Valuing Carbon Abatement Benefits of Intermittent Renewable Energy

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Abstract

Using historical data on the randomness of solar and wind generation, I estimate how much carbon is abated when adding variable renewable energy (VRE) to the electric grid in California, a worldwide leader in its adoption. This requires identifying the marginal emissions offsets related to the instantaneous displacement of the highest marginal cost generator (merit order effect) but also the indirect hydropower reallocation that occurs due to VRE effects on locational marginal prices. Controlling for this indirect effect via a dynamic model renders sensible estimates of wind and solar marginal emissions offsets in electric grids powered by a significant share of hydropower. The proposed dynamic approach could also be applied to grids with increasing adoption of storage technologies.

Keywords: Intermittent renewable energy, Emissions offsets, Hydropower
(JEL L94, Q42, Q54).

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1. Introduction

In the US, the recent Clean Power Plan has a 30% reduction in carbon dioxide emissions by 2030, from the 2005 level, as one of its key goals (EPA, 2015). In order to achieve this, an electric grid powered by a significant share of renewable energy is a proposed alternative. However, the intermittent nature of variable renewable energy (VRE), particularly solar and wind, the lack of utility scale electricity storage and the complex congestion configurations in power transmission make it challenging to assess VRE carbon emissions offsets. Overcoming these methodological difficulties is necessary to estimate the economic value of renewable energy and to evaluate its policies.

In this paper, using historical data on the randomness of solar and wind generation, I estimate how much carbon is abated when adding VRE to the electric grid in California, a worldwide leader in its adoption. The novel challenge lies in identifying the marginal generation and emissions offsets caused by adding two intermittent sources to an electric system that has a significant share of hydropower. Previous literature, centered on grids with small fractions of hydro generation, has identified marginal emissions offsets related to the instantaneous displacement of the highest marginal cost thermal generators, through the merit order effect (Kaffine et al., 2012, Cullen, 2013, Novan, 2015).

Nevertheless, adding significant amounts of VRE at low or zero value bids causes a reduction in the wholesale locational marginal price (LMP), which changes hydropower generators' price expectations and optimal allocation leading to another contemporaneous but indirect displacement of hydro generation away from periods with the largest price reductions. The above effect can be conceptualized through a dynamic electricity market model: hydropower producers allocate their generation arbitraging between the realized price and the expected future price. If the current realization of VRE reduces current prices relative to future ones, then storing hydropower is optimal. Nevertheless, this stored energy will be added to the grid at a later time, replacing future fossil fuel generation and offsetting emissions. Hence, in grids with a significant share of hydropower production, estimating marginal emissions offsets requires modelling not only on the contemporaneous renewable energy generation but its history through a dynamic estimator.

Using a time series system of estimating equations, I model the usual merit order effect and the existence of the indirect price effect with a static framework that identifies the contemporaneous marginal generation offsets that solar and wind induce on thermal, hydro generation and imports. The results show that each additional MWh of solar generation instantaneously displaces 0.147 MWh of hydropower and each additional MWh of wind relocates 0.087 MWh of water generation, on average.

However, the displaced hydro generation is switched to a higher LMP hour where it should displace a marginal natural gas plant. Hence, using a dynamic model, I estimate the appropriate average marginal carbon dioxide emissions offsets of solar (0.231 ± 0.03 tCO_2/MWh) to be less than those of wind (0.417 ± 0.08 tCO_2/MWh). Also, the dynamic model calculates larger marginal natural gas generation offsets and smaller marginal hydropower offsets than its static counterpart. Using the US social cost of carbon of USD 56 / $tCO_{2,}$ wind power carbon abatement benefits range between 22.5 to 24.3 USD/MWh and solar benefits among 9.4 to 16.1USD/MWh (IAWG, 2015). Ideally, we can use these values of external environmental benefits along the grid cost reductions via LMP reductions to compute the short run marginal value of VRE generation and compare them against the different incentives perceived by wind and solar generators (Baker et al., 2013).

Even with the dynamic correction for the indirect effect, I cannot reject the null hypothesis of having no net hydropower generation displacement caused by VRE. This could be the result of noise in the estimate, due to the nature of the data generating process, since it uses averages across all time hours. Or it could be showing that the change in hydropower producers' expectations, due to VRE changes on the LMP, has modified the optimal allocation and bidding in such a way that storing water for its future value is the expected profit maximizing decision. However, further inquiry and modelling are necessary to contrast this finding. The current research leaves an open question based on this counterintuitive result.

From a broader perspective, the proposed dynamic modelling is key for understanding electricity generation and grid level emissions in systems with increasing adoption of storage technologies since the same insights about the hydropower arbitrage condition and generation reallocation would also apply to profit maximizing storers. Furthermore, several emerging economies with electric grids powered by a significant share of hydropower are increasingly adopting wind and solar plants. To the extent that these countries operate a wholesale electricity market with bidding hydropower producers, this research's methodology could be a good approach for estimating abatement benefits based on historical data.

2. Estimating variable renewable energy carbon offsets

Using historical data and projections of fossil fuel generation, load and variable renewable energy, several studies have quantified the pollution and GHG offsets that occur when electricity coming from solar or wind power plants substitutes any fossil based electricity on the grid. Callaway et al. (2015) focused on how additional VRE generation and energy efficiency measures displace carbon emissions in 6 power system regions of the US (CAISO, ERCOT, ISONE, MISO, NYISO, PJM).

They estimated the marginal emissions for each hour by regressing emissions on dispatchable fossil generation, and then computed the "average emissions displacement rates" using the previous estimate and projections of renewable energy production. In summary, the authors estimated econometrically the marginal emissions of six US regional power grids and used projected profiles of VRE generation to identify shifts in the supply of fossil generation which lead to carbon emissions displacement.

Cullen (2013) recognizes that adding VRE (intermittent supply) has a different effect on the electric grid and dispatch schedule than reducing load (demand) or fossil generation (dispatchable supply). Using historical data for Texas (ERCOT), the author regresses conventional generation types on the exogenous wind electricity production and other controls to infer what changes occurred to the power mix when an intermittent supply of renewable energy was added. This estimate along with EPA's average annual emission rates for fossil fuel plants is used to compute offset emissions.

The study highlights that in order to capture the dynamic factors that play into the generators' decision making, we need to incorporate lags of wind generation and controls in the econometric model. The static and dynamic model yield different results; basically, the latter finds less emissions offsets coming from coal and more coming from the expensive and inefficient steam and gas turbine generators. Neither model finds significant hydropower offsets, but also these generators have a share of less than 1% in total capacity and generation (Cullen, 2013).

Kaffine et al. (2013 and 2012) also used historical patterns of VRE generation in ERCOT to directly estimate emissions offsets by regressing the amount of pollutants on renewable energy production, demand, temperature and other controls. Since fossil fuel power plants do not have a constant emissions rate, but rather it varies according to the level of operation, the study's approach captures more accurately the average emissions savings of the displaced marginal generators.

The hourly variation in electricity demand and VRE generation imply that there are different marginal generators throughout the day, each with diverse emissions rates. Novan (2015) captures this key feature of the power grid by modelling generation and emissions as a function of the interactions between renewable energy generation and load, while controlling for certain fixed effects. Hence, this research finds that wind power causes larger emissions offsets than solar in Texas, given that the former displaces coal base power during low demand night hours. Furthermore, new capacity increases in wind power would bring larger emissions offsets while solar capacity increases would not.

In Novan (2015), the dynamic model renders similar results than its static counterpart, meaning that wind power brings mainly contemporaneous emissions offsets. It is worth noting that wind causes practically zero hydropower offsets in a grid where water has a share of less than 1%.

In this paper, using historical data on the randomness of solar and wind generation, I estimate how much carbon is abated when adding two intermittent renewable energy sources to an electric grid that has a significant share of hydropower. There are two novel challenges in this work. First, following Novan (2015), I model dispatchable generation and emissions as a function of both VRE generation interacted with load. Furthermore, given the increase in solar generation in the last 5 years, both VRE sources are jointly modelled in the estimating equation in order to capture the interactions between wind, solar power and load.

Second, as recognized by Cullen (2013), dynamics play an important role in generators' decision making. Hence, I model the estimating equations using lags of the controls and interactions in order to capture the reallocation of hydropower generation throughout the day. The changes in the scheduling of peak hydro units accommodate the inelastic and intermittent supply of VRE since water generation reacts to changes brought by VRE to its opportunity cost: the locational marginal price (LMP). This idea is developed and supported with further details in the following section.

3. A dynamic model of electricity generation and emissions with hydropower and VRE.

In the following paragraphs I develop a short run partial equilibrium dynamic stochastic model of the electricity market whose main goal is to understand hydropower reallocation caused by renewable energy penetration and its effects on fossil generation and emissions. For simplicity, the model assumes perfect competition, no startup costs or dynamic frictions, no transmission externalities, no intermittency costs and fixed capacities for all generation types.

The objective function of the planner is to maximize Social Welfare at the initial time by choosing the amount of fossil fuel n_{it}^{FF} and hydropower generation h_{it}. Variable renewable energy (VRE) is produced at different rates during both periods (offpeak being night, and peak the day) following the stochastic bounded process $\{n_t^{RE}\}_{t=0}^{\infty}$ [2]. Assuming no losses, total load is given by $Q_{it} = n_{it}^{FF} + n_{it}^{RE} + h_{it}$, where peak load is larger than offpeak. There is an inverse demand function $P_i(Q_{it})$ for each period of the day with all the conventional properties. Fossil fuel production has the usual convex costs of

[2] We allow for different distributions for the night and the day n_{nt}^{RE} and n_{dt}^{RE}. In this sense, renewable energy is modelled as a cyclic stochastic process, which is a natural approach to wind and solar generation patterns. There are recurring distributions, and means, of VRE for each day and night.

production $C(n_{it}^{FF})$ and hydropower has no marginal cost. For simplicity, assume hydropower reservoir levels depend on the endogenous extraction (h_{it}) and on the exogenous fixed recharge rate r_t.

Hence, the problem becomes[3]:

$$(1)\ \ Max_{n_t^{FF},h_t} = E_o \sum_{t=0}^{\infty} \beta^t \left[\int_0^{Q_p} P_t(n_t^{FF} + n_t^{RE} + h_t) da - C(n_t^{FF}) \right]$$

s.t: $\quad s_{t+1} = s_t + r_t - h_t$

$h_t \geq 0\ ,\ h_t \leq h_{max},\ s_t \geq 0$

stochastic processes n_{pt}^{RE} *and* n_{ot}^{RE} and the exogenous flow rate r_t

We can approach this problem through Bellman's equation:

$$(2)\ v(s_t, n_t^{RE}) = max_{n_t^{FF},h_t} \left\{ \int_0^{Q_p} P_t(n_t^{FF} + n_t^{RE} + h_t) da - C(n_t^{FF}) + \right.$$

$$\left. \beta E_t(v(s_{t+1}, n_{t+1}^{RE}) \middle| t \in \{peak, offpeak\}) \right\}$$

$$\rightarrow \mathcal{L} = \int_0^{Q_p} P_t(n_t^{FF} + n_t^{RE} + h_t) da - C(n_t^{FF}) + \beta E_t(v(s_{t+1}, n_{t+1}^{RE}) \middle| t \in \{peak, offpeak\})$$

$$+ \lambda(h_{max} - h_t) + \mu s_t$$

FOC $[n_t^{FF}]$: $(3)\ \ P_t(n_t^{FF} + n_t^{RE} + h_t) \leq C'(n_t^{FF})$

FOC $[h_t]$: $(4)\ \ P_t(n_t^{FF} + n_t^{RE} + h_t) \leq \beta E_t(v'(s_{t+1}, n_{t+1}^{RE}) \middle| t \in \{peak, offpeak\}) + \lambda$

Using the envelope theorem

$$(5)\ v'(s_t, n_t^{RE}) = \beta E_t(v'(s_{t+1}, n_{t+1}^{RE}) \middle| t \in \{peak, offpeak\})$$

[3] Bold characters denote vectors

Assuming an interior solution, substitute back into FOC and lead forward.

$\rightarrow$ (6) $P_{t+1}(n_{t+1}^{FF} + n_{t+1}^{RE} + h_{t+1}) = v'(s_{t+1}, n_{t+1}^{RE}) + \lambda$

Hence, the arbitrage condition for hydropower allocation becomes:

(7) $P_t(n_t^{FF} + n_t^{RE} + h_t) \leq \beta E_t(P_{t+1}(n_{t+1}^{FF} + n_{t+1}^{RE} + h_{t+1}) \middle| t \in \{peak, offpeak\}) + \lambda(1 - \beta)$

And the optimal fossil fuel use condition is defined by (3)

Notice that without hydropower, the dynamic problem above becomes a degenerate one where the optimal fossil fuel use is determined just by the static rule equating marginal willingness to pay to marginal cost in each time period, and no arbitrage condition. Thus, the conventional static model estimates the optimal peak and off-peak fossil fuel use $\boldsymbol{n_t^{FF}}(\boldsymbol{n_t^{RE}})$ **as a function of only contemporaneous renewable energy**. In the dynamic model, the fossil fuel function is simultaneously solved with the hydropower function using the arbitrage condition (7) and the fossil fuel FOC (3) for peak and off-peak respectively.

From (3) we can find $\boldsymbol{h_t}(\boldsymbol{n_t^{FF}}, \boldsymbol{n_t^{RE}})$ which can be replaced in (7) leading to a expectational difference equation whose solution will give us the optimal fossil fuel use as a function of the stochastic bounded processes $\{n_{it}^{RE}\}_{t=0}^{\infty}$. Hence, in grids with a significant share of hydropower production, the optimal fossil fuel use at time t depends **not only on the contemporaneous renewable energy generation** but its history influences the current optimal allocation $\boldsymbol{n_t^{FF}}(\boldsymbol{n_{t-k}^{RE}})$.

If we assume linear functional forms for the inverse demand and marginal cost functions: $P_t(n_t^{FF} + n_t^{RE} + h_t) = a_i - b(n_t^{FF} + n_t^{RE} + h_t)$ and $C'(n_t^{FF}) = cn_t^{FF}$, using the arbitrage and optimal production conditions at an interior solution we can state:

(8) $cn_t^{FF} = \beta E_t(cn_{t+1}^{FF} \middle| t \in \{peak, offpeak\}) + \lambda(1 - \beta)$

From (3) we can find

$$n_t^{FF} = \frac{(a_i - bn_t^{RE} - bh_t)}{b + c}$$

Which implies in (8)

$$\frac{(a_i - bn_t^{RE} - bh_t)c}{b + c} = \beta E_t\left(\frac{(a_{-i} - bn_{t+1}^{RE} - bh_{t+1})c}{b + c}\middle| t \epsilon \{peak, offpeak\}\right) + \lambda(1 - \beta)$$

$$(a_i - bn_t^{RE} - bh_t) = \beta E_t\left((a_{-i} - bn_{t+1}^{RE} - bh_{t+1})\middle| t \epsilon \{p, op\}\right) + \frac{\lambda(1 - \beta)(b + c)}{c}$$

$$\beta E_t\big((bh_{t+1})\big| t \epsilon \{p, op\}\big) - bh_t = a_{-i} - a_i + \frac{\lambda(1 - \beta)(b + c)}{c} - \beta E_t\left((bn_{t+1}^{RE})\middle| t \epsilon \{p, op\}\right) + bn_t^{RE}$$

And we get the expectational difference equation:

(8a) $E_t\big((h_{t+1})\big| t \epsilon \{p, op\}\big) - \frac{1}{\beta} h_t = \frac{1}{\beta}\left(\frac{a_{-i} - a_i}{b}\right) + \frac{\lambda(1-\beta)(b+c)}{\beta c} - E_t\left((n_{t+1}^{RE})\middle| t \epsilon \{p, op\}\right) + \frac{1}{\beta} n_t^{RE}$

Solving the above equation yields:

(9) $h_t = -\frac{(a_{-i} - a_i)}{(1-\beta)b} + \frac{\lambda(b+c)}{c} + \sum_{i=1}^{\infty} \beta^i E_t\left(\left(n_{t+i}^{RE} - \frac{1}{\beta} n_{t-1+i}^{RE}\right)\middle| t \epsilon \{p, op\}\right)$

(10) $n_t^{FF} = \frac{\left(a_i - bn_t^{RE} + \frac{(a_{-i} - a_i)}{1-\beta} - \frac{\lambda(b+c)}{c} - \sum_{i=1}^{\infty} \beta^i E_t\left(\left(n_{t+i}^{RE} - \frac{1}{\beta} n_{t-1+i}^{RE}\right)\middle| t \epsilon \{p, op\}\right)\right)}{b+c}$

where, $\frac{\partial h_t}{\partial E_t(\beta n_{t+1}^{RE} - n_t^{RE})} > 0$, $\frac{\partial n_t^{FF}}{\partial E_t(\beta n_{t+1}^{RE} - n_t^{RE})} < 0$ and $\frac{\partial n_t^{FF}}{\partial n_t^{RE}} < 0$

Hydropower and fossil fuel generation are functions not only of the contemporaneous renewable energy generation but of the difference between future expected peak and offpeak realizations. Basically, hydropower allocation is an increasing function of the expected difference in renewable energy generation between the peak and offpeak periods. Due to the cyclic nature of the renewable energy generation, the steady state will have one stable allocation for each period. Hence, if *t* is the peak demand period (day) and the only source of renewable energy is wind power, knowing that on average wind power production is larger at night (the offpeak period *t+1*) the expected difference of the discounted future VRE generation and the current one will be positive.

Now, given that hydropower producers expect to have a larger zero marginal cost VRE generation in the following period, they will expect lower prices at *t+1,* choosing to allocate more hydro generation in the current period in order to get a higher expected price and increase profits. Thus, hydro allocation is an increasing function of the expected differences in VRE generation.

If additional wind power capacity is added to the grid, say 1 MW, it is usually the case that this additional MW will not contribute evenly throughout the day. On average, it will generate more during the night. Given this, adding additional wind power capacity would increase hydropower reallocation.

The derivatives for fossil fuel generation show: $\frac{\partial n_t^{FF}}{\partial E_t(\beta n_{t+1}^{RE} - n_t^{RE})} < 0$ and $\frac{\partial n_t^{FF}}{\partial n_t^{RE}} < 0$

The first term states that if future expected renewable generation increases, then prices will likely drop and hydro generation will switch to the present, requiring less current fossil generation. On the other hand, increasing the current VRE generation, independent of any expected realization, decreases contemporaneous fossil generation due to the merit order effect. For the case of no interior solution for hydro, fossil generation is perfectly described only by equating price and marginal cost (3) and clearly increasing renewable generation would displace fossil generation.

In summary, since in competitive wholesale electricity markets hydropower producers bid based on the opportunity cost of generating at a different time, which is determined by the expected price (Borenstein et al., 2002), a reduction in the relative price between offpeak and peak hours can shift hydro generation. In both cases, reservoir storage plays the role of facilitating, the intertemporal allocation. Therefore, if a exogenous shock in VRE generation at time t reduces prices, then the stored hydropower will be generated at a later time, replacing future fossil fuel generation and offsetting emissions. Capturing this dynamic effect requires modelling emissions with lagged variable renewable energy values.

Since emissions are an increasing function of fossil fuel use $e\left(n_{it}^{FF}\right)$ with $e'(.) > 0$, they will be a decreasing function of VRE, since $\frac{\partial n_t^{FF}}{\partial n_t^{RE}} < 0$ as was shown in eq (10). In the dynamic/hydropower case we get $e_t = e\left(\boldsymbol{n_t^{RE}}, \boldsymbol{n_{t-k}^{RE}}\right)$ while in the static model we have $e_t = e\left(\boldsymbol{n_t^{RE}}\right)$. If we assume an additively separable emissions function notice that $e_t = e\left(\boldsymbol{n_t^{RE}}\right) + \sum_{\boldsymbol{k}} e\left(\boldsymbol{n_{t-k}^{RE}}\right)$ and that marginal emissions offsets caused by VRE are given by $\sum_k \frac{\partial e(.)}{\partial \boldsymbol{n_{t-k}^{RE}}}$.

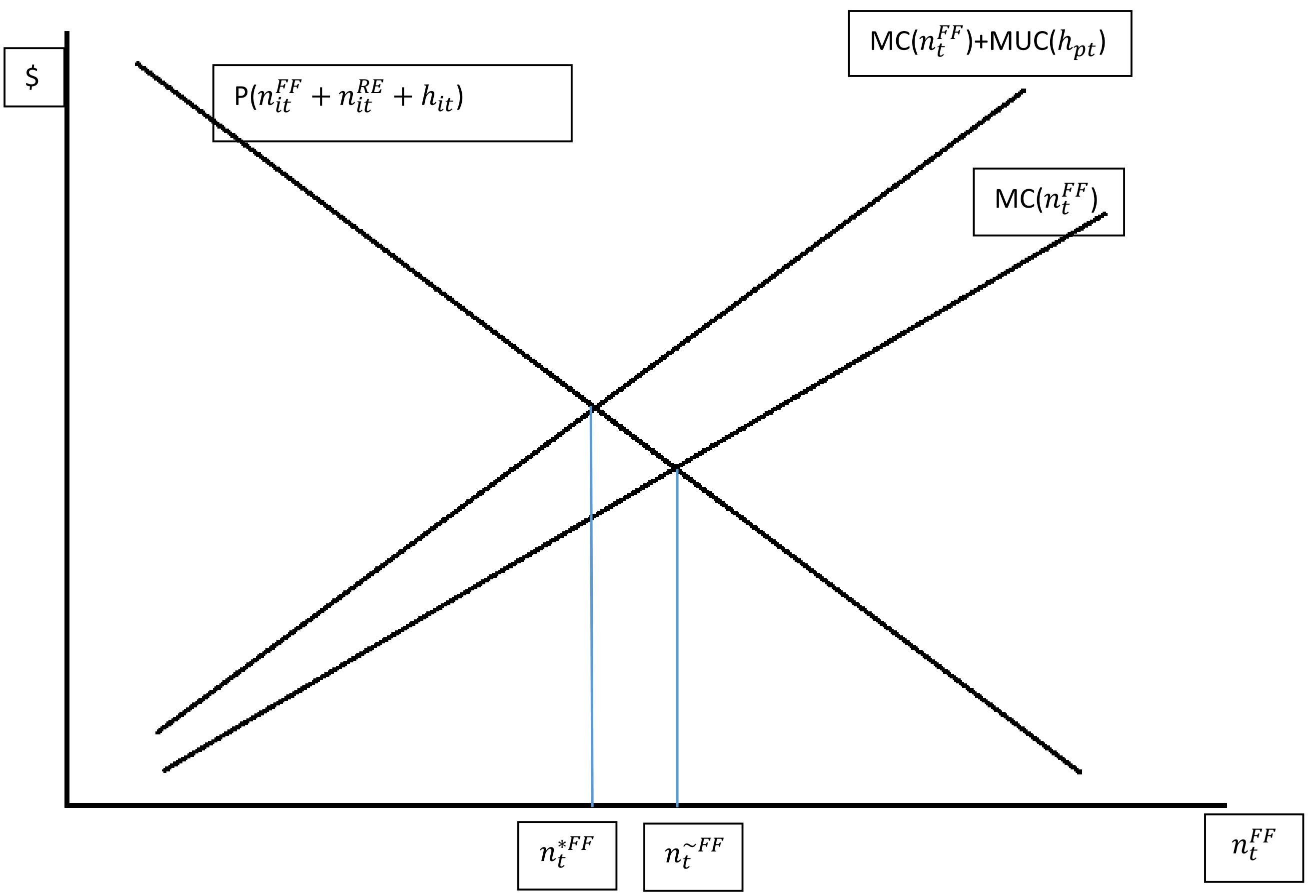
If the grid has a significant share of hydropower, the true underlying process determining the fossil fuel use and emissions is dynamic. However, if in this case we use a static estimator for emissions $\widetilde{e_t} = \tilde{e}\left(\boldsymbol{n_t^{RE}}\right)$ and marginal emissions offsets $\widetilde{e_t'} = \frac{\partial \tilde{e}\left(\boldsymbol{n_t^{FF}}, \boldsymbol{n_t^{RE}}\right)}{\partial \boldsymbol{n_t^{RE}}}$ we will get a biased result. This bias is given by:

$$E\left(\widetilde{e_t'} - e_t'\right) = E\left(e'\left(\boldsymbol{n_t^{RE}}\right)\right) - e'\left(\boldsymbol{n_t^{RE}}\right) - e'\left(\boldsymbol{n_{t-k}^{RE}}\right)$$

$$E\left(\widetilde{e_t'} - e_t'\right) = -e'\left(\boldsymbol{n_{t-k}^{RE}}\right) > 0 \text{ since } e_{RE}(*) < 0$$

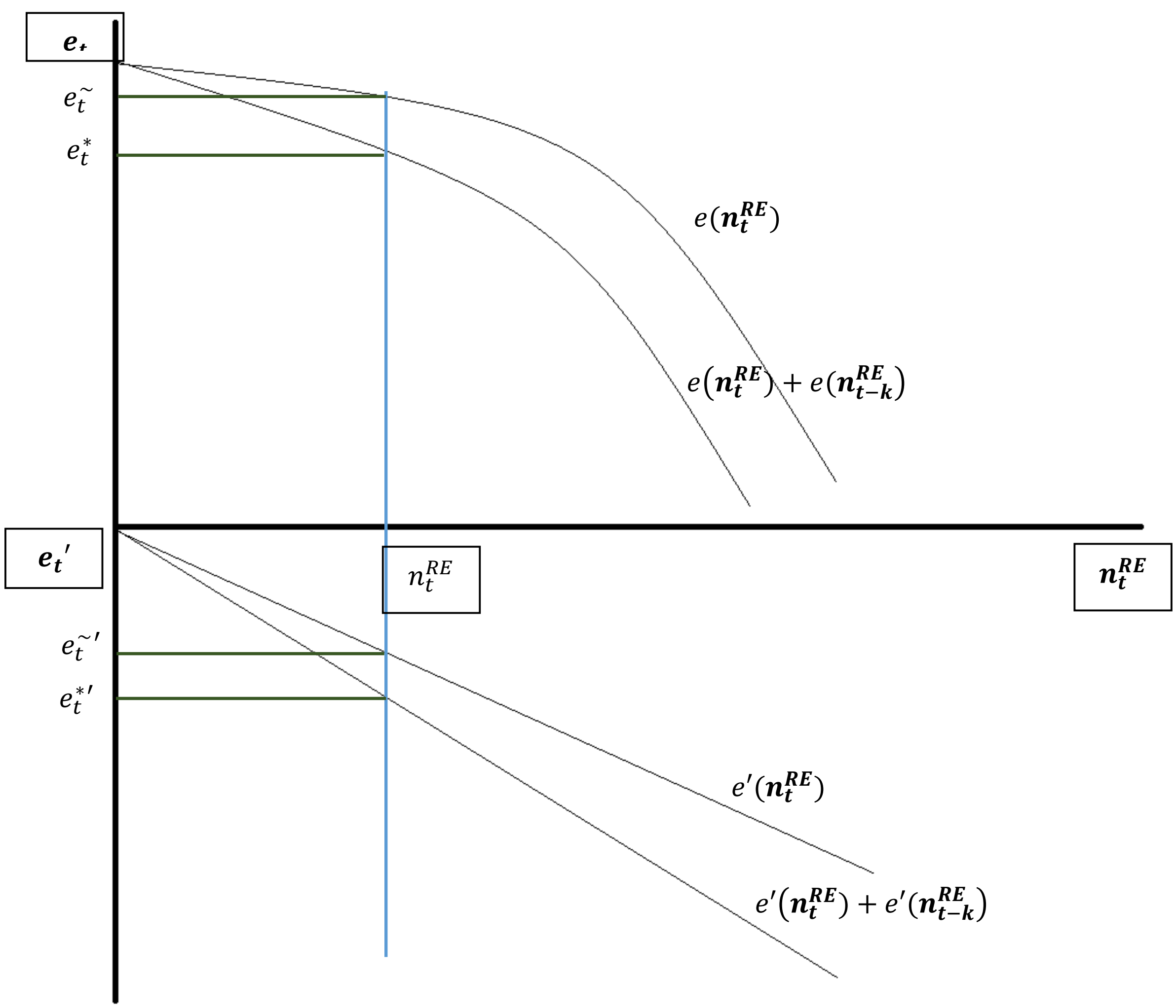
Even if the static estimator is unbiased for the contemporaneous component, it will underestimate the marginal external benefits of renewable energy by missing the lagged component. Therefore, in order to estimate the emissions function we need to account for the dynamics. The above social planner problem and optimality conditions can also be applied to the general case of a power system with storage that allows for recharging ($h_{pt} < 0$). If there is no hydropower or storage, the dynamic problem becomes static and the usual static estimator of marginal emissions is unbiased.

Graph 1. Static and dynamic allocation with linear demand and marginal cost functions



Graph 1 illustrates that by not taking into account the dynamics and the MUC of hydropower/stored energy, we would be overestimating fossil fuel use and total emissions in each period. Assuming a concave emissions function inversely related to the amount of renewable energy (increasing VRE penetration would be displacing more inefficient and dirtier generators at the margin) we can depict the bias of the static total and marginal emissions estimators in comparison with the dynamic parameter (Graph 2).

Graph 2. Total and marginal emissions estimators



Notice that the contemporaneous component of fossil fuel use, and its associated emissions, comes from the optimality condition (3), which is just stating a mathematical formulation of the merit order effect: adding significant amounts of VRE cause a net load or demand reduction determining a lower cost marginal generator and price (Hirth, 2013). This is the main underlying mechanisms in the literature reviewed, in the previous section, on estimating variable renewable energy carbon offsets.

Nevertheless, the lagged component appears due to the price arbitrage condition dealing with hydropower reallocation. The extended arbitrage equation (8) states that if the current realization of VRE reduces prices relative to the expected future price, then storing hydropower is optimal. Both equations, merit order (3) and arbitrage (8), determine how peak and offpeak generation should be allocated. Thus, if VRE production is higher during any stage of the day (say at night in grids with wind power), the price profile will reflect larger price reductions during this time.

4. Variable renewable energy effect on price and hydropower allocation in CAISO

In the previous section we assumed that hydropower generation has a virtually zero marginal cost of production. This is in line with previous work which recognizes that hydro's storage capability and ramping flexibility allow an almost frictionless generation reallocation to those time periods that pay the largest locational marginal prices (LMP) (Thompson et al., 2004). Due to these reallocation characteristics, VRE can shift hydropower generation not directly through the merit order effect but via a LMP change.

From an individual profit maximizing hydropower producer perspective, the dynamical optimal allocation releases more water during periods of expected high prices, and stores, or even pumps, water during periods of expected low prices (Thompson et al., 2004). Kanamura and Ōhashi (2007) extended the previously cited work by simulating prices with a structural demand and supply model, which allowed them to formulate a similar operation policy in terms of demand: "the optimal strategy is to pump when both the water level and the demand for electricity are low", and releasing water during most high demand periods.

Therefore, demand patterns and uncertainties shape price expectations which in turn determine the optimal hydropower allocation. It is reasonable to assume that as VRE generation plays an increasing role in the grid, its intermittent patterns and uncertainties will also affect hydropower producers' price expectations and production decisions. The large scale addition of VRE decreases the wholesale electricity price through the merit order effect.

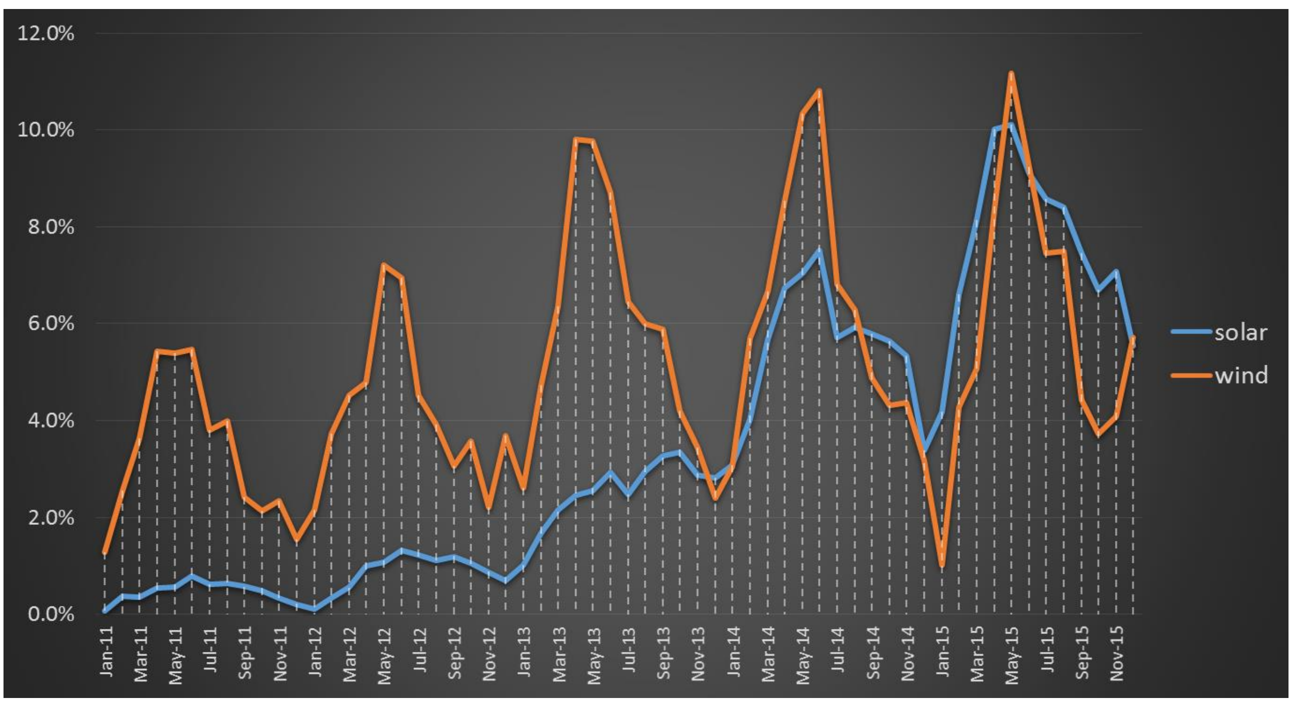
This price reduction caused by VRE has been documented in several empirical estimations for countries with different shares of renewable generation in the power mix. In Europe, the largest wholesale price reductions have been found on small markets, and the smallest on large markets[4]. Nevertheless, when the comparison is made accounting for differences in market size, the merit order effect on price is similar between both markets (Würzburg et al., 2013).

In the last 5 years in the California Independent System Operator (CAISO), a significant share of VRE capacity and generation has been added to the grid (Figure 1). In fact, between 2011 and 2015, the

[4] The effect was measured in €/MWh per each additional GWh of VRE and it was in large markets; Nordpool −1.7; Germany −0.24 to −2.83; Spain −1.1 to −3.99, and in small markets; Netherlands −6.17; Denmark −1.33 to −9.87; Ireland −9.9 as documented by Würzburg et al. (2013) based on standardization of previous studies.

average share of solar generation in the power mix grew from less than 1% to 7%, while for wind it grew from 3% in 2011 to 6% in 2014 and then it decreased to 5% in 2015. California has a goal of reaching a 33% share of VRE in the grid by 2020 (CAISO, 2013). The increasing VRE generation has already modified the net load profile. From 2011 to 2015, net load has been reduced throughout the day, but especially during sunlight hours due to the combine production of solar and wind. Its profile has change to reflect the “duck curve” (Figure 2): a concave shape (belly) in the midafternoon and a quick ramp up (arched neck) during evening hours (CAISO, 2013).

Figure 1. Share of wind and solar generation in CAISO power mix



Source: CAISO, 2016a

As predicted by the merit order effect, this change in net load has caused a similar alteration in the LMP profile, both in the day ahead market (DA, price expectations) and the real time figure (RTM)

(Figure 2). The same "duck curve" shape appeared in the last two years for hourly average prices in the CAISO wholesale electricity market[5]. To formally test whether and the extent to which adding VRE has changed the LMP in CAISO, I take advantage of wind and solar exogenous variation in generation to run a regression that controls for fuel costs, load, nuclear generation, temperature and other fixed effects, using hourly data for the period 2011-2015:

$$(10)\ LMP_t = \beta_s S_t + \beta_w W_t + \beta_d D_t + \beta_h G_t + \beta_n N_t + \beta_f F_d + \beta_m Temp_d + \alpha_d + \varepsilon_t$$

where

LMP_t is the average of the three CAISO hub trading real time interval locational marginal prices measured in USD/MWh at hour t

S_t, W_t, G_t, N_t are CAISO aggregate solar, wind, geothermal and nuclear generation in MWh at hour t

D_t is CAISO aggregate demand (load) in MWh at hour t

F_d is CAISO average fuel cost (natural gas) for day d[6]

$Temp_d$ stands for daily temperature and α_w stands for daily fixed effects.

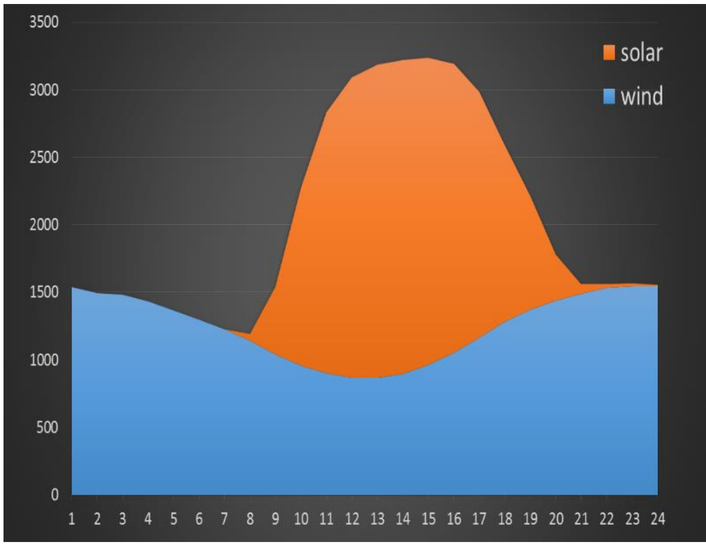
The parameters on equation 10 are estimated using OLS with Newey-West standard errors with a 24 hour-lag.

[5] Hourly average prices are calculated as the average of the three trading hub prices or zones (NP15, SP15, ZP26).

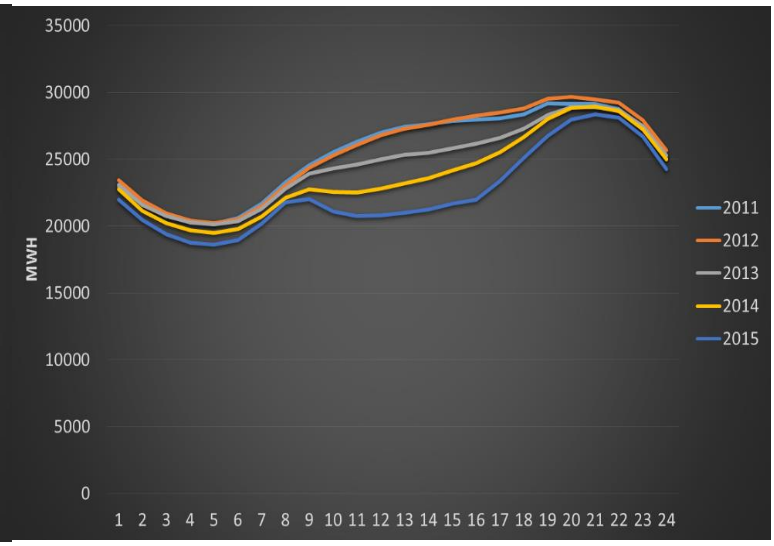
[6] Average of the fuel costs in the subregions CISO, PGE2, SCE1, SCE2, SDG1, SDG2

Figure 2. CAISO hourly average net load and wholesale electricity market LMP

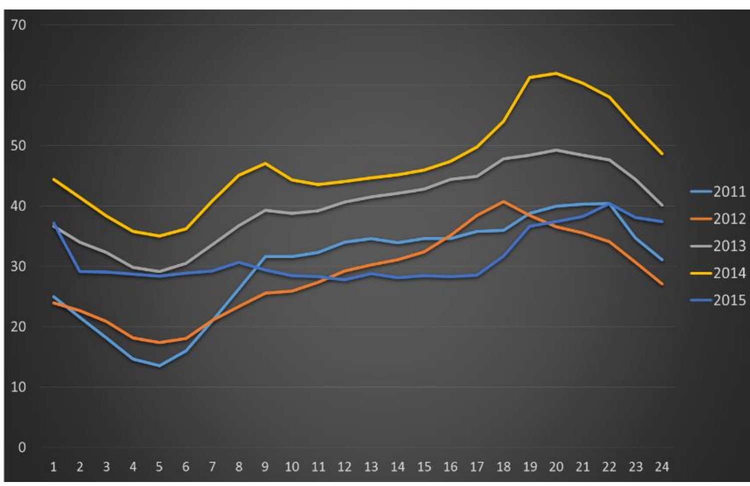
(a) Hourly average wind and solar generagtion



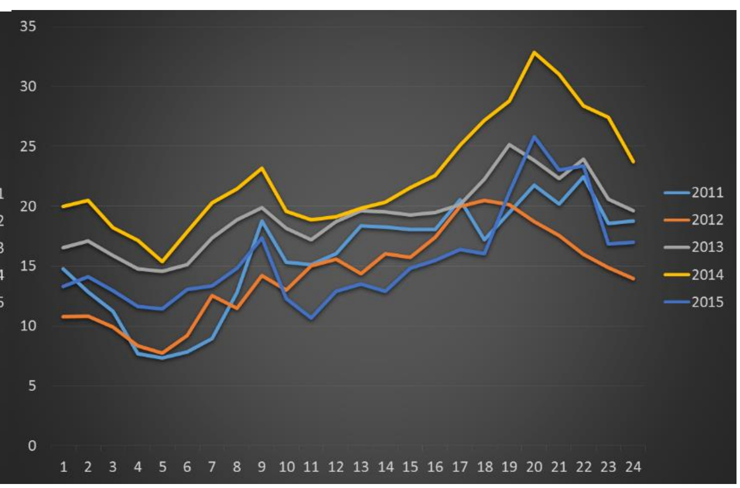
(b) Net load



(c) DA LMP in USD/MWh



(d) RTM LMP in USD/MWh



Source: CAISO, 2016a; CAISO, 2016b; CAISO, 2016c

The above specification follows a similar identification approach than Woo et al. (2011) and CAISO (2013) since it controls for the exogenous generation types and fuel costs to capture the effect of the endogenous thermal generation. Notice that this specification controls for demand, since most end consumers do not face real time prices, and their load profile is highly inelastic. But the equation does not control directly for the likely endogenous imports. Nevertheless, this omission does not alter the consistency of the VRE estimators, given the short term exogeneity of their generation profile. Furthermore, the previous estimating equation can be modified to obtain specific hourly effects of VRE on the real time LMP:

$$(11) \quad LMP_t = \sum_{h=0}^{23} \beta_{hs} \, HOUR_h S_t + \sum_{h=0}^{23} \beta_{hw} \, HOUR_h W_t + \sum_{h=0}^{23} \beta_{hd} \, HOUR_h D_t + \beta_m \, Temp_t$$

$$+ \beta_h \, G_t + \beta_n \, N_t + \beta_f \, F_d + \alpha_d + \varepsilon_t$$

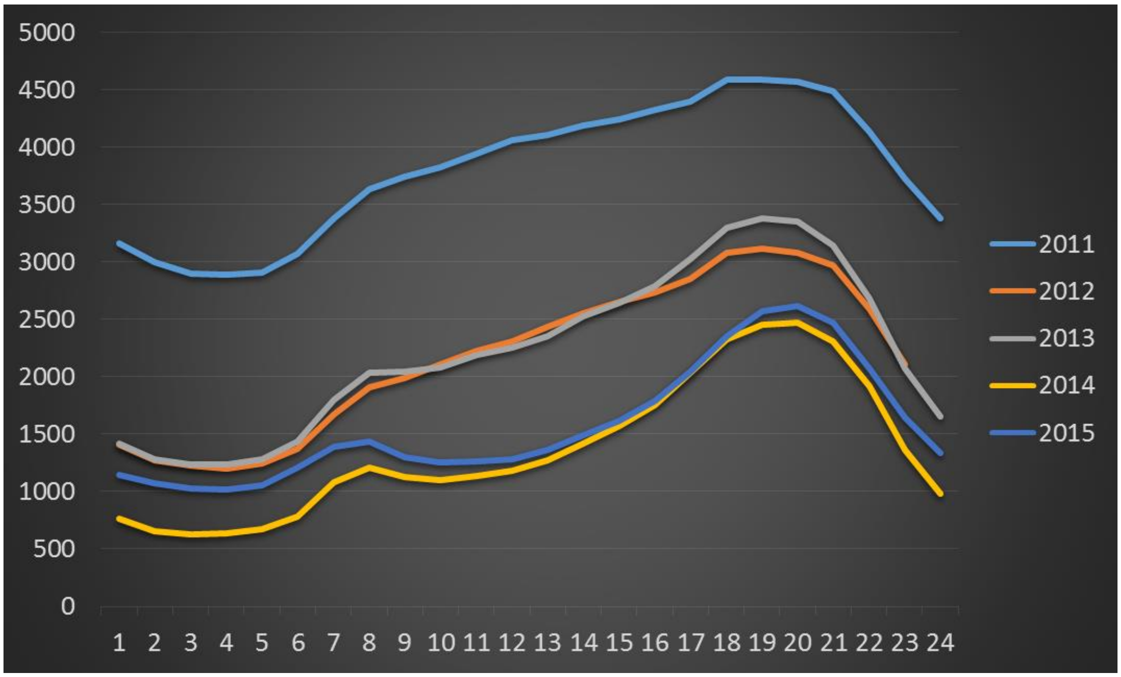
The results from equation (10) basically state that at all conventional significance levels, on average and controlling for the described factors, adding 1 GWh of wind power reduces in 4.58 ± 0.21 USD/MWh the real time LMP, while one MWh of solar generation reduces the LMP in 2.27 ± 0.09 USD/MWh. The larger average price reduction delivered by wind can be attributed to its 24 hour aggregate power contribution in CAISO.

Furthermore, the model for hourly price reductions shows that VRE has a larger detrimental effect on the LMP during daylight hours (6-17H) since the joint production of solar and wind drives the price even lower than at evening hours (18-20H), where wind is the only source. On average, 1 GWh of wind and solar power combined at midday reduces the LMP in 3.26 USD/MWh more than mostly wind energy at 7 pm[7]. Given the above described changes to the LMP, it is reasonable to expect changes to hydropower producers' price expectations and to the optimal allocation. These changes can be observed

[7] For regression details please see Appendix

on the aggregate hydropower generation curve, whose transition is similar to that of the net load and LMP profiles in the last five years (Figure 3).

Figure 3. CAISO hourly average aggregate hydropower generation



Source: CAISO, 2016d

To sum up, adding significant amounts of VRE to a power grid causes an instantaneous displacement of the highest marginal cost generators, usually fossil fuel powered units, but it also causes a change in the wholesale LMP profile. Hence, in grids with significant shares of hydropower generation, this change to the LMP causes another instantaneous and indirect effect which consists in switching hydro allocation away from periods with the largest price reductions. Appropriately addressing the second effect in the estimation of VRE offset thermal generation and its related offset carbon emissions is the main objective of the following sections.

5. Data and identification

This research uses hourly data on load, generation and trading hub (LMP) for the period 2011-2015, which come from publicly available sources: the California Independent System Operator (CAISO) web database OASIS and its renewables watch portal (CAISO, 2016a; 2016b; 2016c and 2016d). More than a 150 GB of data which boils down to 43,000 observations for each variable were automatically extracted from the OASIS server[8]. I also use hourly average temperature and carbon dioxide emissions data. The former was obtained from U.C. Davis Integrated Pest Management publicly available information on several California weather stations (IPM, 2016), and the latter from EPAs Continuous Emission Monitoring system (CEMS) (EPA, 2016).

One limitation with the emissions data is that CEMS only compiles information for fossil fuel powered units whose capacity is greater than 25 MW. Nevertheless, most power plants in CAISO report their emissions to CEMS. Missing variables represent less than 0.3% of the total number of hours in the five year span[9].

To identify the thermal generation offsets, and their related offset carbon emissions, caused by wind and solar power, I take advantage of the short term exogeneity and randomness of variable renewable energy generation. Since wind and solar output are determined by nature's cycles, which are exogenous to the economic decision making process that settles electricity generation in the wholesale

[8] Using web mining codes programmed in the R statistical software.

[9] This minimum fraction of missing variables is due to either missing information on the OASIS web server or a failure in the web mining code. Therefore, they can be assumed to be missing completely at random, without any systematic trend in their unavailability.

market, their hourly variation can identify changes in the electricity dispatch and the subsequent emissions.

Given the exogeneity in the variables of interest, I use the OLS estimator with Newey West standard errors to perform inference robust to heteroscedasticity and serial correlation in the generation, emissions and price time series (Newey and West, 1987). Based on the augmented Dickey-Fuller test, neither of these series show the presence of unit roots. This allows to identify causal effects without using any cointegration procedures.

In the proposed identification strategy I argue that controlling for daily temperature and daily or weekly fixed effects can address the drought and snow pack loss detrimental effects on hydropower generation. Furthermore, the one time closure of the San Onofre Nuclear Generation Station in February 2012 (Davis and Hausman, 2014) should not cause any major issues with the identification strategy since it relies on very granular hourly variation. Finally, I might be underestimating emissions and thermal generation offsets since the generation data is based on grid level information, which reflects net generation rather than gross generation[10], and it does not include details about the thermal generation displaced at foreign grids when CAISO's solar and wind power are exported. However, since a small percentage of total generation is exported, this error should not amount to a significant share.

[10] Gross generation being larger since it includes thermal plants' own consumption.

6. Static average generation and emissions offsets

A. Econometric specification

The estimating equation that identifies the impact of VRE on generation and emissions is:

$$(12) \qquad G_t^m = \sum_{k=0}^{1}\sum_{j=0}^{1}\sum_{i=0}^{1}\beta_{mi,j,k}\, S_t^i * W_t^j * D_t^k + \sum_{l=0}^{L}\lambda_{d-l}T_{d-l} + \sum_{l=0}^{L}\eta_{d-l}PPT_{d-l} + \alpha_w + k_d + \gamma_s + \delta_d + \varepsilon_t$$

where:

G_t^m represents the m different groups of conventional generation in CAISO: thermal, hydro, nuclear, other renewables and imports measured in MWh at hour t.

S_t, W_t, D_t are CAISO aggregate solar, wind generation and demand (load) in MWh at hour t

T_d is daily average temperature and PPT_d is daily total precipitation.

α_w represents weekly fixed effects (FE), k_d stands for weekend FE, γ_y represents fixed effects for each season and δ_d stands for daily fixed effects. Notice that if the latter is selected, all the previous ones cannot be.

This identification approach requires the joint modelling of wind and solar generation effects. Furthermore, following Novan (2015), it allows for interactions among both sources and load, up to a first degree, in order to control for possible complementarities that unfold in the electricity dispatch process each hour. The simpler approach of modelling the effect of each source separately fails to identify offsets properly due to the negative correlation between wind and solar generation.

This paper estimates offsets of five groups of conventional generation: thermal generation, which in California only includes combined cycle units, combustion turbines and boilers; hydropower generation which includes large and small scale plants; other renewables which comprises geothermal, biomass and biogas; nuclear and finally imports from other system operators. Standard errors for hypothesis testing are computed using the Newey-West estimator using the conventional 24-hour lag (Novan, 2015; Kaffine et al., 2013). For identifying the marginal emissions offsets, I use the same models but the dependent variable is hourly carbon dioxide emissions measured in tCO_2.

The specific instantaneous marginal generation offsets caused by adding VRE are identified via the average partial effect (APE) of equation (3):

APE for solar generation:

$$(13) \qquad \hat{E}\left(\frac{\partial G_t^m}{\delta S_t}\right) = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=0}^{1}\sum_{j=0}^{1}\sum_{i=0}^{1} i * \hat{\beta}_{i,j,k}\, S_t^{i-1} * W_t^j * D_t^k$$

APE for wind generation:

$$(14) \quad \hat{E}\left(\frac{\partial G_t^m}{\delta W_t}\right) = \frac{1}{T}\sum_{t=1}^{T}\sum_{k=0}^{1}\sum_{j=0}^{1}\sum_{i=0}^{1} i * \hat{\beta}_{i,j,k}\, S_t^{i} * W_t^{j-1} * D_t^k$$

The marginal emissions offsets $\hat{E}\left(\frac{\partial E_t}{\delta W_t}\right)$. are also identified by the APE estimator but with the results from regressing emissions on the specified controls.

Notice that the APEs estimate the instantaneous displacement of the highest marginal cost generators, through the merit order effect, and the switching of hydropower allocation due to the indirect price effect. A key condition for testing the appropriateness of the model is whether the energy identity holds. This requirement implies that adding 1 MWh of VRE displaces 1 MWh of all other conventional generation types combined. The preferred specification described in (3) is the model which yields a closest match to the one for one displacement without imposing any restrictions on the summation of the APEs.

Nevertheless, three models were estimated as robustness checks: the same first order polynomial interactions model but with daily FE[11]; and two simple linear models, without any interactions but both VRE sources in the same equation and with daily and weekly FE respectively.

B. Generation offsets

Table 1. Static average generation offsets (APE) by type and model

Generation type	Offsets (MWh/MWh VRE)									
	Linear polynomial		Linear polynomial		Linear		Quadratic		Quadratic	
	Solar	Wind	Solar	Wind	Solar	Wind	Solar	Wind	Solar	Wind
Thermal	-0.61	-0.65	-0.53	-0.64	-0.52	-0.66	-0.58	-0.70	-0.52	-0.64
	0.01	0.01	0.00	0.01	0.00	0.01	0.02	0.01	0.01	0.01
Hydro	-0.11	-0.06	-0.15	-0.09	-0.15	-0.07	-0.11	-0.05	-0.13	-0.08
	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00
Other	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
renewables	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nuclear	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Imports	-0.25	-0.33	-0.29	-0.31	-0.31	-0.31	-0.25	-0.29	-0.29	-0.33
	0.01	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01
Total market (grid)	-0.97	-1.02	-0.97	-1.04	-0.98	-1.04	-0.94	-1.02	-0.94	-1.05
	0.02	0.01	0.00	0.01	0.00	0.01	0.02	0.01	0.02	0.01
Daily FE	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Weekend FE	Yes	Yes	-	-	-	-	Yes	Yes	-	-
Weekly FE	Yes	Yes	-	-	-	-	Yes	Yes	-	-
Season FE	Yes	Yes	-	-	-	-	Yes	Yes	-	-

Standard errors are displayed

All estimates are significant at less than 1% level, except for those at 5% (*), 10% (°) and those not significant at any conventional level (~)

All static econometric models show that, on average and controlling for load, temperature, weekend, season and weekly fixed effects, solar and wind generation displace mostly natural gas

[11] In the daily FE model, season fixed effects are no longer required, otherwise they would drop out of the estimation due to collinearity.

generation and imports. This first instantaneous displacement occurs due to the merit order effect. The preferred specification, a polynomial model with daily FE, estimates that one MWh of solar power displaces 0.534 MWh of natural gas, while one MWh of wind replaces 0.642 MWh, on average.

Furthermore, I reject the null hypothesis, at all conventional significance levels, of having no hydropower reallocation caused by adding VRE $\left[Ho: E\left(\frac{\partial Hydro_t}{\delta VRE_t}\right) = 0\right]$. The previous test leads me to conclude that there is a second instantaneous and indirect displacement which reschedules hydropower generation due to variable renewable energy effects on the wholesale electricity price. This finding is confirmed by all the alternative specifications in contrast to the results of the Texan wholesale electricity market ERCOT, where adding wind did not displace any substantial amount of hydropower during 2005-2011 (Cullen, 2013; Novan, 2015). One possible explanation for this divergence is the low hydropower share, less than 1%, in total capacity and generation in ERCOT.

On average, the preferred model gives an estimate of 0.147 MWh of displaced hydropower for each additional MWh of solar generation and 0.087 MWh for each additional MWh of wind. This outcome points out that a considerable share of hydropower producers are reacting to the change in the LMP profile by changing their price expectations and generation decisions.

There is barely any base power displacement coming from the nuclear, geothermal, biomass, or biogas generation. This reassures that the identification approach is not affected by the closure of the nuclear power plant SONGs, since it relies on short term hourly variations. The preferred specification yields the closest compliance with the one for one displacement energy identity requirement. In the case of solar the market estimate is below the ideal benchmark (0.97) while in the case of wind it is above (1.04).

As argued previously, a downward bias might be due to exports outside CAISO, while an upward bias can be caused by using net generation and not accounting for a thermal plant own consumption. In either case, the omissions do not represent a large share of total generation and the grid estimates are very close to one.

C. Emissions offsets

Table 2. Static average carbon emissions offsets (APE) by model

	Offset tCO2/MWh VRE	
	Linear polynomial	
	Solar	Wind
CO_2	-0.075	-0.499
	0.003	0.006

Standard errors are displayed

All observations are significant at less than 1% level

Table 2 displays the average marginal emissions offsets estimates of equations 13 and 14. The model states that the static or instantaneous effect is low abatement potential for solar and a larger potential for wind. This difference can be explained by the 24 hour continuous aggregate wind generation in CAISO, while solar generation is present mostly for ten to twelve hours. Another key reason for this difference is the indirect hydropower reallocation that occurs during midday, making solar power displace some non-fossil generation. Nevertheless, this displaced hydro is relocated at a different time and it will substitute natural gas generation and reduce even more carbon emissions than what is captured in the static APE. Thus, we need to model the dynamic process to estimate emissions offsets accurately.

7. Dynamic average generation and emissions offsets

A. Econometric specification

The estimating equation that identifies the dynamic impact of VRE on generation and emissions is:

$$(15)\quad Y_t^m = \sum_{l=0}^{72}\sum_{k=0}^{1}\sum_{j=0}^{1}\sum_{i=0}^{1}\beta_{mi,j,k,l}\, S_{t-l}^{i} * W_{t-l}^{j} * D_{t-l}^{k} + \sum_{l=0}^{L}\lambda_{d-l}T_{d-l} + \sum_{l=0}^{L}\eta_{d-l}PPT_{d-l} + \alpha_w$$

$$+ k_d + \gamma_s + \varepsilon_t$$

The above model identifies how contemporaneous and past wind and solar generation affected the conventional generation types and their emissions. By modelling the effect throughout 3 days, using 72 lags, I can estimate how hydropower generation is reallocated due to changes in the LMP and its additional displacement of thermal generation. This allows an appropriate inference of marginal generation and emissions offsets via computing the APEs:

APE for solar:

$$(16)\quad \widehat{E}\left(\sum_{l=0}^{72}\frac{\partial G_t^m}{\delta S_{t-l}}\right) = \frac{1}{T}\sum_{t=1}^{T}\sum_{l=0}^{72}\sum_{k=0}^{1}\sum_{j=0}^{1}\sum_{i=0}^{1} i * \widehat{\beta}_{mi,j,k,l}\, S_{t-l}^{i-1} * W_{t-l}^{j} * D_{t-l}^{k}$$

A similar expression but with the derivative with respect to wind estimates its marginal effect. Both APEs capture not only the static marginal effect but also the dynamic effect, which includes changes in the scheduling of peak hydro units that accommodate the inelastic and intermittent supply of VRE. I compute the same three robustness check models than in the static case: full interactions with daily FE, and two simple linear models with daily and weekly FE respectively[12].

[12] In the case of the two simple linear models, the dynamic marginal offsets are identified by the summation of the estimators $\sum_{l=0}^{23}\widehat{\beta_{VREt-l}}$.

B. Generation offsets

Table 3. Dynamic average generation offsets (APE)

	Offsets (MWh/MWh VRE)	
	Solar	**Wind**
Thermal	-0.689	-0.834
	0.049	0.013
Hydro	-0.099	-0.029
	0.015	0.005
Other	-0.002	0.001
renewables	0.002	0.001
Nuclear	0.048	0.038
	0.010	0.004
Imports	-0.248	-0.228
	0.042	0.012
Total grid	-0.99	-1.05
	0.07	0.02

All observations are significant at less 1% except for other renewables displaced by solar power.

Once we control for the indirect effect of hydropower reallocation by modelling the lags that capture the recovery of the displaced generation at a later time we can infer the correct average marginal generation offsets. Therefore, the dynamic estimates show that thermal offsets increase while the hydro offsets decrease compared to their static counterparts. The chosen model delivers the best energy identity calibration, which signals that its detailed level of controlling for weekly fixed effects is not appropriate when hourly lags are modelled.

Nevertheless, I reject the null hypothesis of having no hydropower generation displacement caused by VRE $Ho: E\left(\sum_{l=0}^{72}\frac{\partial G_t^m}{\delta S_{t-l}}\right) = 0$ at all conventional significance level. One plausible explanation for overestimating the hydropower reallocation has to do with modelling and computing average partial effects for all 72 hours. Since the APE computed with equation 16 uses point estimates of all hours during the day, the night hours that have no solar generation will still show a hydro displacement by picking the effect of any of the morning hours included in the lags.

This overestimation also occurs when I model either less lags (12,24) or more (96) or even when only using sunlight hours (6-19H00)[13]. This overestimation can be the result of this noise in the dynamics, due to the nature of the data generating process, or it could be indicative of a more complex pattern and behavior of hydropower generation rescheduling decisions, which will be briefly stated in the discussion section.

Emissions offsets

Table 4. Dynamic average carbon emissions offsets (APE) by model

	Offset tCO2/MWh VRE	
	72 lags all hours	
	Linear polynomial	
	Solar	Wind
CO_2	-0.231	-0.417
	0.030	0.008

Standard errors are displayed

All observations are significant at less than 1% level

For solar power, the dynamic APE corrects the low abatement estimate from the static model and it reduces the wind abatement estimate in all models. In the first case, since solar displaces considerable hydropower generation due to early morning to midday price reductions, when the model is calibrated with lags, it recovers some of that water generation that is switched to a higher LMP hour. Hence, the abatement estimate will go up since it considers the full effect: the direct displacement of the high

[13] See appendix.

marginal cost thermal units and the indirect effect of relocating hydropower which will displace even more thermal output but at a later time. The summation of both effects, or the total marginal emissions offsets are larger in this dynamic case than in the static case as sketched in the theoretical model.

The estimated average wind marginal emissions offsets (0.417 ± 0.08 tCO_2/MWh) are larger than those reported by Kaffine et al. (2012) for CAISO (between 0.202 and 0.299 tCO_2/MWh) based on 2009 data. This is plausible since wind generation has been increasing, in absolute and relative values, since that year. A more recent estimate based on 2010-2012 data from Callaway et al. (2015) finds that the average marginal emissions offsets for solar is higher than for wind, and both oscillate around 0.4 tCO_2/MWh. I find a different relation between both effects and a similar magnitude for the wind estimate, even though, I use more recent data which should reflect an increasing share of VRE in the grid. The lower abatement coefficient for solar power could be caused by the shortcomings of my dynamic model (using 72 lags) in capturing a full relocation of the displaced hydropower.

While the Callaway et al. (2015) estimates are not directly comparable since they are based on identifying grid level marginal emissions using shifts in the supply of fossil generation and projecting how potential VRE would directly substitute the marginal thermal generator, analyzing why larger additions of VRE to the grid have not increased the marginal emissions offsets is a salient point.

8. Valuing carbon abatement benefits, policy implications and discussion

In the US, the recent Clean Power Plan (CPP) has a 30% reduction in carbon dioxide emissions by 2030, from the 2005 level, as one of its key goals (EPA, 2015). In order to achieve this, an electric grid powered by a significant share of renewable energy is one of the “Best System of Emission Reduction BSER” guidelines (Caldwell and Anderson, 2015). Nevertheless, the intermittent nature of variable renewable energy (VRE), the lack of utility scale electricity storage and the complex congestion configurations in power transmission make it challenging to assess VRE carbon emissions, which is essential for measuring progress and compliance with the CPP.

This research has argued that VRE has an effect on hydropower reallocation due to the changes it causes on the LMP. Hence, wind and solar have direct and indirect carbon emissions, the latter include the recovery of the displaced hydro generation at a future time and its related thermal generation and CO_2 offsets. Understanding these dynamics is important for measuring VRE carbon abatement potential, but also for addressing current shortcomings and challenges with the large scale adoption of wind and solar technologies at the wholesale market level. A similar pattern was found by Green and Vasilakos (2012) but between Denmark and the Scandinavian countries, where the former exports wind generation on breezy days and imports electricity on calm days. The authors argue that Scandinavian hydropower basically acts as a storage for Denmark, smoothing the intermittency of its wind power.

Estimating the carbon abatement potential of VRE is necessary to assess the economic value of renewable energy and evaluate current policies. Using the latest US EPA social cost of carbon (USD 56/ tCO_2[14] from IAWG, 2015) renders solar power marginal carbon abatement benefits between USD 9.6 and USD 16.3 per MWh, while for wind power it is from USD 22.5 to USD 24.3 per MWh. Ideally, we can use these values of external environmental benefits along the grid cost reductions via LMP reductions to

[14] Average value for a discount rate of 2.5%

compute the short run marginal value of VRE generation, which would be the desired metric to compare against the different incentives perceived by wind and solar generators (Baker et al., 2013).

From a broader perspective, the proposed dynamic modelling is key for understanding electricity generation and grid level emissions in systems with increasing adoption of storage technologies. Such devices can help managing the short term (day vs night) intermittency and the seasonality (summer vs winter) of VRE. To the extent that the main cost of operating storage comes from the capital investment, the insights about the hydropower arbitrage condition and generation reallocation would also apply to profit maximizing storers. Thus, dynamics would play a key role in identifying renewable energy emissions offsets even in grids that have historically shown negligible levels of hydropower production (ERCOT).

Furthermore, several emerging economies with electric grids powered by a significant (or even mostly) share of hydropower are increasingly installing wind and solar plants (some examples include China, Brazil and India). To the extent that these countries operate a wholesale electricity market with bidding hydropower producers, this research's proposal for estimating marginal emissions offsets can be a feasible replication methodology for evaluating VRE abatement outcomes.

Finally, my findings state that I cannot reject the null hypothesis of having no hydropower generation displacement caused by VRE. As discussed previously, this conclusion can be the result of noise in the dynamics, due to the nature of the data generating process, and picked up by the APE formula when averaging across all time hours. Further work is required to model these dynamics appropriately.

From an aggregate wholesale market perspective, if individual hydropower producers' expectations cannot adjust quickly and continuously to the price consequences of adding variable renewable energy, some bids might end up being too high and probably rejected. In either case, further research and modelling are required to contrast with the hydro displacement finding. In this regard, the current research leaves an open question based on a counterintuitive result.

9. Conclusions

This research tackled the novel challenge of identifying the marginal generation and emissions offsets caused by adding two intermittent renewable energy sources to an electric grid that has a significant share of hydropower. Using a static model based on recent (2011-2015) historical data of random solar and wind generation, I estimated the instantaneous displacement of the highest marginal cost generator, through the merit order effect, but also the indirect hydropower reallocation that occurs due to VRE effects on locational marginal prices.

On the other hand, using a dynamic model, I identified how hydropower generation is reallocated due to changes in the LMP and the associated additional displacement of thermal generation and emissions. Hence, the dynamic model estimates larger marginal natural gas generation offsets and emissions offsets than its static counterpart. Even with the dynamic estimate I find no evidence of a full hydropower reallocation that would lead to zero displacement. While this finding could be caused by an overestimation related to accumulated noise in modelling the lags, further research is required to understand this effect and whether hydropower producers' expectations play any role in having an imperfect rescheduling of their electricity output.

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11. Appendix

10.1 RTM LMP regressions on VRE and controls

Dependent: RTM LMP (USD/MWh)	
wind (in MWh)	-0.00458
	0.00021
solar (in MWh)	-0.00228
	0.00010
load	0.00137
	0.00004
Fuel cost	7.87108
	2.36629
Weekly FE	Yes
Weekend FE	Yes

Standard errors are displayed

All observations are significant at less than 1% level

10.2 RTM LMP regressions on hourly VRE and controls

|	Robust			
RTM_LMP	|	Coef.	Std.	Err.
--				
hour#c.wind	|			
1	|	-0.0045294	0.0002554	-17.74
2	|	-0.0045334	0.0002533	-17.89
3	|	-0.0050029	0.0003066	-16.32
4	|	-0.0053229	0.0002926	-18.19
5	|	-0.0049069	0.0002834	-17.31
6	|	-0.004726	0.0002904	-16.28
7	|	-0.00617	0.0005391	-11.45
8	|	-0.0055742	0.0004774	-11.68
9	|	-0.0059611	0.0003979	-14.98
10	|	-0.0057921	0.0004337	-13.36
11	|	-0.0052275	0.000511	-10.23
12	|	-0.005428	0.0004222	-12.86
13	|	-0.0057899	0.000413	-14.02
14	|	-0.0056241	0.0003917	-14.36
15	|	-0.0055606	0.0004487	-12.39
16	|	-0.0065173	0.0006112	-10.66
17	|	-0.0063052	0.0006598	-9.56
18	|	-0.0074921	0.0008467	-8.85
19	|	-0.005818	0.0005717	-10.18
20	|	-0.0037482	0.0004322	-8.67
21	|	-0.0038706	0.0004232	-9.15
22	|	-0.0043075	0.0004265	-10.1
23	|	-0.0045379	0.0002774	-16.36
24	|	-0.0043467	0.0002393	-18.16

hour	|	Coef.	Std. Error
|			
1	|	-0.0814458	0.0913229
2	|	-0.1330256	0.1406528
3	|	-0.1936466	0.2193553
4	|	-0.5384707	0.4129938
5	|	0.0304829	0.0134514
6	|	0.0162607	0.0089232
7	|	-0.0014057	0.0031807
8	|	-0.0037736	0.0006084
9	|	-0.0023285	0.0002579
10	|	-0.0020364	0.000175
11	|	-0.0017957	0.0001517
12	|	-0.0016636	0.0001504
13	|	-0.0016058	0.0001858
14	|	-0.0014226	0.000183
15	|	-0.0015609	0.0001854
16	|	-0.0017754	0.0004016
17	|	-0.0013695	0.0004411
18	|	0.0003469	0.000773
19	|	0.0019864	0.0011574
20	|	0.0000199	0.003733
21	|	-0.0062838	0.0045281
22	|	-0.0030701	0.0048011
23	|	0.0021054	0.00462
24	|	-0.0306278	0.0382496