

MARKET POWER IN POWER MARKETS: THE CASE OF FRENCH WHOLESALE ELECTRICITY MARKET

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ABSTRACT

The French wholesale market is set to expand in the next few years under European pressures and national decisions. In this paper, we investigate the performance of the French wholesale power market to examine whether or not the equilibrium outcomes are competitive. After a literature review on the different existing models, an extension of the Bresnahan - Lau (1982) method in panel data framework is employed with hourly dataset during 2009-2012 on the French wholesale market. The model-based results suggest that though market power is found statistically significant in several peak-load hours, it stays at very low level. On average, no market power is exercised over the examined period. These results correspond with the extremely regulated wholesale power market in France. It is of high interest given the future evolution of the French wholesale market which will be among the biggest in Europe in 2016 after the end of regulated tariffs for all firms.

Keywords:

Electricity, market power, France, oligopolistic market, panel data.

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1. INTRODUCTION

The electric power sector worldwide has experienced an exceptional policy trends that fundamentally reshaped the industry over the last 20 years: liberalization and deregulation, or more generally "electricity reform". This policy refers to a transition from economic model of "*vertical integration monopoly under regulation*" to a market-based system with regulatory restructuring. Reforming the electricity industry was much harder than it appeared at the first glance. One cannot simply break up the monopoly, cease to regulate and wait for the market forces to rush in making competition work. One of the problems arose from the shift to reliance on market prices instead of regulated tariffs for electric generation has been market power.

"Market power" is not a new and recent concept. It is defined in economics as the ability to alter profitably prices away from competitive level, i.e., the marginal cost level. Theoretical and empirical studies of "market power in electricity markets" however, have only been developed recently. It raises concerns in both sides of the Atlantic, as regard to the way of defining, detecting, and monitoring it. Up to the late 1980s, empirical studies of market power in liberalized generation electricity markets are scarce since it had rarely been contemplated outside the United States (Borenstein [2000]). Most studies had attempted to assess the potential for exercising market power by measuring the extent of market concentration in regional submarkets. Studies in Europe were developed a bit latter but were not out of this line. However, over the last 10 years, market power detection techniques have dynamically evolved, varying enormously from theoretical to empirical models, from market structure to market outcome approaches; from direct to indirect estimations, etc. Indeed, the issue arose for any attempt to assess market power level has been the calibration of marginal cost levels.

In this paper, we employ a structural model developed in New Empirical Industrial Organisation (NEIO), usually named as the Bresnahan-Lau (BL) method (Bresnahan [1982] and Lau [1982]), to investigate the exercise of market power. A great advantage of using this method is to overcome the problem of not knowing accounting datum of economic marginal cost. The BL method was extended in the dynamic framework taking into account time series' properties by Steen and Salvanes [1999] and popularized recently in electricity industry in Hjalmarsson [2000], Bask, Lundgren and Rudholm [2011], Mirza and Bergland [2012]. However, except for the last one, none of these papers take into account the distinguished feature of the data in electricity market. As mentioned, electricity is the unique good with a market where there exist 24 different prices for 24 hours per day due to the combination of strong variability of demand for electricity and non-storability of electricity. Most papers use daily or weekly aggregated data. This probably ignores the exercise of market power in short run and especially during the low-demand elasticity hours. In this paper, we consider a different modelling strategy: we treat the data as a panel framework. We apply this model to the French wholesale market.

The French wholesale market is the third largest in Europe after the German and British ones, and is about to change drastically. Following the European Commission decision, the regulated rates for electricity will discontinue in 2016 for small businesses on the retail market. Therefore, the number of electricity contracts

offered by suppliers with market prices will increase. That is why the French wholesale market should become more liquid with more participants in the near future. It is highly relevant to study the wholesale electricity prices in France at this stage. Indeed, there have been some doubts provoked in electricity market in France on the issue of market power as Electricité de France (EDF), the biggest producer of electric power in Europe, still dominates the domestic market after the reform. Moreover, despite the market opening, wholesale prices in France have drastically increased: the index of Pownext Baseload Forward Year Ahead almost tripled between 2004 and 2008, increasing even faster than oil price. The wholesale prices in France have been increasingly higher than those in Germany since the end of 2012 after a long period of strong price convergence between the two markets.

This paper analyzes the level of competition in the French wholesale markets. The extended Bresnahan-Lau [1982] model is conducted using the data from the French spot market during 2009-2012. In particular we attempt to address several issues which are still debatable in market power modelling, for example, the unknown accounting datum of economic marginal cost and the treatment of hourly data on electricity spot prices.

The paper proceeds as follows. In the first section, we present different models to investigate the exercise of market power in power markets that have been employed in literature. The second section describes the French electricity markets with a focus on the wholesale one. The third section explains our model which is an extension of Bresnahan-Lau [1982] and the data we used. The fourth section provides the results and some analysis. The last section concludes.

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2. DIAGNOSING MARKET POWER IN ELECTRICITY MARKETS

2.1 Electricity is a specific "good"

Electricity market exhibits unusual characteristics that make exercising market power particularly likely. First, the inelasticity of demand by prices in short term is one of fundamental flaw. Indeed, electricity is an essential good with very low elasticity of demand and most of the customers do not have means to respond to real time price. Second, several technical attributes in electricity make diagnosing market power particularly challenging. In fact, electricity cannot be stored economically on a large scale. The implication is that when capacity is tight, demand exceeds the maximum capacity there is no storage available, even a supplier with 1% of total output can have incentive to exercise market power (pivot actors). Furthermore, electricity is transmitted over a network and follows laws of physics.

The transmission system is quite fragile; any unexpected events like changes in customers' use or sudden loss of output at a generating plant can destabilize the network and make it congested. When transmission constraints bind at a given point of the network, no electricity can be imported/exported in/to the local area where there is congestion: the local suppliers become the only to sell electricity - they have market power. Therefore a merely high price spike observed in the market in certain hours can reveal nothing about the existence of market power. Unfortunately, high price spike in electricity are not uncommon, and it is extremely hard to distinguish

whether an abnormal high price is resulted from exogenous factors or abuse of market power. Any attempt to estimate market power in electric power markets needs to take into consideration these specific features of electricity.

2.2 Literature review on diagnosing market power in power markets

Market power detection techniques developed over the last 10-15 years in the power markets vary enormously from theoretical to empirical models, from market structure to market outcome approaches; from direct to indirect estimations, each of which has strengths and weaknesses. Up to present, though there is still no definitive method for diagnosing market power in power industry, a lot of advances have been made.

The first attempt of empirical studies in market power was developed in the 1930s, known as Structure Conduct Performance approach (SCP). It holds that an industry's performance depends on the conduct (behavior) of sellers and buyers, which depends on the structure of the market. The structure is often summarized by market share or the relative market shares of the largest firms (Herfindahl-Hirschman Index-HHI). Though these indices are likely to serve as a potential screening of market power in long term ex-ante studies, there is very little empirical evidence supporting the application of these indices in predicting market power in electricity markets (Twomey, Green, Neuhoff and Newbery [2006]). In fact, they ignore many factors that contribute to the potential exercise of market power particularly demand conditions. In electricity market where demand and supply conditions can change rapidly, these static indices are not appropriate measurement of market power.

The Pivotal Supplier Index (PSI) and Residual Supply Index, designed particularly for electricity market by California ISO in 2002 (Sheffrin [2002]), are alternative structural indices which address some weaknesses of the classical concentration indices by taking into account the demand-side conditions. They measure the extent to which a generator's capacity is indispensable to supply the market after taking into account other generators' capacity. These indices, though being recently introduced, are increasingly applied in the US as a tool for market power analysis. However, the difficulties in defining the relevant markets still remain. And, like other structural indices, they only reveal the information about the potential of market power, not the actual level of market power exercise.

A more sophisticated powerful method of market power diagnose using residual demand analysis was developed by Wolak [2000]. The method involves the estimation of the residual demand curve faced by a company. It is derived by subtracting from the total demand curve all the offer curves bid into the market by other participants. The slope of residual demand at production level is firm's market power for that demand realization. If a firm is pivotal, slope of residual demand curve is infinite and firm can name any price for pivotal quantity of demand. The regulatory intervention is needed to set price in these circumstances. Distribution of slopes of residual demand curves for a given hour quantifies market power. This was usually constructed ex-post because in real time residual demand curve was unknown at time generator submits bids. A limitation of this analysis is that the burden of requiring data might be high. Furthermore, it is always required a clear definition of relevant market. It has, so far, not taken into account transmission

constraints in constructing the residual demand curves. Such constraints would decrease the residual demand elasticity and thus increasing the potential to exercise market power. Ignoring this factor might lead to underestimate the level of market power.

Perhaps the most sophisticated means of measuring market power have been involving market simulation models. While SCP studies focus on the question of "what causes market power" with assumption that the level of this market power is known, market simulation models take market power as an unknown factor and attempt to measure it. Named in different ways and implemented in different methods from simplest to the most complicated, the decisive clue of this approach concerns the estimation of marginal cost and oligopoly equilibria in different wholesale electricity markets. Direct estimation of marginal costs is derived from engineering data of fuel costs - the main cost component for nuclear and fossil fuel plants - and of heat rate-the efficiency with which fuel is converted into energy. Multiplying the heat rate with fuel prices allows reliable estimation of the fuel cost component. The system benchmark price and quantity equilibrium is then found by two categories of models : the first approach concerns optimization/simulation models as done by for example Boweret al. [2001], Bushnell and Saravia [2002], Green [2004], Lang and Schwarz [2006], Müsgen [2006], Weigt and Von Hirschhausen [2008], Competition [2007], Möst and Genoese [2009]; the second ones with various oligopoly models such as supply function equilibrium done by Green and Newbery [1992], Halseth [1999], Arellano [2003], or simple Cournot - Bertrand - Nash equilibrium as done by a series of papers of Borenstein and Bushnell [1999] , Borenstein, Bushnell and Wolak [2000] in Californian electricity market.

These models have been applied to many electricity markets throughout the world because they are firmly-grounded in oligopoly theory. However, they are intractable in empirical estimation because they require a proper calculation of marginal cost. Weigt and Von Hirschhausen [2008] show that the non-linear complexity of electricity pricing makes it difficult to design a realistic model. As pointed out by Harvey and Hogan [2002] every model has some level of uncertainty and thus produces a range of possible outcomes. In fact, the common approximation of assimilating the variable costs of fuels and plant performance seems unsatisfactory in many cases, particularly for nuclear power generation and hydropower whose variable costs are close to zero but opportunity costs might be very high. This is the case in French electricity market where the merit curve has a particularly flat-shaped due to the large part of nuclear power in the generation mix (over 85%). This makes the calibration of price-cost margins less reliable and thus negates the certitude of conclusions.

One approach to overcoming the problem of not knowing marginal cost is to use the New Empirical Industrial Organisation (NEIO) method which was first introduced in the late 1980s. The model has been conducted for example in Hjalmarsson [2000]; Bask, Lundgren and Rudholm [2011], Mirza and Bergland [2012]. In Section 3, we are employing this model using data in French electricity market.

3. FRENCH MARKET DESIGN

3.1 The French energy situation

The energy sector in France has changed dramatically since the first oil shock in 1973 and the government's decision in March 1974 to increase the nuclear power capacity rapidly. Following this decision, the use of coal and oil declined markedly, substituted mainly by the growth in electricity and natural gas consumption. Today, France is the eighth largest producer of electricity in the world and the second in term of nuclear production. Contrary to several European countries which benefit from an abundance of raw materials, France is poor in energy resources (Meritet [2007]). Between 1973 and 2012, electricity consumption almost tripled despite a minor decline in the years 2009 and 2011 (due to the economic crisis and weather conditions). Without fossil fuel reserves, the civil nuclear power program led to a substitution in electricity generation. The increase in nuclear power generation (15TWh in 1973 to 405TWh in 2012) is therefore accompanied by a reduction of the use of classic thermal units. Today, France represents 17% of the nuclear power generation in the world with 58 reactors. EDF, the former vertical integrated public monopoly, controls 80% of the country's power generating capacity including all atomic reactors, two-thirds of thermal capacity, 81% of hydroelectric capacity and about a third of renewable output.

The French energy mix points to a large consumption of oil (used especially in transport) and nuclear power. In 2012, 75% of electricity was generated by nuclear power plants and 12% by hydro plants which are used for base load in the merit order. The residential sector is the country's largest electricity user, currently representing about two thirds of the total. Next in importance is the industrial sector. The French nuclear electricity production amounts to 63 130 MW in 2012; the rest is 6 160 MW for coal plants, 5 009MW for natural gas, 6 945MW for fuel and peak load, and 24 301MW for hydro. The demand was divided up as follows: residential and services 67.3%, industries 28.1%, transport 2.8% and agriculture 1.7%.

While French consumption is the second largest in Europe after Germany (in terms of number of consumers and in output), its power trading market is not as dynamic due to the limited number of market players. It can also be particularly constrained in winter, since French demand is very sensitive to temperature. In 2012, for example, the level of electricity consumption reached more than 102 000MW on February 8, the highest recorded level in France. A one degree drop in the temperature is estimated to increase the 7 pm electricity demand peak of up to around 2 300MW. When temperatures are very low, France may not have enough installed capacity, it has to import power from the neighboring countries in order to guarantee the supply.

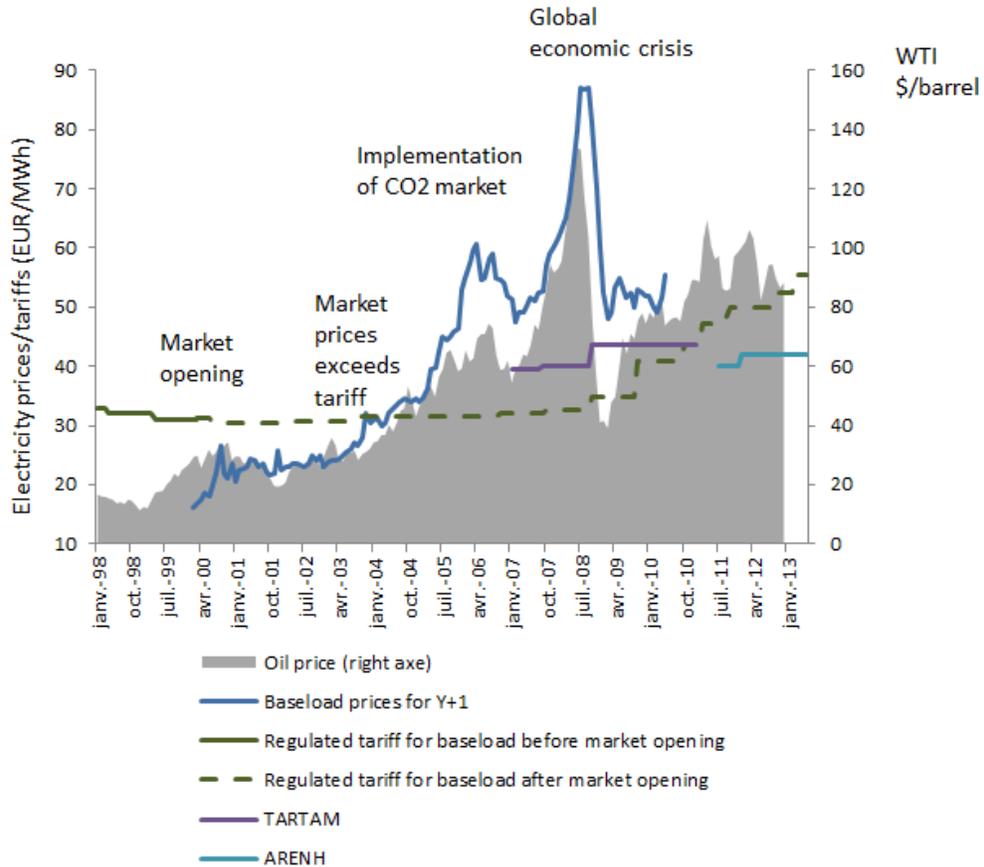
3.2 The French wholesale market

The French wholesale market is the third largest in Europe after the German and British ones, and has been drastically evolved during recent years. The total volume traded in wholesale level increases from around 50GW per day in 2005 to around 200GW per day in 2013, representing about 17% of the total electricity produced and sold in France. This share is supposed to increase with the termination of

regulated tariffs for small businesses on retail market planned in 2016 by the 2000 NOME Law (New Organization of Electricity Market).

One particular characteristic of French wholesale power market is an overlap of different types of prices and tariffs, which are resulted from a number of regulatory instruments - the government's attempt to reconcile the economic, social, and political contradictions.

With the gradual market opening since 2000, a certain number of "eligible consumers" decided to quit the system of regulated tariff to participate in the system of competitive prices on the market which, at that time, was relatively low (see figure 1). This choice was, however, irreversible.



Source: Authors, based on data from EPEX, CRE, Eurostat

Figure 1. Evolution of French electricity prices and tariffs (1998-2012) ta from EPEX, CRE, Eurostat

Since 2005, the market price began to surge well above the regulated tariffs, almost tripled between 2004 and 2008, soaring from 30 to 87 €/MWh while the regulated tariffs remained almost unchanged, around 30 €/MWh. This is because the regulated tariffs are based largely on the costs of production of nuclear and hydroelectric power which represent about 90% of total production in France. They

were, therefore, little impacted by the increase of fossil fuels prices or the implication of CO₂ prices since 2005. On the other hand, market prices reply to all these changes. In fact, market prices are set equal to marginal cost of the last plant mobilized to fulfil the demand (marginal plant). If the French electricity system was isolated, i.e., no exchanges with neighboring systems, the nuclear plants would be the marginal plants for almost 50% of time and the market prices would be generally set based on marginal cost of nuclear power; the gap between regulated tariffs and market prices thus would be shortened. However, with market opening and interconnexion between France's and neighboring countries' network, the marginal plants of production necessary to satisfy the demand of interconnected zone are thus most of the time coal or gas plant. The market prices align to the production cost of these plants, which, in turn, vary with the volatility of fossil fuel prices.

Figure 1 illustrates also the correlation of electricity market prices and crude oil prices - the leading price in energy sphere¹. The surge of crude oil prices from 2004 leads to an increase of the two other fossil fuels' prices: coal and gas, and thus, have some impacts on electricity market prices. Therefore, although a coal or gas plant represents a very small part of total generation in France, the production cost of this plant will still become the reference price for the market because it is connected with other markets like Germany or Italy where half of electricity is produced from coal and gas. During peak load, electricity is imported from, for example, Germany and the prices would align to the gas plant which is relatively expensive. During the base load, electricity is exported to Germany. Even if the prices correspond to certain marginality of nuclear in France, the coal-fired plants which function almost all the time in Germany could influent market prices in France. The price convergence between France and Germany has been even more significant since the creation of market coupling contracts in the Central western European which covers Benelux, France and Germany in November 2010.

The great divergence between market price and regulated tariff had made the consumers having quitted the regulated system manifest their malcontent toward the liberalization (generally competition would have induced lower price). This contradiction led the French Government to authorize, by a law on energy in 2006, that the consumers having quitted the tariff can return to the protective tariff system - the so called TARTAM, the transitional market adjustment tariffs² or, more prosaically "tariff of return". The TARTAM is calculated from the regulated tariff, increased by 10 %, 20 %, or 23% matching with a mechanism of compensation ex-post³.

¹ The evolution of natural gas and coal prices is highly correlated with the oil prices largely because they are substitute in the power and heating markets; high price differences cannot remain for long. Indeed, natural gas is frequently purchased by long term contracts which contain a price clause setting an automatic link between gas price and the price of petroleum products.

² Tarif réglementé et transitoire d'ajustement au marché

³ The TARTAM is considered as a Government aid for big enterprises and set with a mechanism of compensation ex-post for the suppliers who suffered from the loss of differences between wholesale market prices and the TARTAM (for energy only). This compensation is financed by a tax on the capacity of hydro and nuclear, most of which are contributed by the EDF. Put in other words, EDF compensated the alternatives suppliers up to 97 % (Champsaur, Percebois and Durieux [2011])

The juxtaposition of regulated tariff, TARTAM, and market prices, as well as the conditions of irreversibility between regulated and market offers caused even more contradictions. Two clients having the same consumption profile do not have access to the same tariff offers. The incoherence of pricing system made market prices now too far from being a signal for new investment. Besides, the new entrants could hardly compete with the actual regulated tariffs, which reflect the amortized production cost of nuclear power of the incumbent to which its competitors have a priori no access. A new contradiction was provoked: competition is generally expected to lower prices but to promote competition in French electricity market, we need to raise the prices.

It was in these conditions that a law on new organization of the electricity market - the NOME law⁴ was enacted in December 2010. This law aims to enhance the competition by abolishing gradually the regulated tariffs and the TARTAM. Furthermore, by this law, the incumbent EDF has obligation to sell part of its nuclear production to its competitors at a regulated price fixed by the regulator - ARENH, Regulated access to historical nuclear energy⁵. The ARENH price was settled by the government at 40 €/MWh at start to be coherent with the TARTAM (from the 1st July 2011) then 42€/MWh from the 1st January 2012.⁶

Although the co-existence of spot prices and regulated tariff system should not have a great impact on the merit order, it reduces the market's liquidity and could make the spot prices more sensitive to supply/demand variations.

4. MODELING MARKET POWER

4.1 The Model

In an oligopolistic market of a few supply firms producing a homogeneous product with q_i is supply of the i th firm, Q is the total supply equal to the total demand ($Q = Q = \sum_{i=1}^n q_i$), the price elasticity of demand is retrieved from the aggregate demand function:

$$Q = D(\text{Price}, X, \alpha) + \varepsilon \quad (1)$$

with X is a vector of exogenous variables affecting demand, α is a vector of parameters of demand function to be estimated and ε is error term.

System marginal cost function takes the form:

$$P = C(Q, W, \beta) + \vartheta \quad (2)$$

where W is a vector of exogenous variables on the supply side (factor price), β is vector of parameters of supply function and ϑ is error term of supply function, $MC(.)$ is marginal cost function. When firms are price takers, i.e. market is competitive, prices equal marginal costs, equation (2) holds, the system marginal cost curve is as same as market supply curve.

⁴ Nouvelle Organisation du Marché de l'Electricité

⁵ L'Accès Régulé à l'Électricité Nucléaire Historique

⁶ The ARENH price is prosoically regulated price at the wholesale level. It is established, according to the Champsaur report in 2011, on the following assumptions: (1) the ARENH price must assure to cover all the costs of actual nuclear park during the period 2011 - 2025, and at the beginning, allow a good transition with the actual price system; (2) the ARENH price does not take into account the cost of replacing the expired nuclear reactors but it does take into account the cost of extension of life expectancy of the these reactors.

Bresnahan (1982) and Lau (1982) suggest that we use a *conduct* parameter, λ to nest various market structures⁷. For example, when firms are not price takers, it is perceived marginal revenue, not price, will be equal to marginal cost. The industry supply relation will no longer be determined by (2) but takes the form:

$$P = MC(Q, W, \beta) - \lambda \cdot h(P, X, \alpha) + \eta \quad (3)$$

where $P+h(\cdot)$ is marginal revenue and $P + \lambda \cdot h(\cdot)$ is marginal revenue as perceived by the firm and $h(P, X, \alpha) = Q / \frac{\partial Q(\cdot)}{\partial P}$. λ is now a new parameter indexing

the degree of market power. In perfect competition, $\lambda = 0$ and price equal to marginal cost, equation (2) holds. $\lambda = 1$ gives perfect cartel, and intermediate λ 's correspond to various oligopoly solution concepts.

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 the demand curve and change the slope of demand curve. The supply relation (3) is written in linear equation as:

$$P = \beta_Q Q + \beta_W W - \lambda \frac{Q}{\alpha_P P + \alpha_{PZ} Z} + \eta \quad (4)$$

By treating α_P and α_{PZ} as known (by estimating the demand equation), λ is now identified⁸. The economic intuition behind this is quite straightforward. The rotation of demand curve around equilibrium will have no effect under perfect competition: supply and demand curve meet at the same equilibrium point before and after rotation. However, under either oligopoly or monopoly, firms with market power will see that elasticity of demand is changing, they will adjust both their conjectures about other rivals' behavior and their perceived marginal revenue then equilibrium price and quantity will respond. Thus, the market power parameter λ is identified.

Bresnahan-Lau in a dynamic framework

Steen and Salvanes [1999] propose a dynamic reformulation of the BL model in an error correcting model and Hjalmarsson [2000] uses the same dynamic concept but in an autoregressive distributed lag ADL model. A general argument in favor of using a dynamic model is that it takes into account both short run and long run

⁷ An alternative is to use non-nested hypotheses tests: see Gasmı and Vuong (1991) and Gasmı, Laffont, and Vuong (1992)

⁸ The inclusion of the rotation variable PZ in the demand function is crucial for the identification of market power degree. To see this, denote $Q^* = \frac{Q}{\alpha_P P + \alpha_{PZ} Z}$; λ is identified as the coefficient of Q^* based on the estimation of (4). If we exclude PZ from the demand function, equation (4) 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 supply relation (tracing market power) will be indistinguishable from supply curve (representing perfect competition)

estimates. The demand function (1) and supply relation (4) can be written in ADL framework:

$$Q_t = \alpha_0 + \sum_{i=1}^k \gamma_i Q_{t-i} + \sum_{i=0}^k \alpha_{p,i} P_{t-i} + \sum_{i=0}^k \alpha_{z,i} Z_{t-i} + \sum_{i=0}^k \alpha_{pz,i} PZ_{t-i} + \varepsilon_t \quad (5)$$

$$P_t = \beta_0 + \sum_{i=1}^k \phi_i P_{t-i} + \sum_{i=0}^k \beta_{Q,i} Q_{t-i} + \sum_{i=0}^k \beta_{w,i} W_{t-i} + \sum_{i=0}^k \lambda_i Q_{t-i}^* + \eta_t \quad (6)$$

where the long-run parameters are given as:

$$\theta_j = \frac{\sum_{i=0}^k \alpha_{j,i}}{1 - \sum_{i=1}^k \gamma_i} \quad j = P, Y, Z, PZ \quad (7)$$

$h(\cdot)$ in (3) can be written as:

$$Q_t^* = \frac{Q_t}{(\theta_p + \theta_{pz} Z_t)} \quad (8)$$

And

$$\Lambda = \frac{\sum_{i=0}^k \lambda_i}{1 - \sum_{i=1}^k \phi_i} \quad \zeta_Q^* = \frac{\sum_{i=0}^k \beta_{Q,i}}{1 - \sum_{i=1}^k \phi_i} \quad \zeta_w^* = \frac{\sum_{i=0}^k \beta_{w,i}}{1 - \sum_{i=1}^k \phi_i} \quad (9)$$

The ADL formulation provides both a short-run measure of market power: λ and a long-run measure, Λ . The demand function (5) incorporates an adjustment speed, $1 - \sum_{i=1}^k \gamma_i$, which measures the impact on Q_t of being away from the long-run target. The supply relation in (6) incorporates also adjustment costs and allows short-run deviations from the requirement that marginal cost should equal perceived marginal revenue (Steen [2003]).

5. MODEL SPECIFICATION AND THE DATA

5.1.1 The nature of data and specification for different model considerations

As discussed in section 2, electricity industry exhibits a distinguished feature which makes modelling it different from other markets. Due to the combination of strong variability of demand for electricity and non-storability of electricity, there exist 24 different prices for 24 hours per day. Any attempt to model electricity price should take this into account. There have been three broad modeling strategies of electricity spot prices in the existing literature⁹:

⁹ Except for Steen [2003] and Bask et al. [2011], those papers do not necessarily concern market power modelling but they give useful implications on price modelling methodologies.

Modeling of the daily/weekly average price: Koopman, Ooms and Carnero [2007], Schlueter [2010], Escribano, Ignacio Pena and Villaplana [2011], Bask et al. [2011].

Treatment of the hourly prices as a single time series: Nogales, Contreras and Conejo [2002], Conejo, Contreras, Espinola and Plazas [2005], Liu and Shi [2013], Steen [2003].

Separate treatment of the hourly prices: Crespo Cuaresma, Hlouskova, Kossmeier and Obersteiner [2004], Weron and Misiorek [2008], Karakatsani and Bunn [2008], Bordignon, Bunn, Lisi and Nan [2012].

Treatment of the data as a panel framework: 24 hours are considered as cross-sectional individuals which are observed over time (daily base): Huisman, Huurman and Mahieu [2007].

Averaging hourly observations to obtain one daily/weekly price and quantity is the least complicated way to treat the dataset and this also introduces smoothness into the data by dampening the fluctuations in the hourly data. However, manipulation the data in this way might remove the possible short run dynamic across hours. In fact, demand elasticity is different in different hours of the day and firms with market power will adjust their perceived marginal revenue then equilibrium price and quantity will respond correspondingly. For this reason we are not considering this method.

The treatment of the hourly prices as a single pooled time series, though being used in several recent papers, is not being considered in this paper either. In fact, we are modelling the day-ahead market, where equilibrium outputs (price and quantity) were determined one day before the delivery through an auction mechanism. In the morning of each day, buyers and sellers submit their bids (price and quantity combination) for each hour of the forthcoming day. The market is closed at 12:00 noon in France. Epex Spot then aggregates demand and supply curves. The results of equilibrium price and volume for each hour of the forthcoming day are published by Epex Spot from 12:40 pm for simultaneous 24 hours (Figure 2). Thus, the information of price and quantity for 24 hours is released at the same time. This is why considering the hourly prices as a continuous single pooled time series is not an appropriate methodology.

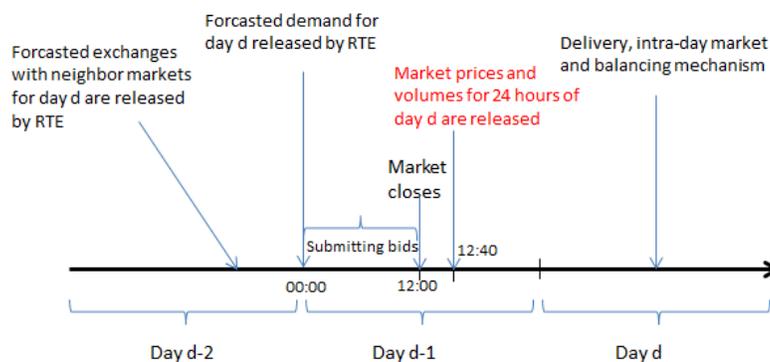


Figure 2. Time framework of market information release

Modelling a multivariate model is appealing because this allows capturing precise coefficients for separate hours. However, there might be too many parameters to estimate as we increase the number of exogenous variables and instruments. An assumption under which the issue of having too many parameters can be solved is contemporaneous correlation between the error terms. This assumption says that the error terms in different equations (hours), at the same point of time, are correlated. The economic intuition behind this is quite straightforward. 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, etc. Since the individual hourly prices share 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 $\eta_t^{(h9)}$ in the equations (5) and (6) will be capturing similar effects and will be correlated. This motivates us to implement a panel data model.

The panel data models that allows a common dynamic across all hours and a variation of the coefficients for each hour. Given this assumption, it follows that all behavioral differences between hours and over time are captured by the error terms. The resulting econometric model for one-way error component panel framework is:

Demand equation:

$$Q_{ht} = \alpha_0 + \sum_{i=1}^k \gamma_i Q_{h,t-i} + \sum_{i=0}^k \alpha_{p,i} P_{h,t-i} + \sum_{i=0}^k \alpha_{z,i} Z_{h,t-i} + \sum_{i=0}^k \alpha_{pz,i} PZ_{h,t-i} + \varepsilon_{ht} \quad (10)$$

with

$$\varepsilon_{ht} = \mu_h + \vartheta_{ht} \quad (11)$$

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

Supply relation:

$$P_{ht} = \beta_0 + \sum_{i=1}^k \phi_i P_{h,t-i} + \sum_{i=0}^k \beta_{Q,i} Q_{h,t-i} + \sum_{i=0}^k \beta_{w,i} W_{h,t-i} + \sum_{i=0}^k \lambda_i Q_{h,t-i}^* + \eta_{ht} \quad (12)$$

with

$$\eta_{ht} = \nu_h + \tau_{ht} \quad (13)$$

where ν_h denotes unobservable hour specific effect and τ_{ht} denotes the remainder disturbance in the one-way error component panel model. Note that μ_h and ν_h are time-invariant which accounts for any individual (hour) specific effect that is not included in the regression (we could think of it as unobserved consumption behavior in different hours). The remainder disturbance ϑ_{ht} and τ_{ht} vary with hour and time and can be thought of as the usual disturbance in the regression.

The Data Description

Hourly data of electricity spot prices (in €/MWh) and volume traded (in MW) from 01/01/2009 to 31/12/2012 in French wholesale electricity market is released at 12:40 a day ahead the physical delivery by the European Exchange market. The 24 hourly day-ahead forecasted load data for continental France is released by the RTE at 0:00 in day $t-1$.

We are considering several demand shifters and price drivers as explanatory variables. We take into account the time release of spot prices and volumes in defining other explanatory variables: only information available up to noon before the market clearing is taken into account. Those variables are published at a daily or hourly frequency, which include:

The hourly temperature in France is the main variable to shift the demand and this is considered in literature a good instrument to identify the supply relation thanks to its pure exogeneity. In fact, the temperature sensitivity in France represents almost half of the total European thermo sensitivity. In France, this influence is particularly noticeable in the winter with the usage related to heating. We use the national temperature index constructed from a range of meteorological stations (32) distributed optimally in the French territory. This data is published by ERDR (French distribution system operator).

Day length is another variable to shift the demand. The influence of the length of day on the electricity usage is represented through the demand for lightening. This is calculated based on the time duration from sunrise to sunset in France.

To be able to identify the degree of market power, we let spot price to interact with temperature ($P*Temp$) as done in Hjalmarsson [2000] and Bask et al. [2011]. This interact term enters to the demand equation to both shift the demand curve and change the demand's slope by prices. It is considered endogenous and needs to be instrumented in the demand regressions.

Gas price (in Eur/MWh): European Gas Index -- EGIX published by the European Energy Exchange AG (EEX) is used. 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.

Carbon price: we use the European Emission Allowances prices (€/tonne of CO₂) which are released by EEX on daily basis.

Forecasted balance of exchanges programs with Germany, Spain, Italy, the UK, Belgium and Switzerland (in GW): The RTE provides the balance for each hour at the end of the afternoon for the following day. For this reason, we use lag-1 values.

Dummy variables: Prices are lower in the weekend and particularly on public holidays due to weak economic activities. They are higher on average in winter than other seasons of the year due to the high need of electricity for heating in the winter. To control the bank holidays effects, we include a dummy variable which takes value of 1 on weekend and on public holidays in France and 0 otherwise. To deseasonalize the price and turnover series, we include a set of dummy variable into both demand function and supply relation: for each season $\sum_{S=1}^3 S_t$ where S stands for seasons of the year.

To avoid endogeneity problem, we use lag-1 of gas and carbon price.

Table 1. Descriptive Statistics

	Unit	Mean	Median	Maximum	Minimum	Std. Dev.
Price	€/MWh	46.3	46.2	1938.5	-50.1	24.5
Turnover	MW	6395.5	6268.0	13251.0	3004.0	1351.8
Load	MW	55643.4	53700.0	99400.0	29900.0	12723.6
Temperature	Celcius	12.5	12.8	27.7	-5.2	6.4
EX_Germany	MW	-697.5	-862.0	2850.0	-5390.0	1704.5
EX_Spain	MW	151.6	0.0	1400.0	-2200.0	694.9
EX_Italy	MW	1872.4	2188.0	2962.0	-1083.0	738.2
EX_UK	MW	456.6	766.0	3794.0	-2000.0	1164.0
EX_Switzerland	MW	2353.2	2667.0	6324.0	-2161.0	870.0
EX_Belgium	MW	380.4	303.0	5202.0	-1799.0	1115.0
Carbon Price	€/t CO2	11.8	13.0	16.8	0.0	3.4
Daylength	hours	12.1	12.2	16.1	8.1	2.7
Gas price	€/MWh	19.7	22.0	28.6	7.8	5.7

Sample period: January 1, 2008 to December 31, 2012. N=35 065 for price, turnover, load, volumes of exchange and temperature and N=1461 for gas and carbon price, daylength.

Table 1 gives summary statistics for sample variables. The power prices, turnover, load, volumes of exchange and temperature have hourly frequency while daylength, the gas price and the carbon price are available at a daily frequency. The whole sample spans from January 01, 2009 to December 31, 2012, yielding 1461 daily observations for each trading hour. Several unit root tests (Augmented Dickey-Fuller, Phillips Perron) are applied to each variable, all series are found stationary at the usual significance levels except for gas price (the results are available upon request). In the following, we are considering gas prices in difference.

We rewrite equations (10) and (12) by substituting in for ε_{ht} and η_{ht} from (11) and (13) to obtain:

Demand Function:

$$Q_{ht} = \alpha_0 + \alpha_1 X_{ht}^d + \mu_h + \vartheta_{ht} \quad (14)$$

where X_{ht}^d is vector of all independent variables in the demand equation and α_1 is vector of parameters associated with X^d .

Supply Equation:

$$P_{ht} = \beta_0 + \beta_1 X_{ht}^s + v_h + \tau_{ht} \quad (15)$$

where X_{ht}^s is vector of all independent variables in the supply relation and β_1 is vector of parameters associated with X^s .

One basic problems introduced by the inclusion of a lagged dependent variable is the bias induced from the correlation between these lagged variables $y_{h,t-1}$ (lagged

Q and lagged P) and μ_h and ν_h components. This is an issue raised uniquely in the dynamic panel data models. It is because y_{ht} is a function of μ_h or ν_h in equations (14) and (15), it immediately follows that $y_{h,t-1}$ is also a function of μ_h or ν_h (because these components are time-invariant). Therefore, $y_{h,t-1}$, a right-hand regressor in (14) and (15), is correlated with the error term, which renders the estimators biased and inconsistent even if the ϑ_{ht} and τ_{ht} are not serially correlated (Baltagi[2008]). There are broadly two methods to overcome this problem by wiping out the individual effects μ_h and ν_h .

Arellano and Bond [1991] proposed a transformation by first differencing to eliminate the individual effects and using the matrix of instruments $W = [W_1', \dots, W_N']'$ where W_i is given by:

$$W_i = \begin{bmatrix} [y_{i1}] & \dots & \mathbf{0} \\ \vdots & [y_{i1}, y_{i2}] & \vdots \\ \mathbf{0} & \dots & [y_{i1}, \dots, y_{iT-2}] \end{bmatrix}$$

The Arellano and Bond method is appealing because it uses the instrument set of lagged values of dependent variables, thus requiring no external instrumental variables. However, this method is uniquely appropriate to a micro panel dataset with $N \rightarrow \infty$ and T very small. When $T \rightarrow \infty$, the matrix of instruments would become quickly unmanageable. With $T=1461$ as in our case, the number of instruments would be exploded, even if we break the whole dataset into several sub-sample.

The second choice to deal with the problem of introducing lagged dependent variable is to include the fixed effects (FE) estimator (Winthin transformation) in order to wipe out the individual effects μ_h and ν_h . Nickell [1981] shows that the dynamic panel models with fixed effects are biased of $(1/T)$. However, as $T \rightarrow \infty$, the fixed effects estimator becomes consistent because the bias will not be large. Therefore, in the following we are considering the fixed effects dynamic panel model. Given that $T=1461$, the bias could be as small as $0.00069=1/1461$ of the true value of the coefficients.

Furthermore, the fixed effects models seems to be a more appropriate specification for our dataset with individual dimension N (hours) is relatively small. Thus, it would not lead to a loss of degrees of freedom. We justify this choice by Hausman specification test (Hausman [1978]), which assumes random effects (RE) estimator to be fully efficient under null hypothesis. The results of the Hausman test give the overall statistics, $\chi^2(7)$ for demand equation and $\chi^2(13)$ for supply relation, having $p\text{-value}=0.000$. This leads to strong rejection of the null hypothesis that RE provides consistent estimates. We are considering therefore the fixed effects model in both demand and supply functions.

The estimation procedures are as follows. We estimate respectively demand (10) and supply equation (12). Because we still have the problem of endogeneity in both demand and supply functions, these models are estimated with two-stage generalized method of moments (GMM). We use Stock-Watson bias-corrected heteroskedastic-robust standard errors (SEs) to make the estimates robust against any problem of heteroskedasticity. The two-way cluster-robust SEs, proposed by

Miller, Cameron and Gelbach [2009] and Thompson [2011], are used to assure that the estimators are consistent to arbitrary within-panel autocorrelation and contemporaneous cross-panel correlation.

6. EMPIRICAL RESULTS

6.1 Demand Function

The two-stage generalized method of moments (GMM) was employed to estimate the demand function (10). 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 are convincing with R^2 is at 0.82 and very high F-statistics (197.66).

In order to choose the number of lags for autoregressive distributed lag terms, we start with $k=7$ then test our models down by excluding non-significant lags. The results suggest that only the lag-1 of the turnovers Q is kept. The long term elasticity of demand (θ_p and θ_{pz}) is then calculated using equation (9).

The second stage GMM estimation results for the demand function with panel dataset are reported in table 2. The parameter estimates are highly significant and with expected signs.

Table 2. Panel data model – Demand Equation

Variables	Coef	Robust Std.Err	X-stat	Prob.	[95% Conf. Interval]	
Price	-0.0210***	(0.00789)	-2.662	0.0077	-0.0365	-0.00554
P*Temp	0.00196***	(0.000674)	2.910	0.0036	0.000640	0.00328
Turnover (-1)	0.522***	(0.0195)	26.84	0.0000	0.484	0.561
Temperature	-0.130***	(0.0416)	-3.129	0.0017	-0.212	-0.0487
Daylength	0.00813	(0.0201)	0.404	0.6860	-0.0313	0.0476
Holidays	-0.249***	(0.0766)	-3.251	0.0011	-0.399	-0.0989
Summer	-0.147	(0.117)	-1.256	0.2090	-0.375	0.0822
Spring	-0.258***	(0.0859)	-3.003	0.0026	-0.426	-0.0896
Fall	-0.0929	(0.0738)	-1.258	0.2080	-0.238	0.0518

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

The coefficient associated with price has negative sign as a standard demand equation should have. This is highly important result because it shows that our instruments have succeeded to identify the demand equation. The elasticities of demand by price are equivalent to -0.15 in short-term and -0.31 in long-term. The coefficient of temperature and holidays are significantly negative as expected. The daylength, on the other hand, is found insignificant. The coefficients associated with seasons' dummies have negative signs though statistically insignificant for summer

and fall¹⁰ as electricity demand is supposed to be higher on average in winter. The coefficient of interacted term $Price*Temperature$ is significant and positive at 0.002.

We use Q^* generated form (8) as an endogenous regressor in the supply relationship to reveal the existence of market power.

6.2 Supply Relation

We arbitrarily choose the quadratic form for the supply function with respect to "forecasted load". The excluded variables temperature, daylength are used as instruments to identify the supply functions. We include seven autoregressive terms AR(1-7).

The second stage GMM estimation results for the supply relations with panel dataset are reported in table 3. The parameter estimates are also generally significant and with expected signs except for gas and carbon prices.

Table 3. Panel data model - Supply Equation

Variable	Coef	Robust Std.		Prob.	[95% Conf. Interval]	
		Err	Z-stat			
Q^*	1.33e-05*	-7.46E-06	1.787	0.0871	-2.10E-06	2.88E-05
Load	0.346***	-0.051	6.797	0.0000	0.241	0.452
Load ²	0.00130***	-0.000309	4.192	0.0003	0.000657	0.00194
Price (-1)	0.276***	-0.0287	9.623	0.0000	0.216	0.335
Price (-2)	0.0783***	-0.0155	5.066	0.0000	0.0463	0.11
Price (-3)	0.0603***	-0.00987	6.106	0.0000	0.0399	0.0807
Price (-4)	0.0533***	-0.0082	6.498	0.0000	0.0363	0.0703
Price (-5)	0.00692	-0.0106	0.652	0.5210	-0.015	0.0289
Price (-6)	0.0350***	-0.00999	3.5	0.0019	0.0143	0.0556
Price (-7)	0.115***	-0.0202	5.683	0.0000	0.0732	0.157
Gas price	0.142	-0.116	1.226	0.2330	-0.0974	0.381
Margin	-0.629***	-0.0569	-11.05	0.0000	-0.747	-0.511
Carbon	-0.0241	-0.0191	-1.259	0.2210	-0.0636	0.0155
EX Germany	0.180***	-0.0625	2.879	0.0085	0.0507	0.309
EX Italy	-1.887***	-0.302	-6.239	0.0000	-2.513	-1.261
EX Spain	-0.960***	-0.233	-4.123	0.0004	-1.442	-0.478
EX Belgium	0.278***	-0.0814	3.409	0.0024	0.109	0.446
Holidays	-6.935***	-1.546	-4.486	0.0002	-10.13	-3.737

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

The insignificance of estimated coefficient of gas price can be explained by the fact that the share of gas generation technology accounts for a very small part in the total annual marginality duration in France. The impact of marginality of gas plants on electricity prices in France is captured mostly through exchanges with neighboring countries like the UK, Italy or Belgium where gas represents a large share in the technology mix. Furthermore, due to the high gas price and relatively

¹⁰ The insignificance of seasonal dummies (summer and fall) can be explained by the fact that Daylength, which represents the similar effects on electricity demand, is also included in the regression.

low coal price in Europe, many of gas plants have been shutdown, which partly explains the non-significance of gas price's coefficient.

The coefficient estimate for carbon price is also showed insignificant. Indeed, we are studying the period of 2009-2012, where CO2 market was at the second phase and carbon price had significantly driven down to the absurdly low level, at around 2.5€/ton of CO2 at the end of period. Thus the relationship between CO2 price and electricity price seems to be not evident during the examined period, as also found in Jouvét and Solier [2013].

Finally and most importantly, the coefficient associated to Q^* is significantly only at 10 %, and is very close to zero ($1.33.e-05$) suggesting that on average we find no market power in the electricity market in France during the examined period.

6.3 Robustness Tests

We conduct the robustness test by employing the model for each hour of the day.

Table 4. Estimates for the market power parameters across hours

λ	Estimate	HAC(N-W)
$\lambda^{(h1)}$	-0.000365	(0.000373)
$\lambda^{(h2)}$	0.000481	(0.000465)
$\lambda^{(h3)}$	3.99E-08	(2.98E-08)
$\lambda^{(h4)}$	0.00251	(0.00205)
$\lambda^{(h5)}$	-0.00569**	(0.00274)
$\lambda^{(h6)}$	-7.92E-06	(9.19E-05)
$\lambda^{(h7)}$	0.00222	(0.00189)
$\lambda^{(h8)}$	-0.00193**	(0.000879)
$\lambda^{(h9)}$	-0.00683**	(0.00320)
$\lambda^{(h10)}$	0.00525***	(0.00116)
$\lambda^{(h11)}$	-0.00621***	(0.00227)
$\lambda^{(h12)}$	-0.00344*	(0.00192)
$\lambda^{(h13)}$	-0.0109	(0.0108)
$\lambda^{(h14)}$	-0.000322	(0.000686)
$\lambda^{(h15)}$	-0.000174	(0.000146)
$\lambda^{(h16)}$	-0.00111	(0.000826)
$\lambda^{(h17)}$	0.000949*	(0.000516)
$\lambda^{(h18)}$	0.000741	(0.00220)
$\lambda^{(h19)}$	-0.00270	(0.00326)
$\lambda^{(h20)}$	0.00265	(0.00570)
$\lambda^{(h21)}$	0.000209***	(7.39E-05)
$\lambda^{(h22)}$	-3.96E-07**	(1.94E-07)
$\lambda^{(h23)}$	0.00124**	(0.000540)
$\lambda^{(h24)}$	-0.0190**	(0.00933)

Standard errors (HAC Newey-West) are in parentheses

***/significant at a 1% level, **/significant at a 5% level, and */significant at a 10% level

The second stage GMM results for both demand and supply equations are reported in tables (6) and (7) in the Appendix. Table (4) presents estimates for the market power parameters $\lambda^{(h)}$ across hours of the day. They are found either statistically insignificant or positively significant at the usual levels except for several peak hours 5, 8, 9, 11, 12, 22 and 24, which are negatively significant. However, the estimates for those hours stay at relatively low level.

Price cost margins can be estimated for the hours with negative coefficients¹¹, the results are given in table 5. The very low levels of Lerner indexes suggest that no market power has been exercised over the sample period.

Table 5. Lerner index across hours

	LI-h5	LI-h8	LI-h9	LI-h11	LI-h22
Short term	0.01963641	0.02803341	0.04188475	0.01715386	4.7438E-07
Long term	0.0446282	0.03467772	0.02644286	0.01000519	8.7443E-07

6.4 Discussion

Despite of some doubts arose about the performance of wholesale electricity market in France, the model-based result suggesting the non-existence of market power is not really surprising. In fact, there are several economic arguments to justify this finding.

The total volume of electricity traded in wholesale market, though increasing since 2005, represents as small as 17% of the total electricity produced and sold in France. More importantly, the wholesale market is extremely regulated with the co-existence of market price and regulated tariff (ARENH price in wholesale market). The ARENH price was set by the French government at 42 €/MWh, which is relatively high. During the examined period, the frequency of spot prices observed in the wholesale market to be lower than 42 €/MWh is up to 40%. The alternative suppliers might sometimes prefer to buy electricity at the spot prices rather than regulated tariff. To make the long story short, as long as "market" comprises about only 17% of domestic delivery, the market integration with neighboring markets is increasingly strengthened, and prices in the spot market stay strictly regulated, it is extremely hard for an incumbent to exercise its market power even if it possesses one.

After all, Electricité de France (EDF), the incumbent in France and also the biggest producer of electric power in Europe, does not have economic incentives to exercise its market power because the possible gains from doing this would fall far behind the risks of being broken up the monopoly by the competition authorities. The high prices observed in French spot market since 2005 could be possibly explained by a number of exogenous reasons but hardly by market power abuse. Indeed, the trend of increased electricity price has been common in many power markets in Europe in the last decade because of many dramatic changes: the

¹¹ Price-cost margin $P - MC = -\lambda \frac{Q}{\partial Q(\cdot)} \frac{\partial Q(\cdot)}{\partial P}$. The Lerner's measure is: $L \equiv \frac{P-MC}{P} = -\lambda \frac{Q}{P} \frac{\partial Q(\cdot)}{\partial P} = -\frac{\lambda}{\varepsilon}$

where ε is the market elasticity of demand.

implication of carbon price since 2005, the global economic crisis in 2008 pushing up the fuel costs to the highest level in the history, the catastrophe of Fukushima in Japan in 2011 adding burden to the costs of nuclear technology, the continuous political turbulence in Arab countries followed by the increase of fuel prices, etc.

The doubts provoked on French spot prices due to the growingly divergence with German spot prices could be justified by the increasing share of renewable power generation in the German electricity portfolio. In fact, the next day of Fukushima nuclear accident, the German government decided to accelerate the phase-out of nuclear fleet by 2022, starting with the immediate closure of the eight oldest nuclear plants. Although fossil fuels fired energy has to put in place during the transitional period, renewable electricity generation is being considered as cornerstone of current and future energy supply. In Germany, a lot of support scheme for the development of renewable electricity generation have been put in place. Over the last ten years, the installed wind turbine capacity in Germany has increased with a factor of 5, from 6 GW in 2000 to 31,3 GW in 2012, and that of photovoltaic has raised from only 100 MW in 2000 up to 32,6 GW in 2012. The massive integration of renewable into electricity system creates a reduction effect (or merit-order effect) on German spot prices because this type of energy is bided zero in the merit order. This would be the reason why price divergence between France and Germany has been increasing despite a strong interconnected network.

7. CONCLUSION

The ongoing reorganization of the French electricity market will lead to an increasing volume of trade on the wholesale market. This being the case, developing relevant market power detection tools for electricity spot markets is a key issue for both academics and regulators.

In this paper we employ a structural model developed in New Empirical Industrial Organization (NEIO) to investigate the presence of market power abuse in the French wholesale electricity market during a panel data framework for hourly data during 2009-2012. The model-based results suggest that on average, no market power has been exercised during the examined period. Although market power is found statistically significant in several peak-load hours, it stays at very low level. There are many economic justifications to support this conclusion. Indeed, market power will hardly be abused if the "market" itself is extremely regulated as the case in France. Indeed, the price of electricity in France is lower than the average level of Europe. This difference reflects less and less the advantage from the "nuclear choice" made in the past, but more and more a good will to protect consumers from the tensions of actual energy world. Although no market power is exercised, the price system in France with the overlap of different prices and regulated tariff seems now to become too far to be able to send the right signals to investors and consumers.

There are several potential extensions to this paper. In particular, it could be interesting to explore the analysis conducted by the French electric regulatory commission for every spike of electric prices in France. It would be also interesting to take into account the impacts of the recent integration of intermittent renewable energies as well as the network congestion on market power level. Given the

important revolution of the electric power markets in France which is about to be significantly more liquid within a year, the market level estimated under different scenario of development would also be worth estimating.

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Appendix

Table 6. Demand Equations

	Price		Temperature		<i>P*Temp</i>		Daylength		Turnover(-1)	
h1	-0.0246***	(0.00481)	-0.143***	(0.0206)	0.00266***	(0.000438)	0.00884	(0.00965)	0.531***	(0.00452)
h2	-0.0251***	(0.00336)	-0.135***	(0.0139)	0.00271***	(0.000290)	0.0170*	(0.00920)	0.514***	(0.00567)
h3	-0.0296***	(0.00261)	-0.129***	(0.00975)	0.00320***	(0.000227)	0.0261***	(0.00700)	0.534***	(0.00532)
h4	-0.0529***	(0.00384)	-0.153***	(0.0138)	0.00526***	(0.000330)	0.0220**	(0.0103)	0.536***	(0.00704)
h5	-0.0736***	(0.00414)	-0.195***	(0.0153)	0.00708***	(0.000385)	0.0279**	(0.0111)	0.550***	(0.00643)
h6	-0.0574***	(0.00407)	-0.206***	(0.0147)	0.00584***	(0.000352)	0.0563***	(0.00939)	0.550***	(0.00857)
h7	-0.0371***	(0.00440)	-0.211***	(0.0185)	0.00476***	(0.000368)	0.0445***	(0.00945)	0.494***	(0.00711)
h8	-0.00912***	(0.00197)	-0.117***	(0.0122)	0.00185***	(0.000196)	-0.000641	(0.0104)	0.488***	(0.00838)
h9	-0.0207***	(0.00265)	-0.128***	(0.0201)	0.00202***	(0.000305)	-0.0312**	(0.0151)	0.426***	(0.0111)
h10	-0.0198***	(0.00309)	-0.139***	(0.0345)	0.00157***	(0.000514)	-0.0110	(0.0119)	0.000439***	(1.02e-05)
h11	-0.0227***	(0.00407)	-0.120***	(0.0338)	0.00114**	(0.000510)	0.00589	(0.0115)	0.455***	(0.00725)
h12	-0.0372***	(0.00492)	-0.180***	(0.0306)	0.00206***	(0.000466)	0.0221*	(0.0115)	0.458***	(0.00739)
h13	-0.0468***	(0.00443)	-0.262***	(0.0275)	0.00376***	(0.000404)	0.0104	(0.0136)	0.438***	(0.00581)
h14	-0.0359***	(0.00494)	-0.140***	(0.0244)	0.00198***	(0.000407)	-0.0108	(0.0114)	0.452***	(0.00849)
h15	-0.0280***	(0.00395)	-0.0900***	(0.0201)	0.00129***	(0.000347)	-0.0249**	(0.0105)	0.471***	(0.00850)
h16	-0.0404***	(0.00520)	-0.130***	(0.0235)	0.00221***	(0.000436)	-0.0702***	(0.0117)	0.492***	(0.00970)
h17	-0.0369***	(0.00444)	-0.119***	(0.0222)	0.00208***	(0.000394)	-0.105***	(0.0123)	0.522***	(0.00812)
h18	-0.0544***	(0.00749)	-0.314***	(0.0341)	0.00537***	(0.000505)	-0.0272	(0.0173)	0.489***	(0.0102)
h19	-0.0287***	(0.00311)	-0.308***	(0.0162)	0.00454***	(0.000213)	0.0750***	(0.0163)	0.415***	(0.00551)
h20	-0.0490***	(0.00506)	-0.377***	(0.0271)	0.00534***	(0.000359)	0.0936***	(0.0174)	0.412***	(0.00896)
h21	-0.0718***	(0.00784)	-0.489***	(0.0461)	0.00729***	(0.000690)	0.111***	(0.0194)	0.491***	(0.00888)
h22	-0.109***	(0.00966)	-0.603***	(0.0516)	0.0100***	(0.000823)	0.127***	(0.0249)	0.487***	(0.00838)
h23	-0.0252***	(0.00339)	-0.212***	(0.0168)	0.00338***	(0.000282)	-0.0345***	(0.0111)	0.481***	(0.00603)
h24	-0.00155	(0.0112)	-0.0892	(0.0567)	0.00142	(0.00109)	-0.0491**	(0.0232)	0.493***	(0.0256)

Standard errors (HAC Newey-West) are in parentheses

*** / significant at a 1% level, ** / significant at a 5% level, and * / significant at a 10% level

Table 7. Supply Estimates

	H1	H2	H3	H4	H5	H6	H7	H8
Q*	-0.000365 (0.000373)	0.000481 (0.000465)	3.99E-08 (2.98E-08)	0.00251 (0.00205)	-0.00569** (-0.00274)	-7.92E-06 (9.19E-05)	0.00222 (0.00189)	-0.00193** (0.000879)
Load	0.272*** (0.0562)	0.365*** (0.0510)	0.363*** (0.0362)	0.378*** (0.0606)	0.708*** (0.128)	0.270*** (0.0377)	0.257*** (0.0306)	0.399*** (0.0738)
Carbon price	0.0420 (0.0526)	-0.0144 (0.104)	-0.0322 (0.0935)	-0.153*** (0.0537)	0.143** (0.0700)	-0.0466 (0.0642)	-0.160** (0.0769)	0.0438 (0.136)
Gas price	-0.171 (0.129)	-0.394* (0.205)	-0.892** (0.423)	-1.710*** (0.481)	0.411 (0.901)	-0.558 (0.454)	1.488*** (0.527)	-0.954* (0.524)
Capacity margin	-0.421*** (0.0716)	-0.479*** (0.0844)	-0.725*** (0.104)	-0.546*** (0.0960)	0.00528 (0.249)	-0.544*** (0.0940)	-1.061*** (0.137)	-0.764*** (0.139)
EX Germany	-0.358*** (0.119)	0.112 (0.114)	0.602*** (0.125)	0.749*** (0.241)	1.050** (0.436)	0.221 (0.155)	0.276** (0.139)	-0.00654 (0.176)
EX EE Italy	-0.311 (0.257)	-0.00318 (0.311)	-0.0705 (0.233)	0.736 (0.673)	-0.427 (0.601)	-0.533* (0.313)	-0.925*** (0.317)	-2.756*** (0.412)
EX Spain	-0.940*** (0.246)	-0.626** (0.280)	-0.182 (0.414)	-0.243 (0.503)	1.463** (0.626)	-0.287 (0.263)	0.106 (0.274)	-1.523*** (0.387)
EX Belgium	0.216 (0.506)	0.298 (0.579)	0.656 (0.593)	0.571 (0.456)	1.570*** (0.509)	0.411** (0.207)	0.119 (0.415)	0.348 (0.734)
	H9	H10	H11	H12	H13	H14	H15	H16
Q*	-0.00683** (0.00320)	0.00525*** (0.00116)	-0.00621*** (0.00227)	-0.00344* (0.00192)	-0.0109 (0.0108)	-0.000322 (0.000686)	-0.000174 (0.000146)	-0.00111 (0.000826)
Load	1.185*** (0.265)	1.327*** (0.187)	1.157*** (0.194)	1.009*** (0.276)	0.388*** (0.0698)	0.246*** (0.0470)	0.262*** (0.0297)	0.319*** (0.0267)
Carbon price	2.257** (0.905)	-0.672 (0.415)	-0.228 (0.379)	0.504 (0.396)	0.345 (0.228)	0.0365 (0.0388)	0.0750 (0.0540)	0.0297 (0.0376)
Gas price	12.61*** (3.368)	6.445*** (2.238)	-4.414 (2.788)	2.913* (1.582)	2.731** (1.334)	0.800*** (0.255)	1.357*** (0.297)	1.524*** (0.455)
Capacity margin	-2.677*** (0.428)	-2.097*** (0.297)	-2.001*** (0.547)	-1.872*** (0.515)	-0.104 (1.667)	-0.663*** (0.0843)	-0.680*** (0.0666)	-0.700*** (0.137)
EX Germany	-5.078*** (1.899)	-1.073 (1.085)	1.287 (0.831)	-0.420 (1.120)	-3.883 (4.276)	0.00885 (0.0963)	-0.119 (0.120)	0.0373 (0.121)
EX EE Italy	-12.47*** (3.051)	-10.73*** (2.218)	-15.50*** (3.638)	-8.822*** (1.603)	2.530 (4.880)	-1.605*** (0.328)	-1.395*** (0.333)	-1.799*** (0.317)
EX Spain	-0.0641 (2.366)	-5.192 (3.505)	-2.925 (4.264)	0.652 (4.791)	1.053 (3.191)	-1.046*** (0.255)	-0.972** (0.394)	-0.665*** (0.235)
EX Belgium	8.897*** (2.690)	-1.324 (0.874)	-3.118* (1.751)	-3.439*** (0.740)	-0.867 (0.906)	-0.0528 (0.318)	0.0832 (0.269)	0.173 (0.300)

	H17	H18	H19	H20	H21	H22	H23	H24
Q*	0.000949* (0.000516)	0.000741 (0.00220)	-0.00270 (0.00326)	0.00265 (0.00570)	0.000209*** (7.39E-05)	-3.96E-07** (1.94E-07)	0.00124** (0.000540)	-0.0190** (0.00933)
Load	0.282*** (0.0384)	0.371*** (0.0340)	0.560*** (0.0759)	0.475** (0.233)	0.245*** (0.0312)	0.239*** (0.0242)	0.280*** (0.0307)	0.593*** (0.206)
Carbon price	0.0843*** (0.0321)	0.0278 (0.0452)	-0.0459 (0.0964)	-0.167 (0.150)	0.0709 (0.0514)	0.0179 (0.0574)	-0.139** (0.0561)	-0.125 (0.182)
Gas price	1.405*** (0.302)	1.018*** (0.278)	1.698** (0.693)	0.922** (0.424)	0.0689 (0.146)	1.043*** (0.352)	0.373 (0.366)	0.970 (0.968)
Capacity margin	-0.599*** (0.0481)	-0.613*** (0.0527)	-0.943*** (0.0838)	-0.776*** (0.140)	-0.667*** (0.137)	-0.395*** (0.0791)	-0.238*** (0.0681)	-0.244 (0.170)
EX Germany	-0.0667 (0.0805)	0.104 (0.141)	0.362 (0.419)	0.486 (0.681)	-0.147 (0.111)	0.0527 (0.108)	0.0440 (0.120)	-0.158 (0.171)
EE Italy	-1.453*** (0.277)	-1.830*** (0.310)	-3.132*** (0.687)	-1.539*** (0.420)	-0.864*** (0.218)	-1.104*** (0.250)	-0.382 (0.303)	2.066 (1.523)
EX Spain	-1.288** (0.640)	-1.138*** (0.364)	-1.716*** (0.244)	-2.827*** (0.457)	-1.069** (0.465)	-1.979*** (0.248)	-1.204*** (0.388)	1.392* (0.830)
EX Belgium	0.861*** (0.244)	0.649*** (0.208)	0.723 (0.630)	-0.513 (0.668)	1.077*** (0.345)	0.662** (0.282)	-0.187 (0.216)	0.638 (0.477)

Standard errors (HAC Newey-West) are in parentheses

*** / significant at a 1% level, ** / significant at a 5% level, and * / significant at a 10% level