Do German renewable energy resources affect prices and mitigate market power in the French electricity market: A need for coordinated energy policies?

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Abstract: Several empirical studies show that renewable energy sources such as wind and solar power, typically supplied at low marginal cost, can cause electricity market prices to fall. Recent theoretical research and simulations also highlight the link between the integration of renewable energy and market performance in an oligopolistic energy market. This article looks at these dynamics in the context of cross-border effects between two highly interconnected electricity markets, France and Germany. Using a rich panel dataset for hourly data from November 2009 to July 2015 and an empirical model developed in New Empirical Industrial Organization (NEIO) in a dynamic framework, we estimate the impact of German wind and solar power production on both prices and market power in the French wholesale market. The findings highlight the importance of coordinating energy policies via joint renewable energy support schemes among interconnected European electricity markets.

Keywords: Oligopolistic market, market power, renewable energy, electricity prices, panel data.

1 Introduction

Modeling price behavior in electricity market is a challenging task involving complex technical and political considerations. Over more than 20 years, Europe has made remarkable progress in creating liberalized and competitive wholesale markets for trading electricity within and across national frontiers. In recent years, policy makers have also come to pay serious attention to the threat of global climate change resulting from the consumption of fossil fuels especially in the electricity production sector. Consequently, energy policies designed to tackle climate change have grown dominant in the European power industry. In particular, many countries have implemented policies for a transition toward a low-carbon economy through the promotion of renewable energy sources (RESs, hereafter) in the electricity balance, driven by generous subsidies and priority dispatch conditions.

The 2030 climate and energy package of the European Council announced in 2014 confirmed the EU's 2030 target for tackling climate change by reducing greenhouse gas emissions by 40% against 1990 levels and increasing the share of renewable energy sources by at least 27%. Achieving this will require high shares of RESs such as wind and solar power in the electricity supply, given the limited opportunities for the expansion of hydro power and the widespread opposition to nuclear power (Newbery et al. [2017]). This target encourages Member States to continue to subsidize RESs and calls for joint support schemes among two or more EU countries to spur renewable energy production in one or both of their territories, as recommended in the 2009 and 2016 Renewable Energy Directives of the European Commission. To date, subsidy regimes are still confined within national action plans while the impact of RESs on the electricity market can be induced at cross-border level.

In Germany, for example, the promotion of electricity generated from RESs has been driven mostly via a preferential access to the grid and a feed-in-tariff (FIT) mechanism that guarantees above-market rates, commonly over a 20-year period. The country has achieved its RES objectives but the question of cost distribution is being raised. Andor et al. [2017] show that the burden of cost borne by customers (around €125 billion via substantially higher electricity bills for RES support schemes in the years between the 2000 *Renewable Energy Act* (EEF) and 2015) can be expected to exceed €400 billion over the next 20 years, which might test the limits of consumers' willingness-to-pay. Given this context, it is important to study the impact of subsidized RESs on electricity markets as they currently operate.

In the short run, RESs such as wind and solar power, typically supplied at low marginal cost, cause wholesale prices to fall. While numerous studies have been made of this for the German electricity market (Sensfuss et al. [2008], Ketterer [2014], Cludius et al. [2014], Ederer [2015]), the magnitude of the ensuing price falls on foreign interconnected markets has been less widely estimated. In the longer run, high shares of RESs can impact market power (the possibility that firms may strategically raise the price above the competitive level (Borenstein et al. [1999])). Such impact is mixed. As proven empirically by Bigerna et al. [2016] in the Italian wholesale market for the period 2009 to 2013, the exercise of market power was considerably weakened by RES competition during peak hours, but it was surprisingly reinforced during some off-peak hours, in the absence of solar RES and in particular zones where congestion led to market splitting. Again, the impact of RESs on market power within a cross-border context has not been adequately investigated. This paper studies the impacts of RES production on wholesale prices and on market power in the context of cross-border effects between two closely interconnected electricity markets, France and Germany.

Together the French and German electricity markets account for one-third of all EU's electricity consumption. The interaction between two markets has a decisive influence on electricity prices in Europe. While the French power market is characterized as a centralized and nuclear-based (75%), the German market is more and more renewable-based and decentralized. In France, concern has grown about competition in electricity industry because of its extremely concentrated structure. Although much criticism has been directed at application of the attributes of market concentration when predicting the actual level of market power exercised in electricity markets (Borenstein et al. [1999], Newbery et al. [2004]), the extremely high market share of the incumbent firms in the French electricity industry does raise concerns about the possible exercise of market power in this market. Few empirical studies have investigated market power in the French power market, and they have been limited to cases in which the interaction with border exchanges was omitted from the estimation (for example, Meritet and Pham [2015]). In Germany, the power market has undergone many fundamental changes in recent years with its policy of promoting renewable energy in its electricity balance. The net installed capacity of wind and solar power has been increasing substantially from 26 GW (wind) and 11 GW (solar) in 2009 up to 56 GW (wind) and 43 GW (solar) in 2017, equivalent an increase from 25% to 48% of total net installed electricity capacity in Germany, of total net installed capacity. In the context of highly interconnected grids and market coupling between two markets, any impact of RES production on the domestic wholesale market can be expected to be transferred across borders. This study assesses the extent of market power in the French electricity market and examines how domestic prices and market power may be impacted by importing wind and solar output from the German electricity market. In the light of the empirical results, we discuss the regulatory implications of European policy with respect to building the framework within which the integrated market is implemented.

The literature over the last 10-15 years offers a wide range of techniques for identifying market power. Recent research on market power in electricity markets employs the supply function equilibrium model or residual demand analysis, which is based on access to bid data for individual firms (Wolak [2000], Wolak [2002], Prete and Hobbs [2015]; Green and Newbery [1992]; Baldick et al. [2004]). However, detailed bid data are required for such analyses (Newbery [2009]) but they are not available in the European Power Exchange. We base our analyses on aggregate market data instead and use insights from New Empirical Industrial Organization (Porter [1983], Bresnahan [1989]), which has been widely developed for the electricity market in a dynamic framework by Hjalmarsson [2000], Bask et al. [2011], Mirza and Bergland [2015]. In those papers, the authors use daily or weekly aggregated data, which obviously miss out on the dynamics of hour-to-hour demand and supply, thereby possibly underestimating market power especially during periods of low elasticity of demand. Instead, in our paper, we employ a rich hourly dataset from November 2009 to July 2015 and process it in a panel framework (Huisman et al. [2007], Keppler et al. [2016]). This enables us to account for the variation in 24 different prices for 24 hours per day due to the combination of the high variability in demand for electricity and the non-storability of electricity. It is also very relevant as data for solar power production are used, the values of which vary significantly from 0 MW during night hours up to 20 GW during daylight hours.

The remainder of the paper is organized as follows. The next section provides theoretical foundations for the impact of renewable energy integration on the strategic behavior of conventional electricity producers. Section 3 presents empirical modeling strategies on the identification of market power under different conditions and describes the data. Section 4 provides the results and discusses policy implications. The final section concludes.

2 RES integration under perfect competition and with market power

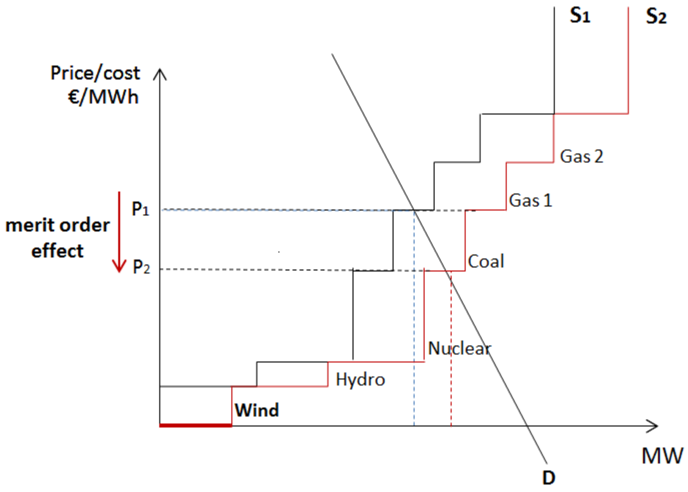
In this section, we first analyze the impact of market designs for RES development on price equilibrium and graphical analyses to show how the magnitude varies under perfect competition and with market power. We then review some recent papers in the literature on relations between renewable energy and market power in the electricity market.

Market designs for electricity trading over the past 15 years have integrated renewable support mechanisms, among others, the Feed-In Law[1], which requires the inclusion of electricity produced by RESs in the market as a priority regardless of classic thermal capacities. The technical and commercial responsibilities for such integration are borne by the grid operator, who is obliged to take delivery of electricity generated by renewable sources and put it on the market immediately. Renewable generators sell their output to the system operators at a guaranteed price. However, while renewable generators are paid at a set price and do not participate directly in the spot market, renewable output does impact spot market prices. In fact, when RES generation such as wind power is integrated in the merit order (supply curve in the electricity market), it takes the value of short-run "*zero marginal cost*", and since it is the first to be dispatched, energy generated from other sources must move to the right of the merit-order curve. This phenomenon is referred to in the literature as the "*merit-order effect*" (Sensfuss et al. [2008]).

Phan and Roques [2015] recently suggested that a similar effect might occur across borders. Based on the data from German wind output and French power prices, the authors found a significant cross-border merit-order effect between two markets. During periods of low demand in Germany and high demand in France, high RES output such as wind power in Germany may depress French spot prices. This does not mean that France directly imports electricity from German wind operators. What happens is that the integration of wind output with zero short-run marginal cost pushes the merit order curve to the right (figure 1). Prices fall and traders in neighboring countries will begin to import, resulting in lower prices for importing countries as

[1] Other means of support my include various forms of low-interest loans and financing packages for investments in plant for generating electricity from renewable energy sources.

Figure 1: Merit order with fed-in RES



well. The cross-border merit-order effect has also been estimated for other interconnected markets, for example, Germany - Austria (Würzburg et al. [2013]) and Germany - the Netherlands (Mulder and Scholtens [2013]).

The merit-order effect is expected to be more significant under a monopoly than under perfect competition. This is because as wind integration is high, the residual demand curve faced by incumbent firms will move to the left, resulting in lower prices, and this amplitude is more significant in the case of a monopoly where the supply function is steeper than in the case of perfect competition (figure 2).

Figure 2: Supply functions with RES integration

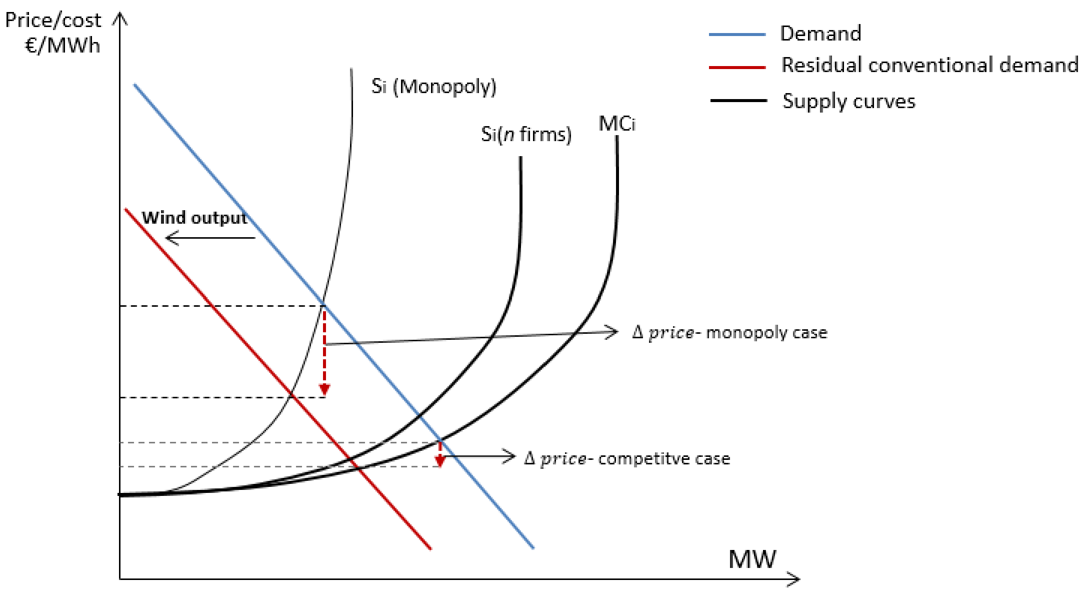


Figure 2 illustrates the impact on price of integrating renewable energy in cases of both perfect competition and market power based on the principle of Nash equilibrium and Green and Newbery [1992]'s supply function equilibrium model, where supply functions for conventional firms are bounded between the monopoly solution $S_i(Monopoly)$ and the Bertrand-Nash solution MC_i. RES integration shifts the demand curve to the left (residual demand curve) and reduces the market price accordingly. The closer the supply function approaches $S_i(Monopoly)$, the greater the extent of price change will be as demonstrated by the difference in magnitude between Δ *price* in the monopoly case and in the competitive case in figure 2. We illustrate these analyses more formally using a simple market model in Appendix A1.

Empirical studies of the impact on wholesale prices of introducing RESs have multiplied in recent years, e.g Gelabert et al. [2011], Würzburg et al. [2013], Ketterer [2014], Cludius et al. [2014], Clò et al. [2015], Woo et al. [2016]. However, the explicit link between wind integration and market power in both theoretical and empirical frameworks remains a potential area for investigation. In the engineering literature, Bitar et al. [2012], for example, investigate how an independent wind power producer might optimally supply its variable power to a competitive electricity market, Dai and Qiao [2013] analyze the optimal bidding strategies of wind and conventional power producers, and Kazempour and Zareipour [2014] study electricity market equilibria in the presence of renewable supplies.

In the economic literature, Twomey and Neuhoff [2010] was perhaps among the first papers to address the issue of RES introduction and market power in a theoretical framework with the consideration of forward contracts. The authors show that under market power conditions, thermal generators with market power can react strategically to the level of wind output: they can further depress prices if they have to buy back energy at times of plentiful wind output and can raise prices if they have to sell additional power at times of little wind output. Thus, while it is difficult to avoid all market power in electricity markets, allowing market power profit margins as a support mechanism for investment in generating capacity is not a technologically neutral policy[2]. Acemoglu et al. [2017], recently extended the analyses to account for the diversification of thermal generators' energy portfolios. They found that if thermal generators control some or all of the renewable supplies, they offset losses from the merit-order effect by strategically withholding their conventional energy supplies when renewable supply is abundant. The authors suggest that diversified energy portfolios might be welfare reducing. Ciarreta et al. [2017] propose a more detailed study of strategic behaviors by each thermal generator. They find that while nuclear, hydro-power, or coal generators do not change their behaviors, combined cycle bidding strategies have evolved to adapt to the introduction of RESs. The authors argue that, in the short run, the massive entry of RESs may make conventional generators' behavior more competitive. In an empirical framework, Bigerna et al. [2016], using data from 2009 to 2013 to construct the residual demand curves and compute the zonal Lerner indexes for main

[2] A limited amount of market power is sometimes accepted if it is necessary to guarantee revenues to cover some of the fixed costs and/or encourage capacity expansion.

generators in the Italian wholesale market, find that market power was considerably weakened by RES competition during peak hours, yet it was exacerbated during some off-peak hours, in the absence of solar power and in particular zones in which congestion led to market splitting. However, the application of such a method requires detailed bid data (Newbery [2009]).

In line with this literature, we propose an empirical investigation of the French electricity market in the context of cross-border analysis using historical time-series data. We study whether German massive RES production (both wind and solar) has induced price falls and competitive behavior in the French wholesale electricity market. While empirical strategies to measure the impact of RESs on wholesale prices are relatively straightforward thanks to the exogeneity of RES data, the impact of RESs on market power level is more challenging due to the problem of identifying the market power parameter.

3 Empirical application

3.1 Empirical model for identifying market power parameter

In this section, we present empirical model used to identify market power. We then extent it to account for solar and wind power output. We base the analyses on aggregate market data and use insights from New Empirical Industrial Organization (Porter [1983] Bresnahan [1989]), which has been widely developed for the electricity market by Hjalmarsson [2000], Bask et al. [2011], Mirza and Bergland [2015], Meritet and Pham [2015] in a dynamic formulation.

Consider the firm-level profit:

$$\pi^i = P(Q,X)q_i - C^i(q_i,W), \qquad \text{for } i = 1,\ldots,m \tag{1}$$

where $P(.)$ is the inverse demand function, P is the price, Q is the quantity demand, X is a vector of exogenous variables affecting demand, q_i is the firm-level output, C^i is the firm-level cost function with W a vector of input prices. The first-order condition for the profit maximizing firm is to equate the perceived marginal revenues (MR_p) with marginal costs (MC):

$$P(Q,X) + q_i P'(Q,X)\frac{\delta Q}{\delta q_i} = MC^i(q_i,W) \tag{2}$$

Since firm-level data is generally unavailable, equation 2 is aggregated over all firms to give the general form of the industry-level supply relation.

Let the demand and supply relation (2) be linear. Price elasticity of demand is retrieved from the aggregate demand function:

$$Q = D(P,X,\alpha) + \varepsilon \tag{3}$$

where α is a vector of parameters of the demand function to be estimated and ε is the error term.

The industry supply relation takes the relation in Eq(2) and empirically gives:

$$P = MC(Q, W, \beta) - \lambda.h(P, X, \alpha) + \eta \tag{4}$$

he where β is the vector of parameters of tsupply function with η the error term. $MC(.)$ designates the marginal cost function. $P + \lambda h(.)$ is the marginal revenue as perceived by the firm (MR_p) with $h(P, X, \alpha) = Q/\frac{\delta Q(.)}{\delta P}$ being the semi-elasticity of market demand. The demand-side parameters and exogenous variable are in $h(.)$ because they affect the marginal revenue. In perfect competition $MC = MR_p = P$ and $\lambda = 0$, but when market power is present, $MR_p < P$ and $0 < |\lambda| < 1$. λ is now a new parameter indexing the degree of market power. From (4), the price-cost margin can be derived as: $P - MC = -\lambda.Q/\frac{\partial Q(.)}{\partial P}$. Lerner's measure is given by:

$$L \equiv \frac{P - MC}{P} = -\lambda \frac{Q}{P}\frac{\partial Q(.)}{\partial P} = -\frac{\lambda}{\varepsilon} \tag{5}$$

where ε is the market elasticity of demand. Because λ lies in the closed set [0,1], it follows that $L \in [0, 1/\varepsilon]$ with $\varepsilon < 0$. Thus, λ can be interpreted as an index of market power[3].

The remaining problem is to identify λ. Bresnahan [1982] and Lau [1982] give conditions on the functional form such that λ is identified by introducing a vector Z, entering the model to both shift and change the slope of the demand curve (rotation vector PZ). The supply relation (4) in linear form is given as:

$$P = \beta_Q Q + \beta_W W + \lambda Q^* + \eta \tag{6}$$

with $Q^* = Q(\alpha_P + \alpha_{PZ} Z)^{-1}$. By treating α_P and α_{PZ} as known (from estimating the demand equation), λ is now identified and takes a negative sign if market power is present under the condition (4)[4]. Another way to identify the market power parameter λ is to allow quantity to interact with input prices (Devadoss et al. [2013]).

Empirical strategy: contemporaneous correlation between the error terms

The electricity industry has a distinguishing feature which makes modeling it different from other markets. Due to the combination of the high variability of demand for electricity and the non-storability of electricity, there are 24 different prices for the 24 hours of each day. However, these outcomes are published **simultaneously** the day ahead. Consequently, the 24 hourly prices should not be treated as continuous observations. Any attempt to model electricity prices should take this into account.

[3] λ is also referred to in the literature as the industry-level conjectural elasticity. In equation 2, $\lambda = \sum_{i=1}^{m} \frac{q_i}{Q} \lambda_i$

[4] The inclusion of the rotation variable PZ in the demand function is crucial for identifying the degree of market power. If we exclude PZ from the demand function, equation (6) would be rewritten as $P = \phi Q + \beta_W W + \eta$ where $\phi = (\beta_Q - \frac{\lambda}{\alpha_P})$. The supply relation is still identified but the degree of market power λ is not. The ϕ that we estimate cannot tell us the degree of market power λ because it depends on both β_Q and λ, thus the supply relation (tracing market power) will be indistinguishable from the supply curve (representing perfect competition).

One common way to treat the data in this market is to implement a multivariate model, as done by Crespo Cuaresma et al. [2004], Bordignon et al. [2012]; Weron and Misiorek [2008]. This method is appealing because it can capture coefficients for separate hours. However, there will be too many parameters to estimate as we increase the number of exogenous variables and instruments. A condition under which the issue of having too many parameters can be solved is to assume contemporaneous correlation between the error terms. This assumption says that the error terms in different equations, at the same point in time, are correlated. Indeed, these errors contain the influence on demand and supply that have been omitted from the model, such as changes in market regulation, the general state of the economy. Since the individual hourly prices share a common dynamic in many respects, it is likely that the effects of the omitted factors on hour, say h8, will be similar to their effect on hour h9. If so, then the error terms $\varepsilon_t^{(h8)}$ and $\varepsilon_t^{(h9)}$ as well as $\eta_t^{(h8)}$ and $\eta_t^{(h9)}$ will capture similar effects and will be correlated (Keppler et al. [2016], Huisman et al. [2007]).

We develop a structural model in a panel framework that allows for a common dynamic across all hours and a variation in the coefficients for each hour. With h denotes hours $h = 1 \ldots 24$ and t denotes days $t = 1 \ldots T$, the resulting econometric model for one-way error component panel framework is:

Demand equation:

$$Q_{ht} = \alpha_0 + \gamma Q_{ht} + \alpha_P P_{ht} + \alpha_Z Z_{ht} + \alpha_{PZ} P Z_{ht} + \varepsilon_{ht} \tag{7}$$

with

$$\varepsilon_{ht} = \mu_h + \upsilon_{ht} \tag{8}$$

where μ_h denotes the *unobservable* hour-specific effect and υ_{ht} denotes the remaining disturbance in the one-way error component panel model.

Supply relation:

$$P_{ht} = \beta_0 + \phi P_{ht} + \beta_Q Q_{ht} + \beta_W W_{ht} + \lambda Q^*_{ht} + \eta_{ht} \tag{9}$$

with

$$\eta_{ht} = \nu_h + \tau_{ht} \tag{10}$$

where ν_h denotes the *unobservable* hour-specific-effect and τ_{ht} denotes the remaining disturbance in the one-way error component panel model.

Model extension: Introducing wind and solar production

To implement parametric tests for a possible shift in the market power parameter λ due to RES integration, we need to extend the model. Two new variables - wind output (*wind*) and solar output (*solar*) - are included in the supply relation (9) in such a way that they interact with Q^*:

$$P_{ht} = \beta_0 + \phi P_{ht} + \beta_Q Q_{ht} + \beta_W W_{ht} + \lambda Q^*_{ht} + \lambda^{wind} Q^{*wind}_{ht} + \lambda^{solar} Q^{*solar}_{ht} + \eta_{ht} \quad (11)$$

λ^{wind} and λ^{solar} are estimated separately because of the high variation of solar data, whose values vary significantly across the hours. This confirms the relevance of our empirical strategy, which allows for this variation.

3.2 Data

The data concern the period from 27/10/2009 to 20/07/2015, providing a very rich panel dataset. Hourly data for electricity spot prices (in €/MWh) and volume traded (in GW) in the French wholesale electricity market are collected from the European Exchange market[5].

Electricity prices exhibit a strong seasonality in the intra-day, daily, weekly and seasonal dynamics due to the strong seasonality of demand for electricity. For example, demand is lower in the weekend and particularly on public holidays due to reduced economic activity. It is higher on average in winter than other seasons of the year due to the high need for electricity for heating in winter. To control for the bank holiday effects, we include a dummy variable which takes the value of 1 at weekends and on public holidays in France and 0 otherwise (Bessec et al. [2016]). To deseasonalize the demand series, we include a set of dummy variables in the demand function: for each season $\sum_{S=1}^{3} S_t$ where S stands for seasons of the year (Hickey et al. [2012]).

The two main exogenous factors affecting the demand for electricity are temperature (demand for heating) and the length of the day (demand for lighting)[6]. Temperature is a purely exogenous instrument for identifying the supply relation and a major determinant of European electricity consumption (Bessec and Fouquau [2008]). In France, this influence is particularly noticeable in winter with the usage related to heating. We use the national temperature index constructed from a range of meteorological stations (32) distributed optimally throughout France for each hour[7]. Hourly temperature date are published by ERDR (the French distribution system operator). The influence of the length of day on electricity usage is represented through the demand for lighting. This is calculated based on the time duration from sunrise to sunset in France. Daylength is available at daily frequency.

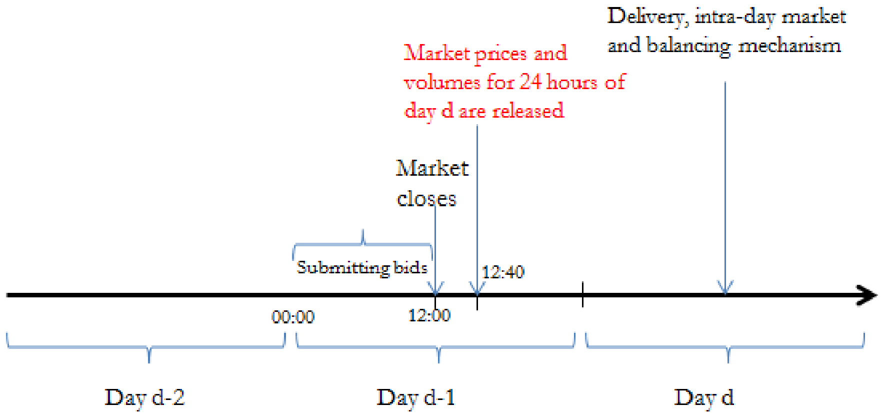
[5]The turnover in the French wholesale electricity market is used to estimate the demand function (7) (Hjalmarsson [2000], Bask et al. [2011]). Though a relatively small part (about 15% in 2014) of the total load, this spot demand is subject to price elasticity unlike total demand, of which a large proportion is sold at regulated tariffs in the retail market or is subject to long term transactions. However, in estimating marginal cost and the supply relation, it is vital to take full account of the total demand.

[6]Other usages that consume electricity are industrial activities and transportation. However, aggregate industrial production is relatively stable for hourly and daily patterns. Seasonal variations are more apparent. This is largely controlled for in the model through the inclusion of dummy variables for season. Electricity consumption for transportation can be varied at hourly frequency but seems to exhibit less stochastic properties than other factors such as Temperature. A large part of its variation is captured through fixed hours effects.

[7]The temperature difference among regions is also covered by the national temperature data.

The main exogenous variables in the input price vector W of the supply equations include: forecasted total load, gas price, carbon price, capacity margin, total net exchanges with Germany, Spain, the UK, Switzerland and Italy; and German RES production (wind and solar), which are available at hourly frequency except for gas and carbon prices. We take into account the time release of spot prices and volumes in defining other explanatory variables in the supply equation: any information released after market clearing (at noon) will be considered in lagged $(t-1)$ – Figure 3.

Figure 3: Time framework of market information release



Forecasted total load gives information about which technology should be mobilized in the merit order, thus helping to determine the marginal plant as well as marginal cost. We used the 24 hourly day-ahead forecasted load data for continental France released by the RTE at midnight on day $t-1$.

We used gas and carbon prices as the main drivers for the marginal costs of the supply relation. Although gas plants make up a very small part of the electricity mix in France (10%), they might affect French electricity market prices following the merit-order logic discussed in section 2. Because the French market is connected with neighboring countries' networks, the marginal plants of the interconnected zone are most of the time coal or gas plants, which constitute half of electricity production in Germany or Italy (Champsaur et al. [2011]). The European Gas Index (EGIX) published by the European Energy Exchange (EEX) was used[8]. The carbon price represents an additional cost for electricity generated from fossil fuels. It may be either a direct cost, if CO2 allowances are purchased, or an opportunity cost, if allowances are received free of charge (De Perthuis and Jouvet [2011]). Thus, electricity producers add the carbon price to their marginal costs. We used the European Emission Allowances prices which are released by EEX on a daily basis. To avoid any endogeneity problems, we used lag-1 of gas and carbon price (Bessec et al. [2016]).

[8]This index is based on all exchange trades concluded in the respectively current front month contracts of the NCG and GASPOOL market areas on the Derivatives Market. On the basis of these trading transactions EEX then calculates a volume-weighted average price across all transactions.

Forecasted cross-border net traded volumes with the neighboring countries in the interconnected zone (Belgium, the UK, Germany, Spain, Italy, and Switzerland) are also taken as factors which alter marginal cost. The French transmission system operator RTE provides the balance for each hour at the end of the afternoon for the following day. For this reason, we used lag-1 values.

The capacity margin, which refers to the difference between the available generating capacity and forecasted load, is also used as input prices. When the margin is large, only the least costly generating means are used, resulting in low system marginal costs and spot prices. Conversely, if there are tensions on electricity system (the margin is small), the more expensive generating means are used, increasing daily auction prices. The RTE publishes the forecasts for the capacity margin of the French electricity grid for the morning and evening peak-load times every day at 8 p.m. We used the margin of the morning peak available throughout the year.

We included German wind and solar power generation in the marginal cost function of the French day-ahead market to estimate the cross-border merit-order effect, as given in Equation (A.15). Wind and solar outputs per quarter-hour were collected from different German transmission system operators (Tennet TSO, 50 Hertz, Amprion, EnBW). We took the average of four quarter-hours to get the hourly data.

Table 1: Descriptive statistics

Variable	Unit	Mean	Median	Sd	Skewness	Kurtosis
Price	€/MWh	43.3	43.47	18.58	2.784	77.15
Turnover	GW	7.078	6.694	2.067	1.503	6.364
German wind	GW	5.38	3.847	4.898	1.69	6.321
German solar	GW	2.797	0.124	4.737	1.989	6.388
Total load	GW	55.17	53.25	12.59	0.528	2.642
Temperature	Celcius	12.42	12.5	6.519	-0.0748	2.28
Daylength	Hours	12.12	12.22	2.724	-0.0286	1.574
Gas price	€/MWh	21.17	22.55	5.247	-0.815	2.575
Carbon price	€/t C02	9.406	7.67	4.091	0.229	1.656
Capacity Margin	GW	7.535	7.063	2.685	0.903	3.996
Net exchanges Germany	GW	-0.807	-1.132	1.684	0.292	1.892
Net exchanges UK	GW	0.873	1	1.13	-0.989	3.111
Net exchanges Belgium	GW	0.897	0.991	1.237	-0.178	1.96
Net exchanges Spain	GW	0.247	0.264	0.782	-0.172	1.632
Net exchanges Italy	GW	1.935	2.256	0.791	-0.687	2.597
Net exchanges Switzerland	GW	2.334	2.569	0.811	-1.296	4.775

Sample period: 27/10/2009 to 20/07/2015, yielding $N = 2092$ for gas, carbon price, and daylength, which are of daily frequency, and $N = 50208$ for prices, turnover, temperature, total load, volumes of net exchanges, capacity margin, wind and solar outputs, which are of hourly frequency.

Table 1 shows summary statistics for sample variables. Skewness and kurtosis suggest a non-Gaussian distribution of price data. Skewness is highly positive and the kurtosis is at a very high level, indicating the presence of extreme values. Several non-linear econometric models have been developed in the literature to take into account this feature of price data, such as the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model or switching models (Markow switching and threshold autoregressive). However, estimating these non-linear parameters in our modeling context is intractable. We therefore decided to remove those extreme observations from our regressions (Cuaresma et al. [2004])[9]. Several unit root tests (Augmented Dickey-Fuller, Phillips Perron, Levin-Lin-Chu, and Im-Pesaran-Shin) were applied to each variable; all series were found to be stationary at the usual significance levels[10].

4 Empirical results

We estimated both the demand function (7) and the supply function (11). Because we encountered the problem of endogeneity in both demand and supply functions, these models were estimated using the two-stage generalized method of moments (GMM). We used Stock-Watson bias-corrected heteroscedastic-robust standard errors (SEs) to make the estimates robust against any problem of heteroscedasticity. The cluster-robust SEs, proposed by Miller et al. [2009] and Thompson [2011], were used to assure that the estimators are consistent to arbitrary within-panel autocorrelation.

We introduced lag terms of dependent variables for two equations (7) and (11). The bias induced from the correlation between lagged variables $y_{h,t-i}$ (lagged Q and lagged P) and μ_h and ν_h components was corrected by including the fixed effects (FE) estimator (Within transformation). Nickell [1981] shows that the dynamic panel models with fixed effects are biased of $(1/T)$ but as $T \longrightarrow \infty$, the fixed-effects estimator becomes consistent because the bias would not be large. Furthermore, the fixed effects models seem to be a more appropriate specification for our dataset in which the individual dimension N (hours) is relatively small. Thus, it would not lead to a loss of degrees of freedom. We justified this choice by Hausman specification test (Hausman [1978]), which assumes the random effects (RE) estimator to be fully efficient under the null hypothesis. The results of the Hausman test gave the overall statistics, $\chi^2(7)$ for the demand equation and $\chi^2(13)$ for the supply relation, having $p - value = 0.000$. This led the clear rejection of the null hypothesis that RE provides consistent estimates.

In the following, results for the demand function (7) and supply relations (11) are presented in turn.

[9] We detected the outliers by a non-parametric method, i.e. removing the values smaller than the lower outer fence $(Q1 - 3 * IQ)$ or greater than the upper outer fence $(Q3 + 3 * IQ)$ where $Q1$ and $Q3$ are the lower and upper quartiles (defined as the 25th and 75th percentiles) and IQ is the interquartile range, defined as $Q3 - Q1$.

[10] Even though the Fisher-type tests cannot reject the null hypothesis (presence of unit-root) of the gas price variable, the Levin-Lin-Chu and Im-Pesaran-Shin tests suggest a stationary variable. We decided to keep the gas price in level in the final specifications.

4.1 Demand function

The two-stage generalized method of moments (GMM) was employed to estimate the demand function (7). To be able to identify the degree of market power, we let the spot price interact with temperature Hjalmarsson [2000], Bask et al. [2011]. This interact term ($P * Temp$) enters the demand equation to both shift the demand curve and change the slope of demand by prices (Bresnahan [1982], Devadoss et al. [2013]). It is considered endogenous and needs to be instrumented in the demand regressions.

To control for endogeneity in P_{ht} and $P_{ht} * Temp_{ht}$, the matrix of excluded variables including lagged (1) values of carbon prices, gas prices and exchange balances with neighboring markets as well as lag-1; lag-7 of power price and forecasted load are used as instruments. The results of the first stage were convincing with very high R^2 and F-statistics (Summary results for first-stage regressions including under-identification and weak-identification tests are presented in A.2.6).

Table 2: Second stage GMM estimation results of the demand equation

Variables	**coef**	**Robust Std.Err**	**t_stat**	**p-values**	**[95% Conf.Interval]**	
Price	-0.0253***	(0.000783)	-32.34	0.000	-0.0268	-0.0238
P*Temperature	0.00117***	(8.80e-05)	13.30	0.000	0.000999	0.00134
Turnover(-1),	0.778***	(0.00211)	368.8	0.000	0.773	0.782
Temperature	-0.0860***	(0.00389)	-22.09	0.000	-0.0936	-0.0783
Daylength	0.0214***	(0.00314)	6.815	0.000	0.0153	0.0276
Holidays	-0.520***	(0.0281)	-18.51	0.000	-0.575	-0.465
Summer	-0.0539***	(0.00854)	-6.317	0.000	-0.0706	-0.0372
Spring	-0.159***	(0.00757)	-21.04	0.000	-0.174	-0.144
Fall	-0.0422***	(0.0105)	-4.006	0.000	-0.0629	-0.0216

Robust standard errors in parentheses; $* * *p < 0.01, * * p < 0.05, *p < 0.1$

We included autoregressive distributed lag terms to get the long-term parameters (Hjalmarsson [2000], Bask et al. [2011]). We started with $k = 7$ then tested our models by excluding non-significant lags. The results suggest that only the lag-1 of the turnover Q is kept. This can be an issue when there is a one-day public holiday, which we would not expect to impact on demand the following day. That is why we introduced the variable *Holiday* which accounts for weekend and public holiday effects.

The second stage GMM estimation results for the demand function are reported in table 2. The parameter estimates are highly significant and have the expected signs. The coefficient associated with *Price* has a negative sign as expected in a standard demand equation. This is a highly important result because it shows that our instruments successfully identified the demand equation. The elasticity of demand by price remains relatively low as expected in the electricity market: $e_P = \alpha_P * \frac{\overline{P}}{\overline{Q}} = -0.154\%$ (-0.164 and -0.145 at 95% CI). The coefficient of *Temperature* is negative, suggesting that demand for electricity decrease with the increase in temperature.

This is because electricity demand in France is highly sensitive on cold days due to heating needs. The corresponding elasticity of demand by temperature is $e_{temp} = \alpha_{temp} * \frac{\overline{temp}}{\overline{Q}} = -0.15\%$ (-0.16 and -0.13 at 95% CI). However, the positive sign of $P * Temperature$ suggests that the elasticity of demand by price tends to increase when temperature increases and the demand is also less elastic to temperature when prices are high. The remaining coefficients are also significant and have the expected signs: Demand tends to be higher with longer Daylength (explained by electricity consumption for lighting) and tends to be lower at weekends and on public holidays (due to the reduction of industrial activities or transportation uses). As expected, demand for electricity is greater in winter with the presence of cold days (the coefficients associated with *Summer*, *Spring*, and *Fall* are significant and negative).

4.2 Supply relations and the market power parameter

The two-stage generalized method of moments (GMM) was employed to estimate the supply relations (11). The excluded variables temperature and daylength were used as instruments to identify the supply functions. We kept the autoregressive terms $AR(1-7)$. In the final specification, marginal costs were assumed to be quadratic in the quantity (Kim and Knittel [2006]). Summary results for first-stage regressions including under-identification and weak-identification tests are presented in A.2.7. The second stage GMM estimation results for the supply relations are reported in table 3.

The parameter estimates for the supply function are also generally significant and have the expected signs, suggesting that the model's estimates have well measured the sensitivity of marginal cost to cost shifters. The results show that the marginal cost is convex in quantity (the coefficient associated with *Load* is positive and that with *Load_squared* is negative). Both gas price and carbon price tend to have positive impacts on electricity prices. As explained earlier, though the share of gas and coal generation technologies account for a very small part of the total annual marginality duration in France, the marginality of gas and coal on electricity prices in France is explained mostly through exchanges with neighboring countries like Germany and Italy where gas and coal represent a large share of the technology mix (the cost for carbon emissions is the highest for coal plants). Both wind and solar output from the German electricity market are found to have a significantly negative impact on French spot prices; i.e, the cross-border merit-order effect of RES output is suggested to be significant between France and Germany. The cross-border merit-order effect of wind is higher than that of solar: An extra 1 GW of wind output in Germany tends to reduce electricity prices in France by 0.325 €/MWh and an extra 1 GW of solar output in Germany tends to reduce electricity prices in France by 0.0672 €/MWh on average, *ceteris paribus*.

The market power parameter, λ, associated to Q^* in the supply relation is statistically significant and has a negative sign. This proves that market power was present in the electricity market in France during the studied period even though it was relatively weak. Price-cost

Table 3: Second stage GMM estimation results of the supply equation

Variables	**coef**	**Robust Std.Err**	**t_stat**	**p-values**	**[95% Conf.Interval]**	
Q*	-0.00428***	(0.00134)	-3.187	0.00144	-0.00691	-0.00165
Q*wind	0.000270***	(9.67e-05)	2.796	0.00518	8.08e-05	0.000460
Q*solar	0.000293***	(8.63e-05)	3.390	0.000700	0.000123	0.000462
Load	0.874***	(0.129)	6.763	0.000	0.621	1.127
Load_squared	-0.00379***	(0.00104)	-3.663	0.000249	-0.00582	-0.00176
Gas price	0.594***	(0.0337)	17.65	0.000	0.528	0.660
Capcity Margin	-1.065***	(0.0452)	-23.56	0.000	-1.154	-0.976
Carbon price	0.326***	(0.0340)	9.588	0.000	0.259	0.392
German wind	-0.325***	(0.0317)	-10.22	0.000	-0.387	-0.262
German solar	-0.0672*	(0.0366)	-1.836	0.0663	-0.139	0.00453
Net exchanges Germany	0.143**	(0.0611)	2.334	0.0196	0.0229	0.262
Net exchanges UK	-0.275***	(0.105)	-2.619	0.00882	-0.481	-0.0692
Net exchanges Belgium	-0.295***	(0.0934)	-3.162	0.00157	-0.478	-0.112
Net exchanges Spain	0.643***	(0.125)	5.141	2.74e-07	0.398	0.889
Net exchanges Italy	-0.893***	(0.183)	-4.870	1.12e-06	-1.253	-0.534
Net exchanges Switzerland	-0.686***	(0.151)	-4.541	5.61e-06	-0.982	-0.390
Holidays	-3.918***	(1.209)	-3.240	0.00119	-6.287	-1.548
AR (1)	0.272***	(0.0167)	16.27	0.000	0.239	0.305
AR (2)	0.0356**	(0.0169)	2.102	0.0356	0.00240	0.0688
AR (3)	0.0485***	(0.0136)	3.578	0.000347	0.0219	0.0751
AR (4)	0.0515***	(0.00741)	6.960	0.000	0.0370	0.0661
AR (5)	-0.0113	(0.0150)	-0.750	0.454	-0.0407	0.0182
AR (6)	0.0680***	(0.0101)	6.731	0.000	0.0482	0.0879
AR (7)	0.0991***	(0.0160)	6.202	5.59e-10	0.0678	0.130

Robust standard errors in parentheses; $***p < 0.01, **p < 0.05, *p < 0.1$

margins (Lerner Index) in the short and long term were estimated using equation (5) and presented in the table 4. The long-term parameter was obtained by incorporating the adjustment speed, $1-\sum_{i=1}^{k}\gamma_i$, where γ_i are estimated parameters for AR_k (Steen and Salvanes [1999]). They are both statistically significant but remain at relatively low levels: prices are suggested to be 0.27% in the short run and 0.14% in the long run above the marginal cost (at industry-level). However, this effect tends to further decrease with increasing import of wind and solar power from Germany. The parameters λ^{wind} and λ^{solar} in equation (11) are both significant and have positive signs. This implies that when wind and solar production increases, the negative value of λ becomes less obvious. It further implies that German RES outputs mitigate the extent of market power level in France. These results support previous theoretical work and simulations such as Twomey and Neuhoff [2010] and Ciarreta et al. [2017].

Table 4: Estimated Lerner Indexes

	Estimates	Std. Err.	t-stat	$p-values$	[95% Conf.	Interval]
LI_short term	0.0276171	0.0086658	3.19	0.001	0.0106324	0.0446018
LI_long term	0.0144364	0.0045429	3.18	0.001	0.0055324	0.0233404

It is important to note that mark-ups were found to be significant in France but relatively low during the studied period. This is probably related to an extremely tightly regulated model in the French electricity market. Indeed, the volumes traded in the "market" segment make up only 15-17% of domestic delivery and there were regulated tariffs in this market, which were generally lower than the market prices[11]. This latter further reduced market liquidity in the electricity sector in France. Accordingly the level of estimated mark-ups should be interpreted in this context.

4.3 Cross-border effects

Based on the results of RES coefficients obtained from the regression of the supply function, the average cross-border merit-order effect as well as the annual financial volume of the merit order-effect can be estimated (as in Sensfuss et al. [2008]; Cludius et al. [2014]) by:

$$v = \Delta RES * Demand = \beta_{RES} * \overline{RES} * Demand \tag{12}$$

where v (in €) refers to the annual financial volume of cross-border merit-order effect created by German wind or solar power generation in the French day-ahead market; ΔRES (in €/MWh) is the average cross-border merit order which is equal to the specified effects multiplied by the volume weighted wind or solar generation. These values are estimated for every year of 2010 to 2014 and given in table 5.

Table 5: Volumes of cross-border merit order effects

	2010			2011			2012			2013			2014		
	Coef.	*[95%*	*CI]*	Coef.	*[95%*	*CI]*	Coef.	*[95%*	*CI]*	Coef.	*[95%*	*CI]*	Coef.	[95%	*CI]*
$\Delta Wind$	**1.34**	*1.6*	*1.09*	**1.69**	*2.01*	*1.37*	**1.69**	*2.02*	*1.37*	**1.94**	*2.32*	*1.57*	**2.08**	*2.48*	*1.68*
$\Delta Solar$	**0.05**	*0.11*	*0*	**0.15**	*0.31*	*0.01*	**0.21**	*0.44*	*0.01*	**0.23**	*0.48*	*0.02*	**0.26**	*0.53*	*0.02*
v (b€)	**0.68**	*0.81*	*0.55*	**0.8**	*0.95*	*0.65*	**0.82**	*0.97*	*0.66*	**0.94**	*1.12*	*0.76*	**0.95**	*1.14*	*0.77*

The average impact of German wind integration on French electricity wholesale prices varies between 1.34 €/MWh in 2010 and 2.08 €/MWh in 2014. The average cross-border merit-order effect created by German solar power, though less significant than that of wind power[12], increased significantly from 0.05 €/MWh in 2010 to 0.26 €/MWh in 2014. The total annual financial volume in the French market is estimated to be between €0.68 billion in 2010 (0.81 and 0.55 at 95% CI) and €0.95 billion in 2014 (1.14 and 0.77 at 95% CI). This non-negligible amount of financial volumes created by German RES production benefited only a privileged group of consumers in the French wholesale market, mainly energy-intensive companies. This result suggests a possible wealth transfer from German households, who bear the cost of supporting

[11] For example, TARTAM "Tarifs réglémentés transitoires d'ajustement au marché ", or, more prosaically "tariff of return" or ARENH (Regulated access to historical nuclear energy) set by the government to protect consumers from high and volatile market prices.

[12] Note that the estimates given in table 5 are weighted values; i.e. the average effects of wind and solar power do not distinguish two possible cases: when high solar production coincides with high prices during peak-hours, the cross-border effect is assumed to be substantially higher than in the case of low solar output during off-peak hours.

RES through their electricity bills, to foreign industrial consumers, who benefit from lower prices in the wholesale electricity market.

Our results also demonstrate that German RES integration also induces market power mitigation in the French day-ahead market. Indeed, at national level, France has a high proportion of nuclear power in its electricity mix, which allows a relatively stable and flat marginal cost curve for most of the time. However, during peak-load periods, prices can reach very high levels (equal to or more than the marginal cost of the most expensive plants). With a high level of RES integration, the supply function is shifted to the right, causing the capacity utilization rates of high marginal cost coal- and gas-fired plant to fall. It is more difficult for incumbent firms to exercise market power in this case than when the mix is more diverse. Consequently, with a high share of RES supply, there would be less scope for conventional operators to exercise their market power by strategically withholding their capacity because withholding nuclear capacity would only be a profitable strategy if there were no higher-cost plants available and conditions were such that a firm would have so much nuclear capacity that it had nothing more expensive to withhold. Thus, the only means of exercising market power in this case is probably to withhold the capacity of hydro plants because they can react rapidly. But this choice is undoubtedly limited when the renewable output is high enough. This effect seems to be true for the cross-border analysis because when the transmission lines are not congested, massive RES output from Germany can flow to the French electricity market inducing the same effect in the French market.

4.4 Robustness check

In the above specifications, the demand function is assumed to be linear. As suggested in Kim and Knittel [2006], the NEIO estimates can be sensitive to functional form changes to demand. Our first robustness check alters the functional forms for the demand function and supply relations in log-linear forms. The results remain robust for almost all estimates (Table A.2.8 and A.2.9). Comparing the Akaike and Bayesian information criteria (AIC and BIC) among linear and log-linear models, the linear specifications (both demand and supply functions) give better model fit.

One shortcoming with our panel specification is that the estimates are not allowed to vary by peak and off-peak hours. The second robustness check adjusts our sample so that this is less of an issue. We implemented four sup-samples of the data corresponding to four demand profiles (Bessec et al. [2016]): the morning peak (from 8 am to 12 am); the afternoon trough (from 01 pm to 4 pm); the evening peak (from 6 pm to 11 pm) and the night trough (from 00am to 7am). The results suggest that demand is most elastic to price during the night trough and least elastic to price during the evening peak (Table A.2.10). The cross-border effects of German wind output on price levels in France are found to be significantly high except for the evening peak hours (-0.32 €/MWh during the night and about -0.571 €/MWh during the day for an additional GW of wind output, *ceteris paribus*). The cross-border effects of German solar output on price levels in France are insignificant during the evening and the night as expected due to the insignificant level of solar production for those hours. However, the merit-order effect of solar power is found to be particularly high in the afternoon trough hours: an additional increase of 1 GW of solar output in the German market would lead to a reduction of nearly 0.7 €/MWh of spot prices in the French market, *ceteris paribus*. Regarding the market power parameter, the results are less robust during the afternoon trough: λ is found to be significantly positive for those 4 hours (h13 to h16). As the results for the other 20 hours of the day are generally consistent with those found in table 4.2, we conclude that our estimates are robust.

5 Conclusion

In this paper we have estimated the impacts of wind and solar integration on electricity prices and on the market power parameter in the context of cross-border effects between France and Germany. We take advantage of unique hourly data that allow us to estimate the market power parameter at industry-level taking into account the variation in demand across hours. Our estimates, based on a sample of 24 hourly French wholesale prices from November 2009 to July 2015, suggest that RES integration can have a significant impact on cross-border power price dynamics, not only reducing prices but also mitigating the level of market power. These results have relevant policy implications for market power mitigation and for coordinated cross-border energy policies in European electricity markets. Given the high burden borne by German households to support RES development, it is crucial that renewable support policies should be discussed on an inter-state instead of a national basis.

Results such as these can be used to support a variety of follow-up analyses, as well as subsequent adjustments to firms' potential strategic behaviors. Our analyses assume that sufficient capacity is made available for wind output from German market to be transmitted to the French market and impact French electricity prices accordingly. However, as many previous studies proved, profit-maximizing firms can take advantage of network congestion moments to exercise their market power; firms knowing about their potential market power as transmission capacity binds could deliberately congest transmission lines to take advantage of it. This would become an issue when a firm has a diversified portfolio. The results of this article can thus be used as inputs for subsequent modeling, assuming that incumbent firms also own wind facilities and including further crossed effects of wind output and network congestion on firms' behaviors.

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A Appendix

A.1 Variation of mark-ups under RES integration and transmission constraints

In this appendix we use simple market models to demonstrate the variation in price-cost markup with respect to changes in RES output. In the first case, we assume sufficient transmission capacity is made available for the RES output from the German market to be transmitted to the French market and impact French electricity prices accordingly. In the second case, cross-border exchanges between France and Germany may be subjected to congestion because of transmission constraints.

We consider two different types of suppliers: (1) conventional generators whose collective output $Q_i = \sum_{i=1}^{n} q_i$ with q_i is supply of the ith firm; and (2) intermittent RES generators whose output is assumed to have a fixed and stochastic component $Q_{w,0} + \varepsilon_w$; with $E[\varepsilon_w] = 0$ and $Var[\varepsilon_w] = \sigma_w^2$. In both case we assume that RES outputs are produced by a set of competitive generators that offers all available outputs at zero marginal cost. They are subsequently rewarded at the price of the marginal bid. For more extensions on the diversification of energy portfolios, see Acemoglu et al. [2017].

The total demand will be equal to:

$$D = Q = Q_i + Q_{w,0} + \varepsilon_w \tag{A.13}$$

and the inverse market demand function is given by:

$$P = f(D) = f(Q) \tag{A.14}$$

which obeys the following conditions: (1) $f(0) > 0$; to ensures that there is a demand, (2) if $Q > 0$ and $f(Q) > 0$, then $f'(Q) < 0$; this condition is the common assumption that the demand curve slopes downward, (3) if $Q > 0$ then $Q.f(Q) \leq M$, where M is some finite number; this condition eliminates any chance for the firms to have infinite profits.

Firm i's *total cost function* is designated as $C_i(q_i)$ and obeys the following conditions: $C_i(q_i)$ must be strictly positive for all output levels [$C_i(q_i) > 0$ for $q_i > 0$]; marginal cost $MC_i = C_i'(q_i)$ should be positive [$C_i'(q_i) > 0$] and fixed cost must be non-negative [$C_i(0) > 0$].

Proposition 1: *The price-cost markup for the conventional generators is decreasing with increasing wind output, i.e.* $\frac{d(P-C')}{d\varepsilon_w} < 0$, *if marginal costs of the strategic generators, and thereby competitive prices, decrease with the increase of RES output* $\frac{dC_i^2}{d^2\varepsilon_w} \equiv C''_{i,\varepsilon_w} < 0$; $\frac{dP}{d\varepsilon_w} < 0$, *and conventional generation is reduced when RES integration increases* $\frac{dQ_i}{d\varepsilon_w} < 0$.

The profit equation for a strategic conventional generator i is given by:

$$\pi_i = Q_i(\varepsilon_w)P(Q_i, \varepsilon_w) - C_i(Q_i) \tag{A.15}$$

The Cournot oligopoly model assumes that oligopolists choose their output simultaneously given their rivals' output. From (A.15), the first-order condition can be written as:

$$P = C'_{i,Q_i} - P'_{i,Q_i}Q_i \tag{A.16}$$

which gives:

$$\frac{d(P - C')}{d\varepsilon_w} = \big[-P'_{i,Q_i}Q_i\big]'_{\varepsilon_w} = -\Big[\frac{dQ_i}{d\varepsilon_w}P'_{Q_i} + Q_iP''_{Q_i}\Big(\sum_i \frac{dQ_i}{d\varepsilon_w} + 1\Big)\Big] \tag{A.17}$$

Using the assumption $\frac{dP}{d\varepsilon_w} < 0$ and the condition from (A.16) gives:

$$\frac{dP}{d\varepsilon_w} = \frac{dQ_i}{d\varepsilon_w}\frac{dC_i^2}{d^2\varepsilon_w} - \frac{dQ_i}{d\varepsilon_w}P'_{Q_i} - Q_iP''_{Q_i}\Big(\sum_i \frac{dQ_i}{d\varepsilon_w} + 1\Big) < 0 \tag{A.18}$$

Substituting (A.18) and using the assumptions $\frac{dC_i^2}{d^2\varepsilon_w} \equiv C''_{i,\varepsilon_w} < 0$ and $\frac{dQ_i}{d\varepsilon_w} < 0$ gives

$$\frac{d(P - C')}{d\varepsilon_w} < -\frac{dQ_i}{d\varepsilon_w}C''_{i,\varepsilon_w} < 0 \tag{A.19}$$

Proposition 2: *The price-cost markup for the domestic conventional generators is decreasing with Import in the absence of transmission constraints and increasing as network congestion binds, if with increasing import, marginal costs of the strategic domestic generators, and thereby prices, decrease* $\frac{dC_i^2}{d^2I} \equiv C''_{i,I} < 0$; $f'(I) < 0$ *and strategic domestic generators' output reduce when import capacity increases* $\frac{dQ_i}{dI} < 0$.

In the case that cross-border exchanges are taken into account, total demand will be supplied by conventional generation and importing capacity ($D = Q = Q_i + I$), and the inverse demand function is given by $P = f(Q_i, I)$. For simplicity, we ignore wind output in this case. The profit equation for a strategic domestic generator, who chooses its output given import form its cross-border rivals, is written as:

$$\pi_i = Q_i(I)P(Q_i, I) - C_i(Q_i) \tag{A.20}$$

which follows the FOC (with respect to Q_i):

$$P = C'_{i,Q_i} - P'_{i,Q_i}Q_i \tag{A.21}$$

Calculating $\frac{d(P-C')}{dI}$ gives:

$$\frac{d(P-C')}{dI} = \big[-P'_{i,Q_i}Q_i\big]'_I = -\Big[\frac{dQ_i}{dI}P'_{Q_i} + Q_iP''_{Q_i}\Big(\sum_i \frac{dQ_i}{dI}+1\Big)\Big] \tag{A.22}$$

- Without transmission constraint: $I <$ Transmission Capacity$_{Max}$

  Using assumption $f'(Q) < 0$ and differentiating (A.21) with respect to I gives:

$$\frac{dQ_i}{dI}\frac{dC_i^2}{d^2I} - \frac{dQ_i}{dI}P'_{Q_i} - Q_iP''_{Q_i}\Big(\sum_i \frac{dQ_i}{dI}+1\Big) < 0 \tag{A.23}$$

  Substituting (A.23) to (A.22) and using assumptions $\frac{dC_i^2}{d^2I} \equiv C''_{i,I} < 0$ and $\frac{dQ_i}{dI} < 0$ gives:

$$\frac{d(P-C')}{dI} < -\frac{dQ_i}{dI}C''_{i,I} < 0 \tag{A.24}$$

- With transmission constraint: $I =$ Fixed Transmission Capacity$_{Max}$

  The price-cost markup for the strategic domestic generators will be equal to $-P'_{i,Q_i}Q_i$, which is strictly positive with $f'(Q) < 0$

A.2 Postestimation tests

Table A.2.6: Summary results for first-stage regression - Demand Equation

	F test of excluded instruments		Under -identification		Week identification	
Endogenous Var	F(10, 23)	P-val	SW Chi-sq (9)	P-val	SW F(9, 23)	P-val
P	8379.18	0.0000	6140.29	0.0000	653.64	0.0000
P*temp	1334.69	0.0000	7926.58	0.0000	843.8	0.0000

Table A.2.7: Summary results for first-stage regression - Supply Equation

	F test of excluded instruments		Under -identification		Week identification	
Endogenous Var	F(10, 23)	P-val	SW Chi-sq (9)	P-val	SW F(9, 23)	P-val
Q*	2.38	0.0619	14.9	0.0000	2.38	0.0619

Table A.2.8: Second stage GMM estimation results of the demand equation: Log-linear

Variables	coef	Robust Std.Err	t_stat	p-values	[95% Conf.Interval]	
Price	-0.00372***	(0.000169)	-22.00	0	-0.00406	-0.00339
P*temp	0.000205***	(1.77e-05)	11.58	0	0.000171	0.000240
AR1	0.0956***	(0.000398)	240.1	0	0.0948	0.0964
Temperature	-0.0151***	(0.000894)	-16.84	0	-0.0168	-0.0133
Daylength	-0.000216	(0.000308)	-0.702	0.483	-0.000819	0.000387
Holiday	-0.0688***	(0.00362)	-19.02	0	-0.0759	-0.0617
Summer	0.00414**	(0.00187)	2.219	0.0265	0.000483	0.00780
Spring	-0.0128***	(0.00132)	-9.690	0	-0.0154	-0.0102
Fall	0.00514***	(0.00156)	3.298	0.000973	0.00208	0.00819

Robust standard errors in parentheses; $***p < 0.01, **p < 0.05, *p < 0.1$

Table A.2.9: Second stage GMM estimation results of the supply equation: Log-linear

Variables	coef	Robust Std.Err	t_stat	p-values	[95% Conf.Interval]	
Q*	-0.000261***	(7.45e-05)	-3.507	0.000454	-0.000407	-0.000115
Q*solar	1.79e-05***	(5.11e-06)	3.495	0.000475	7.85e-06	2.79e-05
Q*wind	1.65e-05***	(4.89e-06)	3.377	0.000733	6.92e-06	2.61e-05
AR 1	0.00667***	(0.000823)	8.107	0	0.00506	0.00828
AR 2	0.000305	(0.000340)	0.897	0.370	-0.000362	0.000972
AR 3	0.00152***	(0.000421)	3.623	0.000291	0.000700	0.00235
AR 4	0.00169***	(0.000319)	5.284	1.26e-07	0.00106	0.00231
AR 5	-0.000726	(0.000499)	-1.455	0.146	-0.00170	0.000252
AR 6	0.000790**	(0.000400)	1.975	0.0483	6.05e-06	0.00157
AR 7	0.00294***	(0.000493)	5.965	2.45e-09	0.00198	0.00391
Load	0.0665***	(0.00385)	17.26	0	0.0589	0.0740
Load squared	-0.000461***	(2.98e-05)	-15.44	0	-0.000519	-0.000402
gas price	0.0134***	(0.00139)	9.623	0	0.0107	0.0161
Carbon price	0.00818***	(0.00133)	6.145	8.02e-10	0.00557	0.0108
Capacity Margin	-0.0359***	(0.00264)	-13.60	0	-0.0410	-0.0307
German wind	-0.0111***	(0.00232)	-4.790	1.66e-06	-0.0157	-0.00658
German solar	-0.00126	(0.00162)	-0.779	0.436	-0.00443	0.00191
Net exchanges Germany	-0.00515	(0.00353)	-1.456	0.145	-0.0121	0.00178
Net exchanges UK	-0.00993**	(0.00412)	-2.408	0.0161	-0.0180	-0.00185
Net exchanges Belgium	0.00157	(0.00534)	0.295	0.768	-0.00889	0.0120
Net exchanges Spain	0.0301***	(0.00670)	4.491	7.10e-06	0.0170	0.0432
Net exchanges Italy	0.00166	(0.00577)	0.287	0.774	-0.00965	0.0130
Net exchanges Switzerland	-0.000700	(0.00867)	-0.0807	0.936	-0.0177	0.0163
Holiday	-0.0776**	(0.0352)	-2.202	0.0276	-0.147	-0.00854

Robust standard errors in parentheses; $***p < 0.01, **p < 0.05, *p < 0.1$

Table A.2.10: Second stage GMM estimation results of the demand equations for four sup-samples

Variable	Night trough	Morning peak	Afternoon trough	Evening peak
Price	-0.0431***	-0.0279***	-0.0247***	-0.0111***
	(0.00409)	(0.00353)	(0.00384)	(0.00282)
P*Temp	0.00434***	0.00116***	-0.000142	0.000258
	(0.000413)	(0.000352)	(0.000272)	(0.000270)
AR1	0.785***	0.772***	0.721***	0.807***
	(0.00674)	(0.00787)	(0.00747)	(0.00670)
Temperature	-0.187***	-0.118***	-0.0157	-0.0262
	(0.0167)	(0.0208)	(0.0155)	(0.0165)
Daylength	0.0715***	0.0675***	-0.0139	-0.0155
	(0.00963)	(0.0119)	(0.0109)	(0.0113)
Holidays	-0.0461**	-0.849***	-1.199***	-0.394***
	(0.0209)	(0.0465)	(0.0387)	(0.0296)
Summer	0.0526	-0.00827	-0.276***	-0.0692
	(0.0596)	(0.0792)	(0.0657)	(0.0636)
Spring	-0.339***	-0.273***	-0.271***	-0.0476
	(0.0445)	(0.0532)	(0.0523)	(0.0490)
Fall	0.0296	0.0669	-0.0998**	-0.128***
	(0.0363)	(0.0464)	(0.0450)	(0.0397)
Observations	13,846	9,893	7,940	11,904
Number of hours	8	5	4	7

Robust standard errors in parentheses; $***p < 0.01, **p < 0.05, *p < 0.1$

Table A.2.11: Second stage GMM estimation results of the supply equations for four sup-samples

Variable	Night trough	Morning peak	Afternoon trough	Evening peak
Q*	-0.00347**	-0.00139*	0.0195***	-0.0275*
	(0.00168)	(0.000784)	(0.00745)	(0.0167)
Q*wind	0.000880**	9.44e-06	-0.00107**	0.00134*
	(0.000429)	(4.34e-05)	(0.000483)	(0.000801)
Q*solar	0.00302	0.000136*	-0.00117***	0.00359*
	(0.00184)	(7.06e-05)	(0.000444)	(0.00216)
AR1	0.340***	0.212***	0.174***	0.407***
	(0.0259)	(0.0173)	(0.0489)	(0.0704)
AR2	0.0238**	0.0456***	0.0636	-0.00423
	(0.0119)	(0.0113)	(0.0471)	(0.0972)
AR3	0.0523***	0.102***	0.0908**	-0.0151
	(0.00965)	(0.0155)	(0.0384)	(0.0710)
AR4	0.0273***	0.0587***	0.00222	0.193
	(0.00984)	(0.0138)	(0.0418)	(0.128)
AR5	-0.0213**	0.0735***	0.0300	-0.102
	(0.0103)	(0.0100)	(0.0412)	(0.101)
AR6	0.0255**	-0.00231	0.0678**	0.130**
	(0.0108)	(0.00967)	(0.0342)	(0.0535)
AR7	0.131***	0.0252**	0.0414	-0.0129
	(0.0101)	(0.0122)	(0.0373)	(0.0473)
Load	0.532***	0.818***	-0.517	0.289
	(0.0709)	(0.138)	(0.531)	(0.469)
Load squared	-0.00160**	-0.00377***	0.00487	0.00139
	(0.000655)	(0.00113)	(0.00394)	(0.00351)
Gas price	0.462***	0.728***	0.824***	0.268
	(0.0247)	(0.0436)	(0.102)	(0.204)
Carbon price	0.200***	0.342***	0.496***	-0.0277
	(0.0275)	(0.0386)	(0.111)	(0.322)
Capacity Margin	-0.983***	-1.265***	-1.667***	-1.410***
	(0.0385)	(0.0571)	(0.343)	(0.444)
German wind	-0.320***	-0.407***	-0.571***	0.148
	(0.0589)	(0.0211)	(0.112)	(0.261)
German solar	-	-0.170***	-0.691***	-
	-	(0.0349)	(0.142)	-
Net exchanges Germany	0.0714	0.114	0.316	-0.629
	(0.0837)	(0.0715)	(0.262)	(0.536)
Net exchanges UK	-0.619***	-0.449***	1.087**	-0.700
	(0.109)	(0.138)	(0.443)	(1.092)
Net exchanges Belgium	0.0405	-0.729***	-1.711***	0.536
	(0.0832)	(0.106)	(0.324)	(1.005)
Net exchanges Spain	0.395***	0.460***	1.043*	1.018
	(0.106)	(0.140)	(0.621)	(1.398)
Net exchanges Italy	0.123	-1.321***	-1.995***	-1.517
	(0.149)	(0.150)	(0.478)	(1.100)
Net exchanges Switzerland	-0.649***	-0.597***	0.615	0.666
	(0.152)	(0.202)	(0.652)	(1.356)
Holidays	-0.00388	-13.91***	-9.175***	-0.0959
	(0.233)	(0.517)	(1.849)	(2.807)
Observations	13,846	9,893	7,940	11,904
Number of hours	8	5	4	7

Robust standard errors in parentheses; $***p < 0.01, **p < 0.05, *p < 0.1$