The cannibalization effect of wind and solar in the California wholesale electricity market

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Increasing penetration of zero marginal cost variable renewable technologies cause the decline of wholesale electricity prices due to the merit-order effect. This causes a “cannibalization effect” through which increasing renewable technologies’ penetration undermines their own value. We calculate solar and wind daily unit revenues (generation weighted electricity prices) and value factors (unit revenues divided by average electricity prices) from hourly data of the day-ahead California wholesale electricity market (CAISO) for the period January 2013 to June 2017. We then perform a time series econometric analysis to test the absolute (unit revenues) and relative (value factors) cannibalization effect of solar and wind technologies, as well as the cross-cannibalization effects between technologies. We find both absolute and relative cannibalization effects for both solar and wind, but while wind penetration reduces the value factor of solar, solar penetration increases wind value factor, at least at high penetration and low consumption levels. We explore non-linearities and also find that the cannibalization effect is stronger at low consumption and high wind/solar penetration levels. This entails that wind and (mainly) solar competitiveness could be jeopardized unless additional mitigation measures such as storage, demand management or intercontinental interconnections are taken.

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1. Introduction

Increasing penetration of zero marginal cost variable renewable energy (VRE) technologies in the wholesale electricity markets pressures electricity prices downwards due to the merit-order effect. This has far-reaching implications, not only for the wholesale electricity market itself (is the marginal market design effective for high shares of zero-marginal cost technologies?), but also for VRE generators (will they ever be competitive if the value of their electricity declines faster than their cost?), policy makers (will support policies be sustainable if policy costs keep increasing due to the widening gap between guaranteed price (e.g. Feed-in Tariffs) and wholesale electricity prices?) and the electricity system as a whole (how high are the integration costs of variable renewables?).

California has seen a significant increase of solar and wind electricity generation in the last years, reaching daily penetration records of 23.5% and 14.7% respectively between January 2013 and June 2017. This has led to the decline of wholesale electricity prices, with this decline being stronger at the times when solar and wind are generating more, undermining their unit revenues (generation weighted electricity prices) and value factors (unit revenues divided by average electricity prices).

We estimate the absolute (decline of unit revenues as penetration increases) and relative (decline of value factors as penetration increases) cannibalization effect of solar and wind technologies in the California wholesale electricity market for the period January 2013 to June 2017. We first calculate daily unit revenues and value factors from hourly data, and then perform a time series econometric model of the four dependent variables (solar and wind unit revenues and value factors) as a function of solar, wind, natural gas and net imports penetration, gas prices and electricity consumption. We further explore non-linearities to test the stability

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Abbreviations and notation

ADF          augmented Dickey–Fuller (unit root test)
CAISO        California Independent System Operator
$D_t$        vector of daily, monthly and yearly dummies
DAM          day-ahead electricity market
EIA          Energy Information Administration
FGLS         feasible generalized least squares
HC           heteroskedasticity consistent (standard errors)
HAC          heteroskedasticity and autocorrelation consistent (standard errors)
OLS          ordinary least squares
$p_h$        hourly day-ahead wholesale electricity prices
$p_t$        daily average day-ahead wholesale electricity prices
PP           Phillips–Perron (unit root test)
p.p.         percentage points
$q_h^{(s,w)}$ hourly quantity of forecast generation of solar and wind $(s,w)$ technologies
$q_t^{(s,w)}$ daily quantity of forecast generation of solar and wind $(s,w)$ technologies
$q_m^{(s,w)}$ monthly quantity of forecast generation of solar and wind $(s,w)$ technologies
$q_c$        centralized-only solar generation
$q_d$        distributed-included solar generation
$(s,w)_h$    solar/wind penetration
$U_{(s,w)}$  solar/wind $(s,w)$ unit revenues
$V_{(s,w)}$  solar/wind $(s,w)$ value factor
VRE          variable renewable energy

of the parameters across different consumption and penetration ranges. With this model we can estimate not only how increasing a technology's penetration undermines its own value, but also the cross-cannibalization effects between technologies.

The absolute cannibalization effect indicates by how much the revenues per MWh decline for generators as their technology's penetration increases. The relative cannibalization shows by how much the value of the technology-specific electricity drops (or increases) with respect to the average value of electricity in the wholesale electricity market as penetration increases. In other words, it represents the cost (or benefit) of the generation variability.

Our primary data are provided by the California Independent System Operator (CAISO) for the day-ahead wholesale electricity market. However, these data do not include solar generation of distributed small-scale installations. Therefore, we use centralized-only data from CAISO, but also combine it with distributed solar generation estimations by the Energy Information Administration (EIA), and find that excluding distributed generation (about a third of total solar generation) would lead to an (under)overestimation of the (wind)solar cannibalization effect.

This paper contributes to the merit-order literature by going one step further and jointly quantifying the effect of wind and solar penetration on their own and each other's unit revenues and value factors ex-post with historical market data. This is the first paper to our knowledge to jointly estimate cannibalization and cross-cannibalization effects within and between technologies of both solar and wind based on actual market data. Finally, by including distributed generation we find that the literature on the merit-order effect might be (under)overestimating the effect of (wind)solar penetration when distributed generation is omitted and it represents a significant share of the total solar generation.

The remainder of the paper is structured as follows: Section 2 reviews the literature on the merit-order effect and the value of renewable electricity. Section 3 presents the data and method. Section 4 explains the results, focusing first on the general results of the relative and absolute cannibalization effects and exploring then potential non-linearities related to the effect of different consumption and penetration levels on wind and solar value factors. Section 5 discusses the results and their implications, and compares them with the previous literature. Section 6 concludes.

2. The merit-order effect and the value of variable renewables

The cannibalization effect is caused by the merit-order effect: for any given demand, zero marginal cost electricity technologies entering the market will shift the supply curve to the right (or equivalently the residual load to the left) and therefore the marginal matched price will decline (Fischer, 2006; Nicolosi and Fürsch, 2009; Zachmann, 2013). This effect has been widely identified and quantified in the literature for markets with high penetration of variable renewables such as Texas (Woo et al., 2011, 2016), Germany (Sensfuß et al., 2008; Tveten et al., 2013; Cludius et al., 2014; Dillig et al., 2016), Italy (Clò et al., 2015) or Spain (Sáenz et al., 2008; Gelabert et al., 2011; Ballester and Furió, 2015). Although these studies focus on different aspects of the merit-order effect, such as its relation to support policies or distributive effects, they all find conclusive evidence of the effect of variable renewables on lowering wholesale electricity prices. The most common methods to quantify the merit-order effect are either market simulations (Sensfuß et al., 2008; Sáenz et al., 2008) or time series econometric models (Clò et al., 2015; Gelabert et al., 2011).

Electricity is a perfectly homogeneous commodity in three dimensions: time, space and lead-time between contract and delivery (Hirth, 2015). This entails that electricity prices vary across these three dimensions even holding all other factors constant, and therefore the value of renewables depends on the time and place of generation and level of uncertainty about future production (Borenstein, 2012; Baker et al., 2013). Since VRE technologies have a higher level of uncertainty and generate electricity only when and where the resource is available, their value significantly differs from the value of conventional dispatchable electricity generation technologies (Lamont, 2008; Joskow, 2011).

The value of variable renewables has been quantified in the literature either ex-ante with dispatch or dispatch and investment models or ex-post with econometric models and historical market data (see Hirth, 2013, 2015 for a comprehensive review). Most of these studies agree that the value of VRE tends to decline as penetration increases. For instance, Zipp (2017) studies how the drop in prices due to the merit-order effect is translated to the decline in the revenues of VRE generators in Germany. Likewise, Clò and D’Adamo (2015) estimate the effect of solar penetration on solar and gas unit revenues and value factors in the Italian day-ahead wholesale electricity market.

For the specific case of California, Woo et al. (2016) find evidence of a small but significant merit-order effect caused by both wind and solar in both the day-ahead and the real-time electricity markets. Likewise, both Borenstein (2008) and Lamont (2008) identify value factors above 1 for solar, declining with penetration at low penetration levels. The most comprehensive study assessing the value of VRE in California has been done by Mills and Wiser (2012), who use a dispatch and investment model to estimate ex-ante the long-term value of wind and solar up to 40% penetration, finding also evidence of a downward trend as penetration increases.

We build upon this previous literature to estimate the cannibalization and cross-cannibalization effects of solar and wind technologies, i.e., how increasing solar and wind penetration affects their own and each other’s unit revenues and value factors. In the discussion section we will expand this brief literature review by comparing our results with the most relevant findings of the aforementioned references.
3. Data and method

3.1. Data collection

We use hourly data from the California day-ahead wholesale electricity market provided by the California Independent System Operator (CAISO) for the period January 2013 to June 2017 (both included): day-ahead electricity prices, day-ahead demand, day-ahead electricity imports and exports (from which we calculate net imports), solar and wind generation day-ahead forecast and gas prices. Since we study the day-ahead electricity market (DAM), it is more accurate to use day-ahead forecast generation and demand rather than realized data, for DAM agents base their decisions on these forecasts given the uncertainty regarding actual future generation/demand. While the correlation between day-ahead forecast and actual demand is almost perfect (0.9977), the correlation between solar, and in a larger extent wind forecast and actual generation is lower (0.9893 and 0.9207 respectively, see Appendix C), so using realized data rather than day-ahead forecasts would likely bias our results.

CAISO does not provide, however, data on natural gas generation, which we obtained from the Environmental Protection Agency Air Markets Program Data. These data have two caveats: it is realized rather than day-ahead and gross load rather than net generation. This entails that gas penetration is overestimated and therefore its parameter is likely to be underestimated (the same effect as with wind penetration when we compare the centralized-only and the distributed included datasets). Therefore, although the specific parameter of the gas penetration variable should not be trusted, it is still a useful control for our interest variables: wind and solar penetration.

Another limitation of the data concerns the electricity trade between electricity markets. Although we control for net imports, it would be more accurate to sum(subtract) solar/wind imports(export) to(from) solar/wind generation to have exact solar/wind penetration. Unfortunately, there is no import/export decomposition at the hourly level so controlling for net imports is the best we can do with the available data.

3.2. Calculation of unit revenues and value factors

Unit revenues (UR\textsubscript{i}^{[s,w]}) are defined as the solar/wind ([s, w]) generation-weighted electricity prices, and value factors (VF\textsubscript{i}^{[s,w]}) are the ratio between unit revenues and the average electricity prices. Eqs. (1) and (2) show the calculation of daily unit revenues and value factors respectively, where \( p_{h} \) stands for hourly day-ahead wholesale electricity prices and \( q_{h}^{[s,w]} \) stands for hourly quantity of forecast generation of solar and wind ([s, w]) technologies. Although Hirth et al. (2015) define the value factor as the ratio of unit revenues and load-weighted average electricity prices, both Hirth (2015) and Oba and D’Adamo (2015) use the unweighted average price for their VF calculations. We therefore use the simple (i.e. unweighted) average to make the results comparable, although this choice is likely to have negligible effects in our results since the correlation between both is almost perfect (0.9978, see Appendix C):

\[
UR_{i}^{[s,w]} = \frac{\sum_{h=1}^{24} p_{h} q_{h}^{[s,w]}}{\sum_{h=1}^{24} q_{h}^{[s,w]}} \quad (1)
\]

\[
VF_{i}^{[s,w]} = \frac{UR_{i}^{[s,w]}}{p_{i}} = \frac{\sum_{h=1}^{24} p_{h} q_{h}^{[s,w]}}{\sum_{h=1}^{24} q_{h}^{[s,w]}} / \frac{\sum_{h=1}^{24} q_{h}}{24} \quad (2)
\]

Fig. 1 shows the daily solar and wind unit revenues and value factors observed in the California DAM for the period January 2013 to June 2017, which will be the dependent variables of our models. While solar and wind unit revenues have a strong positive correlation, solar and wind value factors move in opposite directions. Both solar and wind UR declined between January 2013 and June 2017. Although the average\(^1\) solar UR were $2.9/MWh higher than those of wind in 2013, solar UR decreased faster than wind UR and started to lay below wind UR from 2015 onwards, in 2016 being $4/MWh lower than wind UR. Within four years (2013–2016), solar UR fell almost $20/MWh, from $45.9/MWh to $26/MWh, and wind UR dropped $13/MWh, from $43/MWh in 2013 to $30/MWh in 2016. Solar UR have even reached negative values due to the negative prices observed in the wholesale electricity market at peak solar generation times. A summary of the descriptive statistics is provided in Table 1, see Appendix A for detailed descriptive statistics.

The average solar VF was 105.5% in 2013, meaning that PV electricity was worth 5.5% more than the average unit of electricity traded in the wholesale electricity market during that year, thanks to the positive correlation between the solar generation profile and the demand load. At the same time, wind VF was 99%, 1% less than a hypothetical flat generation profile, because its generation is more randomly distributed along the day instead of being concentrated around demand-peak time as solar. However, while solar VF decreased over the studied period down to 85.7% in 2016 and only 63.7% in the first half of 2017, wind VF slightly increased up to 102% in 2016, entailing that wind VF surpassed solar VF since 2014. In summary, while solar value was 6.5 percentage points (p.p.) higher than wind in 2013, their opposite evolution during this time entailed that in 2016 wind VF was 16.3 p.p. higher than solar.

3.3. Trends and distributions

The evolution of unit revenues and value factors is determined by the levels and hourly distribution of solar/wind generation (Fig. 2), and wholesale electricity prices (Fig. 3). Electricity prices declined in California during the studied period due to three main causes: the merit-order effect, the decline of gas prices and the decline of net electricity consumption. Whereas total consumption increased when distributed electricity is considered, net consumption declined due to the stronger increase of self-consumption (see descriptive statistics in Appendix A). The downward trend of unit revenues is a reflection of the merit-order effect, and therefore their evolution mimics that of wholesale electricity prices (see Fig. 4 in Appendix C).

Fig. 2 shows the average hourly distribution of wind and solar generation during the years 2013 and 2016. While both wind and solar have the same seasonal pattern (both produce more in summer than in winter in California), they have opposite daily patterns: solar generation is concentrated around noon whereas wind generation is more randomly distributed along the day with its minimum generation around noon. The comparison between both panels of Fig. 2 shows that whereas wind generation was higher than solar in 2013, solar installed capacity and generation increased faster than wind surpassing it in 2014 (when we include distributed generation, or in 2015 otherwise, see Appendix A for more details).

Fig. 3 shows likewise the average hourly distribution of wholesale electricity prices per month and year between 2012 and 2017. We can observe that not only the price levels generally fell during this period, but the hourly distribution changed. As solar penetration increases, prices drop at noon and spike in the evening when solar generation declines, creating a pattern that resembles the “duck curve” caused by solar generation in the net load profile.

\(^1\) All the values provided in this section refer to annual averages of daily values.
Table 1
Summary statistics.

| Variable                  | Unit   | 2013   | 2016   | Diff. 2016–2013 | 01/2013–06/2017 |
|---------------------------|--------|--------|--------|-----------------|-----------------|
| Solar UR                  | $/MWh  | 45.9   | 26.0   | −19.9           | 35.9            |
| Wind UR                   | $/MWh  | 43.0   | 30.0   | −13.0           | 37.7            |
| Solar VF                  | %      | 105.5  | 85.7   | −19.8           | 92.5            |
| Wind VF                   | %      | 99.0   | 102.0  | 3.0             | 101.2           |
| Solar penetration         | %      | 2.5    | 11.2   | 8.7             | 8.0             |
| Wind penetration          | %      | 4.1    | 5.3    | 1.2             | 4.7             |
| Net imports penetration  | %      | 22.4   | 27.1   | 4.7             | 23.7            |
| Gas penetration           | %      | 38.2   | 30.4   | −7.9            | 34.6            |
| Consumption               | GWh    | 648.3  | 654.6  | 6.3             | 648.9           |
| Gas price                 | $/MMBtu| 4.4    | 3.4    | −1.0            | 4.1             |

Yearly averages of daily values. Distributed solar included.

Fig. 1. Daily unit revenues and value factors.

Fig. 2. Solar (centralized only) and wind hourly average generation per month in the years 2013 and 2016.
Therefore, whereas at low penetration solar generation is usually correlated with electricity prices, the drop in prices caused by the merit-order effect at the times when there is high solar penetration reverses this correlation causing the downwards trend of the solar value factor observed in Fig. 1.

3.4. Wind and solar penetration

We calculate daily solar/wind penetration \(\{s, w\}_h\) as the sum of the hourly solar/wind generation forecast \(q_{h}^{s,w}\) divided by daily electricity consumption, which is equal to the sum of the hourly demand forecast \(d_h\):

\[
\{s, w\}_h = \frac{\sum_{h=1}^{24} q_{h}^{s,w}}{\sum_{h=1}^{24} d_h}
\]

(3)

The CAISO data, however, only captures generation from centralized solar power plants, omitting generation from small-scale distributed installations, which could cause a bias in the estimation—as we will confirm in the results section. Therefore, we interpolate monthly Energy Information Administration (EIA) distributed photovoltaic generation data to daily values assuming the same pattern as the one observed in the CAISO data according to the following algorithm:

\[
q_{t}^{ds} = \frac{q_t^{c} - q_t^{cm}}{q_{t}^{cm}} q_{t}^{ds}
\]

(4)

where the superscripts indicate whether solar generation is centralized (cs) or distributed (ds) and the subscripts indicate the periodicity of the data: daily \((t)\) and monthly \((m)\).

From the centralized-only dataset and the daily solar distributed generation interpolation we build the distributed-included dataset by summing up, on the one hand, centralized and distributed generation; and on the other hand, daily consumption and distributed generation. Thus, when computing the solar penetration of the distributed-included dataset we take into account distributed generation both in the numerator (as higher solar generation) and the denominator (as demand-side self-supplied consumption).

The omission of distributed solar generation has two opposite effects. On the one hand, omitting distributed generation underestimates the effect of solar penetration, since the drop in wholesale prices caused by the lower net load would be attributed to lower demand rather than higher penetration derived from the self-consumed electricity. On the other hand, omitting distributed generation overestimates the cannibalization effect since the drop in prices occurs at an apparently lower solar penetration level than actually realized when distributed generation is considered. As we will see in the results section, the latter effect is stronger so the omission of distributed generation causes an (under)overestimation of the (wind)solar cannibalization effect.

Finally, we do not take into account curtailment, understood as a “reduction in the output of a wind or solar generator from what it could otherwise produce given available resources” (Bird et al., 2014). By ignoring curtailment, we estimate the cannibalization effect of actual generated electricity. An alternative approach would be to include curtailment and estimate the cannibalization effect of potential rather than actual electricity generation.

3.5. Econometric approach

Once we have the UR and VF time series, as well as wind and solar penetration and all the control variables, we test for the presence of unit roots. We perform augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests (Table 2) with constant and linear trend and the number of lags determined by the Akaike Information Criterion (AIC) on each of the time series in levels and first differences. Although the ADF does not reject the null hypothesis of unit root for the solar penetration, gas price and consumption time series in levels, the PP test safely rejects the unit root null of all the time series in both levels and differences at 1% significance. Since
the PP test is non-parametric and asymptotically more efficient we take our data as stationary.

We model solar and wind unit revenues ($UR_{s,w}$) and value factors ($VF_{s,w}$) as a function of solar, wind, natural gas and net imports market penetration ($sht$, $wht$, $gsh$ and $net_{imports_{sh}}$ respectively), consumption ($consumption_t$) and gas prices ($gas_{price_t}$), including a vector of daily, monthly and yearly dummies ($D_t$) to account for trends and different levels of season-

| Table 2 |

| Solar UR | Wind UR | Solar VF | Wind VF | Solar % | Wind % | Net imports % | Gas % | Consumption | Gas price |
|----------|---------|----------|---------|---------|--------|---------------|-------|-------------|-----------|
| ADF (levels) | −4.889 | −4.710 | −5.036 | −8.146 | −2.972 | −6.058 | −4.228 | −4.814 | −2.881 |
| p-value | 0.010 | 0.010 | 0.010 | 0.010 | 0.167 | 0.010 | 0.010 | 0.010 | 0.205 |
| PP (levels) | −261 | −219 | −472 | −1448 | −112 | −422 | −130 | −260 | −139 |
| p-value | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 |
| ADF (diff.) | −18.907 | −17.722 | −18.581 | −19.496 | −18.554 | −19.764 | −17.885 | −20.583 | −19.646 |
| p-value | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 |
| PP (diff.) | −1233 | −1314 | −1319 | −1661 | −1313 | −1018 | −1138 | −856 | −895 |
| p-value | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 |

ADF: augmented Dickey–Fuller; PP: Phillips–Perron.
ality as shown in Eq. (5). This specification is similar to that of Cludius et al. (2014) and Clò et al. (2015) for the estimation of the merit-order effect:

\[
y_{t}^{[\text{w}]} = \alpha + \beta_{1} \text{Ssh}_{t} + \beta_{2} \text{wind} \text{sh}_{t} + \beta_{3} \text{gas} \text{sh}_{t} + \beta_{4} \text{net imports} \text{sh}_{t} + \beta_{5} \text{consumption} + \beta_{6} \text{gas price}_{t} + \gamma_{t}^{	ext{D}} + \epsilon_{t}^{	ext{D}}
\]

This model allows us to not only quantify the absolute and relative cannibalization effect (i.e., how increasing market penetration of one specific technology undermines its own unit revenues and value factors), but also test the cross-cannibalization effect between technologies. Although we tried more complex specifications with an interaction term between consumption and solar/wind penetration and a quadratic form on the penetration variable, we decided to stick to this simple functional form and estimate different regressions on subsets of data across different penetration and consumption ranges, as will be shown in Section 4.3. This allows us to directly compare our results with the previous literature (see Section 5.2), which has so far used only linear specifications, while still being able to acknowledge and quantify potential non-linearities. Likewise, we also controlled for CO2 prices (5-day moving average price of California Carbon Allowance Futures from ICE End of Day Reports as provided by the California Carbon Dashboard and with linear interpolation for missing data) but we found no significant effects and lower adjusted Rs2 so we omitted this variable from the final specification to avoid introducing unnecessary noise. The models are estimated with daily data between January 2013 and June 2017 (both included), totaling a minimum of 1631 observations in the full dataset regressions (42 missing observations due to data availability/retrieval, see summary statistics in the Appendix A for more details).

Since we find both autocorrelation and heteroskedasticity when performing an OLS (ordinary least squares) estimation in levels, we compare two different approaches:

- OLS estimation on differenced data (as in Gelabert et al., 2011), except the wind relative cannibalization regression, whose \(\rho\) parameter is below 0.2 indicating low autocorrelation, and entail that differencing the data would actually worsen the fit.
- Feasible generalized least squares (FGLS) with Prais–Winsten estimator (Prais and Winsten, 1954) (as in Clò and D’Adamo, 2015). The Prais–Winsten estimator assumes that the residuals follow a first order autoregressive process AR(1) such that

\[\epsilon_{t} = \rho \epsilon_{t-1} + \omega, \text{where } |\rho| < 1 \text{ and } \omega \text{ is a white noise.}\]

In both cases, we use heteroskedasticity (and autocorrelation) consistent (HC/HAC) standard errors when the Durbin–Watson and Breusch–Pagan tests detect autocorrelation and/or heteroskedasticity respectively.

4. Results

This section presents the main results of the analysis in terms of absolute (unit revenues) and relative (value factors) cannibalization (within technologies) and cross-cannibalization (between technologies) effects of wind and solar technologies for centralized-only (CAISO data) and distributed-included (daily interpolation from monthly EIA data) solar generation with two econometric approaches: differenced OLS and Prais–Winsten FGLS; with HC/HAC standard errors when there is autocorrelation and/or heteroskedasticity.

Fig. 4 summarizes the main results, which are presented in detail in Tables 3–6. First, the consistency between both econometric approaches, widely used in the literature, confirm the robustness of our estimation. Additionally, Appendix B presents the results of the same regressions using total generation rather than penetration and showing consistent results, which again supports the robustness of our approach. Second, we observe that omitting distributed solar generation (31% of the total solar generation during the studied period) leads to an overestimation of the solar cannibalization effect and an underestimation of the wind cannibalization effect, while barely affecting the cross-cannibalization effects. It is therefore likely that the merit-order effect caused by (wind)solar penetration is (under)overestimated in the literature when distributed generation is not included and it represents a significant share of the total solar generation. Given these preliminary observations, we will focus on the results of the Prais–Winsten FGLS estimation (since it is asymptotically more efficient than the OLS) with the distributed-included dataset.

Our results confirm both absolute and relative cannibalization effects for both technologies, being stronger for solar than for wind. The same applies for the absolute cross-cannibalization effects (effect of one technology’s penetration on the other technology’s unit revenues). The value factor effects between technologies (relative cross-cannibalization), however, are opposite: while wind penetration reduces the solar VF, solar penetration increases the wind VF.

4.1. Absolute cannibalization (unit revenues)

We define the absolute cannibalization effect as the decline of the technology-specific unit revenues (UR: solar/wind generation-weighted electricity prices, Eq. (1)) as their respective market penetration increases. The upper panels of Fig. 4 show the partial effects of solar and wind penetration on solar and wind UR according to the model presented in Eq. (5), and Tables 3 and 4 present the detailed regression results for solar and wind UR respectively.

These results confirm both solar and wind absolute cannibalization effect: i.e., increasing penetration of both solar and wind undermines their respective UR. This explains the decline in both solar and wind UR during the last four and a half years (see Fig. 1) as penetration increased (see Table 1). However, the absolute cannibalization effect is stronger for solar (UR fall by \(-$1.295/MWh\) for each percent point (p.p.) penetration increase—Table 3) than for wind (\(-$0.838/MWh\)—Table 4). These results also confirm the cross-cannibalization between technologies, although the effect of one technology’s penetration on the other technology’s UR is weaker than the increase of their own penetration.

Regarding the control variables, both consumption and gas prices have positive effects on both solar and wind UR as expected, since their positive effect on electricity prices, already identified in the merit-order literature, is directly reflected in the technology-specific UR. Gas penetration also has a positive effect but of very small magnitude. Finally, net imports penetration negatively affect both solar and wind UR.

The evolution of the UR is generally a reflection of the evolution of electricity prices, and therefore our results are consistent with the previous merit-order literature. More interesting (and less intuitive) is, however, the evolution of the value factors, on which we will focus from now on.

4.2. Relative cannibalization (value factor)

We define relative cannibalization effect as the decline of the technology-specific value factors (VF: ratio between unit revenues and average wholesale electricity prices, Eq. (2)) as their respective market penetration increase. The lower panels of Fig. 4 show the partial effects of solar and wind penetration on solar and wind VF according to the model presented in Eq. (5), and Tables 5 and...
### Table 3
Solar absolute cannibalization effect.

|                      | Solar unit revenues | Prais–Winsten FGLS |
|----------------------|---------------------|---------------------|
|                      | Diff. OLS           | Distributed included | Centralized only | Distributed included |
|                      | (1)                 | (2)                 | (3)               | (4)                 |
| Solar penetration    | −1.886***           | −1.400***           | −1.603***         | −1.295***           |
|                      | (0.168)             | (0.118)             | (0.125)           | (0.091)             |
| Wind penetration     | −0.774***           | −0.740***           | −0.721***         | −0.703***           |
|                      | (0.039)             | (0.046)             | (0.043)           | (0.047)             |
| Gas penetration      | 0.025               | 0.046***            | 0.058***          | 0.079***            |
|                      | (0.019)             | (0.020)             | (0.023)           | (0.023)             |
| Net imports penetration | −0.056           | −0.076***           | −0.063***         | −0.065***           |
|                      | (0.043)             | (0.044)             | (0.035)           | (0.036)             |
| Gas price            | 4.751***            | 4.771***            | 5.236***          | 5.292***            |
|                      | (0.408)             | (0.488)             | (0.338)           | (0.334)             |
| Consumption          | 0.069***            | 0.069***            | 0.080***          | 0.080***            |
|                      | (0.006)             | (0.006)             | (0.006)           | (0.006)             |
| Constant and DMY dummies | Yes           | Yes                 | No                | No                |
| Standard errors      | HAC                 | HAC                 | HAC               | HAC               |
| Rho                  | −                   | 0.645               | 0.617             |                   |
| Durbin–Watson (stat) | 2.386               | 2.423               | 2.024             | 2.029             |
| Durbin–Watson (p-value) | 0               | 0                   | 0.856             | 0.826             |
| Breusch–Pagan (stat) | 60.814              | 62.95               | 56.797            | 57.971            |
| Breusch–Pagan (p-value) | 0                | 0                   | 0.001             | 0                 |
| Observations         | 1631                | 1635                | 1632              | 1636              |
| R²                   | 0.655               | 0.633               | 0.950             | 0.954             |
| Adjusted R²          | 0.646               | 0.627               | 0.949             | 0.954             |
| Residual std. error  | 3.586 (df= 1603)    | 3.675 (df= 1607)    | 3.287 (df= 1604)  | 3.333 (df= 1608)   |
| F statistic          | 111.313*** (df= 27; 1603) | 102.845*** (df= 27; 1607) | 1078.711*** (df= 28; 1604) | 1204.822*** (df= 28; 1608) |

**Note:** HC/HAC: heteroskedasticity (and autocorrelation) consistent standard errors.

- **p < 0.1.**
- **p < 0.05.**
- **p < 0.01.**

### Table 4
Wind absolute cannibalization effect.

|                      | Wind unit revenues | Prais–Winsten FGLS |
|----------------------|---------------------|---------------------|
|                      | Diff. OLS           | Distributed included | Centralized only | Distributed included |
|                      | (1)                 | (2)                 | (3)               | (4)                 |
| Solar penetration    | −0.634***           | −0.469***           | −0.439***         | −0.430***           |
|                      | (0.117)             | (0.077)             | (0.087)           | (0.062)             |
| Wind penetration     | −0.651***           | −0.893***           | −0.620***         | −0.838***           |
|                      | (0.036)             | (0.037)             | (0.037)           | (0.038)             |
| Gas penetration      | −0.020              | 0.008               | 0.034             | 0.049***            |
|                      | (0.019)             | (0.018)             | (0.020)           | (0.021)             |
| Net imports penetration | −0.059           | −0.080***           | −0.124***         | −0.120***           |
|                      | (0.036)             | (0.034)             | (0.028)           | (0.028)             |
| Gas price            | 5.033***            | 5.071***            | 5.630***          | 5.598***            |
|                      | (0.560)             | (0.546)             | (0.374)           | (0.362)             |
| Consumption          | 0.045***            | 0.038***            | 0.054***          | 0.047***            |
|                      | (0.005)             | (0.005)             | (0.006)           | (0.006)             |
| Constant and DMY dummies | Yes           | Yes                 | No                | No                |
| Standard errors      | HAC                 | HAC                 | HAC               | HAC               |
| Rho                  | −                   | 0.557               | 0.595             |                   |
| Durbin–Watson (stat) | 2.536               | 2.467               | 2.065             | 2.053             |
| Durbin–Watson (p-value) | 0               | 0                   | 0.32              | 0.424             |
| Breusch–Pagan (stat) | 56.664              | 55.956              | 43.811            | 42.443            |
| Breusch–Pagan (p-value) | 0.001            | 0.001               | 0.022             | 0.03              |
| Observations         | 1631                | 1635                | 1632              | 1636              |
| R²                   | 0.647               | 0.522               | 0.973             | 0.970             |
| Adjusted R²          | 0.458               | 0.514               | 0.972             | 0.970             |
| Residual std. error  | 3.300 (df= 1603)    | 3.121 (df= 1607)    | 2.946 (df= 1604)  | 2.811 (df= 1608)   |
| F statistic          | 51.976*** (df= 27; 1603) | 65.050*** (df= 27; 1607) | 2026.237*** (df= 28; 1604) | 1882.817*** (df= 28; 1608) |

**Note:** HC/HAC: heteroskedasticity (and autocorrelation) consistent standard errors.

- **p<0.1.**
- **p<0.05.**
- **p<0.01.**
Table 5  
Solar relative cannibalization effect.

| Solar value factor | Diff. OLS | Prais–Winston FGLS |
|--------------------|-----------|------------------|
|                    | Centralized only | Distributed included | Centralized only | Distributed included |
| Solar penetration  | −6.927*** | −4.773*** | −5.680*** | −4.122*** |
| (0.702)            | (0.473)   | (0.481)       | (0.325)       |
| Wind penetration   | −1.173*** | −1.036*** | −1.046*** | −0.961*** |
| (0.159)            | (0.168)   | (0.151)       | (0.148)       |
| Gas penetration    | 0.128***  | 0.164*** | 0.128***  | 0.153***  |
| (0.043)            | (0.045)   | (0.041)       | (0.042)       |
| Net imports penetration | −0.172* | −0.197*** | −0.089     | −0.072    |
| (0.118)            | (0.118)   | (0.080)       | (0.078)       |
| Gas price          | −0.358**  | −0.374** | 0.112      | 0.111     |
| (0.153)            | (0.156)   | (0.510)       | (0.569)       |
| Consumption        | 0.018     | 0.027** | 0.041***  | 0.048***  |
| (0.012)            | (0.011)   | (0.009)       | (0.009)       |
| Constant and DMY dummies | Yes | Yes | Yes | Yes |
| Standard errors    | HAC       | HAC             | HAC          | HAC       |
| Rho                | 0.643     | 0.614          |              |           |
| Durbin–Watson (statistic) | 2.355 | 2.348          | 1.974        | 1.952     |
| Durbin–Watson (p-value) | 0      | 0               | 0.414        | 0.192     |
| Breusch–Pagan (statistic) | 265.521 | 259.572       | 242.129      | 214.57    |
| Breusch–Pagan (p-value) | 0      | 0               | 0            | 0         |
| Observations       | 1631      | 1635           | 1632         | 1636      |
| R²                 | 0.535     | 0.509          | 0.557        | 0.561     |
| Adjusted R²        | 0.527     | 0.500          | 0.956        | 0.961     |
| Residual std. error| 8.054 (df = 1603) | 8.246 (df = 1607) | 7.365 (df = 1604) | 7.454 (df = 1608) |
| F statistic        | 68.327*** (df = 27; 1603) | 61.631*** (df = 27; 1607) | 1265.384*** (df = 28; 1604) | 1434.060*** (df = 28; 1608) |

Note: HC/HAC: heteroskedasticity (and autocorrelation) consistent standard errors.

- * p < 0.1.
- ** p < 0.05.
- *** p < 0.01.

Table 6  
Wind relative cannibalization effect.

| Wind value factor | OLS | Prais–Winston FGLS |
|-------------------|-----|------------------|
|                   | Centralized only | Distributed included | Centralized only | Distributed included |
| Solar penetration | 1.018*** | 0.741*** | 1.018*** | 0.728*** |
| (0.152)           | (0.116)   | (0.160)       | (0.126)       |
| Wind penetration  | −0.126** | −0.480*** | −0.135** | −0.578*** |
| (0.058)           | (0.063)   | (0.058)       | (0.064)       |
| Gas penetration   | −0.034***| −0.02017     | −0.037*** | −0.024     |
| (0.015)           | (0.015)   | (0.015)       | (0.015)       |
| Net imports penetration | −0.023 | −0.01617       | −0.021     | −0.008     |
| (0.025)           | (0.027)   | (0.026)       | (0.028)       |
| Gas price         | 0.017     | 0.094          | 0.027        | 0.117      |
| (0.164)           | (0.173)   | (0.169)       | (0.178)       |
| Consumption       | 0.002     | −0.006***    | 0.002        | −0.008***  |
| (0.003)           | (0.003)   | (0.003)       | (0.003)       |
| Constant and DMY dummies | Yes | Yes | Yes | Yes |
| Standard errors   | HAC       | HAC           | HAC          | HAC       |
| Rho               | 0.066     | 0.152          |              |           |
| Durbin–Watson (statistic) | 1.87 | 1.728          | 1.985        | 1.977     |
| Durbin–Watson (p-value) | 0      | 0               | 0.482        | 0.368     |
| Breusch–Pagan (statistic) | 330.094 | 316.093       | 333.784      | 331.555   |
| Breusch–Pagan (p-value) | 0      | 0               | 0            | 0         |
| Observations      | 1632      | 1636           | 1632         | 1636      |
| R²                | 0.286     | 0.321          | 0.998        | 0.998     |
| Adjusted R²       | 0.274     | 0.309          | 0.989        | 0.998     |
| Residual std. error| 4.321 (df = 1604) | 4.284 (df = 1608) | 4.312 (df = 1604) | 4.240 (df = 1608) |
| F statistic       | 23.799*** (df = 27; 1604) | 28.104*** (df = 27; 1608) | 27.999,800*** (df = 28; 1604) | 23,954,650*** (df = 28; 1608) |

Note: HC/HAC: heteroskedasticity (and autocorrelation) consistent standard errors.

- * p < 0.1.
- ** p < 0.05.
- *** p < 0.01.
present the detailed regression results for solar and wind VF respectively.

The results confirm both solar and wind relative cannibalization effect; i.e., increasing penetration of both solar and wind undermines their respective VF. The relative cannibalization effect is stronger for solar (the VF of solar with respect to the average wholesale electricity price falls by \(-4.122\) p.p. for each p.p. increase in solar penetration) than for wind (\(-0.578\) p.p.).

Regarding cross-cannibalization effects, wind penetration undermines the VF of solar (\(-0.961\) p.p.) even in a larger extent than its own (\(-0.578\) p.p.). On the contrary, the effect of solar penetration on the wind VF is positive: the VF of wind power increases by 0.728 p.p. for each p.p. increase in solar penetration. This explains the slightly positive trend in the wind VF observed during the last years (Fig. 1), i.e. since solar penetration increased faster than wind, the positive cross-cannibalization effect of solar penetration on the wind VF has more than compensated the wind cannibalization effect itself. Although the VF of solar electricity was higher than that of wind at low penetration levels, these combined effects caused that wind VF surpassed the VF of solar as solar penetration increased.

Regarding the control variables, both gas penetration and consumption have a positive effect on solar VF but negative on wind VF, whereas neither net imports penetration nor gas prices have a significant effect on wind/solar VF.

### 4.3. Exploring non-linearities

As already mentioned, when testing a quadratic functional form of penetration and an interaction term between penetration and consumption, the results, although inconclusive, suggested potential non-linearities regarding these two variables (penetration and consumption). Instead of including quadratics and interactions, we decided to subset the (distributed-included) dataset into smaller chunks of data for different penetration and consumption ranges and estimate again regressions for each subset in order to have a more detailed illustration of these non-linearities.

#### 4.3.1. Consumption

For the analysis of the consumption non-linearities we subset the dataset into four chunks corresponding to four quartile ranges with the same number of observations and then estimate a regression on each of the subsets. Since the subsetting process eliminates time series nature of the data, we now estimate the regressions specified in Eq. (5) by OLS with heteroskedasticity and autocorrelation consistent (HAC) standard errors, which has been demonstrated to be robust in the previous sections. Fig. 5 shows the relative cannibalization effect across consumption levels, with point estimates located in the average value of each range and a 95% confidence intervals, and Tables 7 and 8 present the detailed regression results.

The left panel of Fig. 5 shows the effect of solar and wind penetration on the solar VF. Although at different magnitudes, the effect of both solar and wind penetration on the solar VF weakens as consumption increases, becoming insignificant in the highest consumption quintile. The right panel of Fig. 3 shows a similar pattern for the wind VF. Although the trend is not as smooth for the wind VF, we can also observe that the effect of solar/wind penetration is weaker at high consumption levels. The main differences are in the extremes. The effect of both solar and wind penetration is strong when consumption is low. When consumption is high, the positive effect of solar penetration on the wind VF vanishes, whereas the relative wind cannibalization effect is weaker than the average but still significant.

#### 4.3.2. Penetration

Finally, we now explore potential non-linearities regarding solar and wind penetration. For that purpose, we define three penetration ranges for solar (0–8%, 8–16%, 16–24%) and for wind (0–5%, 5–10%, 10–15%) of equal spread within each technology. Fig. 6 illustrates the results presented in Tables 9 and 10.

The left panel of Fig. 6 shows the effect of solar penetration on solar and wind VF (first row of Table 9), indicating that the effect of solar penetration becomes stronger as penetration increases. This effect is however of opposite sign for solar (negative) and wind (positive) VF, as already suggested by the previous results. The positivity
The relative effect on solar consumption of solar penetration is only significant in the higher range of solar penetration (16–24%).

The right panel of Fig. 6 shows the effect of wind penetration on solar and wind VF (second row of Table 10). The effect of wind penetration is in both cases stronger at high than at low wind penetration, although the trend of increasing marginal effect as penetration increases is clearer for solar than for wind VF.

### Table 7
Solar relative cannibalization effect across consumption levels.

| Dependent variable | Solar value factor (quartiles) |  |  |  |
|--------------------|--------------------------------|---|---|---|
|                    | (1)                            | (2)                      | (3)   | (4) |
| Solar penetration  | –4.585***                     | –3.260***                | –2.326*** | –0.217 |
|                    | (0.558)                       | (0.406)                  | (0.275) | (0.305) |
| Wind penetration   | –1.135***                     | –0.912***                | –0.360** | 0.137 |
|                    | (0.310)                       | (0.247)                  | (0.201) | (0.109) |
| Gas penetration    | 0.355*                        | 0.216**                  | 0.075   | 0.032 |
|                    | (0.116)                       | (0.076)                  | (0.039) | (0.020) |
| Net imports penetration | 0.234*                  | 0.309***                | –0.022  | 0.078 |
|                    | (0.133)                       | (0.092)                  | (0.062) | (0.056) |
| Gas price          | 1.116                         | 0.311                    | 0.367   | 0.008 |
|                    | (0.908)                       | (0.400)                  | (0.499) | (0.468) |
| Consumption        | 0.157**                       | 0.151**                  | 0.079** | 0.083** |
|                    | (0.050)                       | (0.068)                  | (0.018) | (0.006) |

**Note:** OLS estimation with HAC standard errors.

* p < 0.1.
** p < 0.05.
*** p < 0.01.

### Table 8
Wind relative cannibalization effect across consumption levels.

| Dependent variable | Wind value factor (quartiles) |  |  |  |
|--------------------|--------------------------------|---|---|---|
|                    | (1)                            | (2)                      | (3)   | (4) |
| Solar penetration  | 1.142**                       | 0.436**                  | 0.525*** | –0.182 |
|                    | (0.205)                       | (0.180)                  | (0.177) | (0.235) |
| Wind penetration   | –0.799***                     | –0.318***                | –0.350*** | –0.422*** |
|                    | (0.128)                       | (0.109)                  | (0.091) | (0.101) |
| Gas penetration    | –0.118**                      | –0.043                   | 0.021   | 0.001 |
|                    | (0.040)                       | (0.039)                  | (0.030) | (0.019) |
| Net imports penetration | –0.006                     | –0.075*                  | 0.026   | –0.058 |
|                    | (0.057)                       | (0.042)                  | (0.040) | (0.043) |
| Gas price          | 0.242                         | 0.034                    | –0.382  | 0.041 |
|                    | (0.414)                       | (0.159)                  | (0.373) | (0.468) |
| Consumption        | –0.039**                      | 0.087**                  | –0.011  | –0.009** |
|                    | (0.018)                       | (0.043)                  | (0.012) | (0.004) |

**Note:** OLS estimation with HAC standard errors.

* p < 0.1.
** p < 0.05.
*** p < 0.01.
5. Discussion

5.1. Cannibalization and cross-cannibalization effects

The cannibalization effect of solar is generally stronger than that of wind (Fig. 4), because solar generation is concentrated in a few hours around noon, whereas wind generation is more evenly distributed during the day (Fig. 2), which causes the reversion of the positive correlation between the solar generation profile and the demand load and therefore electricity prices (Fig. 3). We also find evidence of decreasing solar/wind cannibalization effects as consumption increases (Fig. 5) and increasing solar/wind cannibalization effects as their respective penetration levels increase (Fig. 6). Whereas the cross-cannibalization effects between technologies are generally negative, we find a positive effect of solar penetration on the wind value factor (down-right panel of Fig. 4), at least at low consumption levels and high solar penetration levels (right panel of Fig. 5 and left panel of Fig. 6 respectively).

As shown in Fig. 2, solar and wind have opposite daily patterns. The increase of solar penetration at noon entails that wholesale
Indeed, electricity prices plummet at that time due to the merit-order effect. When the sun sets, solar generation declines fast, causing spikes in the wholesale electricity market (Fig. 3). Bushnell and Novan (2018) show that the solar generation ramp up in the morning and the ramp down in the evening cause a shift in the type of gas power plants generating during those times, from efficient combined cycle gas turbines to more flexible but higher marginal cost gas turbines, causing therefore an increase in wholesale prices at those times as shown in Fig. 3.

There is a chain of causation: whereas the immediate cause of the price spike and the consequent increase of the wind value factor is the shift from combined cycle to gas turbines, this shift is likewise caused by the increased flexibility needs caused by the sudden drop of solar generation. Therefore, the gas turbine shift is the mechanism through which increasing solar penetration increases the wind value factor.3 Indeed, looking at Figs. 2 and 3 together, we can see that the change in the hourly distribution of electricity prices caused by increasing solar penetration shifts the correlations between the hourly distribution of electricity prices and the hourly distribution of solar and wind generation. Thus, whereas at low penetration the positive correlation between solar generation and electricity prices entails a solar value factor above one, the solar VF declines as this correlation becomes negative. On the opposite, the value factor of wind increases due to the shifting positive correlation of prices and generation when solar penetration is high. This explains the trends in wind and solar value factors observed in California during the last years (Fig. 1).

Whereas an increase in supply causes ceteris paribus a drop in prices in any market, the cannibalization effect is specific for the case of variable renewables due to the combination of five factors: (i) zero marginal cost and (ii) non-dispatchability of variable renewable energy technologies; electricity being a (iii) (in principle) non-storable and (iv) perfectly homogeneous good (in three dimensions: time, space, and lead-time between contract and delivery); and (v) the power system stability constraint. Factors (i) and (iv) entail that an increase in supply directly translates to prices (opposite to zero-marginal cost non-homogeneous goods, e.g. software, or homogeneous goods with positive marginal cost, which would set the floor price). Additionally, (v) entails that the floor is not even zero, but prices can become negative when there is oversupply due to the constraint that supply must equal demand at every time. Finally, (ii) and (iii) entail that producers do not have any control over their supply once capacity has been installed beyond curtailable.

5.2. Comparison with previous literature

For the case of California, our results are consistent with the early findings of Borenstein (2008) and Lamont (2008) who identified VF above 1 for solar at low penetration levels, declining with penetration. Likewise, the results observed for the solar and wind unit revenues are a direct reflection of the merit-order effect caused by these technologies and identified by Woo et al. (2016) in the day-ahead electricity market.

Mills and Wiser (2012) carried out the most comprehensive study about the value of renewables in California. They use a dispatch and investment model, which accounts for the long-term evolution of simulated "energy-only" day-ahead and real-time wholesale electricity markets. This entails that our results have to be compared with caution, since our methods differ significantly: while we estimate the ex-post cannibalization effect based on historical market data, their ex-ante model allows for the opti-

### Table 10
Relative cannibalization effect across wind penetration levels.

| Solar penetration | Wind value factor |
|-------------------|-------------------|
| 0–5%              |                   |
| (1)               |                   |
| –2.854**          | 0.056             |
| (0.432)           | (0.170)           |
| 5–10%             |                   |
| (2)               |                   |
| –2.663***         | 0.077             |
| (0.720)           | (0.404)           |
| 10–15%            |                   |
| (3)               |                   |
| –6.673***         | 0.239             |
| (1.855)           | (2.282)           |
| 0–5%              |                   |
| (4)               |                   |
| 0.779***          | –0.028            |
| (0.230)           | (0.149)           |
| 5–10%             |                   |
| (5)               |                   |
| 1.115***          | –0.014            |
| (0.229)           | (0.101)           |
| 10–15%            |                   |
| (6)               |                   |
| 1.292***          | –0.024            |
| (0.512)           | (0.615)           |

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1.

3 Conversely, an anonymous reviewer pointed out that the spike in wholesale electricity prices after noon could be solely driven by gas production and gas price regardless of the extent of solar penetration, in which case the cross-cannibalization effect would only be the reflection of a spurious correlation. Although we provide a plausible explanation of the cross-cannibalization effect based on the findings of Bushnell and Novan (2018), more research is needed to clarify the channels through which the penetration of one variable renewable technology might affect the value of the other.

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nal capacity adaptation of the electricity system and therefore for endogenous mitigation of the cannibalization effect. Our conclusions are still consistent in several ways: (i) the solar VF is above 1 at low penetration thanks to its capacity value, but drops considerably as its penetration increases; (ii) the unit revenues of solar are higher than those of wind, but due to the stronger decline of the solar UR, they are at some point surpassed by wind UR; and (iii) both solar UR and VF decline as their respective penetration levels increase.

Our results are directly comparable with those of Clò and D’Adamo (2015) for Italy since we use a similar ex-post econometric approach. Our results are also consistent since we both find a negative effect of both solar (−2.23 in Italy vs. −4.12 in California) and wind penetration (−0.27 vs. −0.96 respectively) on the solar VF. Both effects are stronger in California than in Italy.

After estimating the merit-order effect of wind and solar penetration in Austria and Germany, Zipp (2017) compares the evolution of the wholesale electricity prices with the evolution of solar and wind unit revenues. Our results are also consistent since he finds that the unit revenues of solar decline faster than the wholesale electricity price (entailing a drop of the VF). The decline of the wind UR was lower than that of wholesale prices from 2015, causing therefore the increase of the wind VF, the same phenomenon observed in the California electricity market.

Finally, we can compare our VF results with the comprehensive review of Hirth (2013, 2015), who presents three different estimations: (i) a review of dispersed results found in previous literature; (ii) a simple econometric model with annual VF of several European countries; and (iii) a dispatch and investment model of the Northwestern European power market (EMMA). The review results (i) suggest the declining trend of the solar VF, as confirmed by our results. The ex-post estimation with market data (ii) indicates a higher cannibalization effect for solar than for wind, as also confirmed by our results. Although the ex-ante results based on dispatch and investment models tend to present lower cannibalization effects (since they account for optimal adaptation of the capacity mix as a response to higher variable generation), the results provided by Hirth based on the EMMA model (iii) are more pessimistic than those presented here for California, since they estimate that the VF of wind will drop to almost 50% at 30% penetration, and to less than 50% for solar at 15% penetration.

5.3. Implications

The cannibalization effect has far-reaching implications for variable renewables in particular and for the whole electricity system in general. Although the levelized cost of solar (mainly photovoltaics)

Table 11
Cannibalization and cross-cannibalization effects.

| Effect of (s,w) penetration on | Absolute | Relative |
|-------------------------------|----------|----------|
|                               | Unit revenues ($/MWh) | Value factor (p.p.) |
|                               | Solar     | Wind     | Solar     | Wind     |
| Solar                         | −1.3      | −0.43    | −4.12     | 0.73     |
| Wind                          | −0.7      | −0.84    | −0.96     | −0.58    |

All parameters significant at 99% confidence. Prais–Winsten FGLS estimator with HC standard errors on the distributed–included data.

has been rapidly declining during last decades (Fraunhofer, 2015), even reaching, or about to reach grid parity in many countries (Breyer and Gerlach, 2012), if the value of solar falls faster than its cost, the value-adjusted levelized cost (Schmalensee et al., 2015) would increase jeopardizing thus the competitiveness of photovoltaics. On the opposite, the positive effect of solar on the wind value factor suggests that there could be some level of complementarity between both technologies thanks to their opposite daily patterns (Fig. 2).

The cannibalization effect could be considered for cost–benefit analyses assessing the optimal penetration of variable renewables. The increasing cannibalization effect as penetration increases entails that the value of flexibility will increase in the future. Therefore, all measures oriented to increasing flexibility (e.g. storage, demand management or spatially diversifying interconnections) will mitigate the cannibalization effect. In this sense, Mills and Wiser (2014) estimate that geographical diversification has the highest potential to mitigate the cannibalization effect of wind at high penetration levels, and low-cost storage has the highest potential for the case of solar.

Finally, policies that guarantee a specific price for the electricity sold for a determined number of years (e.g. Feed-in Tariffs) will have an increasing cost for the government due to the widening gap between unit revenues and the guaranteed price. Likewise, once socket parity has been achieved, in terms of policy costs, net billing self-consumption regulation is preferable to net metering, since it sets a price incentive for prosumers to self-consume the maximum possible amount of electricity generated minimizing thus the impact of distributed solar on the electricity system.

6. Conclusion

We have first calculated daily solar and wind unit revenues (generation-weighted electricity prices) and value factors (unit revenues divided by the average wholesale prices) from hourly data of the day-ahead wholesale electricity market in California (CAISO) for the period January 2013 to June 2017. While both solar and wind unit revenues declined during this period, solar and wind value factors evolved in opposite directions. Wind value factor slightly increased whereas the solar value factor strongly declined (Fig. 1).

We then performed a time series econometric model with solar centralized-only and distributed-included data. We find that omitting distributed solar generation leads to an (under)overestimation of the (wind)solar cannibalization effect. Our results confirm both the absolute and relative cannibalization effects of both solar and wind technologies (Table 11). In other words, increasing solar and wind penetration undermines their own unit revenues (absolute cannibalization) and value factors (relative cannibalization). Both solar and wind cannibalization effects are stronger at high solar/wind penetration and low consumption levels.

We have also identified cross-cannibalization effects between technologies. While wind penetration generally undermines the value of solar (although in a lower extent than solar penetration itself), the effect of solar penetration on the wind value factor is positive. This is caused by the opposite daily patterns of wind and
solar generation and the fact that the latter is more concentrated around noon time (causing, therefore, a deeper drop of electricity prices at that time, and a spike when solar generation declines and wind generation rises in the evening).

The cannibalization effect has far-reaching implications. First, it jeopardizes the competitiveness of variable renewables if their value falls faster than their cost. It might increase the policy costs of promoting renewables (since governments must bridge the gap between declining unit revenues and the guaranteed price).

Since the VRE electricity has practically zero marginal cost, the stronger the cannibalization effect, the higher the value of flexibility (e.g. storage, demand management and interconnections). Storage and demand management allow the transfer of electricity loads between periods of low/high value, flattening thus the hourly distribution of electricity prices and interconnections allow to geographically link regions of complementary supply and demand patterns.

Finally, these results could be useful to adjust the leveled cost of electricity of wind and solar for the value of their electricity and perform more accurate cost–benefit analyses, as well as to calibrate ex-ante dispatch and investment models. Further research should explore how measures to mitigate the cannibalization effect, such as storage, demand management and interconnections, possibly acknowledging seasonal patterns, would affect the value of variable renewables.

Conflict of interest

The authors declare no competing financial interests.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.eneco.2019.104552.

References

Baker, E., Fowlie, M., Lemoine, D., Reynolds, S.S., 2013. The economics of solar electricity. Annu. Rev. Resour. Econ. 5 (1), 387–426, http://dx.doi.org/10.1146/annurev-resource-091912-151843.

Ballester, C., Furió, D., 2015. Effects of Renewables on the Stylized Facts of Electricity Prices. Pergamon, http://dx.doi.org/10.1016/j.jser.2015.07.168.

Bird, L., Cochran, J., Wang, X., 2014. Wind and Solar Energy Curtailment: Experience and Practices in the United States. National Renewable Energy Laboratory (NREL), No. March; 5R, www.nrel.gov/publications.

Borenstein, S., 2008. The Market Value and Cost of Solar Photovoltaic Electricity Production. www.ucer.org.

Borenstein, S., 2012. The private and public economics of renewable electricity generation. J. Econ. Perspect. 26 (1), 67–92, http://dx.doi.org/10.1257/jep.26.1.67.

Breyer, C., Gerlach, A., 2013. Global Overview on Grid-Parity, http://dx.doi.org/10.1002/pip.1254.

Bushi, J., Novak, K., 2018. Setting with the Sun: The Impacts of Renewable Energy on Wholesale Power Markets. NBER Working Paper. 24980, http://dx.doi.org/10.3336/w24980.

Cló, S., D’Adamo, G., 2015. The dark side of the sun: how solar power production affects the market value of solar and gas sources. Energy Econ. 49 (May), 523–530, http://dx.doi.org/10.1016/j.eneco.2015.03.025.

Cló, S., Cataldi, A., Zoppoli, P., 2015. The merit-order effect in the Italian power market: the impact of solar and wind generation on national wholesale electricity prices. Energy Policy 77 (February), 79–88, http://dx.doi.org/10.1016/j.enpol.2014.11.038.

Cludius, J., Hermann, H., Chr Matthes, F., Graichen, V., 2014. The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016 estimation and distributional implications. Energy Econ. 44 (July), 302–313, http://dx.doi.org/10.1016/j.eneco.2014.04.020.

Dillig, M., Jung, M., Karl, J., 2016. The Impact of Renewables on Electricity Prices in Germany – An Estimation Based on Historic Spot Prices in the Years 2011–2013. http://dx.doi.org/10.1515/ep-2015-12003.

Fischer, C., 2006. How Can Renewable Portfolio Standards Lower Electricity Prices? Resources For the Future the econpapers.repec.org/paper/rid/pdp/06-20.htm.

Fraunhofer ISE, 2015. Current and future cost of photovoltaics. Long-term scenarios for market development, system prices and LCOE of utility-scale PV systems. Agora Energiew., 82, doi:059/01-S-2015/EN.

Geistert, L., Labandera, X., 2011. An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices. Energy Econ. 33 (Suppl. 1), 559–565, http://dx.doi.org/10.1016/j.eneco.2011.07.027.

Hirth, L., 2013. The market value of variable renewables. The effect of solar wind power variability on their relative price. Energy Econ. 38 (July), 218–236, http://dx.doi.org/10.1016/j.eneco.2013.02.004.

Hirth, L., 2015. Market value of solar power: is photovoltaics cost-competitive? JET Renewable Power Gen. 9 (1), 37–45, http://dx.doi.org/10.1016/j.jep-rg.2014.01.010.

Hirth, L., Leenderst, F., Edenshofer, O., 2015. Integration costs revisited – an economic framework for wind and solar variability. Renew. Energy 74 (74), 925–939, http://dx.doi.org/10.1016/j.renene.2014.08.065.

Jobnson, P.L., 2011. Comparing the cost of intermittent and dispatchable electricity generation technologies. Am. Econ. Rev.: Papers Proc. 101 (3), 238–241, http://dx.doi.org/10.1257/aer.101.3.238.

Lamontt, A.D., 2008. Assessing the long-term system value of intermittent electric generation technologies. Energy Econ. 30 (3), 1208–1231, http://dx.doi.org/10.1016/j.eneco.2007.02.007.

Mills, A.D., Wiser, R.H., 2012. Changes in the economic value of variable generation at high penetration levels: a pilot case study of California. In: 2012 IEEE 38th Photovoltaic Specialists Conference (PVSC) PART 2, June, pp. 1–9, http://dx.doi.org/10.1109/PVSC.2012.6650761.

Mills, A., Wiser, R., 2014. Strategies for mitigating the reduction in economic value of variable generation with increasing penetration levels. LBNE 36 (2), 119–127, http://dx.doi.org/10.1016/j.experim.2007.09.002.

Nicolosi, M., Fürsch, M., 2009. The impact of an increasing share of RES-E on the conventional power market — the example of Germany. Zet. Energiewirtschaft. 33 (3), 248–254, http://dx.doi.org/10.1016/j.surenergy.2008.07.003.

Praiss, S.J., Winsten, C.B., 1954. Trend Estimators and Serial Correlation. Cowles Com- mission Discussion Paper No. 383.

Sáenz de Miera, G., del Río González, P., Vizcaíno, I., 2008. Analysing the impact of renewable electricity support schemes on power prices: the case of wind electricity in Spain. Energy Policy 36 (9), 3345–3359, http://dx.doi.org/10.1016/j.enpol.2008.04.022.

Schmalensee, R., Bulović, V., Armstrong, R., Battle, C., Brown, F., Deutch, J., Jacoby, H., et al., 2015. The Future of Solar Energy. MIT, https://mitismit.mit.edu/system/files/MIT Future of Solar Energy Study-compressed.pdf; https://mitismit.mit.edu/futuresolar.

Sensfuß, F., Raptopoulou, M., Genoese, M., 2008. The merit-order effect: a detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 36 (8), 3076–3084, http://dx.doi.org/10.1016/j.enpol.2008.03.025.

Tveten, A.G., Bolteza, T.F., Martens, T., Hvarnes, H., 2013. Solar feed-in tariffs and the merit order effect: a study of the German electricity market. Energy Policy 61 (October), 761–770, http://dx.doi.org/10.1016/j.enpol.2013.05.080.

Woo, C.K., Horowitz, I., Moore, J., Pacheco, A., 2011. The impact of wind generation on the electricity spot-market price level and variance: the Texas experience. Energy Policy 39 (7), 3939–3944, http://dx.doi.org/10.1016/j.enpol.2011.03.084.

Woo, C.K., Moore, J., Schneiderman, B., Ho, T., Olson, A., Alagappan, L., Chawla, K., Toyanwa, N., Zarnikau, J., 2016. Merit-order effects of renewable energy and price divergence in California’s day-ahead and real-time electricity markets. Energy Policy 92 (May), 299–312, http://dx.doi.org/10.1016/j.enpol.2016.02.023.

Zachmann, G., 2013. A stochastic fuel switching model for electricity prices. Energy Econ. 35 (C), 5–13.

Zipp, A., 2017. The marketability of variable renewable energy in liberalized electricity markets – an empirical analysis. Renew. Energy 113 (December), 1111–1121, http://dx.doi.org/10.1016/j.renene.2017.06.072.