The Market Value of Wind and Solar Energy: an Analytical Approach

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Abstract – Several recent studies have shown that the revenues of wind and solar power generators on spot markets ("market value") decline with increasing deployment. This "value drop" is often assessed quantitatively but infrequently analytically, a gap that this paper aims to fill. We derive a formal expression of the market value as a function of the penetration rate. At low deployment, the market value is driven by the *covariance* over time between winds or sunshine and electricity consumption. In countries where power demand peaks at noon during summer, the value of solar power is initially high; the equivalent is true for wind power in those regions where stormy winters coincide with periods of high demand for heating. As deployment increases, however, we show that the market value declines linearly with the penetration rate in energy terms (market share). The slope of the decline is determined by the relative *variance* of wind or sun: the more the output is concentrated in a few hours of the year, the steeper the drop in value. It is in this sense that variability (intermittency) "causes" the value drop. A drop in market value is also a feature of a power generation technology that operates constantly, but the drop is smaller in size. Innovations that reduce the variation of wind and solar power output tend to mitigate the value drop, an observation with direct implications for technology development and policy.

Key words – wind power; solar power; variable renewables; market value

JEL – Q42, L94, D40

Highlights

- The economic value of renewable is often estimated quantitatively, but has not been derived analytically.
- The covariance over time between winds and electricity demand drives low-penetration value.
- The variance of winds drives high-penetration value.

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1. Introduction

Renewable energy-based power generation is on the rise. In 2015, world-wide wind and solar power capacity exceeded 600 GW (Figure 1). Almost half of recently global added power generation capacity was based on renewable sources – of which wind and solar power represented about 70% (IEA 2015). In several countries the combination of wind and solar supplied 10% or more of electricity consumed, with Denmark being the world leader at over 40% (Figure 2). Wind and solar power also provide a large market share of power in jurisdictions such as Texas, California, and Eastern Mongolia. Large-scale deployment of wind and solar power, until recently thought to be a long-distant future scenario, is taking place right now.

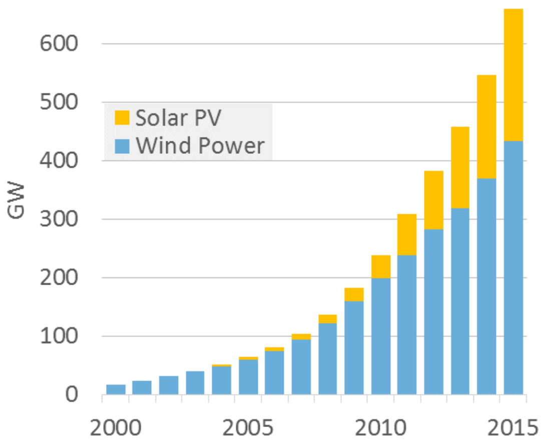


Figure 1. Wind and solar power capacity installed globally. Source: own illustration based in REN 21 (2015) data.

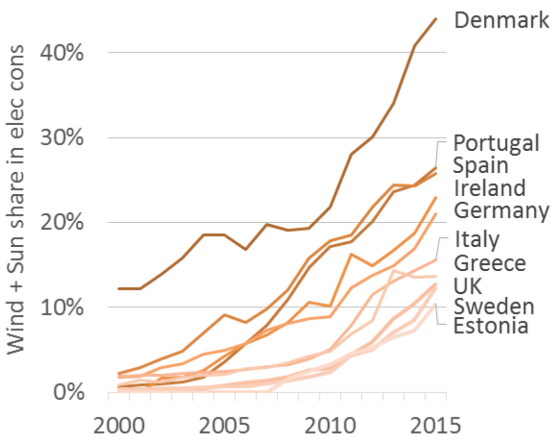


Figure 2. In a number of countries, wind and sun supply more than 15% of power demand. Source: own illustration based in IEA data.

The variable, or "intermittent", nature of renewable energy sources such as wind power, solar power, and ocean energy poses challenges when integrating these technologies into power systems. Several properties specific to variable renewables are problematic for system integration (Grubb 1991a, IEA 2014). Most important of these is the simple fact that the availability of the primary energy source fluctuates over time. Integration challenges affect the economics in different ways, for example through grid expansion or increased balancing needs.[2] The single most significant economic impact of variable renewables is likely to be on the spot market value of sun- and wind-powered electricity (Ueckerdt et al. 2013, Hirth et al. 2015).

Wholesale electricity markets clear at a high frequency such as hour-by-hour, or more frequent. We define the "market value" of wind power as the wind-weighted average electricity price

$$\bar{P}_{wind} = \frac{\sum_{t=1}^{T} W_t \cdot P_t}{\sum_{t=1}^{T} W_t}, \tag{1}$$

where $t\epsilon T$ denotes all hours (or other time periods) of a year, W_t is the generation of wind power and P_t is the equilibrium electricity price. The wind market value is the wind-weighted average electricity price, or the average $/MWh revenue that wind investors earn (leaving aside support schemes and other income streams). The market value of solar, or any other power generating technology, is

[2] On balancing requirements, see Ortega-Vazquez & Kirschen (2009), Holttinen et al. (2011) and Hirth & Ziegenhagen (2015).

analogous to this.[3] For brevity, we will refer to "wind power" in the following – all theoretical arguments also apply to other variable renewables.[4]

We are interested in how $\bar{P}_{wind}$ behaves for increasing penetration rates Π. We define the penetration rate, or market share, in energy terms: the sum of annual wind generation relative to the sum of load L_t (electricity consumption):

$$\Pi = \frac{\sum_{t=1}^{T} W_t}{\sum_{t=1}^{T} L_t}. \quad (2)$$

Empirically, we can observe that the market value of wind and solar power declines as their contribution to annual electricity consumption increases. This is shown by German data (Figure 3).

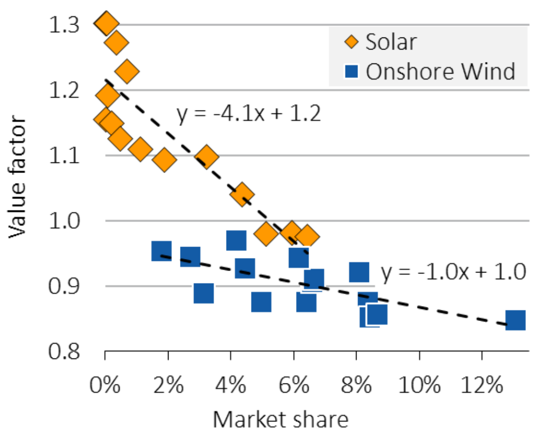


Figure 3. The market value of wind power and solar power in Germany 2001-15, expressed as market value over average power price. Own illustration based on data from Destatis, TSOs, and EPEX Spot.

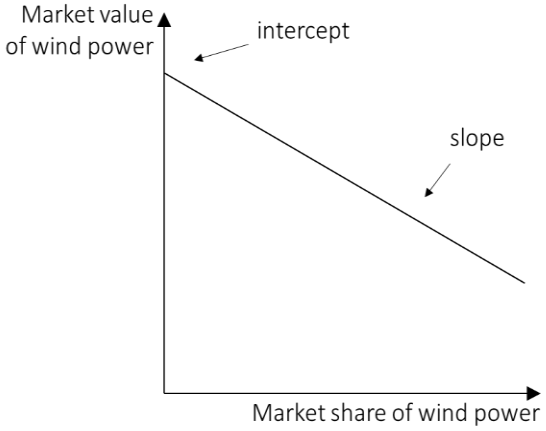


Figure 4. The linear fall of wind market value (illustrative).

Previous studies confirm this observation (see literature review in the following section). However, these studies are empirical in nature, being based on numerical or econometric models. This paper contributes to the literature by deriving an analytical expression of the market value of variable renewables.

Under certain assumptions, the market value turns out to fall linearly with penetration

$$\bar{P}_{wind}(\Pi) = \bar{P}_0 \cdot (\beta_0 - \Pi \cdot \beta_1), \quad (3)$$

where $\bar{P}_0$ is the simple average electricity prior to the introduction of wind power the βs are constant parameters (Figure 4). We are interested both in the y-intercept β_0 ("market value at low penetration") and in the slope β_1 ("value drop"). We show that β_0 can be expressed in terms of the covariation between wind power generation and load and β_1 in terms of the variation of wind generation. These are the three central findings of this paper:

[3] Note that, in general, the market value of each technology is different. For this reason the comparison of generation costs between technologies has little economic meaning. See Hirth et al. (2016) for further discussion.

[4] In fact, our theoretical arguments apply to all types of generators that produce electricity according to a pattern that is independent from power prices. Such generators include run-of-river hydro plants and some combined heat and power plants.

1. At low penetration, the market value of wind and solar power depends on the covariation of generation and consumption patterns.
2. *Ceteris paribus*, the market value drops linearly with increasing penetration.
3. The slope of the drop depends on the coefficient of variation of generation patterns.

Calibrating the model with German data, we provide illustrative quantitative estimates of the size of the drop. Comparing this, the existing (empirical) literature indicates that the theoretical model, despite its stylized nature, seems to capture the phenomenon well. In two applications, we show how our findings can be used in practice.

2. Literature Review

Many authors have stressed that the market value of wind and solar power is not the same as that of other power generating technology, and that it drops with penetration (Grubb 1991b, Lamont 2008, Borenstein 2008, 2012, Joskow 2011, Mills & Wiser 2012, 2014, Gowrisankaran 2015, to name a few). A number of studies provide quantitative estimates of the size of the value drop. This section first reviews these empirical studies, thereby updating the review of Hirth (2013, 2015). These studies derive the market value either on either numerical optimization models based on simulated prices, or econometric estimates based on realized prices observed on wholesale electricity markets. We proceed in the second part of this section by discussing the few analytical approaches to the topic, notably Lamont (2008).

2.1. Empirical literature

We were able to identify 16 studies that provide quantitative estimates of the market value of wind power. Appendix A provides a list of these studies.

Figure 5 summarizes this literature. We have extracted the minimal and maximal penetration rates and the corresponding value factors for each study. The value factor is the market value divided by the average electricity price. It is evident that every single study that provides a range of penetration rates finds that the value drops with penetration. On average, this drop is 1.5 percentage points for each percentage point increase in market share.

Figure 6 summarizes the literature in a different way. For this figure, we have pooled the observations of all studies, and clustered them by model type: short-term (dispatch) and long-term (investment) models. As expected, long-term studies that allow for the adjustment of the capital stock tend to form a flatter value curve.

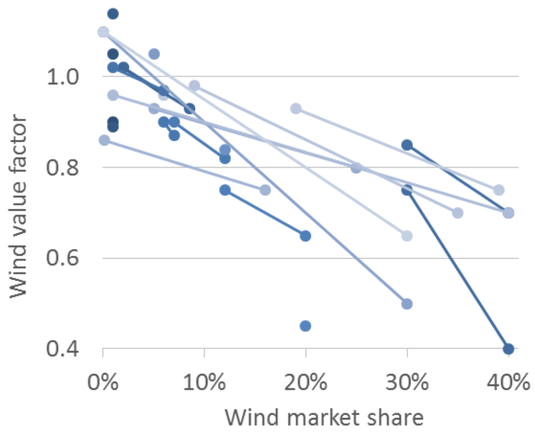


Figure 5. The market value of wind power (studies plotted individually).

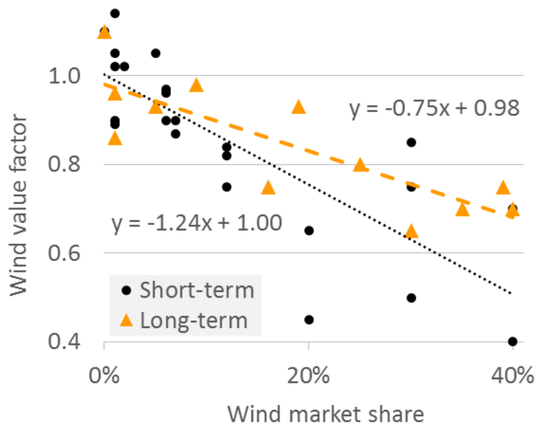


Figure 6. The market value of wind power (OLS fit of all studies).

Table 1 synthesizes the findings as the drop in value factor per percentage-point increase in market value. The first block of rows correspond to Figure 5 (observations pooled across studies), the second block of rows to Figure 6 (no pooling across studies). The intercept coefficient is around unity. The slope coefficient varies between -0.7 and -1.9.

Table 1. The market value of wind power: literature estimates.

	intercept (β_0)	slope (β_1)
Short-term models individually (Fixed effects)		-1.9
Long-term models individually (Fixed effects)		-0.9
All models individually (Fixed effects)		-1.5
Short-term models pooled (OLS)	0.98	-1.3
Long-term models pooled (OLS)	1.00	-0.7
All models pooled (OLS)	1.00	-1.0

2.2. *Theoretical analyses*

Few authors have studied the drop of wind and solar power market value analytically. Grubb (1991a) shows that for low penetration, a variable source that is uncorrelated to load will have a market value that is identical to the average market value of all sources. In his words, "fuel savings are the same whether the energy comes from a firm or a variable source, as long as the amount involved is not too large, and the variation is independent of the demand". Grubb does not provide a formal expression for higher market shares. Our results confirm Grubb's intuition.

Schmidt et al. (2013) and May (2015) study the market value of an *individual* wind turbine. They find that the value tends to be higher if the turbine's output is weakly correlated with the output of the other wind generators in the power system. They do not, however, provide an expression for the market value of wind power as a whole.

Green & Léautier (2015) provide an expression for the demand-weighted electricity price, but not the wind-weighted price.

We deem the seminal paper by Lamont (2008) to be the most relevant analytical paper on the market value of variable renewables, and we build upon this.[5] His "primary theoretical result" states that the market value of an intermittent generator depends on the covariance between the generator's (normalized) output and the electricity price.[6] In our terminology, Lamont's core equation (10) reads

$$\bar{P}_{wind} = \bar{P} + cov(P_t; w_t), \tag{4}$$

where $\bar{P}$ is the average price (base price). The market value is formulated as a function of the covariation between wind generation and *electricity prices*. Prices, however, are not fixed. Rather, price patterns will change with wind deployment. As a consequence, this covariation itself depends on the penetration rate; usually it will decline with increasing penetration. In fact, a crucial property of variable renewables is that the greatest fall in price occurs during those hours when they produce the most output. In Lamont's words, "understanding the penetration of intermittent technologies […] is basically a matter of understanding how the pattern of system marginal costs changes". This paper contributes to the literature by endogenizing the electricity price and expressing the market value in terms of *electricity demand* patterns, rather than price patterns. Electricity demand patterns can be expected to be much less responsive to changing wind penetration rates than price patterns.[7]

In other words, the contribution of this paper is to analytically derive an expression of the market value that depends exclusively on relatively stable parameters.

3. A stylized short-term model of the power market

This section introduces a new stylized model of the power market. The power price P_t is determined by the intersection of residual supply and residual demand R_t. There are two power generation technologies in the model: wind power and thermal power plants such as nuclear or fossil fueled power station. Residual supply is supply from thermal power, hence we also call it "thermal supply". Residual demand is load L_t net of wind power generation W_t:

$$R_t = L_t - W_t. \tag{5}$$

Both demand and wind power generation vary hour-to-hour, while thermal capacity remains constant. This is the reason for treating wind power generation as negative consumption: it allows us to use a supply curve that is stable throughout the year, while the demand curve varies over time.

The thermal supply curve is sometimes called a "supply stack" or "merit-order" curve (Figure 7). The merit-order curve shows the variable costs (expenses for fuel, emissions, and operations) of power plants ordered in increasing size. We assume the supply curve to be linear (and relax this assumption

[5] Baker et al. (2013) and Reichelstein & Sahoo (2013) apply Lamont's results in different contexts.
[6] This refers to equation (10) in Lamont (2008). Note that Lamont uses a slightly different terminology. He specifies the marginal value of the generator in capacity terms and refers to "marginal costs on the system", which is, if markets are undistorted, the power price.
[7] Incorporating price-elastic demand into our model is a promising step for further research.

in Appendix D – without qualitative impact on results). The intersection of the (static) supply curve and the (fluctuating) residual demand establishes the equilibrium price in each hour (Figure 8).

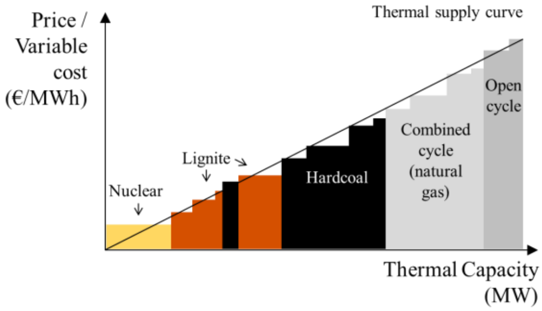


Figure 7. A schematic linear merit-order curve / supply-stack curve (short term supply curve) of thermal electricity generation.

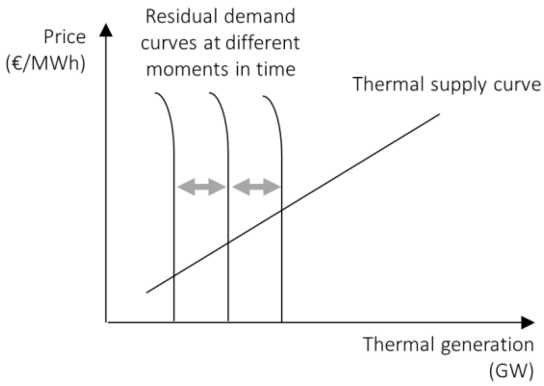


Figure 8. The market equilibrium in different hours of the year, assuming a linear supply curve. Demand varies exogenously over time and is assumed to be price in-elastic around market-clear price levels.

We assume that the thermal power plant system is scalable, such that the hourly electricity price P_t[8] is a function of hourly relative residual load relative to peak load $L_{max} = \max_t L_t$:

$$P_t = \alpha \cdot \frac{R_t}{L_{max}}. \tag{6}$$

During hours in which thermal plants have to serve peak load, the power price is α, independent of the absolute size of the power system. Hence the scalar α is independent from system size and determines the slope of the thermal supply curve. At zero residual load the price is assumed to be zero.

This model is short-term in the sense that the thermal supply curve does not respond to the introduction of wind power. It models an existing power system into which wind power is introduced. Long-term models account for the response of the power system, i.e. the change of the slope and shape of the thermal supply curve.[9]

This model a very simple microeconomic model of market clearance, with the main feature being that we solve it many times – for every hour of the year. The model rests on a number of simplifying assumptions, relaxing which would be promising for further research: perfectly price inelastic demand, no hydroelectricity, no electricity storage, no international trade, no curtailment of wind power, a fully competitive power market, no network constraints, and no restrictions on power plant dispatch.

We will use the model to estimate the market value of wind power. These mentioned assumptions are likely to bias the estimate. Table 2 lists real-world features of power markets that the model does not capture and indicates the direction of bias.

[8] In the electric engineering power system literature, the marginal costs of power generation is often labeled "system lambda", because it is derived from shadow price of one of the constraints of an optimization model. Here, $\lambda_t = P_t$.
[9] It is well known that the introduction of large-scale variable renewables will not only lead to a modest reduction of peak residual load but to a significant shift in the thermal generation mix. It is likely that the supply curve will become "more convex".

Table 2: Model assumptions and their effect on the market value of wind power.

Phenomenon (not accounted for in the model)	**Effect on wind market value** (at high penetration rates)
Capacity mix adjusts	positive
Hydro reservoir power	positive
Demand price-elastic	positive
Electricity storage	positive
Curtailment	positive (no more negative prices)
Shorter dispatch intervals (15 min)	unclear
International trade	positive or negative; more likely positive
Market power of wind generators	positive
Market power of non-wind generators	likely negative
Network constraints	negative
Forecast errors	negative
Must-run constraints of combined heat and power plants	negative
Must-run constraints of ancillary service provision	negative
Ramping and cycling constraints / costs	negative

4. The market value of wind power

We derive an analytical expression for the wind market value as a function of the wind penetration rate, first in terms of normalized time series (4.1), then in terms of variance and covariance (4.2). We find that the market value can be expressed as a linear function of the penetration rate.

Some researchers prefer to study the *relative* market value of wind (value factor). Appendix B provides an analytical expression.

4.1. *Market value in terms of normalized wind and load*

We normalize load and wind time series with their respective maximal values:

$$l_t = \frac{L_t}{L_{max}}, \tag{7}$$

$$w_t = \frac{W_t}{W_{max}}. \tag{8}$$

where $W_{max} = \max_t W_t$ is wind power capacity, defining the upper bound to wind generation W_t. Lower case letters denote normalized values: w_t is the share of wind capacity that produces electricity during a specific hour, referred to as the "wind production factor". The time series is often called the "wind power generation profile". Correspondingly, l_t is called the "load profile".

Substituting (5) and (6) into (1), the wind market value becomes the wind-weighted average residual load,

$$\bar{P}_{wind} = \frac{\alpha}{L_{max}} \cdot \frac{\sum_{t=1}^{T} W_t \cdot R_t}{\sum_{t=1}^{T} W_t}. \tag{9}$$

Using (7) and (8), this can be expressed as a (negative) linear function in wind capacity W_{max}:

$$\bar{P}_{wind} = \frac{\alpha}{L_{max}} \cdot \left\{ L_{max} \cdot \frac{\sum_{t=1}^{T} w_t \cdot l_t}{\sum_{t=1}^{T} w_t} - W_{max} \cdot \frac{\sum_{t=1}^{T} w_t^2}{\sum_{t=1}^{T} w_t} \right\}. \tag{10}$$

Note that L_{max} is independent of wind capacity. Wind capacity and penetration rate are related by

$$W_{max} = \Pi \frac{\bar{L}}{\bar{w}} = \Pi \frac{\bar{l} \cdot L_{max}}{\bar{w}}. \tag{11}$$

Bars always denote yearly averages. $\bar{w}$ is the annual average wind capacity factor. The market value can be expressed as a function of wind penetration rate:

$$\bar{P}_{wind} = \alpha \cdot \left\{ \frac{\sum_{t=1}^{T} w_t \cdot l_t}{\sum_{t=1}^{T} w_t} - \Pi \cdot \frac{\bar{l}}{\bar{w}} \cdot \frac{\sum_{t=1}^{T} w_t^2}{\sum_{t=1}^{T} w_t} \right\}, \tag{12}$$

which resembles equation (3) and Figure 4. This is the first crucial theoretical result of the paper. The market value of wind power is a function of the wind penetration rate, and this expression turns out to be linear. We now derive a more convenient expression of the coefficients of this linear function.

4.2. *Market value in terms of (co-)variances*

The terms $\sum_{t=1}^{T} w_t l_t$ and $\sum_{t=1}^{T} w_t^2$ are scalar products that can be expressed in terms of covariances and variances, or in terms of coefficients of correlation ρ and variation c_v. We use the following standard definitions:

$$cov(w, l) = \frac{1}{T} \sum_{t=1}^{T} w_t \cdot l_t - \bar{w}\bar{l}, \tag{13}$$

$$var(w) = \frac{1}{T} \sum_{t=1}^{T} w_t^2 - \bar{w}^2, \tag{14}$$

$$c_v(w) = \frac{\sqrt{var(w_t)}}{\bar{w}}, \tag{15}$$

$$\rho(w, l) = \frac{cov(w_t, l_t)}{\sqrt{var(w_t)} \cdot \sqrt{var(l_t)}}. \tag{16}$$

The market value can then be re-written as

$$\bar{P}_{wind} = \alpha \cdot \bar{l} \cdot \left\{ \left(1 + \frac{cov(w,l)}{\bar{w} \cdot \bar{l}} \right) - \Pi \cdot \left(1 + \frac{var(w)}{\bar{w}^2} \right) \right\} \tag{17}$$

$$= \alpha \cdot \bar{l} \cdot \left\{ \left(1 + \rho(w,l) \cdot c_v(w) \cdot c_v(l) \right) - \Pi \cdot (1 + c_v(w)^2) \right\}. \tag{18}$$

Equation (17) displays a notable symmetry of the coefficients of the linear function (intercept and slope): the intercept is a function of $cov(w,l)$, where the slope is a function of $var(w)$. Equation (18) expresses the intercept and the slope coefficient as the coefficients of correlation $\rho(w,l)$ and variation $c_v(w)$, respectively.

This expression can be more easily interpreted when compared to the average electricity price. Using (5)-(8) and (11), the simple average electricity price ("base price") can be written as follows[10]:

$$\bar{P} \equiv \frac{1}{T} \sum_{t=1}^{T} P_t$$

$$= \alpha \cdot \bar{l} \cdot (1 - \Pi) \tag{19}$$

$$\bar{P}(\Pi = 0) = \bar{P}_0 = \alpha \cdot \bar{l} \tag{20}$$

The base price prior to the introduction of wind power is simply $\bar{P}_0 = \alpha \cdot \bar{l}$. Substituting this into (17) and (18) yields

$$\bar{P}_{wind} = \bar{P}_0 \cdot \left\{ \left(1 + \frac{cov(w,l)}{\bar{w} \cdot \bar{l}} \right) - \Pi \cdot \left(1 + \frac{var(w)}{\bar{w}^2} \right) \right\} \tag{21}$$

$$= \bar{P}_0 \cdot \left\{ \left(1 + \rho(w,l) \cdot c_v(w) \cdot c_v(l) \right) - \Pi \cdot (1 + c_v(w)^2) \right\}. \tag{22}$$

We proceed with a closer look at the intercept and the slope in turn.

5. Interpreting the market value

In this section, we assess the market value at low penetration rate (5.1) and the rate at which it drops as penetration increases (5.2). Two crucial results emerge: the low-penetration value is a function of the covariation of wind and load and of the wind capacity factor; the rate of value drop is a function of the coefficient of variance of wind power. The more "peaky" (or "intermittent") the behavior of wind power, the faster its value declines with increasing penetration.

[10] A side benefit of this model, this expression explains the "merit-order effect" (Sensfuß et al. 2008). To the best of our knowledge, this is the first analytical expression of the merit-order effect, despite the wide attention this phenomenon has received in the literature. We elaborate in Appendix C.

5.1. *Market value at low wind penetration (y-intercept)*

We are interested in the market value of wind power at low wind penetration, i.e. the market value of the first wind turbine built. Formally,

$$\begin{aligned}\bar{P}_{wind}(\Pi = 0) &= \bar{P}_0 \cdot \left(1 + \frac{cov(w,l)}{\bar{w} \cdot \bar{l}}\right) \\ &= \bar{P}_0 \cdot \big(1 + \rho(w,l) \cdot c_v(w) \cdot c_v(l)\big). \end{aligned} \tag{23}$$

Hence the wind market value can be expressed as the average price plus a mark-up, where the mark-up depends on the covariance of wind generation and consumption patterns. In view of equation (3), we can write

$$\beta_0 = 1 + \rho(w,l) \cdot c_v(w) \cdot c_v(l). \tag{24}$$

This is our second crucial theoretical result. At low penetration (near-zero) rates, the market value of wind power is the base price $\bar{P}_0$ plus a mark-up. The mark-up is positive for a positive covariance of w, l and vice versa. It is larger in absolute size for a smaller wind capacity factor $\bar{w}$.

We illustrate this result for both wind and solar power with 2010 data from Germany that comes in hourly granularity (Table 3), assuming $\alpha = 100$ €$/MWh$, which yields a base price of $\bar{P}_0 = 70$ €$/MWh$.

Table 3. Wind and solar power characteristics from German data (2010)

	Wind power	Solar power
Covariance $cov(w,l)$	0.0024	0.0028
Time scale of covariation	mainly seasonal	mainly diurnal
Mean renewable generation $\bar{w}$	0.15	0.09
Mean normalized load $\bar{l}$	0.70	0.70
Mark-up $\frac{cov(w_t,l_t)}{\bar{l}\bar{w}}$	0.02	0.05
Correlation $\rho(w,l)$	0.15	0.17
Variation of load $c_v(l)$	0.17	0.17
Variation of wind/solar $c_v(w)$	0.90	1.59
Mark-up $\rho(w,l) \cdot c_v(w) \cdot c_v(l)$	0.02	0.05
Intercept (value factor) $\bar{P}_{wind}/\bar{P}$	1.02	1.05

Data source: load data from ENTSO-E, wind and solar in-feed data from German TSOs.
All data are available from the authors on request.

At low penetration, wind power has a market value that is about 2% higher than the base price. Each MWh of wind power is worth more than one MWh from a constant electricity source, because wind power and electricity demand are positively correlated: wind generators benefit from higher prices during the winter when wind speeds also tend to be higher. We confirmed this result by calculating prices for each hour and total them afterwards.

Solar power is slightly stronger correlated with load than wind power, the reason being diurnal correlation: during the day, when the sun is shining, people tend to consume more electricity. It also has a lower capacity factor, resulting in a mark-up of 5%. In both cases, the mark-up is small, which is consistent with the literature reviewed.

5.2. The value drop (slope)

The "value drop", i.e. the speed at which the wind power market value declines, is the slope of the market value functions (3) and (22). Formally, it is the first derivative with respect to the penetration rate, $\partial \bar{P}_{wind} / \partial \Pi_{wind}$. Taking the derivative of (22), we find the following:

$$\frac{\partial \bar{P}_{wind}}{\partial \Pi} = -\bar{P}_0 \cdot (1 + c_v(w)^2). \tag{25}$$

In terms of equation (3),

$$\beta_1 = 1 + c_v(w)^2. \tag{26}$$

This is our third crucial theoretical result. The derivative is constant, implying that the function is linear. The gradient is larger in absolute size (hence the value drop steeper) for a larger variance of wind generation, expressed as its coefficient of variation $c_v(w)$.

The coefficient of variation is a measure of "peakiness" or "intermittency" of wind power generation. In this sense it can be said that "intermittency causes the value loss". More precisely, it should be said that *intermittency increases the size of the value loss*. In fact the market value of *any* generator falls as penetration increases.[11]

Let us study two extremes. First, if wind power output is constant (i.e. it produces at full capacity at all times), $\bar{w} = 1$ and $var(w) = 0$, such that the gradient reduces to

$$\frac{\partial \bar{P}_{wind}}{\partial \Pi} = -\bar{P}_0. \tag{27}$$

For a given pattern of load, this is the least possible value loss. Any non-constant pattern of wind power generation will lead to a steeper loss of value.

Second, if wind power output is concentrated in one time step (i.e. it produces at net capacity during one hour of the year, but not at all during the rest of the year), $\bar{w} = 1/T$ and $var(w) = \frac{T-1}{T^2}$, such that the gradient increases to

$$\frac{\partial \bar{P}_{wind}}{\partial \Pi} = -\bar{P}_0 \cdot T. \tag{28}$$

If wind only produces during one hour of the year, the value drop is about T times as pronounced as if it were constant, because the production in that hour (and hence installed capacity) needs to be T higher to reach the same yearly energy penetration rate Π. As the supply curve is linear, that leads to a price drop that is T times as large. This is the steepest possible value loss.

[11] Recall that we use a short-term power model. In a long-term model, this is not necessarily the case. See Lamont (2008) and Green & Léautier (2015) for proofs.

We use the same data as above to calibrate the value drop (Table 4).[12]

Table 4. Wind and solar value drop as estimated from German data (2010).

	Wind power	Solar power
Coefficient of variation $c_v(w)$	0.90	1.59
Slope $\frac{\partial \bar{P}_{wind}}{\partial \Pi}$	-126	-247

A slope of -126 €/MWh implies a value drop of 1.26 €/MWh (about 2% of the initial base price) for each percentage-point increase of wind power. For solar power, the drop is about twice as steep, reflecting the fact that the squared coefficient of variation is about twice as large. This is quite close to the empirical estimates reviewed above and reported by Hirth (2015a). For solar power, Hirth reports a drop of 5.5% based on market data; 3.6% based on meta-analysis of published studies; 4.6% based on numerical simulations with a power market model. Appendix D shows that a cubic supply curve yields a somewhat larger drop in wind value.

This result is valid only, of course, as long as our model assumptions hold. If the power system adopts to the increase in wind penetration with increasing flexibility, the value drop might become less pronounced (recall Table 2). If demand was price-elastic, $\rho(w, l)$ would be a function of Π and the expression for the value drop would become more complicated.

6. Applications

We illustrate the implications of the value drop (22) in two applications. First, we present data on the value drop of wind power for different sites in Europe (across space). Then, we present the value drop for wind power in one region for different types of wind turbines (across technologies).

6.1. Value drop cross space

The coefficient of variation of generation profiles in different regions is not identical. In areas where winds blow constantly it is lower than in areas with string seasonal, diurnal, or random fluctuations. The variation of solar power generation tends to be smaller close to the equator than at high latitudes. We illustrate this fact by calculating the drop in wind market value for different locations, using the same values for the power system parameters, $\alpha = 100$ and $\bar{l} = 0.7$. We use wind speed data from the ERA-Interim[13] re-analysis model for Europe and create a time series of wind power output by applying the same power curve on all sites. Figure 9 shows the resulting wind capacity factor and the coefficient of variation. Coefficients of variation (right panel) vary by a factor of five, implying a value drop that is five times as steep in the dark areas compared to the light areas, holding everything else fixed. It is obvious that areas with a high capacity factor tend to feature less variation.

[12] As in section 5.1, this "top down" calculation was confirmed by a "bottom-up" calculation for the purpose of verification.
[13] http://www.ecmwf.int/en/research/climate-reanalysis/era-interim

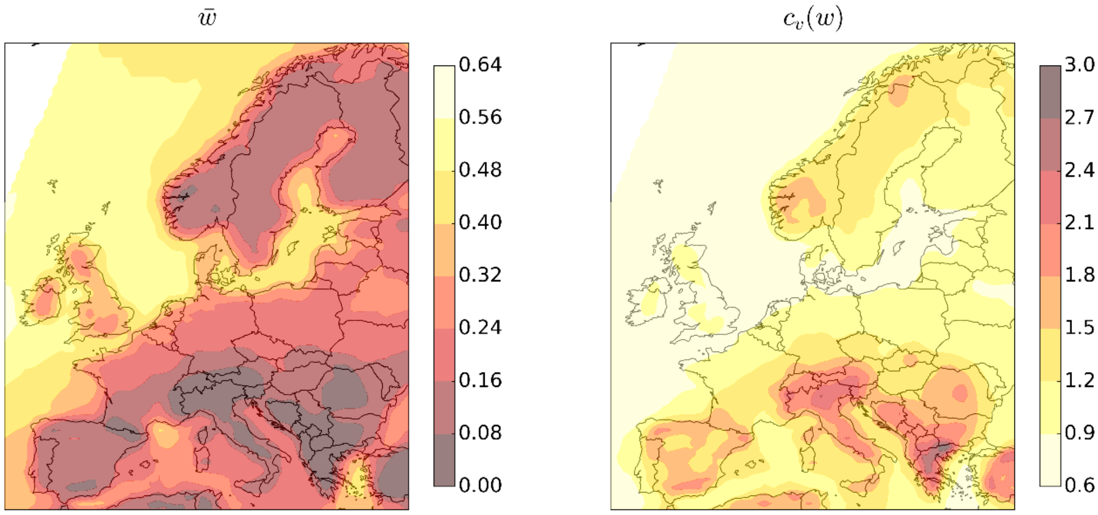


Figure 9. Wind power capacity factor $\bar{w}$ (left) and coefficient of variation $c_v(w)$ (right).

6.2. Value drop across technologies

Wind turbine technology has evolved substantially during the past decade. "Low wind speed" turbines have entered the market that are taller and have a larger rotor-to-generator ratio (a lower specific rating per area swept by the rotor). These turbines capture more energy at low wind speeds. This advancement in wind turbine technology has been described as a "silent revolution" (Chabot 2013, 2014). In the United States, the specific rating of newly installed turbines has dropped from 400 W/m² to 250 w/m² during the past 15 years (Wiser & Bolinger 2015), and a similar development in Germany (Fraunhofer IWES 2013). With a lower specific rating, electricity is generated more constantly, which can potentially decreases the variation of output, mitigating the value drop. Tafarte et al. (2014), McInerney & Bunn (2015), Hirth & Müller (submitted) provide quantitative estimates of the economic benefits of low wind-speed turbines from numerical models.

We estimate the coefficient of variation for different turbine types. We use wind speed data for two different heights above ground (90m and 120m) at three-hourly resolution from the re-analysis model ERA-Interim, 2010 data from Germany. We transform those data into power generation time series using power curves of different wind turbines. Power curves were extracted from the websites of the turbine manufacturers (Figure 10). We assumed for each case that only one type of turbine is installed. Table 5 provides the descriptive statistics of the turbines and the resulting generation time series. Figure 11 displays the wind power market value derived from a subset of these turbines. At low penetration the value differs only slightly. High wind-speed turbines (high specific rating) tend to lose value quicker than low wind-speed turbines. At 30% market share, the wind turbines with lowest specific rating in the sample, GE's 1.6-100 has a nearly 40% higher market value than the turbine with the highest specific rating, Enercon's E-82.

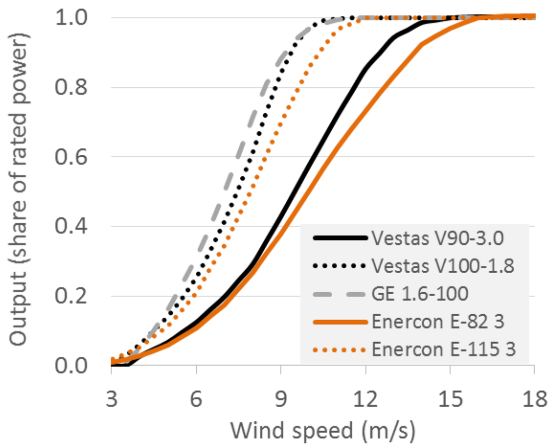


Figure 10. The power curves of five wind turbines: Vestas V90-3.0, Vestas V100-1.8, Enercon E-44, Enercon E-115, General Electric 1.6-100.

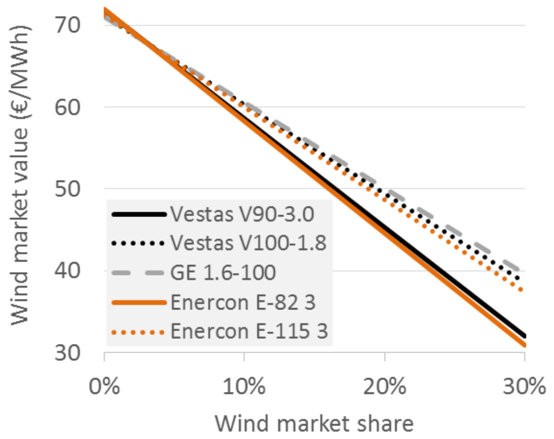


Figure 11. The market value of wind power in Germany for different wind turbine types, calculated from equation (18).

Table 5. Properties of wind generation profiles based on different types of wind turbines (2010 data from Germany).

Turbine model	Specific rating	Capacity factor $\bar{w}$	Coefficient of variation $c_v(w)$	Coefficient of correlation $\rho(w, l)$	Intercept	Gradient
Enercon E-70	581 W/m²	0.18	1.03	0.174	72	-144
Enercon E-82	568 W/m²	0.17	0.98	0.172	72	-137
Vestas V90	472 W/m²	0.18	0.95	0.171	72	-133
Enercon E-115	285 W/m²	0.31	0.78	0.142	71	-113
Vestas V110	230 W/m²	0.34	0.74	0.137	71	-109
GE 1.6-100	206 W/m²	0.38	0.70	0.124	71	-105

Data left of the dotted line is taken from manufacturers' websites. Data right to the line are calculated from ERA-interim weather data.

Using data from Table 5, Figure 12 displays capacity factors and coefficients of variation of all six profiles. Wind profiles with higher capacity factors clearly tend to have a lower coefficient of variation, and hence a more stable market value. This is consistent with the observation from Figure 9.

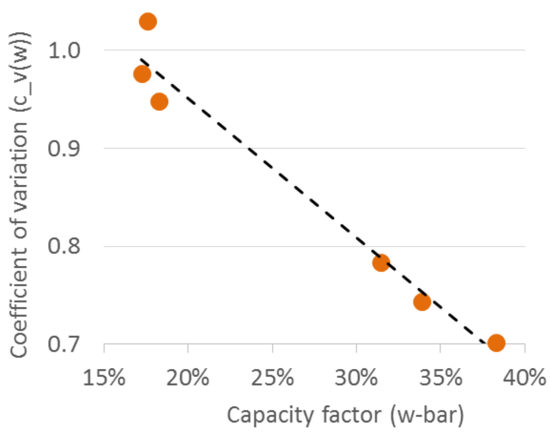


Figure 12. Coefficient of variation vs. capacity factor. A stark negative relationship is obvious.

7. Conclusion

This paper contributes to the literature on the market value of wind and solar power by developing a stylized analytical model of the power market and deriving a formal expression of the market value. This yields three core results:

- The market value of wind (or solar) power drops linearly with its energy market share.
- The market value at a low market share is determined by the *covariance* between consumption and wind (or solar) power production patterns. Power generation technologies produce high-value output if the production occurs at times of high electricity demand.
- The market value at higher market shares is primarily determined by the relative *variance* of wind (or solar) power production. Technologies produce high-value output if they produce electricity rather constantly.

The latter result has three implications. First, it helps explain why the market value of solar power drops faster than that of wind power (Hirth 2015a): surface solar radiation varies much more than wind speeds.

Second, it might guide policy and research into finding solutions for mitigating the value drop. Innovations that help reduce the variability of output tend to increase the market value of output. Low wind speed turbines with higher towers and lower specific ratings are an example of such technological advancements, solar modules that are oriented towards the East and the West is another.

Finally, and more fundamentally, it indicates that variable renewables face a substantial difficulty in becoming economical at high market shares. Without fundamental technological breakthroughs, a deep decarbonization of power systems will be hard to achieve based on wind and solar power alone. Other supplementary low carbon technologies are likely to be needed.

Notation

Notation	Interpretation	Unit	Empirical value (GER)
Time series			
t	Time	h	8760 per year
L_t	Hourly electricity demand	MW	*fluctuating*
W_t	Hourly wind power generation	MW	*fluctuating*
P_t	Hourly wholesale electricity price	€/MWh	*fluctuating*
$R_t = L_t - W_t$	Hourly residual load (generation other than wind power)	MW	*fluctuating*
$L_{max} = \max_t L_t$	Peak load	MW	80.000
$W_{max} = \max_t W_t$	Wind capacity, assumed to be identical to maximum generation.	MW	*f(penetration)*
$l_t = \frac{L_t}{L_{max}}$	Hourly load factor ("load profile") / normalized load	1	*fluctuating*
$w_t = \frac{W_t}{W_{max}}$	Hourly wind generation factor ("wind profile")	1	*fluctuating*
Averages of time series			
$\bar{L} \equiv \frac{1}{T}\sum_{t=1}^{T} L_t$	Average electricity demand	MW	56.000
$\bar{W} \equiv \frac{1}{T}\sum_{t=1}^{T} W_t$	Average wind power generation	MW	*f(penetration)*
$\bar{l} \equiv \frac{1}{T}\sum_{t=1}^{T} l_t = \frac{L}{L_{max}}$	"Load capacity factor"	1	70%
$\bar{w} \equiv \frac{1}{T}\sum_{t=1}^{T} w_t = \frac{\bar{W}}{W_{max}}$	Wind capacity factor, identical to average output over capacity	1	15%
Summary statistics			
$var(w_t)$	variance of normalized wind power generation	1	0.019
$cov(w_t, l_t)$	covariance of normalized wind power and load	1	0.0024
$c_v(w_t), c_v(l_t)$	coefficient of variation of normalized wind power generation and load, respectively	1	1.59
$\rho(w_t, l_t)$	coefficient of correlation	1	0.15
Average prices (market value)			
$\bar{P} \equiv \frac{1}{T}\sum_{t=1}^{T} P_t$	Average price (time-weighted average price, "base price").	€/MWh	*f(penetration)*
$\bar{P}_0 = \alpha \cdot \bar{l}$	Average price at zero wind penetration	€/MWh	70
$\bar{P}_{wind} \equiv \frac{\sum_{t=1}^{T} W_t \cdot P_t}{\sum_{t=1}^{T} W_t}$	Market value of wind power (wind-weighted average price).	€/MWh	*f(penetration)*
Other notation			
$\Pi \equiv \frac{\bar{W}}{\bar{L}}$	Wind penetration rate	1	*f(penetration)*
α	Power price at peak load	€/MWh	100

Appendix A: Literature review

Metho-dology	Source	Region	Multiple penetration rates?	Multiple scenarios / cases?	Market share	Value factor min	Gradient (%pt per %pt)
Market data	Sensfuß (2007), Sensfuß & Ragwitz (2011)		yes	no?	2%	1.02	
	Sensfuß (2007), Sensfuß & Ragwitz (2011)		yes	no?	6%	0.96	-1.5
	Fripp & Wiser (2008)		no	min	1%	0.90	
	Fripp & Wiser (2008)		no	max	1%	1.05	
	Lewis (2010)		no	location 1	1%	0.89	
	Lewis (2010)		no	location 2	1%	1.14	
Short-term / Medium-term (dispatch) model	Grubb (1991a)		yes	min	30%	0.75	
	Grubb (1991a)		yes	min	40%	0.40	-3.5
	Grubb (1991a)		yes	max	30%	0.85	
	Grubb (1991a)		yes	max	40%	0.70	-1.5
	Obersteiner et al. (2009)				1%	1.02	
	Obersteiner et al. (2009)				6%	0.97	-1.0
	Boccard (2010)	Germany			6%	0.90	
	Boccard (2010)	Germany			7%	0.87	-3.0
	Boccard (2010)	Spain			7%	0.90	
	Boccard (2010)	Spain			12%	0.82	-1.6
	Boccard (2010)	Denmark			12%	0.75	
	Boccard (2010)	Denmark			20%	0.65	-1.3
	Green & Vasilakos (2012)				20%	0.45	
	Energy Brainpool (2011)				12%	0.84	
	Valenzuela & Wang (2011)				5%	1.05	
	Hirth (2013)	NW Europe		yes	0%	1.10	
	Hirth (2013)	NW Europe		yes	30%	0.50	-2.0
Long-term (dis + inv) model	Swider & Weber (2006)		yes		5%	0.93	
	Swider & Weber (2006)		yes		25%	0.80	-0.7
	Lamont (2008)		yes		1%	0.86	
	Lamont (2008)		yes		16%	0.75	-0.7
	Mills & Wiser (2012)		yes	yes	1%	0.96	
	Mills & Wiser (2012)		yes	yes	40%	0.70	-0.7
	Nicolosi (2012)		yes		9%	0.98	
	Nicolosi (2012)		yes		35%	0.70	-1.1
	Kopp et al. (2012)		yes		19%	0.93	
	Kopp et al. (2012)		yes		39%	0.75	-0.9
	Hirth (2013)	NW Europe	yes	yes	0%	1.10	
	Hirth (2013)	NW Europe	yes	yes	30%	0.65	-1.5

Appendix B: Relative prices (value factor)

For many applications, it is convenient to study the *relative*, rather than the absolute market value. Historical observations of electricity prices, for example, vary with business cycles. Assessing the market value of wind power relative to the average electricity price (value factor) as a straightforward way to correct for factors. Note that Figure 3 reports such value factors.

The value factor is calculated as the ratio of the hourly wind-weighted average wholesale electricity price and its time-weighted average (base price). Hence the value factor is a metric for the valence of electricity with a certain time profile relative to a flat profile (Stephenson 1973). The wind value factor compares the value of actual wind power with varying winds with its value if winds were in-variant (Fripp & Wiser 2008). In economic terms, it is a relative price where the numeraire good is the base price. A decreasing value factor of wind implies that wind power becomes less valuable as a generation technology compared to a constant source of electricity.

As discussed above, the base price is defined as

$$\bar{P} \equiv \frac{1}{T}\sum_{t=1}^{T} P_t = \alpha \cdot \bar{l} \cdot (1 - \Pi).$$

The value factor of wind power can be written as

$$\begin{aligned} VF_{wind} &\equiv \frac{\bar{P}_{wind}}{\bar{P}} \\ &= \frac{1}{1-\Pi}\left\{\left(1 + \rho(w,l) \cdot c_v(w) \cdot c_v(l)\right) - \Pi \cdot \left(1 + c_v(w)^2\right)\right\} \\ &= \frac{\beta_0 - \beta_1 \Pi}{1 - \Pi}. \end{aligned} \tag{29}$$

This expression is in natural units and closely resembles equation (18).[14] It is, however, not linear in the penetration rate Π anymore. Using equation (19) and (20), we can rewrite the value factor as a Taylor approximation:

$$VF_{wind} = \frac{\beta_0 - \beta_1 \Pi}{1 - \Pi} = \beta_0 + (\beta_0 - \beta_1)\sum_{i=1}^{\infty} \Pi^i \tag{30}$$

For small penetration rates, a first- or second-order Taylor approximation can give satisfactory results. Using the values from Table 3 and Table 4, we can calculate the value factor and approximations for both wind and solar power (Figure 13, Figure 14).

[14] Furthermore, this expression has the nice property that it does *not* rely on the otherwise employed assumption $R_{max} = L_{max}$.

Table 6. German data (2010)		
	Wind power	Solar power
β_0	1.02	1.05
β_1	1.80	3.54

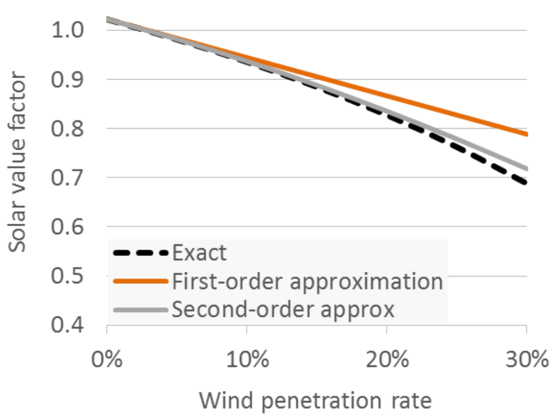


Figure 13. The value factor (relative market value) of wind power, exactly and as first- and second-order Taylor approximation.

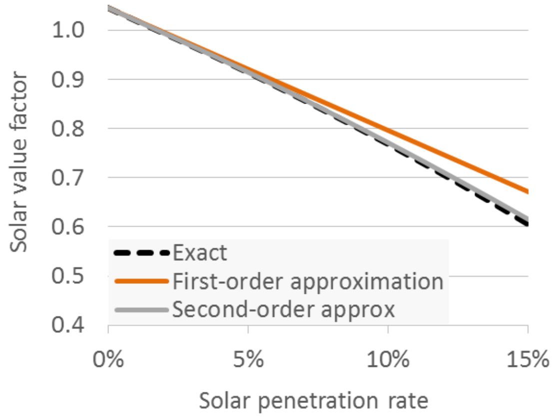


Figure 14. The value factor of solar power. Note the differently scaled x-axis. The solar value factor declines about twice as fast as the wind value factor.

Appendix C: Merit-order effect

In a special issue of *Energy Policy*, Sensfuß et al. (2008) and Sáenz de Miera et al. (2008) and Munksggard & Morthorst (2008) observed that in Germany, Spain, and Denmark, where wind power had been introduced early, average wholesale power prices declined as a consequence of wind power deployment. Sensfuß et al. coined the term "merit-order effect" to describe this phenomenon. To be very clear: the merit-order effect – the impact of wind power on the simple average electricity price (base price) – is quite a different phenomenon than its impact on the wind-weighted average price (market value). As several authors immediately noted, the merit-order is, for moderate penetration rates, likely to be a transitory phenomenon of a market pushed away from the long-term equilibrium, while the market value drop is not.

Many studies have subsequently explored the merit-order effect empirically (sometimes using a different label), including Olsina et al. (2007), Rathmann (2007), MacCormack et al. (2010), Mount et al. (2011), O'Mahoney & Denny (2011), and Gil et al. (2012).

To the best of our knowledge, no analytical expression of the merit order effect has been published. Using equation (22) from above,

$$\bar{P} \equiv \frac{1}{T}\sum_{t=1}^{T} P_t = \alpha \cdot \bar{l} \cdot (1 - \Pi),$$

we can derive the merit-order effect as the first derivative of the base price $\bar{P}$ with respect to an increase in wind power penetration Π:

$$\frac{\partial \bar{P}}{\partial \Pi} = -\alpha \cdot \bar{l}. \tag{31}$$

Appendix D: Nonlinear merit-order curve

A crucial assumption is the linearity of the thermal marginal cost curve (merit-order curve), as expressed in equation (6). In this appendix, we relax this assumption. Particularly, we want to allow for increasing marginal costs in thermal electricity generation, a property often observed in empirical data. While the literature has proposed various functional forms of the curve (e.g., He et al. 2013, Hirth 2015b), we restrict our analysis on a cubic (third-order polynomial) specification. Deriving the wind market value – as expressed in (18) – remains feasible for polynomial marginal cost curves, but becomes somewhat burdensome.

We have derived the market value for both linear-quadratic and linear-cubic marginal supply curves. A quadratic curve has the undesirable property that prices fall with declining residual load but then start rising again if residual load becomes negative (and large enough in absolute terms). Since a linear-cubic expression lacks this unwanted feature, we restrict our presentation to the thermal supply curve:

$$P_t = \alpha_1 \cdot \frac{R_t}{L_{max}} + \alpha_3 \cdot \left(\frac{R_t}{L_{max}}\right)^3. \tag{32}$$

We omit a constant term ($\alpha_0 = 0$), meaning that we assume a price of zero at zero residual demand, and a quadratic term ($\alpha_2 = 0$), to avoid positive prices at negative residual load. Note that equation (32) resembles (6) for $\alpha_3 = 0$. For $\alpha_3 > 0$, the supply curve is convex.

The market value then reads as

$$\begin{aligned} \bar{P}_{wind} &= \alpha_1 \bar{l}\{\gamma_0 - \Pi\gamma_1\} \\ &\quad + \alpha_3 \bar{l}^3\{\delta_0 - 3\Pi\delta_1 + 3\Pi^2\delta_2 - \Pi^3\delta_3\} \end{aligned} \tag{33}$$

where

$$\gamma_0 = 1 + \rho(w, l)c_v(w)c_v(l) \tag{34}$$

$$\gamma_1 = 1 + {c_v}^2(w) \tag{35}$$

$$\delta_0 = [1 + \rho(w, l^3)c_v(w)c_v(l^3)] \quad [1 + \rho(l, l^2)c_v(l)c_v(l^2)] \quad [1 + {c_v}^2(l)] \tag{36}$$

$$\delta_1 = [1 + \rho(w^2, l^2)c_v(w^2)c_v(l^2)] \, [1 + {c_v}^2(w)] \quad [1 + {c_v}^2(l)] \tag{37}$$

$$\delta_2 = [1 + \rho(w^3, l)c_v(w^3)c_v(l)] \quad [1 + \rho(w, w^2)c_v(w)c_v(w^2)] \, [1 + {c_v}^2(w)] \tag{38}$$

$$\delta_3 = [1 + {c_v}^2(w^2)] \quad [1 + {c_v}^2(w)] \quad [1 + {c_v}^2(w)]. \tag{39}$$

The equations are set block-wise to facilitate observing the symmetry. For $\alpha_3 = 0$, the second line of (33) disappears and the first line resembles (18). Note that $var(w) = cov(w, w)$ and that $cov(w, w^2) = cov(w^2, w)$, etc.

Hence the market value of wind power depends on the properties of the load time series

- $c_v(l)$
- $c_v(l^2)$
- $c_v(l^3)$

… the properties of the wind time series:

- $c_v(w)$
- $c_v(w^2)$
- $c_v(w^3)$

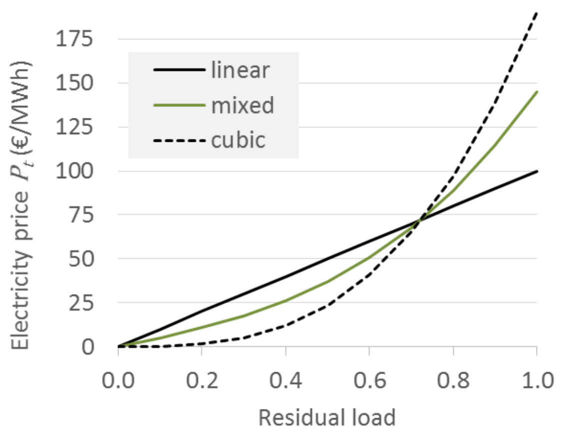
… and the joint properties (correlations) of both time series:

- $\rho(w, l)$
- $\rho(w, l^3)$
- $\rho(w^2, l^2)$
- $\rho(w^3, l)$

The second line of (33) carries the factor α_3 that stems from the cubic term of (32). It comprises four terms that are of different degree of wind penetration: constant (mark-up), linear, quadratic, and cubic. They all contain correlations of higher degrees such as $\rho(w, l^2)$, $\rho(w^2, l^2)$, etc. These can be interpreted as covering the effect of extraordinarily high load and wind respectively. In case of $\alpha_3 > 0$, i.e. a convex merit-order curve, the correlation of wind with extreme high load $\rho(w, l^3)$ provide an mark-up on the value.

Empirically, the relative size of the additional terms from the nonlinear extension depend on the degree of nonlinearity of the merit order. We obtain pairs of (α_1, α_3) by keeping the average electricity $\bar{P}_0$ price fixed at 70 €/MWh. Figure 15 displays three of the resulting thermal supply functions, including the extremes (only linear term and only cubic term).

Figure 16 shows the result wind market value. For convex supply curves, the wind value drops faster. When increasing the wind penetration from zero to 30%, the drop is 50% for a linear supply curve, but 80% for a (purely) cubic curve.



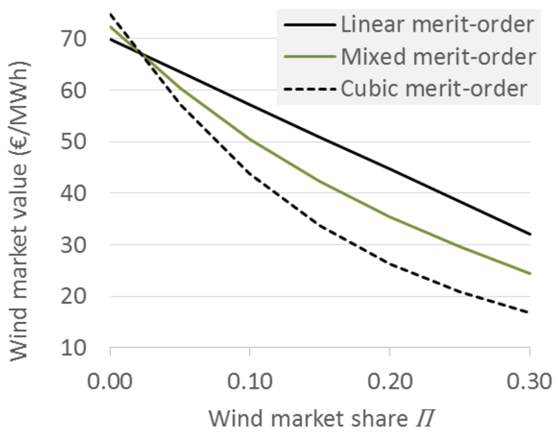


Figure 15. Three thermal supply functions with different combinations of (α_1, α_3), all of which lead to $\bar{P}_0 = 70€/MWh$.

Figure 16. Resulting market value curves.

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