decisions. The market model is consequently kept as simple as possible, assuming a deterministic and perfectly competitive context.

[2]This statement is no longer entirely true due to the reforms in the EU ETS. The cancelation policy has punctured the waterbed effect and one can thus argue that renewable electricity is producing some external generation-based benefits (i.e. avoided greenhouse gas emissions) (Perino, 2018). In this paper, however, we abstract from the magnitude of these drivers.

[3]Concerning renewable electricity, learning externalities comprise both knowledge spillovers in R&D and innovation spillovers through learning-by-doing (Jaffe et al., 2005). It is well-understood that the former should ideally be addressed by R&D subsidies or an equivalent instrument, and that learning-by-doing externalities are to be corrected by deployment subsidies (Fischer and Newell, 2008). In this paper, we solely focus on the latter.



(a) Feed-in Tariff (b) Sliding feed-in premium (c) Fixed feed-in premium

Figure 1: Per-MWh payment for the three generation-based subsidies considered in this paper.

The remainder of this paper is structured as follows. In Section 2, we introduce the five support instruments included in this paper and summarize what is known in terms of investment incentives and welfare effects. Section 3 presents a stylized numerical example that allows to gain some theoretical insights into the support instruments. The model set-up and case-study data are introduced in Sections 4 and 5, respectively. Section 6 then presents the model outcomes and Section 7 concludes.

2. RES-E support instruments

This section introduces the remuneration schemes of the support instruments and situates our work in the literature. Recall that we are considering five support instruments:

- Feed-in tariff (FIT)
- Sliding feed-in premium (SFIP)
- Fixed feed-in premium (FFIP)
- Investment-based subsidy (INV)
- Capacity-based subsidy (CAP)

The former three are generation-based (i.e. producers are subsidized per MWh) and their remuneration scheme is illustrated in Figure 1. Under a FIT, renewable generators receive a fixed payment per MWh of electricity generated, regardless of the electricity price[4]. Under a FFIP (Figure 1c), renewable generators receive a fixed premium on top of the electricity price. Investors are fully exposed to the electricity price volatility which is considered to be the main drawback of this instrument, i.e. a higher investment risk. The SFIP resembles the FFIP, but the premium paid on top of the electricity price varies per time block (e.g. monthly) and is calculated as the difference between a fixed strike price (which is the support level), and the average electricity price during that block[5]. Furthermore, if the average electricity price exceeds the fixed strike price, the premium is set to zero and thus cannot become negative. By resetting the premium level every block based on mean electricity prices, investors are shielded from long-term price trends because the mean remuneration will always at least equal the strike price. The SFIP is consequently seen as less risky compared to the FFIP (Huntington et al., 2017). In sum, investors are fully shielded from electricity prices under the FIT, shielded from long-term price trends but exposed to short-term price variability under the SFIP, and fully exposed to both short- and long-term price variability under the FFIP. The final two

[4]Contract-for-difference systems (as implemented in the UK) provide the same incentives as the feed-in tariff (Neuhoff et al., 2018).

[5]This is just one possible interpretation of the SFIP, following i.a. Huntington et al. (2017). Other variations may employ a generation-weighted average electricity block price such as implemented in Germany (Bundesministeriums der Justiz und für Verbraucherschutz, 2017).

Table 1: Literature overview on the performance of diverse support instruments.

	Support Instruments					Investment options		Externality	Transmission
	FIT	SFIP	FFIP	INV	CAP	Siting	Technology		
Rosnes (2014)	x		x		x			None	No
Winkler et al. (2016)	x		x		x		x	None	No
Schmidt et al. (2013)	x		x			x		MWh	No
Pahle et al. (2016)			x		x		x	MWh	No
Pechan (2017)	x		x			x		MWh	Yes/No
May (2017)	x	x					x	MWh	No
Wagner (2019)	x		x		x	x		MW	Yes
Andor and Voss (2016)	x				x			MW/MWh	No
Özdemir et al. (2019)			x		x	x	x	MW/MWh	Yes
This paper	x	x	x	x	x	x	x	MWh	No

instruments are not based on generation and producers are fully exposed to electricity price signals. Instead, renewable generators are reimbursed a share of their initial investment under the INV and are subsidized proportionally to their nominal capacity under the CAP.

Note that this paper only examines price-based instruments. Quantity-based instruments such as tradable green certificates (TGC) are not explicitly being considered as these are identical to fixed feed-in premiums in our deterministic context. In a fully deterministic setting, the TGC price emerging from the market perfectly corresponds to the FFIP level required to achieve the target and both equilibria coincide (Meus et al., 2019). In practice, however, TGC markets expose investors to an additional certificate price risk which explains why most Member States abandoned these systems (Held et al., 2014). Renewable electricity within the EU instead is commonly promoted via auctions based on price-based instruments. Investors bid the support level required to make their project viable and policy makers then select the lowest bids up till a predefined energy- or capacity target is satisfied. The price-based instrument on which the tender is based determines investor behavior and is therefore one of the key design aspects of renewable auctions (del Río, 2017).

Table 1 connects our work to papers that directly compare different support instruments under a risk-neutral setting[6]. The table of course cannot capture every intricacy, but instead categorizes the papers in terms of the considered support instruments[7], renewable investment options, externalities, and the consideration of transmission constraints. In all papers, renewable investors typically make generation and investment decisions. Regarding the latter, these can have (i) one single investment option, (ii) investment options covering multiple locations (indicated by the siting column), (iii) investment options covering multiple technologies (indicated by the technology column) and (iv) the combination of (ii) and (iii). Note that one needs to include multiple locations to reveal siting distortions, and multiple technologies to reveal technological distortions. Furthermore, several papers consider one uniformly-priced zone while others include price-differences across zones by modelling a transmission network.

In the remainder of this review, we respectively discuss the optimality of the instruments, the siting incentives, and the technological incentives. Given capacity-based externalities, it is optimal to implement a capacity-based subsidy partly because it does not distort the functioning of the electricity market (Andor and Voss, 2016). Indeed, renewable producers bid their true marginal cost and not, for instance, the negative of their premium level. The fixed feed-in premium is optimal to correct for generation-based externalities (Pahle et al., 2016). Negative bidding here is beneficial from the global perspective as RES-E

[6]Note that we thus omit several interesting strands of literature such as the interaction between support instruments and transmission cost charging (Bjørnebye et al., 2018), risk implications of support instruments (Bunn and Yusupov, 2015), cross-jurisdictional renewable energy trade (Meus et al., 2019), etc.

[7]Both May (2017) and Özdemir et al. (2019) consider support instruments not included in the table, but these are outside the scope of this paper.

generation has a value outside the electricity market (Höfling et al., 2015). Furthermore, a feed-in tariff is never optimal as renewable generators are isolated from electricity price signals and do not consider their electricity market value (Rosnes, 2014). The sliding feed-in premium has, to the best of our knowledge, never been quantitatively assessed, but should perform somewhere in between the feed-in tariff and the fixed feed-in premium (Huntington et al., 2017). From Table 1, one can see that May (2017) considers the sliding feed-in premium in his analysis, but he focuses solely on distortions in wind turbine technologies. We will extend his analysis by also considering system costs.

Renewable siting decisions are determined by two drivers. First, investors exposed to electricity price signals tend to aim for some complementarity in their RES-E production. Generation profiles that are less correlated with current RES-E output typically capture more market revenues as generation will correlate better with electricity prices because of a less pronounced merit-order effect (Grothe and Müsgens, 2013; Elberg and Hagspiel, 2015). Given perfect market prices, such a generator also is more valuable from a system perspective as it replaces higher marginal cost generation. By considering the example of wind speed profiles, which become less correlated with increasing distance, multiple authors have argued that turbines should be spatially diversified instead of being concentrated in high-potential areas (Schmidt et al., 2013; Pechan, 2017). Because renewable investors granted a feed-in tariff are not exposed to electricity prices, their siting decisions might imply highly correlated and less valuable electricity generation. Feed-in premiums and generation-independent support instruments, in contrast, incentivize more diversification. The second driver is zonal price differences. Investors exposed to electricity prices have an incentive to bias their capacity towards the zone with the higher electricity prices, which again is desirable from a system perspective. As such, the inefficiency of feed-in tariff and sliding feed-in premium systems will be exacerbated if implemented over multiple pricing zones (Meus et al., 2019).

In this paper, we take on a uniform pricing context since it better aligns with the perspective of most Member States. From Table 1, one can see that both Schmidt et al. (2013) and Pechan (2017) assessed siting distortions in such a setting. The analysis of Schmidt et al. (2013) was based on an imperfectly competitive setting, whilst the one of Pechan (2017) on a competitive setting and a stylized case-study. We aim to expand the analysis of Pechan (2017) by including more support instruments and by considering a more realistic case-study.

Moving to technological distortions, the four articles including multiple technology options (Table 1) generally consider one wind investment option and one PV investment option (possibly per price-zone). The exception is May (2017) who concentrates on wind turbines and comprehensively examines the impact of support instruments on turbine selection incentives. Hirth and Müller (2016) and May (2017) make a distinction between system-friendly (or advanced[8]) turbines and less system-friendly variants. Advanced wind turbines are technologies that enable generating electricity more constantly[9] and, similar to the siting discussion, enable capturing more value in the electricity market. These are, however, subject to a higher investment cost. May (2017) concludes that feed-in tariffs lead to a portfolio of relatively system-unfriendly turbines exhibiting a volatile generation profile, whilst sliding feed-in premiums incentivize a more advanced portfolio with a relatively constant electricity output. We build upon the work of May (2017) to assess the technological distortions under the five support instruments considered in this paper.

3. Numerical illustration

The aim of this section is to present some insights into renewable investment behavior under various support instruments via a hypothetical numerical example. The example is highly stylized and solely serves to gain a theoretical intuition while the importance of such effects will be analyzed later. We exclude the sliding feed-in premium for conciseness and remind the reader that it would perform somewhere in between the feed-in tariff and fixed feed-in premium. We first introduce the set-up which constitutes a technology

[8]In this paper, we use advanced wind turbines and system-friendly wind turbines interchangeably.

[9]Technologies that generate proportionally more during times when the electricity price is high would be a more accurate definition of system-friendly wind turbines. As of a specific, relatively small share of wind penetration, however, both definitions imply the same (Hirth and Müller, 2016).

Table 2: Technology parameterization considered in the numerical example (CF = capacity factor).

	CF period 1 [−]	CF period 2 [−]	Investment cost [€/MWy]
Tech 1	0.6	0	150,000
Tech 2	0.25	0.25	150,000
Tech 3	0	0.4	150,000
Tech 4	0,2	0	75,000

selection problem[10]. We then determine (i) what technology gets selected under the respective support instruments and (ii) what technology would be optimal to install from a system perspective. Linking both outcomes provides some insights into the renewable promotion instruments.

The stylized example considers one year comprising two periods of equal length, i.e. 4,380 hours per period. We assume a constant electricity price of 20 €/MWh during the first period and 50 €/MWh during the second. RES-E generation is more valuable during the second period because it replaces higher marginal-cost thermal generation. Now suppose that a renewable investor can select one out of four potential RES-E technologies depicted in Table 2. Each technology is characterized by an average capacity factor for every period and an annualized investment cost. When moving from technology 1 to technology 3, the average capacity factor decreases, the correlation between generation and the electricity price increases, and the annualized investment cost remains the same. Technology 4 is a variant of technology 1, which has half of the investment cost but only a third of the generation potential.

We begin by analyzing which technology is most likely to be installed under the different support instruments. We therefore calculate the support level required to make investments viable for each instrument/technology combination. Given any support scheme, the technology requiring the lowest support level is most likely to be selected (consider, for instance, renewable auction environments). All required support levels can be extracted from the zero-profit conditions[11]:

$$fit_k = \frac{C_k^{inv}}{\sum_p N_p CF_{k,p}} \tag{1}$$

$$ffip_k = \frac{C_k^{inv} - \sum_p N_p CF_{k,p} p_p^e}{\sum_p N_p CF_{k,p}} \tag{2}$$

$$\tau_k = 1 - \frac{\sum_p N_p CF_{k,p} p_p^e}{C_k^{inv}} \tag{3}$$

$$\sigma_k = C_k^{inv} - \sum_p N_p CF_{k,p} p_p^e \tag{4}$$

In which fit_k, $ffip_k$, τ_k, σ_k represent respectively the required support level under a feed-in tariff, fixed feed-in premium, investment subsidy and capacity subsidy for technology k. C_k^{inv} is the per-MW annualized investment cost for technology k and $CF_{k,p}$ represents the average capacity factor for technology k during time-period p, both are shown in Table 2. Finally, N_p represents the length of period p (i.e. 4,380 hours per year) and p_p^e the electricity price during time-period p (discussed above).

From the left-hand side of Table 3, which presents all required support levels, one can notice that the technology that gets selected entirely depends on the support instrument. Investors granted a feed-in tariff will prefer technology 1, which essentially maximizes renewable electricity output per unit of investment (Eq. 1). Under a feed-in premium, investors will make a trade-off between (i) maximizing renewable electricity

[10] Although we present the numerical example in terms of potential renewable technologies, it can equally well be interpreted as potential locations or a combination thereof.

[11] E.g. the profit under a fixed feed-in premium equals $\sum_p N_p CF_{k,p}(p_p^e + ffip_k) - C_k^{inv}$. Setting this expression equal to zero directly yields Eq. 2. The formal optimization problems for renewable investors under varying support instruments (from which these conditions can be derived) will be presented in Section 4.

Table 3: Outcomes of the numerical example. Left-hand side: support levels required to attract investments in the different technologies. Right-hand side: system cost components to promote 1 additional MWh of yearly RES-E generation for the different technologies. AIC = additional investment cost, AGC = avoided generation cost, ASC = additional system cost (= AIC - AGC).

	Minimum support levels				System cost components		
	FIT [€/MWh]	FFIP [€/MWh]	INV [$-$]	CAP [€/MW]	AIC [€/MWh]	AGC [€/MWh]	ASC [€/MWh]
Tech 1	**57**	37	0.65	97,400	**57**	20	37
Tech 2	68	**33**	0.49	73,400	68	35	**33**
Tech 3	86	36	**0.42**	62,400	86	**50**	36
Tech 4	86	66	0.77	**57,480**	86	20	66

output per unit of investment and (ii) maximizing the market value of their generation (Eq. 2). In this case, investors will prefer technology 2 over technology 1 since electricity can be generated during higher price periods, even though the total generation is lower. Investors granted investment-based subsidies tend to maximize the market value per unit of investment (Eq. 3) and select technology 3 as it has the highest value in the electricity market. Finally, investors granted capacity-based subsidies make a trade-off between the per-MW investment cost and the per-MW market value of their renewable energy generation (Eq. 4). Such investors have a stronger incentive to minimize the per-MW investment cost and therefore select technology 4 even though it has the lowest market value.

The next step is to consider which of the four technologies should be selected from the optimal system-perspective. To do so, we have to assume an externality base, i.e. MWh-based, MW-based, investment-based, etc. This paper considers the Member State's perspective—per-MWh externalities via national quotas—and we correspondingly calculate the additional system cost to promote 1 additional MWh of RES-E generation per year. The technology with the lowest additional system cost per MWh RES-E generation is then best suited to correct for generation-based externalities[12].

The additional system cost comprises two elements: the additional investment cost and the avoided generation cost. The former represents the renewable investment cost incurred to generate 1 MWh of renewable electricity and can be calculated by dividing the annualized per-MW investment cost [€/MWy] by the per-MW yearly generation [MWh/MWy], see Eq. 5. The latter component arises because additional renewable electricity replaces thermal generation and thus also their generation costs, which should be reflected by the electricity prices. The avoided generation cost per MWh of RES-E generation can be calculated by Eq. 6. The total additional system cost then is the difference between these two elements (Eq. 7).

$$AIC = \frac{C_k^{inv}}{\sum_p N_p CF_{k,p}} \tag{5}$$

$$AGC = \frac{\sum_p N_p CF_{k,p} p_p^e}{\sum_p N_p CF_{k,p}} \tag{6}$$

$$ASC = \frac{C_k^{inv} - \sum_p N_p CF_{k,p} p_p^e}{\sum_p N_p CF_{k,p}} \tag{7}$$

The right-hand side of Table 3 presents these system cost-components for the four technologies. Technology 1 has the lowest additional investment cost as it has the highest average capacity factor per unit of

[12]Similarly, if we want to assess what technology is optimal given capacity-based externalities, the additional system cost to promote 1 additional MW of capacity has to be assessed.

investment (Table 2). Technology 3 only generates during the high price period and has the highest electricity market value per unit of generation. Technology 2 has the lowest additional system cost per MWh and yields the best trade-off between the additional investment cost and avoided generation cost. As such, this technology is best suited to be installed given generation-based externalities. Finally, technology 4 has the highest additional investment cost, the lowest market value and clearly should not be selected when aiming to correct for generation-based externalities.

Now compare the feed-in tariff levels with the additional system-level investment cost in Table 3 (or similarly, compare Eq. 1 and Eq. 5). The feed-in tariff perfectly corresponds to the additional investment cost and investors awarded tariffs are thus incentivized to minimize the additional investment cost, which is only one element of the total additional system cost. In this case, technology 1 has a relatively low value in the electricity market (i.e. 20 €/MWh) and is not optimal from a system-perspective. This example serves as an illustration of the well-known result that investors granted feed-in tariffs are shielded from electricity prices and ignore their value in the electricity market.

Similarly, one can compare the required investment-based subsidies with the avoided generation costs (i.e. market value) in Table 3. We already mentioned that investors granted such subsidies aim to maximize the market value and consequently, they will select technology 3 even though it requires the highest additional renewable investment costs. Perhaps more intuitively, investors granted investment offsets are best aligned with electricity market signals, but ignore the existence of per-MWh externalities and are not sufficiently incentivized to opt for technologies with a higher generation potential. One thus needs more installations to achieve the same amount of generation, and also more investment.

The feed-in premium yields the optimal outcome as it incentivizes renewable investors to make a trade-off between maximizing renewable electricity generation per unit of investment, and maximizing the market value of their generation. One can notice that both Eq. 2 and 7 are identical, and thus also the corresponding columns in Table 3. If a policy maker sets the premium equal to the value of the per-MWh externalities, investors will select technologies that are optimal from the system-perspective.

Investors receiving capacity-based subsidies select technology 4 as they aim to minimize the additional system cost per MW (and not per MWh), see Eq. 4. These investors have a greater incentive to minimize the per-MW investment cost and seem to be subject to the steel-in-the-ground phenomenon. The main contribution of this stylized example is to show that investment-based and capacity-based subsidies might provide different incentives and should not be used interchangeably.

A final important insight concerns the equivalence of support instruments, which can be deduced from Eqs. 1 - 4. Two support instruments will provide identical incentives if their respective support levels differ only by a constant scaling factor, implying that the technology with the lowest support level will be the same under both support instruments. As an example, consider the investment-based and capacity-based subsidies. Based on Eqs. 3 - 4, one can see that the support levels only differ by the factor C_k^{inv}. Provided that the per-MW investment costs remain roughly constant (or if one considers a single technology), both instruments essentially are the same. Similarly, by comparing Eqs. 2 - 3, one can deduce that investment-based subsidies and fixed feed-in premiums will lead to similar results if the total renewable electricity generation scales perfectly with investment costs for each technology. Eqs. 1 - 2 finally show that feed-in tariffs and feed-in premiums converge if the electricity prices remain constant.

4. Model

To quantify the magnitude of the distortions presented in Section 3, we formulate a market equilibrium model for which the general model structure is presented in Figure 2. The complementarity framework allows to capture the discrepancy between the centralized social optimum and the competitive equilibrium under inefficient support instruments. This model has been set-up as a static, one-shot game, reflecting an equilibrium solution under the assumed (static) boundary conditions. We include the five support instruments (FIT, SFIP, FFIP, INV, CAP) as cases and therefore have to specify multiple model formulations. The policy maker acts as a clearing agent and sets the support level such that an additional renewable electricity target is satisfied, e.g. an additional 10 TWh/y compared to the current yearly generation. The

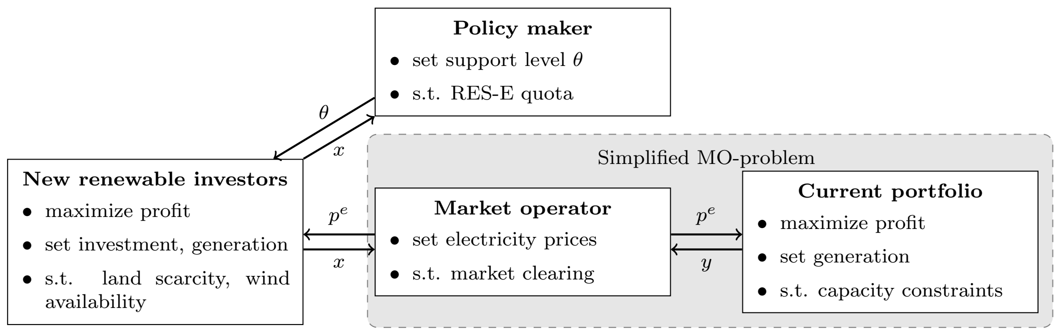


Figure 2: Overview of the market equilibrium modelling framework.

current power plant portfolio may contain both thermal and renewable power plants, but is assumed to be fixed. The additional renewable energy must then be generated by new renewable investors, which make both generation and investment decisions based on the support instrument, support level and electricity prices. All producers (current and new) aim to maximize their profit under a perfectly competitive setting (i.e. price-taking behavior, perfect information, etc.). For the purposes of this paper, new renewable investments are restricted to onshore wind turbines, but the modeling framework can easily be adapted to include other sources of renewable electricity as well. Finally, the market operator sets the electricity price to ensure the balance of demand and supply in the electricity market under the copper-plate assumption.

In settings similar as ours, the current generation portfolio is often modelled by a set of producers, each defined by their variable cost (usually constant), and maximum capacity. Recently, Ward et al. (2019) have shown that these formulations consistently underestimate the variability of electricity prices. As our results will be highly driven by the correlation between electricity prices and renewable generation (and thus by the variability of electricity prices), such an approach would be inadequate. Instead, we draw upon Schmidt et al. (2013) and correct historical electricity prices by the merit-order effect to approximate the link between renewable generation and electricity prices. This approach encapsulates both the market operator and the current generation portfolio (see Fig. 2), and will be explained in Subsection 4.1.

The problems faced by new renewable generators and the policy maker will respectively be formulated in Subsections 4.2 and 4.3. Combined, these elements build up to an MCP (mixed complementarity problem), in which the respective optimization problems can be replaced by their Karush–Kuhn–Tucker (KKT) conditions (Gabriel et al., 2012). It proved possible to solve larger instances by reformulating the MCP structure into a single-objective problem that should be solved iteratively. This solution strategy will be presented in Section 4.4.

4.1. Simplified MO-problem

To avoid underestimating the variability of electricity prices, we introduce a constant merit-order coefficient inspired by Schmidt et al. (2013). This merit-order coefficient (in €$/(MWh \cdot GW)$) represents the average decrease of wholesale electricity prices (in €$/MWh$) per additional unit of renewable electricity injection (in GW). In this subsection, we introduce the market framework underlying the merit-order effect (shared area in Figure 2) and link it to the first welfare component.

Injecting zero-marginal cost power into an electricity system pushes the supply curve rightward and the electricity price downward, which is the most common interpretation of the merit-order effect[13]. Similarly, one can link the merit-order coefficient to the slope of the generation portfolio's marginal cost curve, as shown in Figure 3 for a specific time-step t. Initially, demand (D_t) is satisfied by the original generation portfolio at the price (or marginal cost) p_t^{init}. Injecting additional zero-marginal cost power (x_t) decreases the original portfolio's output to y_t, accompanied by a reduction of the marginal cost to $p_t^e = p_t^{init} - MO \cdot x_t$. During a

[13] see e.g. Sensfuß et al. (2008) for a comprehensive overview.

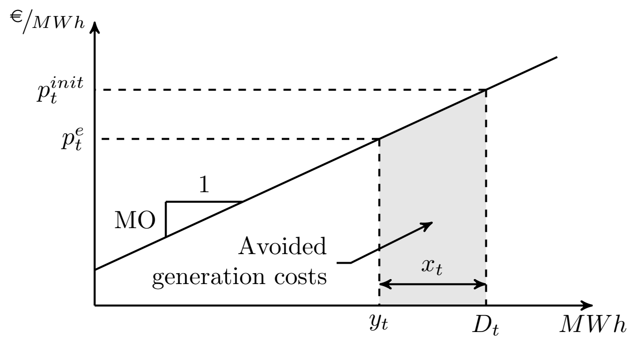


Figure 3: Illustration of the simplified MO-problem.

specific time-step, the original power plant portfolio's marginal cost curve can thus be approximated based on the merit-order coefficient, the initial electricity price, and the initial electricity demand.

We therefore employ a linear merit-order curve for which the slope remains constant, but the intercept (determined by $[D_t, p_t^{init}]$) varies over time. The former allows to include the diminishing value of additional renewable electricity in the electricity market, whilst the latter allows to include the variability of historical electricity prices. Of course, this approach is a fairly coarse approximation. Typical merit-order curves are convex implying that the actual merit-order coefficient is higher during periods of high demand (Morthost et al., 2010). Moreover, the coefficient depends on the current generation fleet and we thus neglect structural changes. Our results will only be valid in the short-term for lower levels of wind power generation (Schmidt et al., 2013).

Formally, one can write down the optimization problem of the current power plant portfolio (Figure 2) as follows:

$$max_{y_t} \sum_t \int_0^{y_t} (p_t^e - VC_t(y_t'))dy_t'$$

$$s.t. \quad y_t \geq 0 \quad \forall t \tag{8}$$

$$VC_t(y_t') = p_t^{init} + MO(y_t' - D_t) \quad \forall t \tag{9}$$

in which y_t represents the current portfolio's generation level during time-step t, p_t^e the electricity price during that time-step and $VC_t(y_t)$ the marginal cost curve defined by Eq. 9 and shown in Figure 3. Conventionally, generators maximize their profit taking the electricity price as given. Assuming an interior solution, the first-order conditions reduce to:

$$p_t^e = p_t^{init} - MO(D_t - y_t) \quad \forall t \tag{10}$$

The market clearing sets the electricity price such that demand and supply are in equilibrium:

$$D_t = y_t + x_t \quad \forall t \tag{11}$$

In which x_t represents the amount of generation from the new renewable investors during time-step t. Note that we thus assume an inelastic demand for electricity. Combining Eqs. 10-11 then yields the lower-level conditions for the simplified MO-problem (Figure 2):

$$p_t^e = p_t^{init} - MOx_t \quad \forall t \tag{12}$$

Although Eq. 12 would have been quite straightforward at the outset, the underlying market framework is important to understand the link between the merit-order effect and the system costs. As the renewable generation sources considered in this paper are not accompanied by any variable costs, injecting their generation avoids a portion of the current portfolio's generation costs. This is the value of renewables in the electricity market shown as the shaded area in Figure 3 and formally given by:

$$AGC = \sum_t \int_{y_t}^{D_t} VC_t(y_t')dy_t' = \sum_t (p_t^{init} - \frac{MO}{2} x_t) x_t \tag{13}$$

In sum, the simplified MO-problem in Figure 2 can be entirely modelled by Eq. 12 and additionally, the underlying market framework allows to assess the decreasing effect of additional renewable production on the current portfolio's generation costs (Eq. 13).

4.2. New renewable investors

Renewable investors make investment and generation decisions to maximize their profit whilst taking the support level and electricity prices as given, i.e. a perfectly competitive setting. In our case study, only additional onshore wind turbines will be considered. Investment decisions are restricted to a set of locations ($l \in \mathcal{L}$) and a set of turbine technologies ($k \in \mathcal{K}$). To reflect the scarcity of favorable sites, we impose an upper limit on the amount of turbines that can be installed per location (n_l^{max}). Furthermore, the maximum power output of a specific turbine ($P_{l,k,t}$) is restricted by wind conditions (which vary across locations and over time) and technological characteristics. Since we consider five support instruments, we have to formulate an equal amount of distinct optimization problems.

4.2.1. Fixed feed-in premium

Under a FFIP, renewable generators receive a fixed premium ($ffip$), set by the policy maker, on top of the electricity price. The optimization problem can be formulated as:

$$\begin{aligned}
max_{x_t, n_{l,k}} & \sum_t (p_t^e + ffip) x_t - \sum_{l,k} C_k^{inv} n_{l,k} \\
s.t. \quad & n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \forall l \quad (\delta_l) \\
& \sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \forall t \quad (\lambda_t) \\
& x_t \geq 0 \quad \forall t, \quad n_{l,k} \geq 0 \quad \forall l, k
\end{aligned}$$

In which decision variables x_t and $n_{l,k}$ respectively represent the aggregate additional renewable power output during time-step t, and the amount of installed turbines of technology k at location l. The objective function maximizes remuneration minus investment costs. Note that the annualized investment cost per turbine (C_k^{inv}) depends only on the turbine technology and that location-specific cost components are omitted. The first constraint imposes the land scarcity condition, while the second restricts the total power output to correspond with wind conditions. We also relax the integrality condition on the amount of installed turbines ($n_{l,k}$). Dual variables are presented between brackets.

To include this optimization program in the MCP model structure, we replace the problem by its first-order (KKT) conditions[14]:

$$n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \perp \quad \delta_l \geq 0 \quad \forall l \tag{14}$$

$$\sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \perp \quad \lambda_t \geq 0 \quad \forall t \tag{15}$$

$$C_k^{inv} - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 \quad \perp \quad n_{l,k} \geq 0 \quad \forall l,k \tag{16}$$

$$\lambda_t - p_t^e - ffip \geq 0 \quad \perp \quad x_t \geq 0 \quad \forall t \tag{17}$$

As such, Eqs. 12, 14-17 represent the new renewable investors, the conventional portfolio and the market operator (Figure 2) under a fixed feed-in premium.

4.2.2. Feed-in tariff

Under a FIT, renewable generators are remunerated a fixed price (fit) per MWh of electricity produced. Instead of introducing the full optimization problem for every support instrument, we only present the relevant KKT-conditions. The full first-order conditions are presented in Appendix B. Eqs. 14 - 16 still hold under the FIT, but the stationarity condition related to x_t, i.e. Eq. 17 alters to:

$$\lambda_t - fit \geq 0 \quad \perp \quad x_t \geq 0 \quad \forall t \tag{18}$$

4.2.3. Sliding feed-in premium

the SFIP resembles the FFIP, but the premium ($sfip_b$) paid on top of the electricity price varies per block ($b \in \mathcal{B}$) and is calculated as the difference between a fixed strike price (sp), which is set by the policy maker, and the average electricity price during that block. Furthermore, if the average electricity price exceeds the fixed strike price, the premium is set to zero and cannot be negative. In this paper, we use a block size of one month, i.e. 12 blocks over our time-frame. Mathematically, Eqs. 14 - 16 remain valid under the SFIP. Furthermore, the following two conditions are needed:

$$\lambda_t - p_t^e - \sum_b B_{b,t} sfip_b \geq 0 \quad \perp \quad x_t \geq 0 \quad \forall t \tag{19}$$

$$sfip_b - sp + \frac{1}{N_b} \sum_t B_{b,t} p_t^e \geq 0 \quad \perp \quad sfip_b \geq 0 \quad \forall b \tag{20}$$

In which $B_{b,t}$ is a binary parameter which equals 1 if block b comprises time-step t, and 0 elsewise. N_b is a parameter representing the block size, i.e. the amount of time-steps within block b. Eq. 19 resembles Eq. 17, but allows for the premium to vary across blocks. Eq. 20 sets the sliding premium equal to the difference between the strike price and the average electricity price if this is positive, and equal to zero elsewise.

4.2.4. Investment subsidy

Under an INV, renewable generators are reimbursed a share (τ) of their initial investment. For instance, 20 % of the investment cost is being paid by the policy maker. They do not receive a subsidy based on generation (in MWh) and thus are fully exposed to the electricity price. Eqs. 14 - 15 remain valid under the INV. Furthermore, both stationarity conditions are updated:

$$(1-\tau) C_k^{inv} - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 \quad \perp \quad n_{l,k} \geq 0 \quad \forall l,k \tag{21}$$

$$\lambda_t - p_t^e \geq 0 \quad \perp \quad x_t \geq 0 \quad \forall t \tag{22}$$

[14] At this point, the necessity for the underlying complementarity framework becomes apparent. Alternatively, one could directly insert the merit-order equation (Eq. 12) into the optimization problem of the renewable investors. By doing so, however, these investors would be price-makers as they see the electricity price as a decision variable. One would thus be modelling one single cartel of renewable investors behaving like a monopolist on the residual demand curve ($p_t^e = p_t^{init} - MOx_t$).

4.2.5. Capacity-based subsidy

Under a CAP, renewable generators get subsidized based on the capacity they install and again are fully exposed to the electricity price. As such, Eqs. 14 - 15 and Eq. 22 again hold under the CAP. The stationarity condition related to $n_{l,k}$ is updated to:

$$C_k^{inv} - \sigma Q_k - \sum_t P_{l,k,t}\lambda_t + \delta_l \geq 0 \quad \perp \quad n_{l,k} \geq 0 \quad \forall l, k \tag{23}$$

in which σ represents the capacity subsidy (in €/MW) set by the policy maker, and Q_k the nominal capacity of a turbine of technology k.

4.3. Policy maker

The policy maker aims to promote additional renewable electricity generation by granting subsidies to newly installed installations. To that end, the policy maker sets the support level (fit under a feed-in tariff, sp under a sliding feed-in premium, $ffip$ under a fixed feed-in premium, τ under an investment subsidy, σ under a capacity-based subsidy) to achieve the additional renewable energy target[15]:

$$Target - \sum_t x_t = 0 \tag{24}$$

We impose an equality constraint as this suits the iterative solution strategy (see Section 4.4). In reality, the amount of additional renewable generation could exceed the target, i.e. the policy maker could grant higher subsidy levels to overachieve the target. Given positive subsidy levels, however, this will always be welfare-decreasing. We therefore model a welfare-maximizing policy maker subject to a renewable electricity quota by imposing the equality condition. It can be shown that, for every support instrument, there only is one support level that exactly satisfies Eq. 24.

In order to evaluate the performance of a support instrument, we assess total welfare. Since demand for both electricity and renewable electricity are inelastic, maximizing welfare coincides with minimizing the total additional cost. The total additional cost comprises two elements: the additional renewable investment costs required to achieve the target, and the current power plant portfolio's avoided generation costs (Eq. 13) as explained in Subsection 4.1. Formally, the total additional system cost can be written as:

$$TAC = \sum_{l,k} C_k^{inv} n_{l,k} - \sum_t (p_t^{init} - \frac{MO}{2} x_t) x_t \tag{25}$$

Eq. 25 can be linked to the sum of capital and operational expenditures, a more commonly used metric in similar studies. The first term only includes capital costs of additional renewable capacity because we are neglecting structural changes to the current generation fleet and thus implicitly assume that the capital cost of the current power plant portfolio is sunk. Instead of presenting the entire operational costs, the second term in Eq. 25 only considers the difference to the current situation. The equation consequently presents the change in total system costs when promoting additional renewable generation. Note also that the generation-based externalities are imposed via Eq. 24. Based on the model formulations, one can actually proof that the fixed feed-in premium is optimal to correct for these externalities. As explained in the next subsection, one can cast the equilibrium problems into single objective optimization formulations. The fixed feed-in premium is optimal because its model reformulation perfectly aligns with the central planner's perspective.

[15]In practice, it is difficult to exactly satisfy a renewable electricity quota. Even despite the current trend towards renewable auctions which allow for better control on the amount of capacity installed, one is likely to slightly overshoot or undershoot the RES target. This approximation, however, will not affect the main conclusions.

4.4. Solution strategy

In its current form, the model is difficult to solve for larger instances. We therefore employ an iterative solution approach by decomposing the MCP into the new renewable investors and the simplified MO-problem on the one hand, and the policy maker on the other. The KKT-conditions of these former agents fulfill a set of requirements that enable to cast it into a single-objective formulation (Poncelet et al., 2019; Gabriel et al., 2012). For each support instrument, we estimate an initial support level and solve the single-objective optimization problem representing the new renewable investors and the simplified MO-problem. Their response then comprises the total amount of additional renewable electricity generation which is used to update the support level iteratively until Eq. 24 satisfies a predefined tolerance. Özdemir et al. (2019) follow a similar approach to model the capacity-based subsidy. Appendix B presents the KKT-conditions and corresponding equivalent optimization problem of the new renewable investors and the simplified MO-problem for every support instrument. The single-objective reformulation typically yields a quadratic objective, except for the feed-in tariff which remains linear and the sliding feed-in premium which becomes bilinear. All single-objective problems remain convex, were implemented in the Julia/JuMP language and were solved by Gurobi.

5. Case Study

Germany has ambitious wind energy targets, has a uniform electricity pricing zone, is sufficiently large to encapsulate locations with relatively uncorrelated wind profiles, and is therefore chosen as our case-study. To limit the computational effort, we only include the year 2018 using an hourly resolution. The data collection and processing is strongly inspired by Ryberg et al. (2019b). We follow their approach to model potential turbine sites (Subsection 5.1), wind speed profiles (Subsection 5.2) and power curves (Subsection 5.3). Furthermore, the modelling of multiple wind turbine technologies draws upon May (2017) and will also be discussed in Subsection 5.3. Figure 4 presents an overview of this methodology. We will briefly discuss the original data sources and processing methods, but interested readers are referred to the original papers for a more comprehensive description and for a validation of the methods. Finally Subsection 5.4 deals with the merit-order coefficient, initial electricity prices and the renewable electricity target.

5.1. Potential turbine sites

To determine the potential turbine sites, and the maximum amount of turbines per site, we draw upon the work of Ryberg et al. (2019b). The authors estimate the future European onshore wind energy potential based on a turbine placement algorithm. First, they select suitable turbine areas via a land eligibility analysis which excludes sites located too close to populated sites, airports, protected sites, etc. (Ryberg et al., 2019a). Second, they assume a fixed turbine type (i.e. a rotor diameter of 136 m) and heuristically pack the suitable areas with as many turbines as possible subject to a minimal turbine separation constraint. For Germany, this leads to a technical potential around 160,000 turbines for which the locational data has been made publicly available.

As we are interested only in additional renewable capacity, we obtained the currently installed turbines from Open Power System Data (2019a) and subtract these from the initial dataset. The 140,000 remaining turbines then are clustered into 3,500 individual sites based on a k-means clustering algorithm to reduce computational effort. Each individual cluster (l) corresponds to a potential site, whilst the amount of turbines allocated to that cluster constitutes the maximum amount of turbines that can be installed on that site (n_l^{max}). Since we are modelling different turbine technologies, with different rotor diameters (see Subsection 5.3), we will neglect the initial assumption of a 136 m rotor diameter, but rather restrict the amount of turbines regardless of the turbine swept area. The final result is shown on the left-hand side of Figure 4, where each individual circle represents a potential site and has an area proportional to the maximum amount of turbines that can be installed at that site.

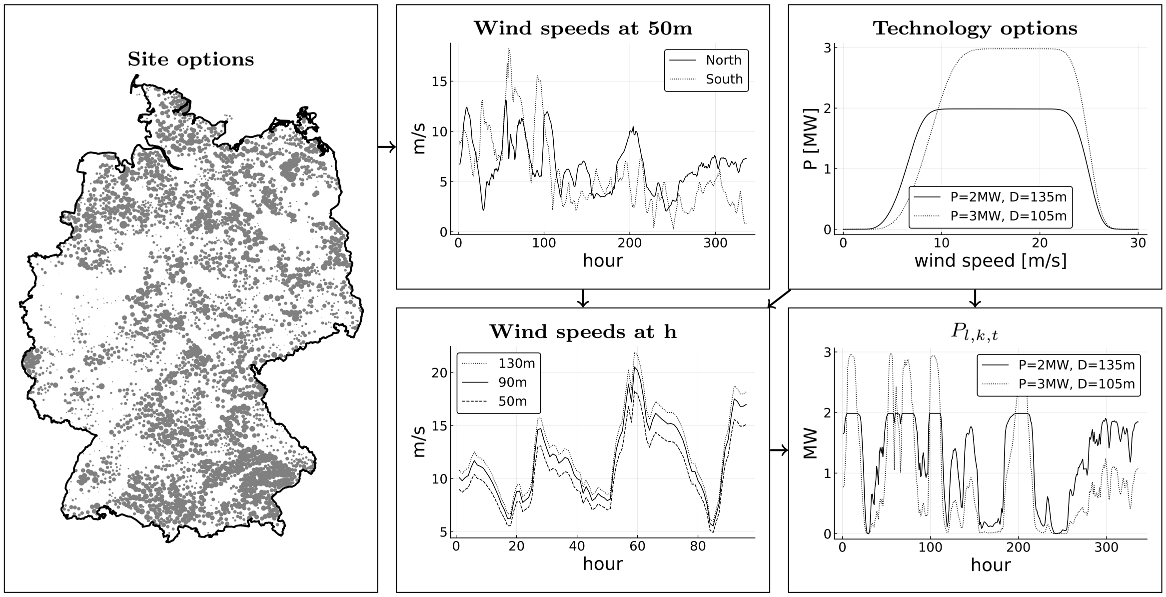


Figure 4: Overview of procedure employed for obtaining the case-study data.

5.2. Wind speeds

The wind speeds are modelled per cluster's centroid, and are based on two datasets following the approach of Ryberg et al. (2019b). The MERRA2 database (Gelaro et al., 2017) is used to extract wind speeds at a height of 50m for the year 2018. The dataset comprises reanalysis data with an hourly temporal resolution, at a spatial grid of 0.5° latitude by 0.625° longitude. For Germany, this roughly corresponds to a fairly coarse spatial resolution of 50km by 50km. These wind profiles are allocated to every cluster's centroid via bilinear interpolation.

The coarse spatial resolution, and the bias resulting from using the reanalysis dataset (as shown by Staffell and Pfenninger (2016)), are corrected via the Global Wind Atlas (GWA) dataset (DTU Wind Energy, World Bank Group). This database comprises time-averaged wind speed values, also at a height of 50m, at a spatial resolution of 1km by 1km. We then compute a scaling factor for each cluster such that the time-averaged interpolated MERRA2 series reflects the average wind speed as represented by the GWA database at the cluster's centroid:

$$v_{l,t} = v_{l,t}^{merra2} \frac{v_l^{gwa}}{\overline{v_{l,t}^{merra2}}} \tag{26}$$

In which $v_{l,t}$ represents the final wind speed (at a 50m height) at time t and cluster l, $v_{l,t}^{merra2}$ represents the MERRA2 profile interpolated at the cluster's centroid, $\overline{v_{l,t}^{merra2}}$ the time-averaged value of this profile, and v_l^{gwa} the mean wind speed at cluster l as extracted from the GWA database. As such, the methodology enables leveraging both the temporal resolution of the MERRA2 database, and the spatial resolution of the GWA database. The intermediate result is shown in the top center entry of Figure 4 for two random clusters in the North and South of Germany during the first week of 2018.

We include multiple turbine technologies, each with a hub height higher than 50m (further explained in Subsection 5.3). The obtained 50m wind profiles thus need to be extrapolated vertically. For this purpose, we resort to the commonly employed logarithmic wind profile:

$$v_h = v_{50} \frac{ln(h/z)}{ln(50/z)}$$

In which v_h represent the wind speed at height h, v_{50} the wind speed at 50m (obtained from Eq. 26), and z the roughness length determining the shape of the logarithmic profile. Again following Ryberg et al. (2019b), the Corine Land Cover dataset is used to determine land cover categories[16], which are then transformed into roughness lengths following Silva et al. (2007). Instead of using the roughness lengths at the cluster's centroid, however, we average the roughness lengths at each individual turbine location within the considered cluster. An example of the final wind profiles, adjusted for hub height, is given by the bottom center entry of Figure 4 for the first four days of 2018. Note that the entry presents the height scaling for one specific cluster, and that the logarithmic scaling factor in fact varies among sites.

5.3. Turbine technologies, costs and power curves

New renewable investors are allowed to optimize the selection of turbine types, but are restricted to a predefined set of technologies. Similar to May (2017), we create this set by varying the nominal power, hub height and rotor diameter across the potential technologies. A higher hub height allows to tap into higher average wind speeds since wind strengths increase with increasing heights (see Subsection 5.2). A larger rotor diameter allows to harvest more energy at any given wind speed. The nominal power determines the maximum conversion level, and thus the maximum amount of power a turbine can harvest at relatively high wind strengths. The total turbine cost, however, increases in all three design parameters due to higher material costs.

This parametrization directly links to the concept of system-friendly wind turbines, i.e. technologies that are able to produce electricity more constantly (see Section 2). From the RES-E generator's perspective, a less volatile generation profile allows these advanced turbines to appropriate a higher market value by generating proportionally more energy during times when the electricity price is high. From a system perspective, these system-friendly turbines obtain their higher value by replacing higher-variable cost generators and avoiding the need for additional ramping capabilities. Both perspectives should coincide if the system perspective is properly reflected by electricity prices (which we assume in this paper).

Advanced wind turbines are typically characterized by a higher hub height and a lower specific rating. The specific rating is defined as the ratio between a turbine's nominal power and the rotor swept area, and determines how fast (i.e. at what wind speed) a turbine reaches its rated capacity. Turbines with lower specific ratings have higher capacity factors for any wind strength and will thus reach their nominal power at lower wind speeds. Turbines with higher hub heights, higher rotor diameters and lower nominal powers are relatively more system-friendly (May, 2017).

For the technology set (k) considered in this paper, the nominal power takes on either 2 MW or 3 MW; the rotor diameter takes on either 105m, 120m or 135m; and the hub height takes on either 90m, 110m or 130m. We thus include 18 ($= 2 \cdot 3 \cdot 3$) potential combinations. Turbine cost information was obtained from the cost model developed by the National Renewable Energy Laboratory (NREL) (Fingersh et al., 2006), which has been updated using 2015 data (Stehly et al., 2018). The model allows to approximate the turbine cost[17] based on a set of design parameters such as nominal power, hub height and rotor diameter. Furthermore, we include balance of system costs (i.e. electrical infrastructure, assembly and installation, etc.) as 33 % of the turbine cost based on Stehly et al. (2018). The resulting cost estimates correspond quite well to those from IRENA (2019b). As we only model one single year, the turbine costs are annualized using an economic lifetime of 20 years and an interest rate of 6 %. An overview of the turbine technologies and their corresponding annualized costs (C_k^{inv}) is provided in Appendix A.

To convert the wind profiles into turbine power profiles ($P_{l,k,t}$), we again draw upon Ryberg et al. (2019b) who have created a mapping between wind speeds, specific power and capacity factor based on 130 manufacturers' power curves[18]. Furthermore, the power curve is convoluted to include the observation that a turbine's generation typically cannot be perfectly forecasted based on an idealized power curve, but in fact is a stochastic response to wind speed. Indeed, power output deviates from the ideal power curve relation

[16]The dataset comprises a spatial resolution of 100m by 100m.
[17]Converted to Euros based on an exchange rate of 0.90 €/\$.
[18]The power curve parameterization from May (2017) yields very similar results.

Table 4: Summary of literature empirically assessing the merit-order coefficient for wind energy in Germany. A more comprehensive version of this table can be found in Gürtler and Paulsen (2018).

Study	Time frame	Estimated MO-coefficient €$/(MWh \cdot GW)$
Würzburg et al. (2013)	2010-2012	1.00
Ketterer (2014)	2006-2012	1.16
Cludius et al. (2014)	2010-2012	1.07
Benhmad (2016)	2009-2013	1.23
Paschen (2016)	2010-2013	1.71
Gürtler and Paulsen (2018)	2010-2016	0.60-1.20
Benhmad and Percebois (2018)	2012-2015	1.28

due to turbulence, large wind speed gradients, inaccuracy of wind speed data, etc. (Ryberg et al., 2019b). The power curve is therefore convoluted by a Gaussian kernel[19]:

$$\sigma(v) = \sigma_{scale} v + \sigma_{base} \tag{27}$$

$$PC_{conv}(v) = \int_0^\infty \frac{1}{\sqrt{2\pi\sigma(v)}} exp\left(\frac{-(v'-v)^2}{2\sigma(v)}\right) PC(v')dv' \tag{28}$$

In which $PC(v)$ represents the original power curve in function of wind speed v, and $PC_{conv}(v)$ the convoluted power curve. Following Ryberg et al. (2019b), we use a wind speed scaling factor (σ_{scale}) of 0.06, a base value (σ_{base}) of 0.1, and finally also include their low generation correction factor.

An illustration of the resulting power curves is provided by the top right entry in Figure 4. The 2 MW profile refers to the most system-friendly turbine within our technology set (i.e. lowest specific power), whilst the 3 MW turbine refers to the least system-friendly. The bottom right entry in Figure 4 represents the power output of these two turbines for the same wind profile (the 'North' wind profile of the top center entry in Figure 4). The system-friendly turbine is able to produce more electricity during times of lower wind speeds and therefore exhibits a less volatile generation profile compared to the 3 MW variant.

5.4. Other parameters

The merit-order coefficient (MO) and the initial electricity price profile (p_t^{init}) both are crucial parameters to model the existing power plant portfolio (see Section 4.1). Table 4 summarizes findings of seven recent empirical studies assessing the impact of wind energy on electricity prices in Germany, i.e. the merit-order coefficient. Based on the most recent estimates, we consider a MO-coefficient of 1.00 €$/(MWh \cdot GW)$ for the base case, and vary the coefficient from 0.50 €$/(MWh \cdot GW)$ to 1.50 €$/(MWh \cdot GW)$ in a sensitivity analysis. Hourly German day-ahead electricity prices for 2018 were obtained from Open Power System Data (2019b). Finally, we impose a 50 TWh/y renewable electricity target from onshore wind resources, corresponding to about 9% of their yearly electricity demand. The resulting capacity extensions roughly correspond to those defined in Germany's draft integrated national energy and climate plan over a 5-year period (Federal Ministry for Economic Affairs and Energy, 2018).

6. Results

We present the results in four parts. Subsection 6.1 covers siting decisions and Subsection 6.2 presents technology selection decisions under all support instruments. Furthermore, we calculate additional performance metrics (Subsection 6.3) and the impact on total system cost (Subsection 6.4). To assess the

[19]The procedure originates from Staffell and Pfenninger (2016).

Table 5: Averaged technology characteristics of the newly installed wind turbines.

	FIT	SFIP	FFIP	INV	CAP
Nominal power $[MW]$	2.63	2.64	2.63	2.60	3.00
Rotor diameter $[m]$	114	126	127	128	106
Hub height $[m]$	102	107	109	112	92
Specific power $[W/m^2]$	255	210	206	200	335

robustness of these results, we also include several sensitivities with respect to the input parameters (i.a. electricity prices, technology costs, etc.). The set-up and cost effects of these sensitivities are not presented in the main body, but in Appendix C. Generally, our conclusions are robust to input parameter variations. One important sensitivity that should be kept in mind is the case in which we limit the technology set to one single turbine type. As such, we effectively eliminate technological distortions and only retain potential differences in siting selection. To properly illustrate the siting incentives, this latter sensitivity will be partly presented in Subsection 6.1.

6.1. Siting

Figure 5 represents the site selection of newly installed wind turbines under the five considered support instruments. The main conclusion is that siting incentives generally are very similar. There are some minor differences between the varying support instruments—less minor when comparing the capacity-based subsidy to one of the other instruments—but these arise because of the interaction between technology selection and the scarcity of favorable locations. More precisely, technology incentives do vary under the different support instruments (Subsection 6.2) and some turbine technologies are able to generate more electricity than others. Given a fixed maximum amount of turbines per location, and a potential need for more turbines to satisfy the same quota condition, one also needs more sites.

As mentioned, we include a sensitivity in which we limit the potential technology set to one single turbine type, thereby eliminating technological distortions. Without technological distortions, the siting decisions under the varying support instruments are nearly identical[20]. Pechan (2017) already showed this when comparing the feed-in tariff and the fixed-feed in premium by using a fairly stylized example. Her conclusions can thus be extended towards more realistic cases and also towards multiple support instruments. For a single turbine technology, investors under the feed-in tariff opt for locations which maximize power output and thus should lead to the lowest amount of diversification. Support instruments including electricity prices incentivize investors to maximize the value of their generation in the electricity market and they should thus make a trade-off between total electricity generation (a volume effect, possibly reinforced by a premium) and the value of their electricity generation (a price effect). Our results suggest that the former consistently dominates. More diversification, and thus sacrificing total electricity generation for higher prices, is not beneficial under any support instrument. Note that this also holds for the central planner's perspective as this aligns with the fixed feed-in premium. The main implication is that, under current market conditions, inefficient support instruments do not significantly distort siting decisions. Of course, this only holds for a uniformly-priced zone on the short-term.

6.2. Technology Selection

Investors typically optimize turbine technologies towards the locational characteristics and as such, most model outcomes include multiple newly installed turbine variants. For instance, the desirability of hub height increases depends on the vertical wind speed scaling factor which is site dependent. Table 5 presents the averaged technology characteristics of the newly installed turbines for all support instruments and shows

[20]The siting decisions in the case of one single technology are not presented in this paper, but one can confirm this statement by looking forward to the cost effects of this sensitivity in Appendix C.

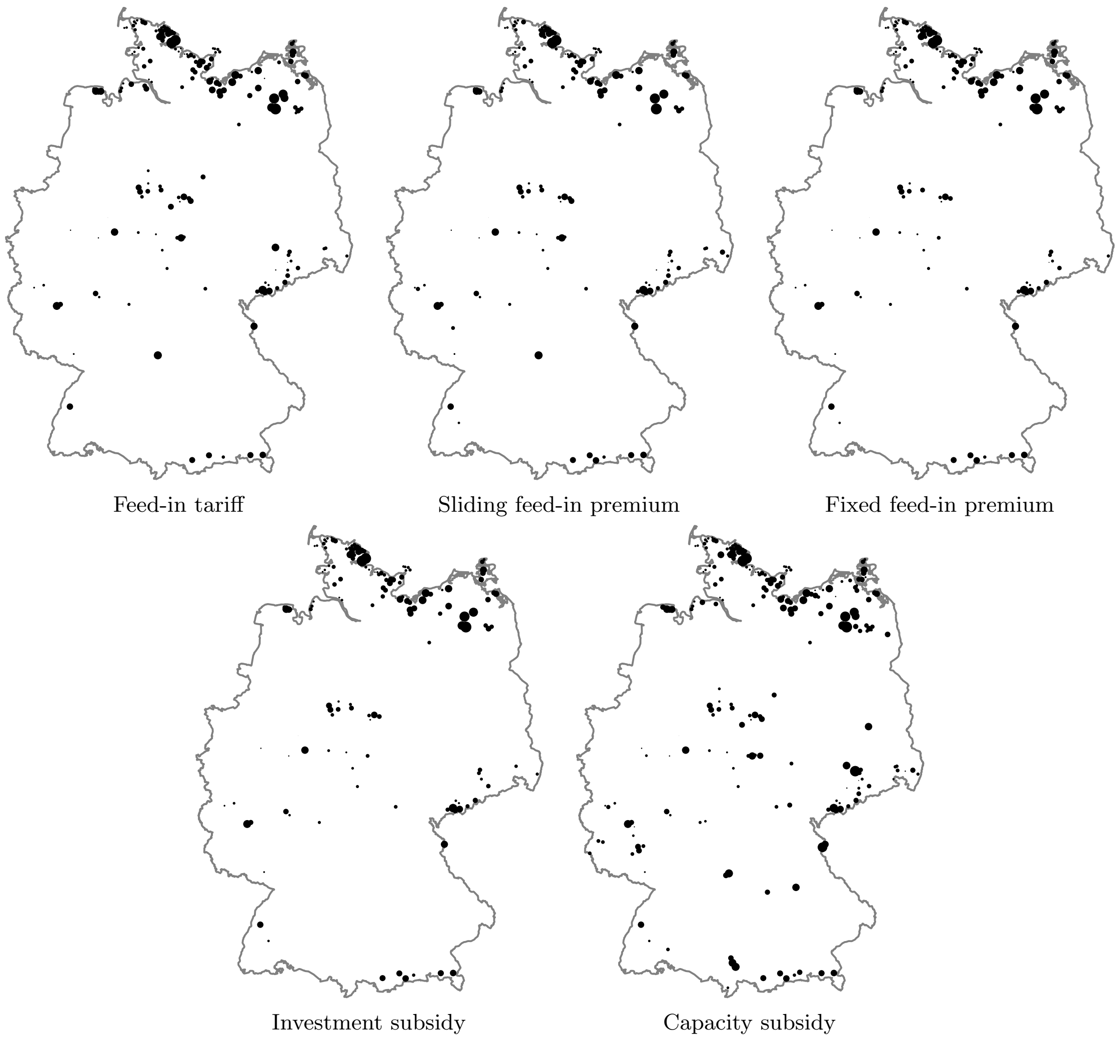


Figure 5: Investment locations under the varying support instruments in the base case. Each circle represents a location where wind turbines are being installed while the area of that circle is proportional to the amount of turbines installed at that site.

Table 6: Additional performance metrics for the base case.

	FIT	SFIP	FFIP	INV	CAP
Support level	43.9	51.2	12.8	0.28	40792
[unit]	[€/MWh]	[€/MWh]	[€/MWh]	[-]	[€/MW]
Fleet capacity factor	0.36	0.43	0.43	0.43	0.25
Curtailment [$\%Target$]	0	1.3	1.5	5.6	9.3
Installed capacity [GW]	15.6	13.4	13.2	13.4	23.2
Number of wind turbines	5943	5065	4998	5141	7749
Correlation wind generation and prices	-0.61	-0.53	-0.51	-0.38	-0.46
Wind value factor	0.77	0.83	0.84	0.88	0.80

that technology characteristics depend strongly on the promotion scheme. Recall that advanced (or system-friendly) turbines are characterized by a higher hub height, lower nominal power, higher rotor diameter and enable less variable generation profiles when compared to less advanced variants. Advanced turbines typically capture a higher electricity market value as these are less subject to the diminishing value of renewable electricity in the market (i.e. the self-cannibalization effect) and thus generate proportionately more energy during times when the electricity price is high (Section 5.3).

From Table 5, one can see that the averaged turbine characteristics selected under the feed-in tariff are relatively less system-friendly, which is consistent with the conclusion of May (2017). As mentioned before, investors granted a fixed tariff will maximize electricity output per unit of investment, without considering their value in the electricity market. When moving from the feed-in tariff to an investment-based subsidy in the table, the average turbine becomes more and more system-friendly. Again, this can be explained by noting that the remuneration from the electricity market becomes more important. Most interesting is the performance of capacity-based subsidies, which have been criticized for exhibiting the steel-in the ground phenomenon. When granted subsidies based on capacity, investors not only consistently select turbines with the highest nominal power (which of course is the subsidy-base), but also tend to select those with the lowest hub heights and the smallest rotor diameter. The turbine fleet generated under capacity-based instruments tends to be extremely system-unfriendly. These results align with our conclusion from the numerical illustration (Section 3), in which we argued that investors granted capacity-based subsidies have a stronger incentive to minimize the per-MW investment cost. As such, the steel-in-the-ground phenomenon is a real concern when one would like to implement capacity-based subsidies. Interestingly, the results also indicate that the steel-in-the-ground phenomenon is not inherent to generation-independent support instruments, but rather to the specific design of these. In fact, the turbine fleet selected under investment-subsidies has the highest potential capacity factor.

6.3. Additional performance metrics

Before moving to the cost components, we first present some additional performance metrics in Table 6. The first row in the table provides the support levels necessary to achieve the RES-E quota, which are consistent with present auction outcomes[21]. The fleet capacity factor of the additional turbines is defined as the total amount of renewable generation (i.e. the target) divided by total available capacity (i.e. installed capacity multiplied by the amount of time-steps). The capacity factor reaches high values (up to 43%) since very advanced turbine designs are being included in the technology set. Such levels do, however, correspond well to Hirth and Müller (2016) their expectations for advanced turbines. One can notice that the fleet capacity factor levels under the FIT and the CAP are relatively low, whilst those under the other three support instruments are about equal. This latter observation is somewhat counterintuitive as one would expect the mean capacity factor under investment-based subsidies (i.e. the most advanced fleet, Table

[21]IRENA (2019a) reports an average strike price (for a sliding feed-in premium system) of about 51.5 €/MWh granted during 2017-2018 in Germany.

Table 7: Overview of system costs under the different support instruments for the base case.

	FIT	SFIP	FFIP	INV	CAP
Renewable investment cost [$M€/y$]	2,006	2,066	2,074	2,175	2,314
Avoided conventional generation cost [$M€/y$]	1,729	1,832	1,846	1,932	1,818
Additional system cost [$M€/y$]	277	234	228	244	496
Additional cost relative to optimum [%]	21.3	2.4	0.0	6.8	117.5

5) to exceed the one under premium systems. Table 6 provides an explanation by presenting renewable energy curtailment. Given the first-order conditions of the various RES-E investor optimization problems (Subsection 4.2), one can see that curtailment never occurs under a FIT, occurs if the electricity price falls below the negative of the premium under the SFIP and FFIP and occurs if the electricity price becomes negative under the INV and CAP. As such, curtailment increases when moving from the feed-in tariff towards the investment-based subsidy in the table, slightly diminishing the increase in potential capacity factors via more advanced turbine designs. The lowest capacity factor results from capacity-based subsidies since it incentivizes an extremely system-unfriendly turbine fleet subject to a significant share of curtailment.

The total installed capacity and the number of turbines required to satisfy the renewable electricity quota are also presented in Table 6. The total installed capacity directly follows from the fleet capacity factor and the fixed renewable electricity quota. The total amount of turbines is roughly equal for the premium systems and the investment subsidies, whilst being higher under the feed-in tariff and capacity-based subsidy. This is predominantly driven by the corresponding capacity factors.

Finally, Table 6 present the correlation between additional wind generation and electricity prices, along with the wind value factor. The wind value factor is defined as the average price wind generators receive for their electricity generation, relative to the mean electricity price. For instance, a value factor of 1 would imply that, on average, wind generators receive the mean electricity price per unit of electricity generation. Both the correlation and the value factor thus are metrics for the value of one unit of wind generation in the electricity market: the higher, the more valuable. The results follow the same line of reasoning as before. Wind generation under a feed-in tariff is the least valuable since investors are not exposed to price signals. Under a capacity-based subsidy, wind generation also will be relatively invaluable since investors opt for the least system-friendly technologies. Finally, when moving from the SFIP towards the INV, wind generation becomes more valuable as investors are better aligned with electricity price signals (and thus tend to invest in more advanced technologies).

6.4. Additional system cost

Table 7 presents several system cost components resulting from the five support instruments. The first row corresponds to the additional renewable investment costs, the second row to the avoided conventional generation costs (Eq. 13) and the third row to their difference, i.e. the additional system cost (Eq. 25). Recall that the latter is a metric for total system cost, which therefore is presented relative to the social optimum in the final row.

The results follow the same line of reasoning as our numerical example (Section 3). Renewable investment costs are minimized under the fixed-feed in tariff and gradually increase when moving towards the investment-based subsidy. The avoided thermal generation costs are maximized under an investment subsidy, and gradually decrease when moving back towards the feed-in tariff. Additional system costs are minimized under the fixed feed-in premium, which yields the optimal trade-off between both cost components. The effect of capacity-based subsidies on these cost components is not as clear-cut since these aim to minimize the additional system-cost per unit of capacity (Section 3), but such a subsidy-mechanism clearly is suboptimal.

Most interesting is the relative size of the increased additional system cost. Under a sliding feed-in premium, the relative cost increase (2.4 %) remains modest. Wind generation could thus perfectly be subsidized via sliding premium systems if also pursuing other rationales such as risk-mitigation. Recall from Section 2 that investors granted sliding feed-in premiums are exposed short-term (intra-block) price-variability, but shielded from longer-term (inter-block) price variability. Our results suggest that this latter is not too important in terms of promoting onshore wind energy, most likely because the monthly aggregated wind output of different locations and technologies is highly correlated. The near-optimality of sliding premium systems, however, is not guaranteed when considering technology neutral auctions. Imagine a technology-neutral, sliding feed-in premium system for both wind and PV capacity. In this case, longer-term generation profiles of both technologies are not necessarily correlated as there typically is more sunshine during the summer and more wind power during the winter. Superimposing typical longer-term price profiles, i.e. electricity prices are typically higher during winter and lower during the summer, directly reveals the potential distortion. Wind generation is more valuable from a system-perspective than what would be recognized by renewable investors as every month, the average remuneration will equal the strike price which effectively masks longer-term value differences. The efficiency of technology neutral sliding premium systems is out of the scope of this paper and remains an open question. Note finally that this paper is restricted to a deterministic model. Including uncertainty and risk-averseness likely favors the SFIP, potentially making it more efficient than the FFIP.

The feed-in tariff induces an excess system cost of about 21%, mostly driven by diverging technology incentives. Furthermore, the additional system cost relative to the optimum under the investment-based subsidy is about 7 %, whilst the one under capacity-based subsidies is about 118 % (more than double of what ideally would be required). Note that the poor performance of capacity-based subsidies likely is driven by two effects: (i) inferior technology selection and (ii), the need for more (and less wind resource-rich) locations. Again, these cost-effects only are valid under the assumption of generation-based externalities.

We conclude this section by reflecting on the implications regarding correcting externalities. It never makes sense to implement feed-in tariff systems, while both sliding and fixed premium systems could be used to address generation-based externalities. To satisfy their national targets at the lowest cost, Member States should thus opt for premium systems. It also is known that capacity-based subsidies are optimal to target capacity-based externalities and similarly, investment offsets will be optimal to target investment-based externalities[22]. In the recent literature, several authors have argued that LbD externalities are related to capacity mostly because (i) it is unlikely that these are related to generation and (ii) investment- and capacity-based subsidies (and thus also externalities) were thought to be equivalent. Given this point of view, capacity-based (or investment-based) externalities seemed to be the sole alternative for generation-based externalities. As illustrated in Section 6.2, however, capacity-based and investment-based subsidies generally are not equivalent and promote very different technologies. Also, these are merely two examples of generation independent support instruments, while there are many. One could for instance conceive a generation independent subsidy scheme that additionally favors advanced technologies by e.g. penalizing wind turbines with a higher specific power. There exists a myriad of generation independent instruments, each promoting different technologies and thus also variously affecting LbD benefits. Capacity-based subsidies consequently no longer are the only alternative for generation-based subsidies, which calls for an investigation on the actual drivers of LbD benefits.

7. Conclusion and policy implications

We aimed to provide an overview on renewable subsidy schemes, under a technology-specific and an uniformly-priced setting, focusing both on renewable investment incentives and cost effects. To that end, we developed a deterministic short-term market equilibrium model that allows to investigate both siting and technological distortions in onshore wind turbine deployment.

One can conclude that inefficient support instruments do not significantly distort siting decisions within such a setting, but they can substantially distort technological characteristics. Specifically, capacity-based subsidies yield extremely system-unfriendly wind turbine portfolios exhibiting highly volatile and reduced electricity output, which confirms past experiences (i.e. the steel-in-the-ground phenomenon). Investors granted subsidies based on capacity indeed have a stronger incentive to minimize the per-MW investment

[22]This is not shown in this paper, but one can somewhat confirm this claim by repeating our numerical illustration under investment-based externalities.

cost and tend to focus on nominal power rather than energy output. On the other side of the spectrum, investment-based subsidies yield the most system-friendly fleet as they are best aligned with electricity market signals. Investors granted feed-in tariffs will also opt for relatively system-unfriendly turbines, whilst those granted premiums (both sliding and fixed) move towards relatively advanced turbines.

The analysis also quantified system cost effects under generation-based (per-MWh) externalities, i.e. the Member State's perspective. Although it is known that a fixed feed-in premium is optimal to correct for per-MWh externalities, we showed that the additional system cost under a sliding feed-in premium relative to the optimum remains modest (2 %). The implication is that Member States could perfectly implement sliding premium systems if also aiming to mitigate renewable investment risks (thereby reducing the cost of capital). This conclusion currently only holds under a technology-specific and an uniformly-priced setting. Since investors granted sliding systems are isolated from structural value-differences, they might not bias their investment decisions towards high-price market zones, or towards technologies that have a better longer term correlation with electricity prices. The efficiency of the sliding premium system given (i) technology-neutral support and (ii) multiple price zones both are valuable avenues for further research. Examining the performance of a SFIP in an uncertain and risk-averse setting, i.e. the trade-off between slightly suboptimal incentives and investment risk reduction, is another valuable avenue for further research.

Finally, the feed-in tariff and by extension contract-for-difference systems induce an additional system cost that is 21 % higher than needed, while the investment-based and capacity-based subsidy induce an additional cost of 7 % and 118 % relative to the optimum, respectively. A sensitivity analysis indicated that these conclusions are generally robust to input parameter variations.

In recent literature, it has been argued that external LbD benefits are directly related to installed capacity. This argument mostly was driven by the belief that there is no distinction between generation independent support instruments, e.g. capacity-based subsidies and investment-based subsidies provide exactly the same incentives. We argue that many generation independent support instruments exist, each of them promoting different technologies and variously affecting LbD benefits. It therefore no longer is clear what the actual drivers of LbD benefits are, which in turn presents an important avenue for further research. Indeed, the actual drivers of LbD benefits need to be well-understood such that RES-E support instruments can be designed accordingly.

Declaration of interest

None.

Appendix A. Turbine technologies

Appendix B. The equivalent optimization models

Appendix B.1. Feed-in tariff

The lower-level first order conditions are given by:

$$
\begin{aligned}
n_l^{max} - \sum_k n_{l,k} \geq 0 \quad &\perp \quad \delta_l \geq 0 \quad \forall l \\
\sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad &\perp \quad \lambda_t \geq 0 \quad \forall t \\
C_k^{inv} - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 \quad &\perp \quad n_{l,k} \geq 0 \quad \forall l,k \\
\lambda_t - fit \geq 0 \quad &\perp \quad x_t \geq 0 \quad \forall t
\end{aligned}
$$

Nominal Power $[MW]$	Rotor diameter $[m]$	Hub height $[m]$	Annualized investment cost $[€/(Turbine \cdot y)]$
2	105	90	261,881
2	105	110	285,926
2	105	130	315,480
2	120	90	329,011
2	120	110	353,055
2	120	130	382,610
2	135	90	410,716
2	135	110	434,761
2	135	130	464,315
3	105	90	288,021
3	105	110	312,066
3	105	130	341,620
3	120	90	357,019
3	120	110	381,064
3	120	130	410,618
3	135	90	440,683
3	135	110	464,727
3	135	130	494,282

The equivalent optimization problem is given by:

$$
\begin{aligned}
& max_{x_t, n_{l,k}} fit \sum_t x_t - \sum_{l,k} C_k^{inv} n_{l,k} \\
& s.t. \quad n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \forall l \quad (\delta_l) \\
& \sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \forall t \quad (\lambda_t) \\
& x_t \geq 0 \quad \forall t, \quad n_{l,k} \geq 0 \quad \forall l, k
\end{aligned}
$$

Appendix B.2. Sliding feed-in premium

The lower-level first order conditions are given by:

$$
\begin{aligned}
n_l^{max} - \sum_k n_{l,k} \geq 0 &\quad \perp \quad \delta_l \geq 0 \quad \forall l \\
\sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 &\quad \perp \quad \lambda_t \geq 0 \quad \forall t \\
C_k^{inv} - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 &\quad \perp \quad n_{l,k} \geq 0 \quad \forall l, k \\
\lambda_t - p_t^{init} + MOx_t - \sum_b B_{b,t} sfip_b \geq 0 &\quad \perp \quad x_t \geq 0 \quad \forall t \\
sfip_b - sp + \frac{1}{N_b} \sum_t B_{b,t} (p_t^{init} - MOx_t) \geq 0 &\quad \perp \quad sfip_b \geq 0 \quad \forall b
\end{aligned}
$$

The equivalent optimization problem is given by:

$$
\begin{aligned}
max_{x_t,n_{l,k}} & \sum_t (p_t^{init} - \frac{MO}{2} x_t) x_t - \sum_{l,k} C_k^{inv} n_{l,k} \\
& + \sum_b \theta_b \Big[\big(sp - \frac{1}{N_b} \sum_t B_{b,t} (p_t^{init} - \frac{MO}{2} x_t) \big) \sum_t B_{b,t} x_t \Big] \\
s.t. \quad & n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \forall l \quad (\delta_l) \\
& \sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \forall t \quad (\lambda_t) \\
& x_t \geq 0 \quad \forall t, \quad n_{l,k} \geq 0 \quad \forall l,k
\end{aligned}
$$

The first factor between square brackets in the final term of the objective function represents the sliding feed-in premium during block b, whilst the second factor represents the total amount of renewable electricity generated during block b. As such, the single-objective formulation resembles the one under a fixed feed-in premium (presented below). We also include an additional binary parameter θ_b per block to ensure that $sfip_b \geq 0$. I.e. if θ_b equals zero, the sliding feed-in premium is set to zero as well (to avoid negative premiums). The proper vector entries are not known beforehand, but are found iteratively such that no contradictions occur (i.e. $\theta_b = 1$ is correct only if the strike price exceeds the block-averaged electricity price, and $\theta_b = 0$ is correct only if the block-averaged electricity price exceeds the strike price). Based on the initial block-averaged electricity prices, the strike price and an estimate of the average merit-order effect, the initial values of θ_b can be estimated fairly accurately. As such, the increase in computational cost remains moderate.

Appendix B.3. Fixed feed-in premium

The lower-level first order conditions are given by:

$$
\begin{aligned}
n_l^{max} - \sum_k n_{l,k} \geq 0 \quad & \perp \quad \delta_l \geq 0 \quad \forall l \\
\sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad & \perp \quad \lambda_t \geq 0 \quad \forall t \\
C_k^{inv} - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 \quad & \perp \quad n_{l,k} \geq 0 \quad \forall l,k \\
\lambda_t - p_t^{init} + MO x_t - ffip \geq 0 \quad & \perp \quad x_t \geq 0 \quad \forall t
\end{aligned}
$$

The equivalent optimization problem is given by:

$$
\begin{aligned}
max_{x_t,n_{l,k}} & \sum_t (ffip + p_t^{init} - \frac{MO}{2} x_t) x_t - \sum_{l,k} C_k^{inv} n_{l,k} \\
s.t. \quad & n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \forall l \quad (\delta_l) \\
& \sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \forall t \quad (\lambda_t) \\
& x_t \geq 0 \quad \forall t, \quad n_{l,k} \geq 0 \quad \forall l,k
\end{aligned}
$$

Appendix B.4. Investment subsidy

The lower-level first order conditions are given by:

$$n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \perp \quad \delta_l \geq 0 \quad \forall l$$

$$\sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \perp \quad \lambda_t \geq 0 \quad \forall t$$

$$(1-\tau) C_k^{inv} - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 \quad \perp \quad n_{l,k} \geq 0 \quad \forall l, k$$

$$\lambda_t - p_t^{init} + MO x_t \geq 0 \quad \perp \quad x_t \geq 0 \quad \forall t$$

The equivalent optimization problem is given by:

$$\begin{aligned} max_{x_t, n_{l,k}} & \sum_t (p_t^{init} - \frac{MO}{2} x_t) x_t - \sum_{l,k} (1-\tau) C_k^{inv} n_{l,k} \\ s.t. \quad & n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \forall l \quad (\delta_l) \\ & \sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \forall t \quad (\lambda_t) \\ & x_t \geq 0 \quad \forall t, \quad n_{l,k} \geq 0 \quad \forall l, k \end{aligned}$$

Appendix B.5. Capacity-based subsidy

The lower-level first order conditions are given by:

$$n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \perp \quad \delta_l \geq 0 \quad \forall l$$

$$\sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \perp \quad \lambda_t \geq 0 \quad \forall t$$

$$C_k^{inv} - \sigma Q_k - \sum_t P_{l,k,t} \lambda_t + \delta_l \geq 0 \quad \perp \quad n_{l,k} \geq 0 \quad \forall l, k$$

$$\lambda_t - p_t^{init} + MO x_t \geq 0 \quad \perp \quad x_t \geq 0 \quad \forall t$$

The equivalent optimization problem is given by:

$$\begin{aligned} max_{x_t, n_{l,k}} & \sum_t (p_t^{init} - \frac{MO}{2} x_t) x_t + \sum_{l,k} (\sigma Q_k - C_k^{inv}) n_{l,k} \\ s.t. \quad & n_l^{max} - \sum_k n_{l,k} \geq 0 \quad \forall l \quad (\delta_l) \\ & \sum_{l,k} P_{l,k,t} n_{l,k} - x_t \geq 0 \quad \forall t \quad (\lambda_t) \\ & x_t \geq 0 \quad \forall t, \quad n_{l,k} \geq 0 \quad \forall l, k \end{aligned}$$

Appendix C. Sensitivities

Apart from the base case, which was comprehensively discussed in the main body, we also include fourteen sensitivities for which we present the additional system cost components. These sensitivities not only serve as a robustness check, but also enable to partially anticipate whether our results hold for structurally different

Table C.8: Additional system cost in $M€/y$ for all sensitivities. Percentage change compared to the considered case's system optimum (FFIP) between brackets.

Case	Description	FIT	SFIP	FFIP	INV	CAP
1	Base	277 (21.3%)	234 (2.4%)	228	244 (6.8%)	496 (117.5%)
2	Pot: −	419 (13.3%)	374 (1.0%)	370	393 (6.3%)	763 (106.4%)
3	Pot: +	121 (44.4%)	90 (7.6%)	84	94 (11.7%)	239 (184.7%)
4	Inv: −	76 (295.1%)	24 (24.7%)	19	26 (35.1%)	109 (466.0%)
5	Inv: +	477 (9.8%)	439 (0.9%)	435	461 (6.1%)	772 (77.6%)
6	$\mathrm{Pe}^{\mathrm{var}}$: −	179 (15.7%)	156 (0.9%)	155	159 (2.4%)	337 (118.7%)
7	$\mathrm{Pe}^{\mathrm{var}}$: +	422 (42.5%)	308 (4.0%)	296	322 (8.7%)	663 (123.7%)
8	$\mathrm{Pe}^{\mathrm{mean}}$: −	402 (13.8%)	359 (1.6%)	353	375 (6.3%)	673 (90.6%)
9	$\mathrm{Pe}^{\mathrm{mean}}$: +	151 (47.1%)	108 (4.6%)	103	113 (9.2%)	282 (173.5%)
10	MO: 0.5	164 (30.8%)	130 (3.6%)	126	134 (6.9%)	205 (63.6%)
11	MO: 0.75	220 (24.6%)	182 (2.7%)	177	189 (6.6%)	380 (114.8%)
12	MO: 1.25	333 (19.3%)	284 (2.1%)	279	300 (7.5%)	601 (115.6%)
13	MO: 1.5	389 (18.1%)	335 (1.7%)	329	357 (8.2%)	709 (115.2%)
14	Tech: 5	309 (3.0%)	304 (1.1%)	300	316 (5.4%)	316 (5.4%)
15	Tech: 14	285 (4.1%)	279 (1.8%)	274	296 (8.2%)	296 (8.2%)

power systems (i.a. storage-dominated). All different sensitivities are presented in Table C.8, in which the first row corresponds to the base case and thus to the values from Table 7.

Case 2 (3) considers a lower (higher) wind resource potential by halving (doubling) the amount of turbines that can be installed per location. Similarly, cases 4 and 5 address the sensitivity towards the turbine investment cost by respectively decreasing and increasing the annualized cost by 10 %. The next four sensitivities assess the impact of the initial electricity price profile. Specifically, cases 6 and 7 respectively decrease and increase the initial price variability, but both retain the average yearly value[23]. Cases 8 and 9 respectively decrease and increase the initial electricity price profile by 2.5 €/MWh for every time step. As such, cases 6 and 7 assess the impact of the variability of the electricity price (but retain the mean value), while cases 8 and 9 test the sensitivity towards the mean value (but retain the variability). For cases 10 to 13, we alter the merit-order coefficient to range from 0.5 to 1.5 $€/(MWh \cdot GW)$. The final two sensitivities limit the technology set to include just one turbine: the average 2 MW turbine for case 14 and the average 3 MW turbine for case 15[24].

From Table C.8, one can notice that the results presented in the body are fairly robust to input parameter variations. Do pay attention to the interpretation of the percentages relative to the case's optimum (FFIP). These are not directly comparable across cases since the additional system cost under the optimum (i.e. the percentage base) also varies per case. Consider for instance cases 8 and 9, for which we altered the average initial electricity price. The equilibrium outcome under the FIT, SFIP and FFIP are identical in both cases, and are identical to the corresponding ones in the base case (one can prove this via insights from Section 3). The efficiencies differ since the avoided conventional generation costs change (to be precise, they differ by the average price difference between the cases multiplied by the total amount of renewable generation).

Nevertheless, one can see that a higher electricity price variability (cases 6 and 7) tends to decrease the efficiency of sub-optimal support instruments. Distortions are thus likely smaller in storage-dominated power systems. When looking at cases 14 and 15 (i.e. the ones that consider a single turbine variant), the efficiency losses are relatively small, while investment- and capacity-based subsidies yield identical results (Section 3). Distortions in technology selection thus seem to be more important than distortions in siting

[23] In case 6, price variability is decreased by changing the initial price profile (p_t^{init}) to $\frac{2}{3}p_t^{init} + \frac{1}{3}\overline{p_t^{init}}$, in which the final factor represents the average initial electricity price. Similarly, price variability is increased in case 7 by altering the initial profile to $\frac{3}{2}p_t^{init} - \frac{1}{2}\overline{p_t^{init}}$. As the mean value of the price profile remains unchanged, we isolate the variability effect.

[24] Average here implies a rotor diameter of 120m an a hub height of 110m, see Appendix A.

decisions, at least for onshore wind support.

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On the research group:

The **Energy Systems Integration & Modeling Group** is part of the division of Applied Mechanics and Energy Conversion (TME) of the Department of Mechanical Engineering of KU Leuven in Belgium. E. Delarue and W. D'haeseleer lead this research group, currently about 15 PhD students and post-doctoral research fellows, dedicated to the modeling of integrated energy systems and markets. This young research group has already gained significant expertise and international recognition in the field. A major strength of this group is its interdisciplinary focus (techno-economic models, link to energy policies and markets). The group is further strongly embedded in EnergyVille, an association of the Flemish research institutes KU Leuven, VITO, imec and UHasselt in the field of sustainable energy and intelligent energy systems. EnergyVille brings research, development, training and industrial innovation together under one name, in close cooperation with local, regional and international partners.