The Optimal Share of Variable Renewables

How the Variability of Wind and Solar Power Affects their Welfare-Optimal Deployment

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How the Variability of Wind and Solar Power affects their Welfare-optimal Deployment

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Abstract – This paper estimates the welfare-optimal market share of wind and solar power, explicitly taking into account their output variability. We present a theoretical valuation framework that consistently accounts for the impact of fluctuations over time, forecast errors, and the location of generators in the power grid on the marginal value of electricity from renewables. Then the optimal share of wind and solar power in Northwestern Europe's generation mix is estimated from a calibrated numerical model. We find the optimal long-term wind share to be 20%, three times more than today; however, we also find significant parameter uncertainty. Variability significantly impacts results: if winds were constant, the optimal share would be 60%. In addition, the effect of technological change, price shocks, and policies on the optimal share is assessed. We present and explain several surprising findings, including a negative impact of CO_2 prices on optimal wind deployment.

JEL – C61, C63, Q42, Q48, D41

Keywords – wind power, solar power, variable renewables, cost-benefit analysis, numerical optimization, competitiveness

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1. Introduction

Many jurisdictions have formulated quantitative targets for energy policy, such as targets for greenhouse gas mitigation, energy efficiency, or deployment of renewable energy sources. For example, the European Union aims at reaching a renewables share in electricity consumption of 35% by 2020 and 60-80% in 2050;[1] similar targets have been set in many regions, countries, states, and provinces around the globe. Implicitly or explicitly, such targets seem to be determined as the welfare-maximal or "optimal share" of renewables, however, it is often unclear how targets are derived. This paper discusses the socially optimal share of wind and solar power in electricity supply. It provides a theoretical analysis that is focused on the variability of these energy sources, a structured methodological literature review, and numerical estimates for Northwestern Europe.

The optimal amount of wind and solar capacity is determined by the intersection of their marginal benefit and marginal cost curves. Both curves are not trivial to characterize, since they are affected by many drivers. Marginal costs are impacted by technological learning, raw material prices, and the supply curve of the primary energy resource. Marginal benefits are driven by the private and social costs of alternative electricity sources, such as investment costs, fuel prices and environmental and health externalities. They are also affected by the variability of wind and solar power. This paper discusses the impact of variability on solar and wind power's marginal benefit curve and their welfare-optimal quantities.

Wind and solar power have been labeled variable renewable energy (VRE) sources (also known as intermittent, fluctuating, or non-dispatchable), since their generation possibilities vary with the underlying primary energy source. Specifically, we refer to "variability" as three inherent properties of these technologies: variability over time, limited predictability, and the fact that they are bound to certain locations (cf. Milligan et al., 2011; Sims et al., 2011; Borenstein, 2012). These three aspects of variability have implication for welfare, cost-benefit, and competitiveness analyses. For example, the marginal value (or price) of electricity depends on the time it is produced, and hence the marginal benefit of solar generators might be increased by the fact that they produce electricity at times of high demand. For unbiased estimates of the optimal amount of wind and solar capacity, their variability has to be accounted for. This paper explains theoretically why variability matters, how it can be accounted for, and presents an empirical application. While this paper focusses on VRE, the theoretical arguments apply to all generation technologies.

This study contributes to the literature in four ways. Firstly, we theoretically explain why variability has economic consequences. We present a framework that allows accounting comprehensively and consistently for of all aspects of VRE variability, but is simple enough to allow for quantifications. Secondly, we provide an extensive review of the existing empirical model landscape to explain which kind of modeling approaches are able to capture which driver of marginal costs and benefits, and specifically, which models are able to represent variability. Thirdly, we present new numerical model results. Results are derived from the power market model EMMA that has been developed to capture variability appropriately. Variability is shown to have a large impact on the optimal share of VRE. Finally, we test the impact of price, policy, and technology shocks on the optimal share numerically. We find and explain a number of unexpected results, for example that higher CO_2 or fuel prices can reduce the optimal VRE share under certain conditions.

The paper is structured as follows. Section 2 discusses welfare analysis theoretically. Section 3 reviews the literature. Section 4 introduces the numerical electricity market model EMMA that is used in section 5 to estimate optimal penetration rates of wind and solar power for Northwestern Europe. Section 6 summarizes the numerical results and section 7 concludes.

2. Theory: the economics of variability

This section discusses the economics of variable renewables theoretically. It applies microeconomic theory to electricity markets to derive the welfare-optimal quantity of wind and solar capacity. This paper focuses on different aspects of variability. Other economic issues such as endogenous learning, externalities, or political economy issues of security of supply are important, but beyond the scope of this paper. The theoretical arguments put forward in this section are not restricted to variable renewables, but apply to all generation technologies.

[1] National targets for 2020 are formulated in the National Renewable Energy Action Plans. Beurskens et al. (2011), Eurelectric (2011a), PointCarbon (2011) and ENDS (2010) provide comprehensive summaries. EU targets for 2050 have been formulated in European Comission (2011).

As common practice in economics, we determine the "optimal amount" of wind and solar power as the welfare-maximizing amount. Elsewhere, the optimal VRE capacity has been determined by minimizing curtailment (Bode 2013), minimizing storage needs (Heide et al. 2010), or optimizing other technical characteristics of the power system. Danny & O'Malley determine the "critical amount" of wind power, where net benefits become zero.

As for all other goods, the welfare-optimal quantity of wind or solar capacity is characterized by the intersection of its long-term marginal costs and marginal value (benefit). However, deriving wind power's marginal cost and marginal benefit is not trivial. Economic cost-benefit analyses of electricity generation technologies require careful assessment and appropriate tools, because electricity as an economic good features some peculiar characteristics that make it distinct from other goods. In this section, we identify those peculiarities (2.1), derive the marginal cost (2.2) and marginal value (2.3) of VRE, and determine its optimal quantity (2.4). Throughout the paper, we expressed VRE quantities as share of total electricity consumption.

2.1. Electricity is a peculiar commodity

Electricity, being a perfectly homogeneous good, is the archetype of a commodity. Like other commodities, trade of electricity often takes place via standardized contracts on exchanges. In that sense, it seems straightforward to apply simple textbook microeconomics to wholesale power markets. However, the physical laws of electromagnetism impose crucial constraints, with important economic implications: i) storing electricity is costly and subject to losses; ii) transmitting electricity is costly and subject to losses; iii) supply and demand of electricity need to be balanced at every moment in time to guarantee frequency stability. These three aspects require an appropriate treatment of the good "electricity" in economic analysis.

As an immediate consequence of these constraints, the equilibrium wholesale spot electricity price varies over time, across space, and over lead-time between contract and delivery:

i) Since inventories cannot be used to smooth supply and demand shocks, the equilibrium electricity price varies dramatically over time. Wholesale prices can vary by two orders of magnitudes within one day, a degree of price variation that is hardly observed for other goods.
ii) Similarly, transmission constraints limit the amount of electricity that can be transported geographically, leading to sometimes significant price spreads between quite close locations.
iii) Because demand and supply has to be balanced at every instant, but fast adjustment of power plant output is costly, the price of electricity supplied at short notice can be very different from the price contracted with more lead-time. Hence, there is a cost to uncertainty.

Across all three dimensions, price spreads occur both randomly and with predictable patterns. While the economic literature has emphasized temporal heterogeneity (Bessiere 1970, Stoughton et al. 1980, Bessembinder & Lemmon 2002, Lamont 2008, Joskow 2011), the other two dimensions have not received similar attention.

In other words, electricity indeed is a perfectly homogenous good and the law of one price applies, but this is true only for a given point in time at a given location for a given lead-time. Along these three dimensions, electricity is a heterogeneous good and electricity prices vary. Figure 1 visualizes the three dimensions of heterogeneity by displaying the array of wholesale spot prices in one power system in one year.

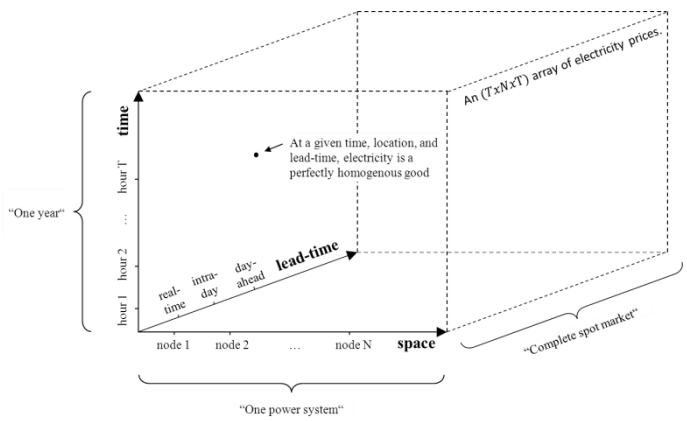

Figure 1: The array of wholesale spot electricity prices. The electricity price varies along three dimensions: time, space, and lead-time (uncertainty). At a

single point in the three-dimensional space of prices, electricity is perfectly homogeneous.

This fundamental economic property of electricity is approximated in real-world power market design: at European power exchanges, a different clearing price is determined for each hour and for each geographic bidding area. U.S. markets typically feature an even finer resolution, clearing the market every five minutes for each of several thousand transmission nodes. In addition, there is a set of power markets with different lead-times: in most European markets, there is a day-ahead market (12-36 hours before delivery), an intra-day market (few hours before delivery), and a balancing power market (close to real-time). As a consequence, there is not *one* electricity price per market and year, but 26,000 prices (in Germany) or three billion prices (in Texas).[2] Hence, it is not possible to say what "the" electricity price in Germany or Texas was in 2012.

The heterogeneity of electricity is not only reflected in market design, but also in technology. For homogenous goods, *one* production technology is efficient. In electricity generation, this is not the case: there exists a set of generation technologies that are efficiently used simultaneously in the same geographic market. There are nuclear and coal-fired so-called "base load", natural gas-fired "mid load" combined cycle gas turbines, and gas- and oil-fired "peak load" open cycle gas turbines. These technologies can be distinguished by their fixed-to-variable costs ratio: Base load have high capital costs but low variable costs. They are the most economical supply option for the share of electricity demand that is constant. Peak load plants have low fixed costs but high variable costs. They are the cheapest supply option for the few hours during a year with highest demand. Classical power market economics translates this differentiation into graphical approaches to determine the optimal fuel mix (section 3.2).

Any welfare, cost-benefit, or competitiveness analysis of electricity generation technologies need to take heterogeneity into account. It is in general *not* correct to assume that i) the average price of electricity from VRE (its marginal value) is identical the average power price, or that ii) the price that different generation technologies receive is the same. Comparing generation costs of different technologies or comparing generation costs of a technology to an average electricity price has little welfare-economic meaning. Specifically, marginal cost of a VRE technology below the average electricity price or below the marginal costs of any other generation technology does *not* indicate that this technology is competitive; still this is repeatedly suggested by lobby groups, policy makers, and academics (BSW 2011, EPIA 2011, Kost et al. 2012, Clover 2013, Koch 2013). Instead, the marginal cost of VRE has to be compared to its marginal value. To derive that marginal value, one needs to take into account when and where it was generated and that forecast errors force VRE generators to sell their output relatively short before real time. After discussing the marginal cost of VRE in the following subsection, we will derive its marginal value taking these aspects into account.

2.2. Marginal costs: levelized electricity costs

It is common and convenient to report long-term marginal value and marginal cost in energy terms (€/MWh). We will follow this convention here. Long-term marginal costs are the discounted average private life-cycle costs (fixed and variable, including the cost of capital) of the last VRE generator built. We will assume there are no externalities in wind turbine manufacturing or construction (supported by Hoen et al. 2013), hence private costs equal social costs. In the field of energy economics, average life-cycle costs are commonly called levelized costs of electricity or levelized electricity costs (LEC). We define the LEC of a generator as

$$LEC = \sum_{y=1}^{Y} \frac{1}{(1+i)^y} \frac{c_y}{g_y} \tag{1}$$

where c_y are the costs that occur in year y, g_y is the amount of electricity generated in that year, i is the real discount rate, and Y is the life-time of the asset in years.

Onshore wind LEC are globally currently in the range of 45-100 €/MWh, depending on wind resource quality, turbine market conditions, and discount rate. Offshore wind costs might be at 100-150 €/MWh and solar photovoltaic costs have reached similar levels after dramatic cost reductions during the past years. For an overview of LEC estimates for various generation technologies, see IPCC (2011, Figure 5), Borenstein (2012), and

[2] The German spot market EPEX clears for each hour of the year as a uniform price; the ERCOT real-time market of Texas clears every five minutes for all 10,000 bus bars of the system

Schröder et al. (2013). IEA (2013) provides recent global investment cost estimates for wind and solar power. Seel et al. (2013) point out the considerable differences between solar costs in Germany and the US.

In economic analyses, marginal costs are often a function of quantity. In the case of VRE, levelized costs might increase with penetration because land becomes scarce, or might decrease because of learning-by-doing and economies of scale. Nemet (2006), Hernández-Moro & Martínez-Duart (2013) and Brazilian et al. (2013) discuss and quantify the drivers for solar cost reductions and Schindler & Warmuth (2013) report recent market data. Lindman & Söderholm (2012) and van der Zwaan et al. (2012) estimate wind learning curves. Nordhaus (2009) provides a critique of the specification of econometric models to estimate learning curves. NREL (2009) and 3Tier (2010) provide estimates of resource-constrained supply curves for wind power in the US. Baker et al. (2013) provide an extensive literature survey on both topics.

Both learning and resource constraints happen outside the electricity market and a detailed analysis is beyond the scope of this paper. The electricity market determines the marginal value, which we will discuss in turn.

2.3. Marginal value: market value

We define the "market value" of a generation technology as the average discounted private life-time income from electricity sales, excluding any direct subsidies such as feed-in-tariffs, green certificates, or investments subsidies (Joskow 2011, Hirth 2013). We will assume perfect and complete power markets in long-term equilibrium, hence the (private) market value coincides with the (social) marginal value, and we will use both terms interchangeably. The market value of wind power can then be written as

$$MV^w = \sum_{y=1}^{Y} \frac{\overline{p}_y^w}{(1+i)^y} \tag{2}$$

where $\overline{p}_y^w$ is the average specific price (€/MWh) that wind generators received in year y. We will use "wind" for simplicity in the rest of this section. All analytics apply to solar power and any other generation technology as well.

a) An exact definition of market value

Assuming there exists one representative year, the wind market value equals the discounted average specific price of wind power in that representative year $\overline{p}^w$. This value can be written as the wind-weighted electricity price of all T time steps in all N price areas at all T lead-times:

$$\overline{p}^w = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{\tau=1}^{\mathrm{T}} w_{t,n,\tau} \cdot p_{t,n,\tau} \tag{3}$$

where $w_{t,n,\tau}$ is the share of wind generation in time t at node n that was sold at lead-time τ and $p_{t,n,\tau}$ is the respective price, one of the elements of the price array displayed in Figure 1.

In some cases the relative price of electricity from wind power is of interest. We define the "value factor" (Stephenson 1973, Hirth 2013) of wind power VF^w here as the market value over the load-weighted electricity price:

$$VF^w = \overline{p}^w / \overline{p}^d \tag{4}$$

$$\overline{p}^d = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{\tau=1}^{\mathrm{T}} d_{t,n,\tau} \cdot p_{t,n,\tau} \tag{5}$$

where $d_{t,n,\tau}$ is the share of load in time t at node n at lead-time τ. Hence the market value can be written as the average price times the value factor

$$\overline{p}^w = \overline{p}^d \cdot VF^w \tag{6}$$

In principle the market value $\overline{p}^w$ can be estimated directly either from observed market prices or modeled shadow prices $p_{t,n,\tau}$ - to the extent that models can be regarded as realistic and markets can be treated as being complete, free of market failures, and in equilibrium.

However, estimating the full array of shadow prices $p_{t,n,\tau}$ (Figure 1) would require a stochastic model with sufficient high temporal and spatial resolution. Such a "supermodel" might not be always available or actually impossible to construct. In the following, we propose a feasible approximation to determine $\overline{p}^w$ from several specialized models or data sources.

b) An approximation of market value

Hirth et al. (2013) have proposed an approximate derivation of market value. The idea of the approach is to estimate the impact of temporal variability, spatial variability, and forecast errors separately using specialized models or empirical datasets where a direct derivation is impossible. Along each dimension of heterogeneity there exist established modeling traditions that can be used for quantifications. We call the impact of timing on the market value of wind power "profile cost", the impact of forecast errors "balancing cost" and the impact of location "grid-related cost". Depending on the market design, these "costs" appear as reduced revenue or actual costs.

$$\overline{p}^w \approx \overline{p}^d - c^w_{profil} - c^w_{balancing} - c^w_{grid-related} \tag{7}$$

Figure 2 illustrates how profile costs, balancing costs, and grid-related costs reduce the wind market value vis-á-vis the average load-weighted electricity price. This is typically the case at high penetrations. At low penetrations, the costs components might become negative, increasing the market value above the average electricity price, for example if solar power is positively correlated with demand.

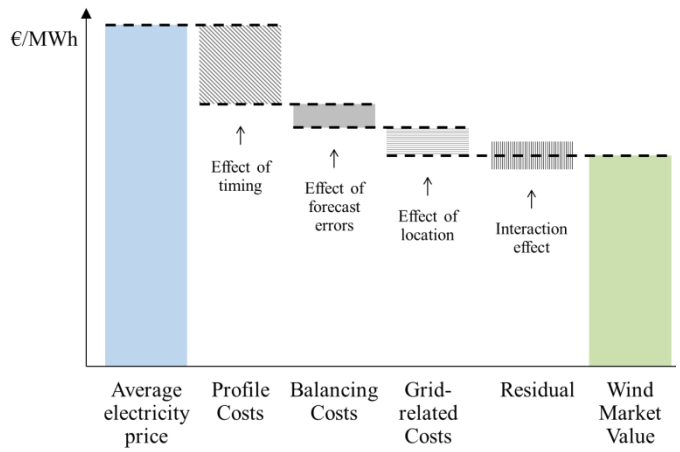

Figure 2: From the average electricity price to wind's market value (illustrative). At high penetration, timing and location as well as forecast errors typically reduce the market value.

We define profile costs as the price spread between the load-weighted and wind-weighted day-ahead electricity price for all hours during one year. Profile costs arise because of two reasons. On the one hand, demand and VRE generation are often (positively or negatively) correlated. A positive correlation, for example the seasonal correlation of winds with demand in Western Europe, increases the value of wind power, leading to negative profile costs. On the other hand, at significant installed capacity, wind "cannibalizes" itself because the extra electricity supply depresses the market price whenever wind is blowing. In other words, the price for electricity is low during windy hours when most wind power is generated. Fundamentally, profile costs exist because electricity storage is costly, recall physical constraint i). A discussion of profile costs and quantitative estimates are provided by Lamont (2008), Borenstein (2008), Joskow (2011), Mills & Wiser (2012), Nicolosi (2012), Hirth (2013), and Schmalensee (2013).

We define balancing costs as the difference in net income between the hypothetical situation when all realized generation is sold on day-ahead markets and the actual situation where forecast errors are balanced on intra-day and real-time or balancing markets. Fundamentally, balancing costs exist because frequency stability requires a balance of supply and demand and short-term plant output adjustments are costly, recall iii). Balancing costs are reviewed by Smith et al. (2007), Obersteiner et al. (2010), Holttinen (2011), and Hirth et al. (2013). Hirth & Ziegenhagen (2013) discuss to what extend balancing markets reflect marginal costs.

We define grid-related costs as the spread between the load-weighted and wind-weighted price across all price areas of a market. Grid-related costs exist because transmission is costly and wind speeds as well as land availability constrain wind power to certain sites, recall ii). Grid-related costs are estimated by Brown & Rowlands (2009), Lewis (2010), Hamidi et al. (2011), and Baker et al. (2013).

c) Market value as a function of penetration

The three cost components are not fixed parameters, but typically increase with penetration (Figure 3). This is no coincidence, but a consequence of the market-clearing role of prices: During windy times the additional electricity supply depresses the price; at windy locations, the additional supply depresses the price; and correlated wind forecast errors systematically lead to balancing costs. All three effects are stronger with larger installed capacities. In other words, both VF and $\overline{p}^d$ are in general a function of the wind share q.

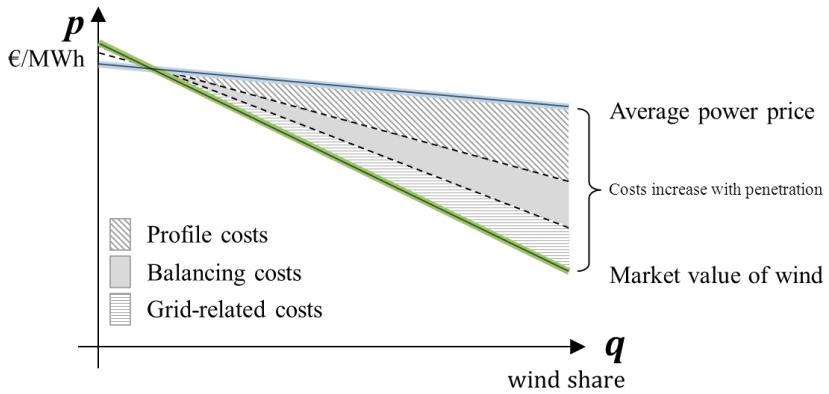

Figure 3: Average electricity price and market value as a function of the quantity of wind power in the system. At low penetration, the wind market value can be higher than the average power price, because of positive correlation between generation and load.

d) Market value and "integration costs"

A number studies discuss the costs that variability induces at the level of the power system under the term "integration costs" (Milligan et al. 2011, Holttinen et al. 2011). Ueckerdt et al. (2013a) discuss the "integration cost" literature in relation to the "market value" literature and Ueckerdt et al. (2013b) and Hirth et al. (2013) propose to define integration costs as the difference between market value and demand-weighted average electricity price.

2.4. The optimal share of wind power

a) Static (For a Given Power System)

The optimal wind capacity q^* in a price-quantity-diagram is given by the point where marginal costs and marginal benefits intersect (Figure 4). The marginal benefit is *not* the average power price, but the market value of wind power. The market value can be either estimated directly (from a "supermodel") or via the approximation proposed in section 2.3.

$$LEC(q^*) = \overline{p}^d(q^*) \cdot VF(q^*) \tag{8}$$

An immediate consequence is that, even if marginal costs were flat and the average electricity price constant, competitiveness is not a "flip-flop" behavior. In the policy debate it is often suggested that, one cost of wind turbines have reached a certain level, "wind is competitive". This is misleading: at a certain cost level, *a certain amount* of wind power is competitive.

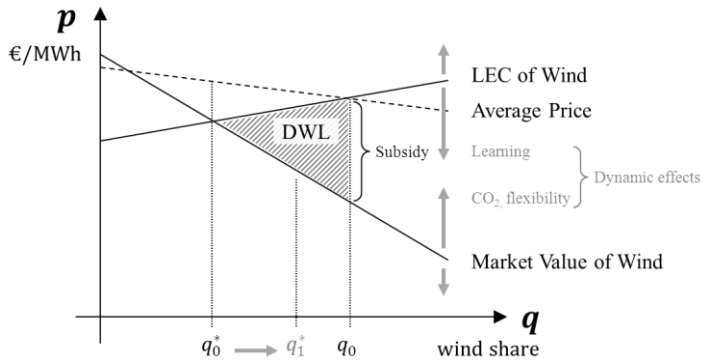

Figure 4: Static partial equilibrium of the electricity market. The optimal share of wind power is given by the intersection of the market value of wind power (marginal benefits) and its levelized electricity costs (long-term marginal costs). The LEC curve can be upward-sloping because of limited land or downward-sloping because of endogenous learning. The market value curve is always downward-sloping. Installing more wind power than optimal, for example q_0 , leads to dead weight losses (DWL). Dynamic effects (grey) such as technological learning and price shocks can reduce marginal costs and benefits, shifting the optimal wind share q^* .

b) Dynamic (For a Changing Power System)

Dynamic effects change the optimal wind share. Such effects can affect either shift the marginal cost curve or the marginal benefit curve. Technological learning of wind turbine technology shifts the LEC curve downwards. Increasing fuel or CO_2 prices increase the electricity price level and shift the market value curve upwards. Introducing "system integration" measures such as more flexible thermal plant fleet, electricity storage, more price-elastic demand, and more interconnector capacity typically pivot the marginal value curve clockwise without affecting the electricity price level much (Hirth & Ueckerdt 2013a).

For a given set of conditions, there exists always a certain optimal amount of wind power. Figure 5 displays such a set of market equilibria, the "optimality frontier". If the wind share is below its equilibrium point, it increases until it reaches the frontier. If higher shares shall be reached under the same conditions, wind power requires subsidies. In the numerical analysis (section 5) we estimate optimality frontiers: we estimate the optimal share as a function of cost reductions, and take additional dynamic effects into account via sensitivities.

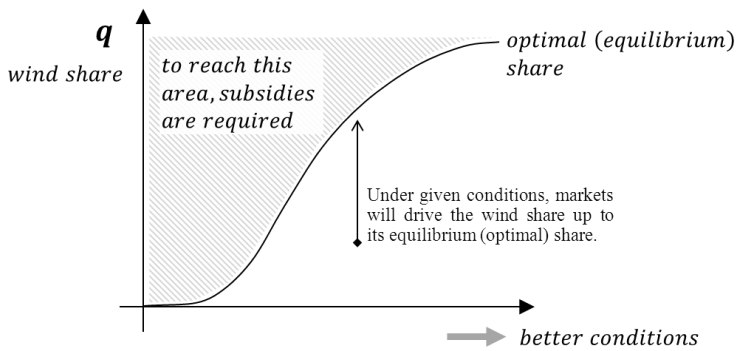

Figure 5: Dynamics of the market equilibrium. Under better conditions, such as reduced costs or increased costs of substitutes, a higher share of wind power is competitive (and welfare-optimal).Competitiveness is not a "flip-flop" behavior, but an equilibrium condition. Higher shares require subsidies and cause dead weight losses.

The following section reviews the model-based literature that estimates the optimal share of wind and solar power. Model approaches are assessed regarding their ability to estimate the three factors of equation (8): marginal costs, average electricity price, and value factor of VRE.

3. Review of the quantitative literature

The welfare-optimal electricity generation mix is one of the most researched topics in numerical model-based energy economics. This study identifies three strands of this literature: Models with low temporal and spatial resolution (integrated assessment and energy system models), models with high resolution that optimize the conventional mix for a given amount of VRE (power market or investment planning models), and high-resolution models with endogenous VRE capacity (like the one employed for this study), see Table 1. Electricity network models and pure dispatch or unit commitment models are not covered by this survey. These are sometimes used to test if a certain amount of VRE can be "accommodated" in a power system, but do not optimizes VRE capacity. The borderline between model classes is gradual, such that classification is to some degree subjective.

Table 1: Overview of vRES model approaches.

	Exogenous VRE capacity	**Endogenous VRE capacity**
Low resolution (years / continents)	-	Integrated Assessment Models Energy System Models
High resolution (hours / countries)	Power Market Models / Investment Planning Models	*This study*

Different classes of models have different merits and caveats when estimating the optimal VRE share. In the following, we structure the discussion along equation 8, which expresses the optimal share of, say, wind power as an equilibrium between marginal costs ($LEC(q^*)$) and the average electricity price or electricity price level ($\overline{p}^d(q^*)$) times the value factor or relative price of wind power ($VF(q^*)$). Some models are well suited to estimate marginal costs, others are well suited to estimate the average electricity price, and some are good in estimating the value factor.

Table 2 lists drivers behind these three factors, and names necessary model features to be able to model the respective driver endogenously. For example, the LEC is determined by technological learning. Modeling learning endogenously as an experience curve requires a global coverage, because VRE technology is traded globally and significant learning takes place at the level of equipment manufacturing. To model the prices of production factors such as steel, copper, fuel and carbon endogenously, these sectors have to be part of the model. To model electricity demand endogenously, consumption sectors such as industry, heating, and transport have to be represented in the model. To model the drivers of the value factor endogenously, models need to feature high temporal and spatial resolution, a consecutive representation of time, and engineering details of the power system such as operational constraints of thermal power plants.

In general, low-resolution models with broad scope tend to be better suited to estimate the marginal cost and the average electricity price, while high-resolution models with narrow scope are better equipped to estimate the value factor.

Table 2: Drivers and model requirements.

	Driver	**Model requirement**
Levelized electricity cost LEC	technological learning of VRE	global geographic scope
	VRE resource supply curve	- (data issue)
	raw material prices	global scope, multi-sector

Average electricity price (Electricity price level) $\overline{p}^d$	fuel prices	global scope, multi-sector
	carbon price	regional scope, multi-sector
	electricity demand	multi-sector
Value factor (Electricity price structure) VF	share of VRE	-
	flexibility of thermal plants	high temporal resolution, power system details
	hydro reservoir power	consecutive time
	transmission grid constraints	regional scope, high spatial resolution
	electricity storage	high temporal resolution, consecutive time
	VRE forecast quality	power system details
	VRE generation profile	high temporal resolution

3.1. Low-resolution models

For numerical and complexity reasons, there is a trade-off between model scope and resolution. Broad multi-sector models with a large geographic coverage have to limit temporal and spatial resolution.

a) *Integrated assessment models*

"Integrated Assessment Models" (IAMs) are numerical macroeconomic models that typically cover the entire world and all sectors of the economy. They are used to determine the optimal share of wind and solar in the electricity generation mix for example as part of greenhouse gas mitigation studies. Well-known IAMs include GCAM (Calvin et al. 2009), IMAGE (van Vliet et al. 2009), MESSAGE (Krey and Riahi 2009), TIAM (Loulou et al. 2009), MERGE (Blanford et al. 2009), EPPA (Morris 2008), and ReMIND (Leimbach et al. 2010). While these models differ considerable in terms of methodology, they usually have a temporal resolution of one or several years and a geographic resolution of world regions, such as Europe. They usually have a temporal scope until 2050 or 2100.

IAMs are capable to capture important drivers of marginal costs and the average electricity price. Cost drivers include global endogenous technological learning and, in the case of biomass, land use by other sectors. The average electricity price is impacted by macroeconomic growth, the carbon price, fuel prices, and the electricity demand for example driven by the electrification of the heat and transport sector, all of which are usually endogenous to these models.

However, they are not able to explicitly represent the heterogeneity of the good "electricity" in any of its three dimensions. They typically treat electricity as one sector with one price. Variability needs to be approximated using parameterizations. Luderer et al. (2013) and Baker et al. (2013) present overviews of how VRE are modeled and Ueckerdt et al. (2010a, 2010b) and Sullivan et al. (2013) propose new approaches for variability representation.

In a comprehensive survey of model inter-comparison studies, Fischedick et al. (2011, figure 10.9) report a median global VRE share of total electricity consumption of 10% by 2050 without climate policy and between 15-20% under climate policy.

b) Energy system models

"Energy system models" have a more narrow scope and a somewhat finer resolution. They are partial equilibrium models of the energy sector of one world region. Some models, such as PRIMES (European Commission 2011, Eurelectric 2013), MARKAL/TIMES (Loulou et al. 2004, 2005, Blesl et al. 2012), or the World Energy Model (IEA 2013) cover all three energy subsectors heat, electricity, and transportation. Others focus on the electricity sector, such as ReEDs (Short et al. 2003, 2011), US-Regen (Blanford et al. 2012), SWITCH (Nelson et al. 2012) and CAPEW (Brun 2011) for North America, and LIMES (Haller et al. 2012), PERSEUS (Rosen et al. 2007), and DEMELIE (Lise & Kruseman 2008) for Europe. Finally, some models cover the power and natural gas sectors and include a gas supply curve and gas infrastructure constraints, such as LIBEMOD (Aune

et al. 2001). These models typically have a geographical resolution of countries or states and represent temporal variability by modeling typical days or weeks or modeling ten to 50 non-consecutive time slices. They are often applied to time horizons between 2030 and 2050.

The capabilities and shortcomings of IAMs discussed above in general apply to energy system models, but to a lesser extent. Global phenomena like technological learning or fuel markets, including carbon and biomass, cannot be modeled. However, regional carbon prices and electricity demand from the heat and power sector are often endogenous. Often these models have more detailed supply curves for wind and solar power than IAMs, allowing estimating their LEC quite accurately at a finer geographic resolution. Variability in the power sector can be modeled, but is subject to the models' limited resolution. If variability is not parameterized somehow, the low resolution introduces a bias towards too high VRE shares. Nicolosi (2011, 2012) reports estimates of the bias introduced by low resolution: the capacity mix is biased towards base load technologies, the capacity factor of VRE is overestimated, and the marginal value of VRE is overestimated. Some models use non-consecutive "time slices" to represent variability. However, time slices impedes to model electricity storage and hydro reservoirs, and selecting appropriate time slices is far from trivial given the multiple time series (wind, solar, load) in all model regions. Furthermore, these models often lack technical constraints of power systems, such as combined heat and power (CHP) generation, ancillary services, and ramping constraints of thermal generators. Typically, they are not back-tested to replicate historical power plant dispatch, electricity price, or interconnector flow patterns.

Knopf et al. (2013) report on a European model intercomparison project that covers both IAMs and energy system models. They report median VRE shares of total electricity consumption in the European Union of 11% without and 25% with climate policy by 2050 in the reference scenarios, but shares of 50-60% if nuclear power is restricted or assumption on VRE are more optimistic. Nelson et al. (2012) report somewhat lower numbers for the Western Interconnection of the United States.

Both IAMs and energy system models are tools that focus on estimating marginal costs and the average power price, but are not appropriate to estimate the value factor. Instead, parameterizations of VF have to be taken from high-resolution models. Moreover, these low-resolution models cannot be used to assess the impact of sectoral policies and technological changes. For example, the impact of heat storages on the marginal value of wind power via CHP plant flexibility can only be assessed if CHP generation is modeled, which is usually only the case in high-resolution models. We will discuss high-resolution models in turn.

3.2. High-resolution models with exogenous VRE

Vertically integrated utilities have used "investment planning models" of "expansion planning models" for decades to optimize their capacity mix. These models explicitly account for variable demand by applying a high, for example hourly, resolution. This comes at the price of reduced scope: these models are partial equilibrium models of a single or few countries. In liberalized markets this class of models is often called "power market models" and used for fundamental long-term price projections. We discuss these models here for two reasons, even though they do not model VRE capacity endogenously: on the one hand, they are sometimes used to calibrate parameterizations of low-resolution models, on the other hand they are the precursors of the models discussed in section 3.3.

The classical version of these models is based on screening curves and load duration curves and can be solved graphically to derive the cost-minimal capacity mix (Stoughton et al. 1980, Grubb 1991, Stoft 2002, Green 2005). Because several constraints of power systems cannot be represented in load duration curves, numerical models were developed starting in the 1960s (Bessiere 1970), for instance WASP (Jenkins & Joy 1974, Covarrubias 1979).

Current power market models account for more details and constraints of power systems, such as CHP generation, ancillary services, pumped hydro storage, price-elastic demand, imports and exports, start-up and ramping costs of thermal plants, and hydro reservoirs. These models have typically a temporal resolution of 15 to 120 minutes and a spatial resolution of countries or bidding areas. They are usually able to reproduce hourly historical price, dispatch, and export patterns. Power market models are typically used in utility companies and consulting firms to forecast prices and guide investment decisions.

While such commercial models are not published, we summarize VRE-related academic studies based on such models in the following. Krämer (2002), Bushnell (2010), Green & Vasilakos (2011), and Nagl et al. (2012) compare the optimal long-term thermal capacity mix with and without VRE. They find that overall thermal

capacity is only slightly reduced, but that there is a noticeable shift from baseload to mid- and peakload technologies with the introduction of VRE. Nagl et al. (2011), Tuohy & O'Malley (2011), and Lamont (2012) model the impact of VRE on storage. These models are also used estimate wind and solar market value, often as a function of penetration. Recent estimates are provided by Swider & Weber (2006), Lamont (2008), Fripp and Wiser (2008), Mills & Wiser (2012, 2013), Nicolosi (2012), and Hirth (2013), who also surveys the respective literature. Early studies include Martin & Diesendorf (1983), Grubb (1991), and Rahman & Bouzguenda (1994).

All these studies take VRE capacity as given and only optimize the thermal plant fleet. This can be explained by the fact that VRE played a marginal role at the times when these models were developed. Furthermore, since VRE were often owned by independent power producers and not the integrated utilities that operated such models, they were not subject to the utility's optimization. Today's commercial power market models usually still regard VRE investments as exogenous, since those are driven by subsidies and subject to political decisions rather than subject to market prices.

3.3. High-resolution models with endogenous VRE

Surprisingly few studies optimize VRE capacities based on high-resolution models. Those that do so usually stem from the tradition of power market models and have endogenized VRE capacity. These models endogenized the VRE value factor by providing high resolution and power system details. However, for reasons of scope, technological learning, power demand, and fuel and carbon prices are typically exogenous.

a) *Pure long-term models (green field)*

Pure long-term models derive optimal VRE capacities "from scratch", without taking existing infrastructure such as power plants into account, but they usually assume today's demand structure.

DeCarolis & Keith (2006) derive the cost-minimal electricity mix for Chicago, but consider only one thermal technology. They find that wind power needs a CO_2 price of at least 150 $/t to be competitive. Doherty et al. (2006) apply a simple linear investment-dispatch model to Ireland, finding the optimal amount of wind capacity strongly dependent on the price of CO_2 and gas. Olsina et al. (2007) derive the optimal capacity mix for Spain. They find that at investment costs of 1200 €/kW virtually no wind power is installed, but if costs drop by 50%, about 20 GW should be installed. One drawback of this study is that the simulated wind profiles do not capture spatial correlations well. Also, the electricity system is modeled as a merit-order approach that omits must-run constraints, storage, or international trade. Lamont (2008) finds that no wind power should be deployed if annualized fixed costs amount to 120 $/kW. If costs drop to 85 $/kW, a third of total capacity should be wind power.

b) Models with existing power plants

A few studies do take existing infrastructure into account. Neuhoff et al. (2008) apply an elaborated investment-dispatch model with 1040 time steps per year to optimize gas-fired plant and wind investments in the UK until 2020, also accounting for grid constraints. They report an optimal wind share of 40% based on very optimistic wind cost assumptions. Möst & Fichtner (2010) couple an investment model with a 15 min-resolution dispatch model. They find that both wind and solar cannot be efficiently deployed in Germany under current conditions. Müsgens (2013) applies a two-hourly model of Europe. Under a strict emission cap, a limit on nuclear power, and endogenous technology learning, he finds optimal shares of 25% wind and 10% solar power by 2050.

The model EMMA, which will be introduced in the following section, belongs to this last class of models. It is comparable to Neuhoff et al. (2008), but covers a larger geographic region, like Müsgens (2013). While Müsgens uses his model to project the optimal amount of VRE capacity under today's political constraints, we use EMMA to understand the impact of a variety of policy, price, and technology shocks on the optimal share. While Müsgens (2013) is comparable to this study in terms of modeling methodology, the research questions are quite complementary.

4. Numerical modeling methodology

This section introduces the European Electricity Market Model EMMA, which is used in the following section to estimate the optimal share of wind and solar power both in the medium and long term. EMMA is a stylized numerical dispatch and investment model of the interconnected Northwestern European power system that has been applied previously in Hirth (2013) and Hirth & Ueckerdt (2013a). In economic terms, it is a partial equilibrium model of the wholesale electricity market. It determines optimal or equilibrium yearly generation, transmission and storage capacity, hourly generation and trade, and hourly market-clearing prices for each market area. Model formulations are parsimonious while representing VRE variability, power system inflexibilities, and flexibility options with appropriate detail. This section discusses crucial features verbally. Equations, GAMS code and input data are available online[3] and as supplementary material of Hirth (2013).[4]

4.1. The power market model EMMA

EMMA minimizes total costs with respect to investment, production and trade decisions under a large set of technical constraints. Markets are assumed to be perfect and complete, such that the social planner solution is identical to the market equilibrium and optimal shares of wind and solar power are identical to competitive shares. The model is linear, deterministic, and solved in hourly time steps for one year.

For a given electricity demand, EMMA minimizes total system cost, the sum of capital costs, fuel and CO2 costs, and other fixed and variable costs, of generation, transmission, and storage assets. Capacities and generation are optimized jointly. Decision variables comprise the hourly production of each generation technology including storage, hourly electricity trade between regions, and investment and disinvestment in each technology, including wind and solar power. The important constraints relate to energy balance, capacity limitations, and the provision of district heat and ancillary services.

Generation is modeled as eleven discrete technologies with continuous capacity: two VRE with zero marginal costs – wind and solar –, six thermal technologies with economic dispatch – nuclear, lignite, hard coal, combined cycle gas turbines (CCGT), open cycle gas turbines (OCGT), and lignite carbon capture and storage (CCS) –, a generic "load shedding" technology, and pumped hydro storage. Hourly VRE generation is limited by generation profiles, but can be curtailed at zero cost. Dispatchable plants produce whenever the price is above their variable costs. Storage is optimized endogenously under turbine, pumping, and inventory constraints. Existing power plants are treated as sunk investment, but are decommissioned if they do not cover their quasi-fixed costs. New investments including VRE have to recover their annualized capital costs from short-term profits.

The hourly zonal electricity price is the shadow price of demand, which can be interpreted as the prices on an energy-only market with scarcity pricing. This guarantees that in the long-term equilibrium the zero-profit condition holds. As numerical constraints prevent modeling more than one year, capital costs are included as annualized costs.

Demand is exogenous and assumed to be perfectly price inelastic at all but very high prices, when load is shed. Price-inelasticity is a standard assumption in dispatch models due to their short time scales. While investment decisions take place over longer time scales, we justify this assumption with the fact that the average electricity price does not vary dramatically between model runs.

Combined heat and power (CHP) generation is modeled as must-run generation. A certain share of the cogenerating technologies lignite, hard coal, CCGT and OCGT are forced to run even if prices are below their variable costs. The remaining capacity of these technologies can be freely optimized. Investment and disinvestment in CHP generation is possible, but the total amount of CHP capacity is fixed. Ancillary service provision is modeled as a must-run constraint for dispatchable generators that is a function of peak load and VRE capacity.

Cross-border trade is endogenous and limited by net transfer capacities (NTCs). Investments in interconnector capacity are endogenous to the model. As a direct consequence of our price modeling, interconnector investments are profitable if and only if they are socially beneficial. Within regions transmission capacity is assumed to be non-binding.

[3] www.pik-potsdam.de/members/hirth/emma

[4] For this paper, VRE cost figures and the model were updated: the ancillary service constraint is now also a function of VRE capacity; it used to be a function of peak load only.

The model is linear and does not feature integer constraints. Thus, it is not a unit commitment model and cannot explicitly model start-up cost or minimum load. However, start-up costs are parameterized to achieve a realistic dispatch behavior: assigned base load plants bid an electricity price below their variable costs in order to avoid ramping and start-ups.

The model is fully deterministic. Long-term uncertainty about fuel prices, investment costs, and demand development are not modeled. Short-term uncertainty about VRE generation (day-ahead forecast errors) is approximated by imposing a reserve requirement via the ancillary service constraint, and by charging VRE generators balancing costs.

Being a stylized power market model, EMMA has significant limitations. An important limitation is the absence of hydro reservoir modeling. Hydro power offers intertemporal flexibility and can readily attenuate VRE fluctuations. Hence, results are only valid for predominantly thermal power systems. Demand is assumed to be perfectly price inelastic up to high power prices. More elastic demand would help to integrate VRE generation. However, it is an empirical fact that demand is currently very price-inelastic in Europe and possible future demand elasticities are hard to estimate. Technological change is not modeled, such that generation technologies do not adapt to VRE variability. Not accounting for these possible sources of flexibility potentially leads to a downward-bias of optimal VRE shares. Hence, results can be interpreted as conservative estimates.

EMMA is calibrated to Northwestern Europe and covers Germany, Belgium, Poland, The Netherlands, and France. In a back-testing exercise, model output was compared to historical market data from 2008-10. Crucial features of the power market can be replicated fairly well, like price level, price spreads, interconnector flows, peak / off-peak spreads, the capacity and generation mix.

4.2. Input data

Electricity demand, heat demand, and wind and solar profiles are specified for each hour and region. Historical data from the same year (2010) are used for these time series to preserve empirical temporal and spatial correlation of and between parameter as well as other statistical properties. These properties and correlations crucially determine the optimal VRE share. VRE profiles are based on historical weather data from the reanalysis model ERA-Interim and aggregate power curves are used to derive profiles. Load data were taken from ENTSO-E. Heat profiles are based on ambient temperature. Based on Hirth & Ziegenhagen (2013), we assume a balancing reserve requirement of 10% of peak load plus 5% of installed VRE capacity. Based on a literature survey by Hirth et al. (2013), balancing costs for wind and solar were assumed to be 4 €/MWh, independent of the penetration rate.

Fixed and variable generation costs are based on IEA & NEA (2010), VGB Powertech (2011), Black & Veatch (2012), and Schröder et al. (2013). Fuel prices are average 2010 European market prices, 9 €/MWh_t for hard coal and 18 €/MWh_t for natural gas, and the CO_2 price is 20 €/t. Summer 2010 NTC values from ENTSO-E were used to limit interconnection capacity. CHP capacity and generation is from Eurelectric (2011b). A discount rate of 7% in real terms is used for all investments, including transmission, storage and VRE.

For wind power we assume investment costs of 1300 €/kW and O&M costs of 25 €/kWa. At 2000 full load hours, as in Germany, this equals LEC of 68 €/MWh. The corresponding numbers for solar power are 1600 €/kW, 15 €/kWa and 180 €/MWh. Learning and resource constraints are assumed to roughly offset each other such that wind and solar supply curves are flat.

4.3. Representing different aspects of variability in EMMA

EMMA models endogenously important aspects of the three dimensions of heterogeneity of electricity and correspondingly the costs of VRE variability. Most importantly, the model features an hourly resolution, uses high-quality hourly input data, and accounts for several restrictions that limit the flexibility of the rest of the power system. In other words, the model accounts quite well for profile costs. Other costs of variability are added as cost mark-ups, as proposed in section 2.3.

However, other aspects are only modeled quite roughly. Geographically, EMMA features only moderate granular detail of countries. International trade is constrained, but internal grid restrictions are not modeled. Furthermore, trade is restricted by NTCs and physical load flows are not modeled. Schumacher et al. (2013) estimates grid-related costs to be small in Germany both for wind and solar, hence we set them to zero.

Forecast errors are not modeled explicitly. EMMA features a spinning reserve requirement that is a function of installed VRE capacity. In addition, VRE generators pay for reserve activation in form of a constant balancing cost charge of 4 €/MWh.

4.4. Optimality at different time horizons

The optimal share of VRE depends crucially on how flexibly the model is allowed to adjust (Ueckerdt et al. 2013, Baker et al. 2013). A crucial point is the previously-existing capital stock, where the literature uses three different approaches.

One option is to take the existing generation and transmission infrastructure as given and disregard any changes. The optimization reduces to a sole dispatch problem. We label this the *short-term* perspective. Another possibility is to disregard any existing infrastructure and optimize the electricity system "from scratch" as if all capacity was green-field investment. This is the *long-term* perspective. Finally, one can take the existing infrastructure as given, but allow for endogenous investments and disinvestments. We call this the *medium term*. Note that the expressions short term and long term are *not* used to distinguish the time scale on which dispatch and investment decisions take place, but refer to the way the capital stock is treated. While all three time horizons are analytical concepts that never describe reality entirely correctly, we believe the long term as defined here is a useful assumption to analyze European power systems in 2030 and beyond. In systems with a higher rate of capital turnover the assumption might be quite valid already in 2020.

In section 5 we present mid-term and long-term results. Typically the long-term optimal share of VRE is higher than the mid-term value, since only in the long-term VRE saves capital costs.

For the short, mid, and long-term framework corresponding welfare optima exists, which are, absent of market failures, identical to the corresponding market equilibria. It is only in the long-term equilibrium that all profits are zero, including those of wind and solar power (Steiner 1957, Boiteux 1960, Crew et al. 1995). EMMA estimates the short, mid, or long-term equilibrium, but not the transition path towards the equilibrium or out-of-equilibrium situations.

5. Numerical results

In this section we use EMMA to estimate the optimal amount of wind and solar power at various levels of cost reduction of up to 30% for wind and 60% for solar. For each cost level, the power system is optimized, including wind and solar capacity. Results are mostly reported as optimal shares of total electricity consumption. We focus on long-term optima, but also discuss the medium term in 5.7. The impact of different aspects of variability is reported and the effects of a number of price, policy, and technology shocks are examined. All findings should be interpreted cautiously, keeping model and data limitations in mind that have been highlighted in sections 3 and 4.

Assuming that onshore wind costs can be reduced by 30% to 50 €/MWh in the long term, we find that the optimal wind share on Northwestern Europe is around 20%, three times today's level, but lower than some policy targets. In contrast, even with solar costs 60% below today's levels to 70 €/MWh, the optimal solar share would be close to zero. We find that variability dramatically impacts the optimal wind share. Specifically, temporal variability has a huge impact on these results: if winds were constant (flat), the optimal share would triple. In contrast, forecast errors have only a moderate impact: without balancing costs, the optimal share would increase by less than half. The large impact of variability indicates that models that cannot represent variability explicitly need to approximate it carefully, and it implies that analyses which ignore variability are strongly biased. These "benchmark" results assume 2011 market prices for inputs and full availability of all generation technology options.

We then assess the effect of three shocks that are often seen as major determinants of VRE deployment: climate policy, technical integration measures, and fuel prices. We find that they do not change the picture qualitatively. Carbon pricing and higher fuel price can have a moderate positive impact on optimal wind shares, but sometimes even *reduce* it as they trigger baseload investments; storage has an insignificant impact; the impact of interconnector expansion and new turbine technology is positive, but moderate in size; flexibilizing thermal plants has the largest impact. The one case where we find very high optimal VRE shares (45% wind plus 15%

solar) is a combination of high VRE cost reductions with high carbon prices and unavailability of the low-carbon technologies nuclear power and CCS.

5.1. Optimal wind share

The long-term market value of wind power is displayed in Figure 6. As theoretically discussed in section 2.3 and empirically estimated in Hirth (2013), the market value is a downward-sloping function of wind penetration: it drops from about 71 €/MWh at low penetration to 40 €/MWh at 30% penetration. The intersection of the market value curve with LEC characterizes the optimal wind share. The demand-weighted average price declines, but only slightly from 76 €/MWh to 71 €/MWh.

Figure 7 shows the optimal share as a function of decreasing costs ("optimality frontier"). At current cost levels of about 68 €/MWh, only marginal amounts of capacity are competitive in Northwestern Europe. However, if costs decrease by 30% to 48 €/MWh, wind power optimally supplies 20% of Northwestern European electricity consumptions, three times as much as today. In other words, if deployment subsidies are phased out, wind power will continue to grow, but only if costs decrease. We use these results that are based on best-guess parameter assumptions as benchmark.

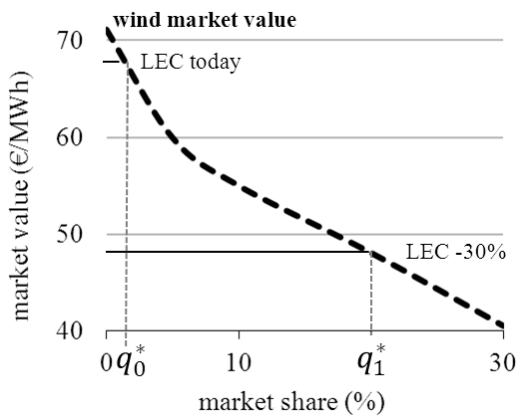

Figure 6: Wind's market value falls with penetration. The intersection between LEC and market value gives the optimal share (section 2.4). At LEC of 68 €/MWh the optimal share is around 3%; if generation costs fall by 30%, the optimal share is about 20%.

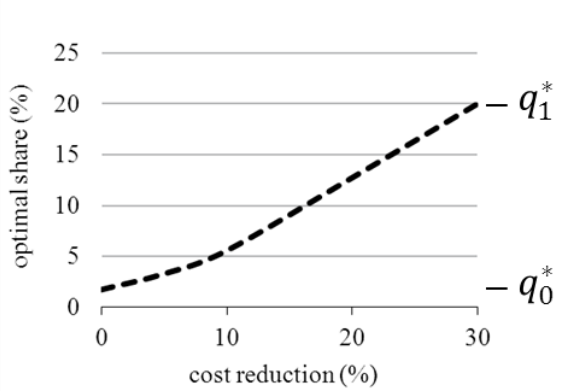

Figure 7: The optimal share of wind power in total electricity consumption as function of wind power cost reduction under benchmark assumptions. In Northwestern Europe, the share increases from 2% to 20%.

5.2. Optimal solar share

Solar power has a marginal value of about 75 €/MWh at low penetration, compared to LEC of currently 180 €/MWh, hence its optimal share is zero. We model cost reductions of up to 60% (LEC of 70 €/MWh), but even then the optimal share is small (2%). However, in a few cases solar becomes competitive in significant amounts (section 5.5). Otherwise we will focus on wind power in the remainder of the section due to space constraints.

Some authors claim that solar power becomes competitive once it reaches "grid parity", which is usually understood as costs falling below end-consumer price. However, grid parity has little to do with economic efficiency. Not only does this measure ignore electricity price heterogeneity (recall section 2), but also that retail electricity prices comprise mainly taxes, levies, and grid fees. Since decentralized solar generation saves at best marginal amounts of grid costs, the market value is the appropriate electricity price to evaluate solar power with.

5.3. The impact of variability

As laid out in section 2, different aspects of variability impact the optimal amount of VRE capacity. Here we quantify two of them, temporal variability and forecast errors. EMMA lacks a representation of the transmission grid, such that the impact of locational constraints on the optimal share cannot be assessed. We find that variability has a dramatic impact (Figure 8). If wind generation was constant, its optimal share would rise above 60%. The impact of forecast errors is much smaller: switching off the reserve requirement and balancing costs increases the optimal share by only eight percentage points. This endorses previous findings that temporal variability is significantly more important for welfare analysis than uncertainty-driven balancing (Mills & Wiser 2012, Hirth et al. 2013). Relaxing grid connections has minor impact, but recall that only cross-border constraints were taken into account in the first place. These findings indicate how dramatically results can be biased if variability is ignored.

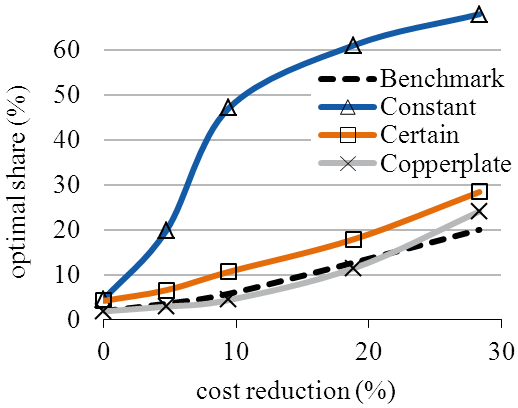

Figure 8: The impact of temporal variability and forecast errors.

5.4. The impact of integration options

Many technical measures have been proposed to better integrate VRE into power systems, and specifically, to alleviate the drop of market value. Electricity storage, interconnector capacity, more flexible thermal plants, and a different design of wind turbines are the most prominent (Mills & Wiser 2013, Hirth & Ueckerdt 2013b).

Both storage and interconnector capacity are endogenous to the model and hence deployed at their optimal level in the benchmark run. Here we test their impact of optimal wind shares by setting their capacities exogenously to zero and twice current capacity.

The first surprising result: wind deployment is only slightly affected by pumped hydro storage capacity (Figure 9). Doubling storage capacity from existing levels results in an optimal share of 22%, setting storage capacities to zero results in 20%. This option would cost about € 1.4bn per year. The driver behind this outcome, besides the fact that doubling storage capacity means adding relatively little capacity compared to installed wind capacity, is the design of pumped hydro plants. They are usually designed to fill the reservoir in about eight hours while wind fluctuations occur mainly on longer time scales. Thus wind requires a storage technology that has a large energy-to-power ratio than pumped hydro storage.

Higher long-distance transmission capacity helps to balance out fluctuations in VRE generation profiles and allows building where resources are best. Doubling interconnector capacity gives a four percentage point higher optimal wind share than setting interconnector capacity to zero (Figure 10). This measure would cost about € 0.8bn per year. Hence, in terms of increased penetration per Euro, interconnector investments are several times more efficient as wind power integration measure than storage investments.

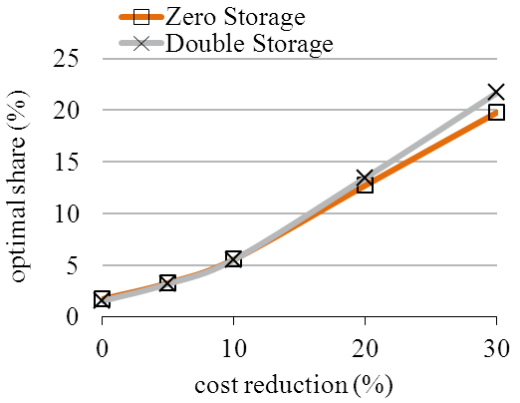

Figure 9: The effect of storage capacity on optimal wind deployment. The effect is very small.

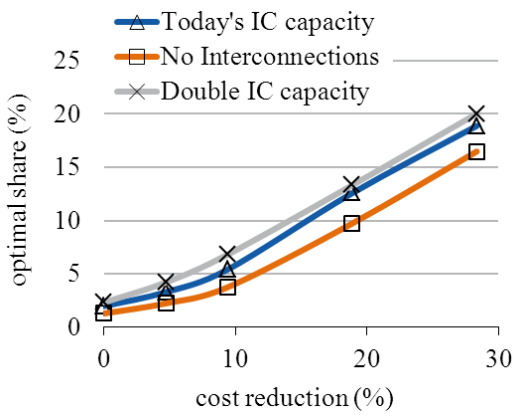

Figure 10: The effect of interconnector capacity is moderate at all wind cost levels.

Technical inflexibility of thermal plants impacts electricity prices and reduces the optimal share of VRE. EMMA features two important must-run constraints for thermal plants, CHP generation and ancillary service provision. Heat storages or heat-only boiler can be used to dispatch CHP plants more flexibly. Batteries, consumer appliances, or power electronics could help supplying ancillary services. Figure 11 shows the effect of taking these constraints out. Switching off CHP must-run increases the optimal share by three percentage points, switching off the ancillary service constraint by three percentage points, and both constraints by five points.

Wind turbine technology is still evolving quickly (IEA 2012, MAKE 2013). Low wind-speed turbines with higher hub heights and larger turbine-to-generator ratios have entered the market, resulting in flatter generation profiles. We tested the impact of flatter profiles by using a more steady offshore profile (without changing costs). As a consequence, the optimal share rises by almost three percentage points (Figure 12). Assessing the cost of thermal plant flexibilization and advanced wind turbine is beyond the scope of this analysis.

All integration measures increase the optimal wind share. The impact of doubling storage capacity on optimal wind deployment is very small, the impact of doubling interconnector capacity and changing the wind generation profile is moderate, and the impact of thermal plant flexibility is quite large. This does neither imply that these measures should be ignored or should be pursued, nor does it imply a ranking between these three options, as each measure comes at a cost. However, comparing storage and interconnector capacity in terms of cost and impact on wind deployment it seems that interconnector expansion is a more efficient integration option.

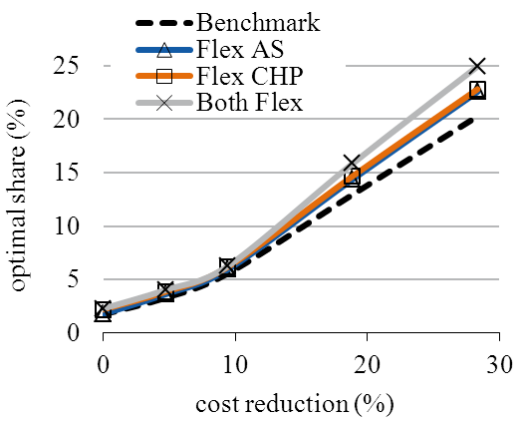

Figure 11: The effect of thermal plant flexibility is large, especially at high cost reduction levels.

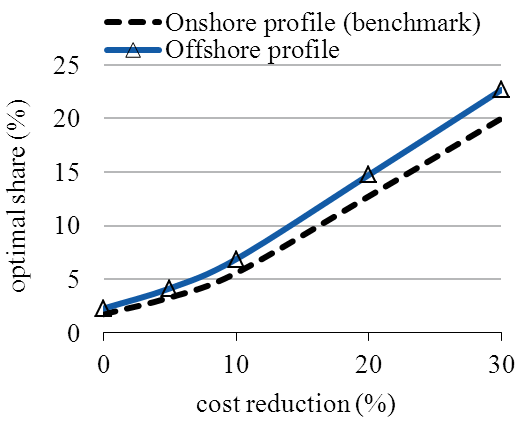

Figure 12: The effect of a flatter profile is moderate.

5.5. The impact of climate policy

Many observers suggest that CO_2 pricing has a positive and significant impact on VRE competitiveness. Many European market actors argue that during the 2020s, renewable subsidies should be phased out, and expect VRE to continue to grow, driven by carbon prices. We estimate the optimal wind share at different CO_2 prices.

Figure 13 displays the optimal wind share at prices of 0 €/t, 20 €/t, and 100 €/t. As one would expect, a CO_2 price of zero results in less deployment than the benchmark price of 20 €/t. Lower costs of emitting plants reduce the marginal value of wind power, and optimal deployment is close to zero.

Yet increasing the CO_2 price from 20 €/t 100 €/t shows a surprising result: wind deployment is *reduced*. Figure 14 shows in more detail the non-monotonic effect of CO_2 pricing on VRE deployment, assuming high cost reductions: the optimal wind share increases initially steeply with higher CO_2 prices, peaks at 40 €/t, and decreases afterwards. The optimal solar share rises until 40 €/t and remains relatively flat afterwards, such that the compound VRE share always remains below 25% and even decreases to 15% at 180 €/t CO_2. This might look counterintuitive at first glance.

The reason for this surprising behavior is investments in competing low-carbon technologies. Nuclear power and CCS are the only dispatchable low-carbon technologies in the model, and these two are base load technologies with very high investment, but very low variable costs. Baseload capacity reduces the marginal value of VRE and hence its optimal share. Carbon prices below 40 €/t do not trigger any nuclear or CCS investments, such that up to that point carbon pricing has a positive impact of VRE via higher costs of emitting plants. Beyond 40 €/t, the baseload investment effect dominates the emission cost effect. To benefit from stricter climate policy, VRE technologies would need low-carbon mid and peak load generators as counterparts. In this context it is important to recall that generation from biomass is not included in the model. If biomass would be available sustainably in large volumes, it could fill this gap and possible change results significantly.

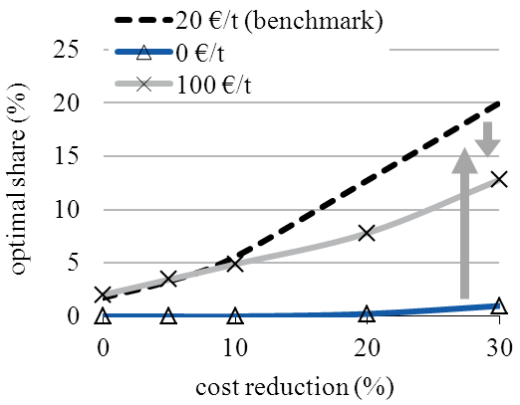

Figure 13: Optimal wind share under different CO_2 prices. Arrows indicate how curves shift as carbon prices increase.

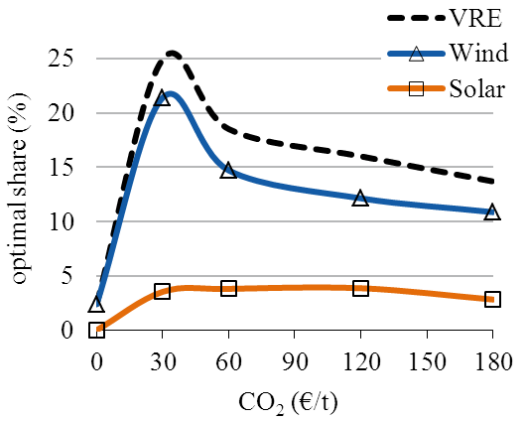

Figure 14: Optimal wind and solar share under different CO_2 prices, assuming high cost reduction. Shares increase with the carbon price up to the point where low-carbon baseload investments become profitable and decrease afterwards.

Of course this effect can only appear if investments in nuclear and/or CCS are possible. However, uncertainty around costs, safety, waste disposal, and public acceptance could imply that these technologies are only available at prohibitive costs. Without nuclear power, the optimal wind share doubles at 100 €/t CO_2 and without both technologies it reaches more than 45% market share (Figure 15). In addition, the optimal solar share reaches 15%, such that VRE would supply almost two thirds of electricity. However, the unavailability of nuclear and CCS comes at the price of increased emissions and welfare losses: CO_2 emissions increase by 100-200% (depending on VRE cost reductions), the electricity price increases by 15-35%, and total system costs by 13-25%. In absolute terms, welfare is reduced by 15-30 €bn per year, which would increase if the assumption of price-inelastic demand was relaxed.

Figure 16 shows which combination of LEC and carbon price would be needed to trigger a 40% wind market share in a contour plot.

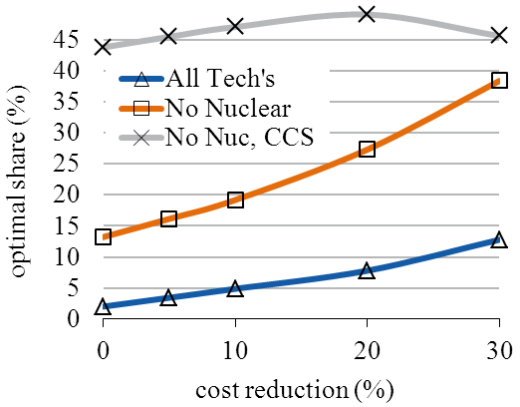

Figure 15: Optimal wind share under 100 €/tCO_2 and different technology assumptions. Excluding low-carbon alternatives leads to dramatically higher shares of wind (and solar) power. The top line decreases because solar power investments are triggered. The combined VRE share keeps rising with cost reductions.

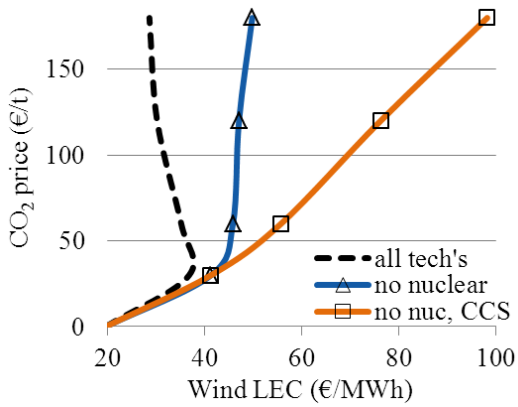

Figure 16: Contour plot of the 40% wind share. The lines indicate which LEC / CO_2 price combination would be needed to achieve 40% wind penetration without wind subsidies. Above/left of the lines wind penetration is above 40%, below/right of the lines it is below 40%. Without restrictions on technologies, wind LEC need to fall below 40 €/MWh to trigger 40% penetration, no matter what the CO_2 price is. The investment cost for nuclear is 4000 €/kW.

Several conclusions can be drawn regarding the effect of CO_2 pricing on the optimal amount of VRE deployment: while increasing the CO_2 price from low levels increases optimal VRE shares, increasing it further reduces VRE deployment. The price that maximizes wind deployment is around 40 €/t, just before nuclear investments are triggered. Carbon pricing is not able to drive up the VRE share above 25%. These findings are obviously sensitive to the availability of alternative low-carbon generation technologies: excluding base load technologies like nuclear and CCS helps wind and solar dramatically. In general, this section indicates how important it is to take the adjustment of the capital stock into account when evaluation policies.

5.6. The impact of fuel prices and investment costs

Rising fuel prices are often believed to drive renewables expansion. At first glance, the situation seems to be straightforward: higher input prices increase the costs of fossil generation, and hence increase the marginal value of competing technologies including VRE. In this subsection, hard coal and natural gas prices are varied to understand the effect of higher fossil fuel prices on optimal VRE deployment. As in the case of CO_2 pricing, results might come as a surprise.

Increasing the price of coal has the expected effect: doubling coal prices increases optimal wind deployment by about five percentage points (Figure 17). Lowering gas prices by half ("shale gas") has a similarly expected effect, dramatically lowering optimal wind deployment. Surprisingly however, doubling gas prices *reduces* the optimal wind share. As in the case of CO_2 pricing, the reason for this seemingly counterintuitive result can be found in the capital stock response to the price shock. Higher gas prices induce investments in hard coal, which has lower variable costs, reducing the value of wind power and its optimal deployment.

In economic terms, gas-fired mid- and peak-load plants are complementary technologies to VRE, since they efficiently "fill the gap" during times of little renewable generation. Hence, one can think of gas and wind generators as a gas/wind "package". Coal plants are a substitute technology to the gas/wind package. Increasing coal prices increases both the share of gas and wind. Increase gas prices increases the share of coal and reduces the share of gas/wind. Of course, wind becomes more competitive versus gas as well, but this effect is too weak to make wind benefit from higher gas prices. This can also be expressed in terms of own-price and cross-price elasticities (Table 3). The elasticity of wind generation with respect to the coal price is positive, but the elasticity with respect to the gas price is negative.

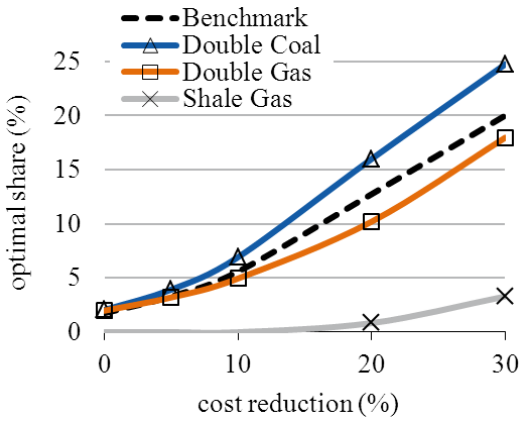

Figure 17: The effect of fuel price shocks. As expected, lower gas prices reduce and higher coal prices increase the optimal wind share. However, higher gas prices *reduce* the optimal share. The reason is the investments in baseload technologies triggered by high gas prices.

Table 3: Price elasticities at the benchmark.

	w.r.t. coal price	**w.r.t. gas price**
Coal generation	-3.9	0.5
Gas generation	1.5	-4.9
Wind generation	1.0	-0.2

The cost of large investment projects is subject to high uncertainty, because projects are seldom conducted. Small, more industrialized projects can be assessed with more certainty because of more experience. Hence, uncertainty of nuclear investment cost is much higher than of wind or solar investment cost, where modularity and the high number of units allow reliable cost assessment. This is reflected in the broad range of cost estimates reported in the literature (section 4.2) and in a higher discount rate for technologies with little investment experience (Oxera 2011). If capital costs of thermal plants are 50% higher than assumed in the benchmark, either because of higher investment costs or a higher discount rate, the optimal wind share jumps by 13 percentage points (Figure 19).

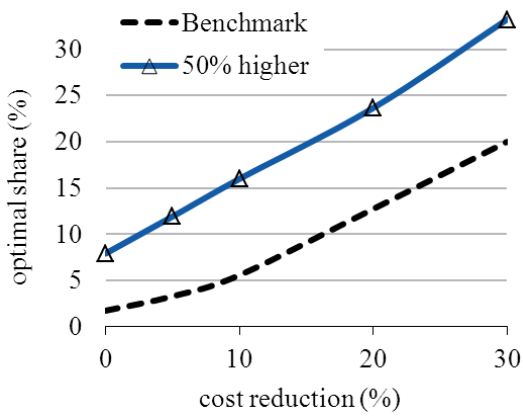

Figure 18: The impact of thermal plants' investment cost is dramatic. This indicates high parameter uncertainty of model results.

5.7. Mid-term: accounting for today's power plants

All results of sections 5.1 to 5.6 are long-term optimal wind shares. In this subsection, we briefly discuss the optimal wind shares in the medium term, when the existing capital stock (plants, storage, interconnectors) is taken into account and modeled as sunk investments.

Typically, the optimal wind share is much lower in the mid-term than in the long-term. The reason is straightforward: in the mid-term, wind only reduces fuel and other variable costs, while in the long-term it also reduces capital costs (section 4.4). The benchmark optimal share is 7% at 30% cost reduction, less than half of the long-term share. The impact of variability and integration options is qualitatively similar, but much smaller in size. In contrast to the long term, increasing the CO_2 price from 20 €/t to 100 €/t increase the optimal share in the medium term, because the capacity mix adjusts much less. For the same reason, higher gas prices have virtually no impact in the medium term.

6. Discussion of numerical results

All numerical findings should be interpreted cautiously, since the applied methodology has important shortcomings that potentially bias the results. Being a regional partial equilibrium model, the power market model EMMA does not account for endogenous learning or wind and solar resource supply curves. Moreover, it disregards hydro reservoirs, demand elasticity and internal grid bottlenecks. Taken together, these factors might result in a moderate downward bias on the estimated optimal share, meaning that our results can be read as conservative estimates.

This section first summarizes the numerical findings, then discusses the impact of suboptimal wind shares on welfare, and finally compares findings to previously published studies.

6.1. Summarizing findings

Figure 19 summarizes the optimal long-term share of wind power in Northwestern Europe under all tested parameter assumptions (not including section 5.3). There is large uncertainty about the optimal wind share driven by parameter uncertainty (1% - 45% at low costs). Our benchmark assumptions fall in the middle of this range. Additional uncertainty might be introduced by model uncertainty, or by parameters that have not been tested here. Moreover, cost reductions play a crucial role. At current cost levels, the optimal benchmark market share is 2%, with a range of 0% - 13%. Reducing wind power's levelized electricity costs is crucial to introduce significant volumes of wind power competitively. If costs can be decreased by 30%, we estimate the competitive share at 20%, which is roughly three times today's level. In other words, wind power can be expected to keep growing even without subsidies - but only if costs come down.

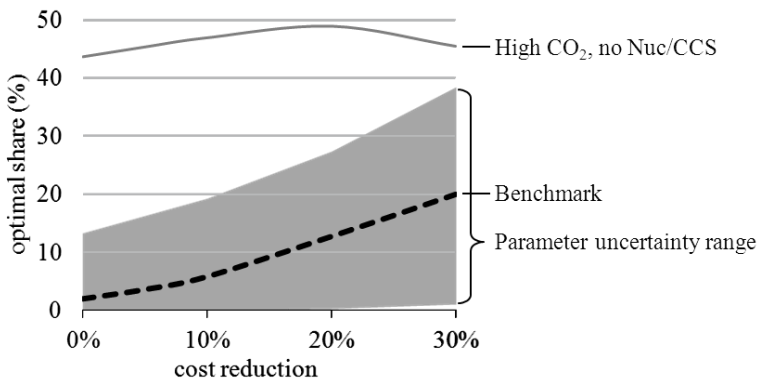

Figure 19: Long-term optimal wind shares in the benchmark run and the range of all sensitivities. The range does not include the noNucCC run at 100 €/t, where the optimal wind share is above 40%.

Figure 20 displays the optimal wind share at 30% cost reduction for all model runs. In 16 out of 20 runs, the share is between 16% and 25%, indicating somewhat more robust results than Figure 19 might suggest.

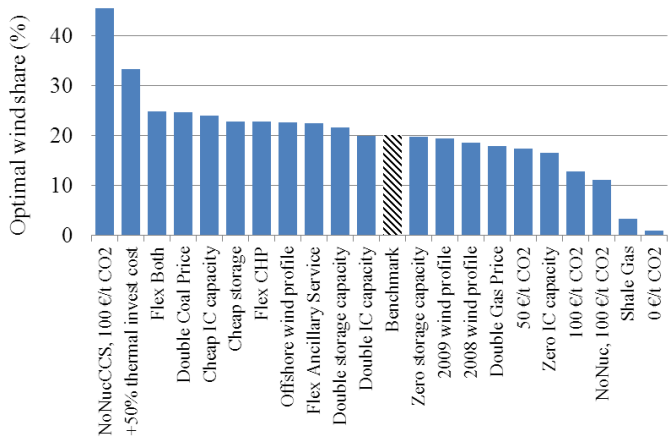

Figure 20: Comparing all sensitivity runs for 30% cost reductions. 16 out of 20 runs are in the range of 16% - 25% optimal share.

The results for solar are more disappointing: even at 60% cost reduction, the optimal solar share is below 4% in all but very few cases. This is consistent with previous findings that the marginal value of solar power drops steeply with penetration, because solar radiation is concentrated in few hours (Nicolosi 2012, Mills & Wiser 2012, Hirth 2013). In regions that are close to the equator, the optimal solar share might be significant higher, both because levelized costs are lower and the generation profile is flatter. In 5.3 and 5.4 we presented results for wind power that show how dramatic the impact of a flatter profile can be.

6.2. What is the cost of sub-optimal shares?

Given the large uncertainty, it is highly likely that realized wind shares will ex post turn out to be sub-optimal, too high or too low. Here we briefly asses the costs of such sub-optimality. With perfectly inelastic demand, welfare losses are equivalent to increases in total system costs. Figure 21 displays the cost increase of sub-optimal wind shares for two cases: current cost levels and 30% lower costs. Total system costs increase moderately by 6% if instead of the optimal share of 2% a large share of 30% is installed. Similarly, costs increase by 2% if no wind is installed at low cost despite an optimal share of 20%. One percentage point of total costs is about € 1bn in absolute terms, or € 0.8 per consumed MWh of electricity. Note that welfare costs would be in general higher if demand is modeled price-elastically, because of the resulting quantity reductions.

As discussed in section 5.5, excluding nuclear and CCS from the set of possible technologies increases total system costs by 13-25% under strict climate policy. Hence such a ban would be more costly than targeting sub-optimal wind shares.

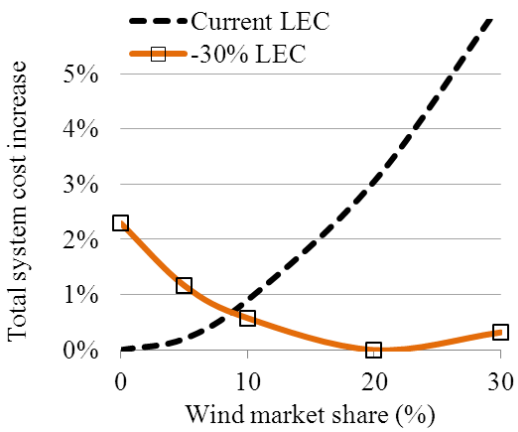

Figure 21: Cost increases for suboptimal wind shares. Under wind current costs, the optimal wind share is 2%; if instead 30% wind power is installed, total system costs increase by 6%. At low wind costs, the optimal share is 20%; if no wind is build, system costs would be 2% higher than in the optimum.

6.3. Comparing with other studies: when do VRE shares become very high?

Policy makers have sometimes set very high targets for VRE during the past years (European Comission 2011). Only in one model run, this study found such high shares to be optimal: a combination of significant cost reductions (30% for wind and 60% for solar), a strict climate policy (CO_2 price of 100 €/t), and a restriction of low-carbon base load generators (nuclear and CCS).

We compare this finding to two recent studies that have very high VRE shares to be optimal, Müsgens (2013) and PRIMES-based PowerChoices Reloaded (Eurelectric 2013). It turns out that these studies also assume these three conditions to be simultaneously fulfilled (Table 4). It seems a quite robust finding that very high VRE shares (>50%) are only optimal if those three premises are all satisfied.

Table 4: Comparing Müsgens (2013), Eurelectric (2013), and the present study

	CO_2 price	Nuclear assumptions	Wind LEC	Wind share
Müsgens (2013)	110 €/t	restricted to current level in country without phase-out	low (precise level not reported)	~40%
PowerChoices Reloaded	300 €/t	restricted to country without phase-out	low (precise level not reported)	~30%
This study	100 €/t	no nuclear allowed	50 €/MWh	~45%

7. Conclusion

The theoretical analysis of section 2 showed that electricity is a heterogeneous good along three dimensions: time, space, and uncertainty. As a consequence, wind and solar variability affects welfare analyses. Ignoring variability leads to biased estimates of the welfare-optimal amount of VRE capacity.

The literature review of section 3 surveyed three classes of models that are in practice used to estimate the optimal VRE share: integrated assessment models, energy system models, and extended power market models. IAMs are appropriate tools to account for technological learning and global commodity markets. Energy system models are strong when it comes to estimating electricity demand and wind and solar resource supply curves. However, both model classes have a too coarse resolution to explicitly represent variability. Power market models provide sufficient details, but are seldom used to optimize VRE capacity endogenously.

The power market model EMMA was applied in section 5 to estimate the optimal share of wind and solar power. Assuming that onshore wind costs can be reduced to 50 €/MWh, we find the optimal wind share in Northwestern Europe to be around 20%. In contrast, even under further dramatic cost reductions, the optimal solar share would be close to zero. We find that variability dramatically impacts the optimal wind share. Specifically, temporal variability has a huge impact on these results: if winds were constant, the optimal share would triple. In contrast, forecast errors have only a moderate impact: without balancing costs, the optimal share would increase by eight percentage points.

In terms of methodological conclusions, both section 2 and section 5 show that variability significantly impacts the optimal share of wind and solar power. Models and analyses that cannot represent variability explicitly need to approximate the impact of variability carefully. Furthermore, while both a long-term and a mid-term perspective have their merits, the stark differences in results indicate how important it is to be explicit about the time scale on which analysis takes place. Finally, several findings of section 5 are counter-intuitive at first glance, underlining the necessity for rigorous analytical methods that can challenge intuition and conventional wisdom. Specifically, numerical models are needed to capture adjustments of the capital stock and policy interaction.

In terms of policy conclusions, the numerical results point out the important role of onshore wind power as a competitive electricity generation technology. The long-term benchmark estimate of a market share of 20% is equivalent to three times as much wind power as today. However, the share would be higher if low-carbon mid and peak load technologies were available to supplement VRE in the transition to a low-carbon electricity

sector. Biomass as well as high-efficient gas-fired plants could play a crucial role in this respect. A second conclusion is that different wind turbine layouts with larger rotors relative to generator capacity could be quite beneficial, since they provide a flatter generation profile. Finally, system flexibility is key to achieve high VRE shares. Must-run units that provide heat or ancillary service severely limit the benefits of VRE. Relaxing these constraints through technological innovation increases optimal wind deployment, as does increasing interconnector capacity.

Significant methodological gaps have been identified that should be filled by future research. On the one hand, integrated modeling of hydro-thermal systems and a more explicit modeling of transmission grids are promising fields for power market model development. On the other hand, developing methods of how to integrate variability into large-scale, coarse models is needed to account for all significant drivers of optimal VRE quantities. These are necessary conditions before final conclusions on optimal shares of variable renewables can be drawn.

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