Virtual bidding: a mechanism to mitigate market power in electricity markets

Some evidence from New York market

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Abstract: Electricity markets are prone to the exercise of market power due to specific characteristics of this commodity. Indeed, different studies have found evidence of market manipulation on liberalized electricity markets (Some evidence might be found for instance in Weiss (1975), Schmalensee and Golub (1984), Green and Newbery (1992), Borenstein, Bushnell & Wolak, (2000 & 2002) Joskow & Kahn (2001) and Hildebrandt (2001)). Nevertheless, some market designs and market rules may increase the efficiency of these markets and mitigate market power. This paper explores the impact of financial trading on spot electricity markets, as a market rule that mitigates market power. This is also referred to as "virtual bidding." In order to provide evidence on the impact of this policy, we estimate a structural model based on Bresnahan (1982) and Lau (1982) using data from the New York market. Results show that financial trading has a positive impact on the reduction of market power. From a public policy perspective, one may therefore argue for the allowance of financial trading in electricity markets, not only to improve liquidity but also to mitigate market power.

Keywords: *virtual bidding, market power, electricity markets.*

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1. Introduction

In contrast to most commodity markets open to financial trading, traders that participate in electricity markets usually have to possess means to produce the traded commodity (i.e. possess electricity generation units), to consume electricity or an intermediary that sell or buy energy with physical implications. However, this aspect has changed in some United States electricity markets. Some US electricity markets have allowed the possibility for traders who do not intend to produce or to consume energy to participate in the electricity spot markets. This has led to a new form of bidding practices in these markets known as "virtual bidding." When virtual bidding is allowed, bids are just financial transactions that do not affect real-time production or consumption of electricity.

Nevertheless, traders who submit financial bids in a day-ahead market have the requirement to sell or buy back in the real time (Isemonger & Rahimi, 2006). For instance, virtual supply bid sell energy in the Day Ahead Market (DAM) and then automatically it will be price taker in the Real Time Market (RTM) for the same amount. On the other way around, a virtual demand, will buy energy in DAM and sell it in RTM. Those transactions modify the DA and RT prices. This framework gives the possibility for pure traders[3] to enter in the electricity markets. Some important US electricity markets that have allowed pure traders or speculators to participate in their day-ahead and real time markets[4] like as follows: PJM since June 2000; New York ISO (NYISO) since November 2001; New England ISO in (ISO-NE) since March 2003 and Midwest

3 Traders are market participants that do not own generation units, neither are consumers nor retailer companies. They could be banks or any other agent that have the solvency requirements to enter in the market.

4 There is under discussion the extension of the policy to other markets like ancillary services in PJM (PJM Interconnection is a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia).

ISO (MISO) since April 2005. Additionally, the California System Operator (CAISO) has also decided to implement this policy in 2011.

To the extent that the implementation of virtual bidding enables agents to more freely participate in a market, such a policy may have consequences on the competitiveness of a market. This aspect may be particularly important for electricity markets, where it is well known by now that these markets are particularly prone to market power issues[5]. If this is the case, virtual bidding could be one of the solutions that one may consider to mitigate market power in electricity markets. This observation prompts us to investigate empirically how virtual bidding affects the competitiveness of an electricity market, using monthly data from the New York electricity market from December 1999 to December 2005. We focus our attention on this particular market as data on this market is publicly available before and after the implementation of virtual bidding. This allows a meaningful comparison of market performance before and after the implementation of the policy. Unfortunately, market data is generally not available before the implementation of virtual bidding for other U.S electricity markets so that it is not possible to meaningfully compare the level of market competitiveness before and after the implementation of virtual bidding.

To this end, we assume an oligopoly model based on Bresnahan (1982) and Lau (1982) and rely on behavioral assumptions to uncover the price-cost margins, which is a measure of market power. We estimate market demand and supply equations, controlling for various factors that may have an impact on market power (fuel prices, weather conditions etc.). This allows us to indirectly estimate system marginal costs and the impact of virtual bidding on market power in the New York market. This approach allows us to overcome the difficulty due confidentiality of cost data to obtain price-cost margins. Our results suggest that virtual bidding has had a positive impact in mitigating market power, and this remains to be true when we take into account other

5 Some evidence might be found in Weiss (1975), Schmalensee and Golub (1984) , Green and Newbery (1992), Borenstein, Bushnell & Wolak, (2000 & 2002) Joskow & Kahn (2001) and Hildebrandt (2001)).

public policies implemented during the period of our study (environmental regulation and on market power detection programs) that might have an effect on market power.

The relation between virtual bidding and market power has not yet been extensively explored in the economic literature.[6] To the best of our knowledge, the only study related to this issue is that by Saravia (2003). Saravia (2003) constructed a Cournot model and showed that the introduction of financial traders lead to a decrease in market power exercised by firms. She also computed price-cost margins of firms participating in New York electricity market using engineering data and finds a negative impact of virtual bidding on the computed margins. Our work differs from hers in that we analyzed a longer period of time, which allows looking a longer term effect of virtual bidding in the NY market. As well we are taking into account all market power mitigation mechanisms that have been implemented in the NY since the creation of market. Additionally, our approach uses a different estimation methodology that incorporates virtual bidding a structural model for the entire market region.

The paper will be structured as follows. Section 2 presents an overview of the New York market and on Virtual Bidding policy on this market. Section 3, presents the basis of the structural model that allows computing the impact of virtual bidding policy in New York. Section 4 presents the data description and empirical results of our model. Section 5, concludes and makes some policy recommendations.

2. The New York electricity market and the Virtual bidding solution

In this section, we give a brief description of the New York electricity market (section 2.1). In section 2.2, we explain some CO2 emission programs that affect the New York market. In section

6 Until now, as discussed in our introduction, the literature on virtual bidding has focused essentially on the financial aspects of virtual bidding i.e., whether virtual bidding has improved the liquidity of electricity markets.

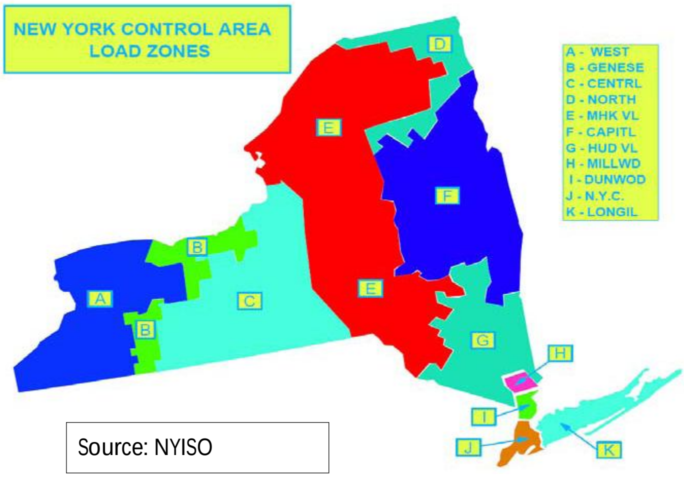
2.3, we describe the existing Market Power mitigation mechanisms that exist for the period analyzed. Finally in section 2.4, we describe the implementation of virtual bidding policy.

2.1 The New York Electricity Market

In 1996, the Federal Energy Regulatory Commission (FERC) issued orders to open access of national grids and encouraged the creation of independent entities to manage the markets. Northeast region and California were the leaders in the creation of organized pools. In 1997, the New York State Public Service Commission put in place the unbundling of the different activities of the electricity industry. A year later, the New York Independent System Operator (NYISO) was formally established and it started running auctions for the DAM and RTM in New York Control Area in November 1999. Prices are computed at the zonal basis. The demand is concentrated in the Southeast region[7]. (Millwood, Dunwoodie, New York City and Long Island) see figure 1.

7 The market is divided in eleven zones: Capital, Central, Dunwoodie, Genesee, Hudson Valley, Long Island, Millwood, Mohawk Valley, New York City, North and West.

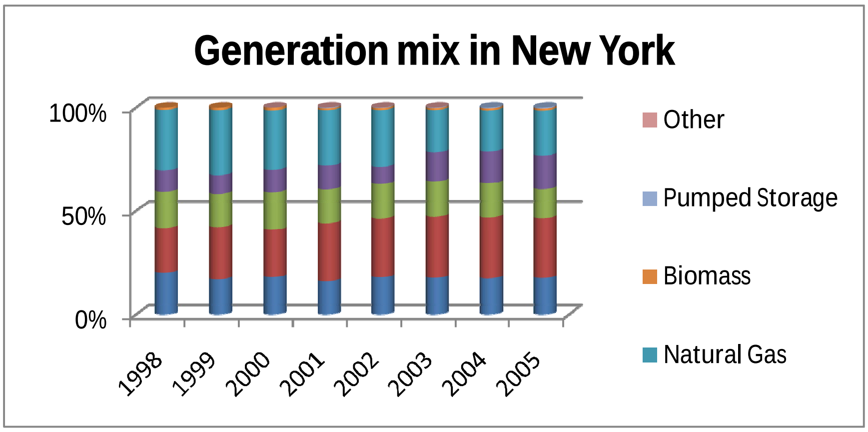
Figure 1. *New York Control Areal Load Zones.*



Regarding the multi-settlement markets, DAM works with hourly auctions. Bids are accepted at 5:00 am the day before and the schedules are posted by NYISO at 11:00 am. While in RTM bids are submitted for each five minutes and they can be submitted 75 minutes before the real time. The generation mix in New York State is somehow diversified in comparison with other states[8]. In New York, less than a third of the generation mix comes from the same fuel source. However, generation from fossil fuel represents almost 60% in the whole period of the study (see figure 2). Therefore, there is a strong dependency on fossil fuels, especially on gas that its prices have had a big impact on electricity prices.

8 For instance states like West Virginia or Wyoming depend 98% and 95%, respectively on coal. While Nevada and Alaska depend 67% and 57% on natural gas (NYISO, 2008).

Figure 2.



Data source: EIA

While there are endogenous fuel sources such as hydro or wind power in the northern regions of New York State, all the opportunities cannot be exploited to provide electricity for the more populated areas because there is limited transmission capacity. In addition, southeastern regions (New York City and Long Island) are the areas which witness the highest growth terms of electricity use. However, gas fire and oil power plants are the predominant fuel sources in these regions to support electricity consumption. Natural gas units represent 95% of New York City capacity and 79% in Long Island; while they represent 15% in the rest of the regions. It is also important identify is the marginal unit in a given hour because marginal units are the ones that set the marginal price of the system. NYISO (2008) stated that fossil fuels are marginal in 87% of the hours; the remaining 13% are set by hydro units for the year 2007. Consequently, fossil fuel costs have an important impact on electricity prices.

2.2 Emission programs in New York Market

Emission limits for power plant producers in the United States are driven by a program known as Acid Rain; this program is launched and managed by the U.S. Environmental Protection Agency (EPA). The program is set at a national level and consists in a cap and trade mechanism, which limit the emissions of SO_2 to half of the emission level of 1980. The SO_2 program has two phases; the first one began in 1995 and affected mainly coal burning power plants in the eastern and Midwest states (including the New York state). This initial program affected electricity costs from coal plants for the year 1999. Since the year 2000, the second phase of the program started, and extends emission limits to a larger range of emitting units including small coal, gas and fuel oil power plants. The program concerns existing plants in the year 2000 with a production capacity of more than 25 megawatts. We can expect that costs and prices of electricity after 2000 are more strongly affected by this second phase. It is therefore important to account for this cost given that there are consequences for is important in terms of computation of marginal system cost.

Regarding NOx emissions, a national program set an emission rate limit for coal-fired units. This rate is set at 27% of reduction of emissions from 1990 levels. In addition, two NOx trade programs at the States level (being New York part of them) have been launched. The first program, the Ozone Transport Commission (OTC) NOx Budget Program, was implemented from 1999 to 2002.[9] The program caps the emissions from less than a half from those registered in 1999. Then it creates a market for emission trading. The NOx program concerns generation units with a production capacity of more than 15 megawatts. In 2003, EPA launched the NOx Budget Trading Program which consists in a cap and trade program as well. This program lasted until 2008 and it concerned power plants and large combustion resources in 20 eastern states of US.

2.3 Market power mitigation programs

Different programs trying to mitigate market power have been implemented since the creation of the New York market in 1999. It is important for us to account for these programs in order to

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9 This program had been applied for the New England region, New York, New Jersey, Pennsylvania, Maryland, Delaware, the northern counties of Virginia, and the District of Columbia.

disentangle their impact on market power from the impact due to the virtual bidding policy. We will focus only in the programs regarding DAM mitigation as we are using data from DAM representing this market the 95% of total energy traded in the New York market.

The NYISO uses a “conduct and impact” mitigation approach. Firstly, this approach tests if a generator bid exceeds the competitive level and then measures if that bid has an impact on system price. If a bid fails both tests then it will be mitigated to a reference bid competitive level. That reference bid is computed as an average for competitive bid period or cost based estimations. The fist program started at the zonal level, it just affected the New York City and Long Island areas. It was implemented since the start of the market. There were two requirements to activate the bid mitigation: the zonal price might be higher than the price of the outside bus of the constraint area (reference bus called Indian Point II) and the generators must exceed their cost-based reference price. If a bid fulfill both requirements then the bid will be set at the fuel cost plus $1.

The Day Ahead Automated Mitigation Procedure (AMP) started in June 2001 and lasted until May 2002. It was applied on a zonal basis. This mechanism has four main components: the zonal LBMP (Locational Based Marginal Pricing) must exceed $150, the generator energy bid must exceed the reference price ($100 or 300%), it should have an impact in the LBMP by more than $100 when the reference prices are substitute for bids and the new solution must not increase the total load cost. If the last two conditions are met, then the LBMP will be determined using default bids at the applicable reference level.

The next program (Day-Ahead AMP II) started in June 2002 and finished in May 2004. This second program adds four specifications to the previous AMP: just applied for plants with more than 50 MW, improvement of the reference curves, test the impact of start-up payments and minimum generation bids in the energy price and improvement in the selectivity of the mitigation in the Security-Constrained Unit Commitment. This last specification takes into account geographical and temporal selectivity limiting mitigation for certain zones and hours in which the tests are met.

The AMP III (started in May 2004) introduced the following changes: the generation are subjected to mitigation just if they are pre-defined in the constraint area (load pocket), the generator is subjected to lower conduct limit rather than the limit applied to the statewide and the LBMP impact is measured at the generator bus level against lower predefined load pocket limit approved by a congested area.

Energy bids are mitigated in a specific hour if the generator fails the price impact test; they are mitigated for all hours if the load pocked (limitation of transmission capacity that isolates certain area) is active. As well, the bid production cost is guaranteed (payment that the generators for load pocket zones receive for supply energy in congested areas). The AMP III specifies a test of impact on prices in order to mitigate those payments. In a same way it is computed for mitigation of start-up costs and minimum generation requirements.

2. 4 Rationales for the Virtual bidding solution and The NY market

We will now discuss how virtual bidding may help to mitigate market power. We believe that the market power mitigation effect of virtual bidding is closely related to the potential benefits of the policy which have been discussed in the literature. We will address the potential benefits from virtual bidding respectively on: first open arbitrage to new entrants, second on local market power market mitigation, third on reduction on retailing market power, and finally on liquidity, risk premium and hedging opportunities. We argue that all of them might help to increase competition in the market and to mitigate market power.

First, virtual bidding allows new players to enter the market and to speculate on the market. If the speculation market is restricted to physical players, they will have market power and will exploit arbitrage opportunities until the marginal benefits from trade will be equal to marginal costs (transaction costs from trading). If physical player can affect the prices, the marginal revenue will not equal to prices. However, if market is open to speculators, the marginal speculation revenue (differences between the prices) will decrease if there is not important of transaction costs. Saravia (2003) argues that the transaction cost in the New York electricity market is close to zero. If this is the case, we can expect the spread between real-time and day-ahead to be statistically close to zero too under a competitive market.

Second, virtual bidding could give also incentives to agents to use transmission capacity in a more efficient way and thereby decrease local market power. Firms on an exporting area might have the incentive to withhold some energy in the day-ahead market in order not to congest the transmission lines, since the transmission price will be zero in this case. The firms will profit from the price differential between the two zones. This strategy is possible as transmission rents in the New York Market are tied just to DAM (Saravia, 2003). However, in real time, exporting firms will congest the line and transmission price will be greater than zero. Speculators could make transmission prices equal between regions and lead to reduce the possibility of exercising of market power.

If virtual bidding is allowed at a local level or nodal level basis, these bids can be used as a way to reduce the ability to exercise market power. Virtual bids at the load pocket might compete with physical bids at a nodal level and might help to mitigate strategic positions of some generators. . In addition, differences on demand forecast or load distribution factors might cause problems in the day-ahead market but it could disappear in the real time, so the system operator could use differences between day-ahead and real time to solve system problems (Isemonger, 2006). Local market power mitigation is improved if virtual bids are allowed at a disaggregated level.

Third, virtual bidding can also have an impact on retail market power. Retail companies are able to pass-through procurement costs; they might just buy energy in the DAM leading to high DA prices. Speculators might decrease those costs with virtual supply in the DAM reducing the prices and finally have an impact on decreasing retail prices. On the other hand, retail companies as they have a big client portfolio, they can have an impact on prices. Retail companies might be marginal in setting the market price, therefore thy can underbid in the DAM to lower prices and buy the remaining energy in the RTM, as long as this strategy is profitable. If DA prices are still lower virtual demand might profitable and reduce the profitability of this strategy. By doing so, speculators might decrease those costs and finally have an impact on decreasing retail prices.

Finally, financial traders can take positions in the market under virtual bidding. They bear some market risk. Since a better risk allocation can be achieved under virtual bidding, a reduction of risk premium on the market may be expected. Traders also could help to increase transparency on the market and reduce price volatility. Saravia (2003) found that the forward premium in the New York market has decreased. This means that forward contracting cost and hedging cost has decreased as well. An increase of traders in the market might lead to a decrease of the transaction costs. Newbery (2003) argues that if there are enough participants trading and sufficient volume low transaction costs will be ensured .All the previous issues might help to reduce entry barriers and expected increase on competition.

Virtual transaction might make physical hedging easier by allowing for more flexibility in the hedging strategies.[10] In addition, it gives the possibility for traders to create hedging products that benefit new participants, especially small players who have needs of hedging products as they have fewer instruments to manage risk. Hedging flexibility is particularly important in the electricity markets where vertical integration or long term contracts are widely used between generation and retail as a coordination mechanism chosen by the companies in order to manage

10 For instance, a generator might schedule the plant in the day-ahead market and receive the real time price. Or in a bilateral contract virtual bidding could allow the opposite party to access the real-time price while the contra-party participates in the day-ahead market. Additionally, it might allow supply and demand different hedging strategies, for instance hedging for operating reserves charges (PJM, 2009).

the balancing risk and management of clients' profile. Increase of hedging opportunities may favor new entrants, especially small players that have more needs of hedging instruments. New entrants might increase competition and decrease possibilities of exercising market power.

However there is one potential risk of virtual bidding that might take into account and has been signaled by Isemonger (2006) and recently by Celebi, Hajos and Hanser (2010). Market participants that have external participation and owns Financial Transmission Rights (FTRs)[11] might use virtual bidding to increase their revenues by for instance increase demand in a constrained area. Market participants may have losses with virtual bidding strategies but those losses may be lower than revenues from FTRs. In order to avoid these abuses, the different ISOs in U.S have implemented different rules for example NE-ISO, MISO and PJM. NYISO prohibits as well this strategy with the Market Behavioral Rule 2.

ISO-NE (2004) concluded that the availability of virtual transactions has increased participation, price convergence, statistical arbitrage and hence liquidity in the market. It also expanded trading options, while it does not led to important implementation or operation costs for the system. ISO-NE suggests that financial trades can help to reduce prices divergences and decrease price volatility.

In NY, from November 1999 to November 2001 only generators and Load Serve Entities (LSEs) were allowed to submit bids into the markets. Additionally, according to Saravia (2003) there were two rules that limited virtual trading: resource specific and feasibility. The first one refers to all generation bids that should specify the type of resource used and demand bids should indicate the area where the physical demand is. The feasibility rule does not allow generators to make bids higher than their capacity. However LSEs were allowed to purchase energy in either DAM or RTM without a penalization. However, most of the purchases from LSEs were done in the DAM.

[11] FTRs are contracts that give revenues equal to price differential between two nodal prices.

This issue was true even in zones were DA prices were higher to Real Time. That might indicate a risk minimizing strategy.

In November 2001, the Virtual Bidding Policy was implemented. This policy permits to buy energy in the DAM and sell it back in the RTM (virtual load) or sell energy in the DAM and sell it in the RTM (virtual supply). Virtual supply bids were subjected to allocation uplift costs[12] if virtual transactions increase them. Virtual bidding loads were not subjected to payments of uplift costs.

3. The model: an econometric analysis of the impact of virtual bidding on market power

3.1 Survey on Market Power Literature

The issue of market power has been extensively discussed in the literature. Indeed, different characteristics of these markets that make them more prone to the exercise of market power include, but are not exhaustive: low demand respond, high entry barriers due to asset specificities, high capital requirement, initial market structure, etc., the requirement to balance production and consumption in real time which makes that some generators are required to solve problems and maintain the security of the system. As well, limited interconnection capacity favors local generators. Furthermore, the fact that electricity is a homogenous product and that there are frequent and periodical bids on the electricity market make electricity markets prone to collusive behaviors.

Market power issues have given rise to numerous of studies since the liberalization of the electricity sector. The first studies on this issue can be found in the seventies and eighties in United States starting with Weiss (1975) who investigated on the concentration of generation

12 These costs refer to additional physical supply in order to maintain the reliability of the system.

ownership capacity for the largest consumption centers in USA. Later, Schmalensee and Golub (1984) used a Cournot model that accounts for transmission capacity and congestions and study the impact of market power. They included regional demand functions and direct computation of generation costs for different US area. They discovered high market concentration and an important effect of transmission capacity on competition performance. Green and Newbery (1992) was one of the first studies carried out on the issue of market power in Europe. They found that two main generators exercised market power by altering transmission capacity, manipulating star-up costs and with collusive behaviors. They showed that market power led to considerable deadweight loss and questioned whether the extra cost from competition justifies its benefits.

The California electricity market has been one of the best studied markets. Different studies have pointed out that the exercise of market power has led the Californian electricity to the System Crisis and to significant changes on market designs (Borenstein, Bushnell & Wolak, (2000 & 2002) Joskow & Kahn (2001) and Hildebrandt (2001)).

Market rules may play an important role in influencing the exercise of market power as well: while some market rules might indirectly create opportunities for exercising market power, others might mitigate it and increase the degree of competition in the markets. The Californian case provides useful lessons on this dimension by showing how different market rules affect the functioning of the market. For instance, the non liberalization of the retail market, the lack of real time pricing, the lack of hedging contracts in this market design played an important role in the California Crisis (Joskow, 2001).

To measure market power, a mark-up or the difference between the marginal costs and the actual system price is usually computed. Marginal costs can basically be measured using two kinds of approaches: direct estimation of costs based on historical unit data or indirect computation based on behavioral assumptions such as profit maximizing. The first approach has been taken in the studies by Wolfram (1999) in England and Wales market or Borenstein & Bushnell (1999); Borenstein et al. (2000) and Joskow and Kahn (2001) for the California market for instance. They computed the marginal cost for thermal units using fuel prices, the heat rate that measures the efficiency of the unit and the operating and maintenance costs. Joskow and Kah (2001) and Mansur (2003) also included emission costs. The inconvenient of this approach is that it requires data on actual costs of the units that is generally confidential. Those studies have been done using this approach usually have privileged access to information on the concerned markets.

On the other hand, other studies assume determined behavioral performance and compute marginal cost and the degree of competition indirectly. This approach is based on the framework and methodology proposed by Bresnahan (1982) and Lau (1982). Hjalmarsson (2000); Vassilopoulos (2003) and Bask et al. (2009) applied this approach to the NordPool market. A similar approach has been developed by Wolak (2002) and is used applied in Wolak (2003), Hortaçsu and Puller (2004), and Bosco et al. (2010). In these studies, marginal cost is computed indirectly from bid data and contract data. However, contract data is private information. For instance, Wolak (2003) had access to data on contracts in the Australian market and Bosco et al. (2010) for the Italian market. On the contrary, Hortaçsu and Puller (2004) computes directly the marginal cost for Texas market using direct cost estimation to indirectly derived the contract quantities.

The model used in this study is based on behavioral assumptions of the firm under the conjectural variation framework. The advantage of this framework is that allows indirect estimation marginal costs that usually are not available. This econometric methodology is part of what is called New Empirical Industrial Organization. It allows an empirical estimation of cost functions under the framework of oligopoly behavior. The solution might indicate an oligopolistic behavior among one of the well-known possible options: Cournot or Bertrand competition, a competitive market or a solution near a monopoly or cartel behavior. In our specification, the virtual bidding policy is included as a structural change to show this policy impacts on market competitiveness. Indeed, the functioning of the market may be changed due to this the implementation of this policy, as discussed previously.

In the following, we will briefly present the methodology proposed by Bresnahan (1982) and Lau (1982) before we discuss in greater details our econometric specification.

3.2 The methodology of Bresnahan (1982) and Lau (1982)

In the approach proposed by Bresnahan (1982) and Lau (1982),market prices and quantities are conceived to be the result of an interception between the demand and the supply function. On the demand side, the consumers are assumed to be price takers (inelastic demand) and on the supply side, firms will behave as profit maximizers. This means that generators will produce until the marginal cost will be equal to the marginal revenue (MC_i=MR_i). If market power is exercised, then we have MR>P. Under perfect competition MC=MR=P, so the suppliers behave as price takers.

The general model assumes the following demand function:

$$P = [D(Q, Z;\ \alpha), \varepsilon]$$

Where Q is the quantity, P the price, Y is the vector of exogenous variables, α is the vector of parameters to be estimated by the model, ε is the error term.

If the market were competitive, the suppliers will bid until the price is equal to marginal cost, as following:

$$P = [c(Q, W;\ \beta), \eta]$$

Where the bidding price is p, the marginal cost is c(.), the bidding quantity is Q, W is a vector of exogenous variables, the βs are the parameters to be estimated and η represents random shocks.

When the firms are not price takers, they could influence on the price and perceive marginal revenue instead of the price; this can be described by the following formula:

$$P = c(Q, W;\ \beta) + \lambda h(Q, Z;\ \alpha) + \eta$$

Where P+h(.) describes the marginal revenue and λ represents the static measure of market power. It can be directly derived that if λ=0 there is perfect competition and when λ=1 there is perfect cartel. Values between 0 and 1 indicate different results from oligopolies models, if λ=1/n, where n is the number of firms in the market one gets the Cournot solution.

Besnahan (1982) has signaled the problem of identification of the equations. He argues that under the previous specifications supply and demand equations are identified, but the degree of market power is not. To ensure identification of this latter variable, Bresnahan (1982) proposed to introduce rotation variables for the demand curve like the interaction between P and Z (PZ). This means economically that the Z variables not only shift the demand equation but also change its elasticity. If one assumes a linear demand function and linear marginal costs, then the equations take the following form:

$$Q = \alpha_0 + \alpha_p P + \alpha_z Z + \alpha_{PZ} PZ + \varepsilon$$

$$MC = \beta_0 + \beta_Q Q + \beta_w W$$

One can then derive as follows the marginal revenue function from the profit equation:

$$\pi = PQ$$

$$\pi = P(\alpha_0 + \alpha_P P + \alpha_Z Z + \alpha_{PZ} PZ + \varepsilon)$$

$$\frac{\partial \pi}{\partial P} = (\alpha_0 + \alpha_P P + \alpha_Z Z + \alpha_{PZ} PZ + \varepsilon) + P(\alpha_P + \alpha_{PZ} Z) = 0$$

$$h(Q, Z;\, \alpha) = P^* = \frac{-Q}{\alpha_P + \alpha_{PZ} Z}$$

As it was previously defined, $P = c(Q, W;\, \beta) + \lambda h(Q, Z;\, \alpha) + \eta$

Finally, $P = \beta_0 + \beta_Q Q + \beta_w W - \lambda \underbrace{\left(\frac{Q}{\alpha_P + \alpha_{PZ} Z}\right)}_{Q^*} + \eta$

Q* can be calculated if the aggregated demand function is estimated, then the degree of market power (λ) can be identified from the previous equation.

3.3 Including virtual bidding policy and market power mitigation mechanisms in the structural model

In order to incorporate the virtual trading in the Bresnahan (1982) and Lau (1982) model (B-L), we will use a dummy variable as a measure of the structural break of this policy. This variable (VB) will take the value of zero before the change (November 2001) and 1 after the implementation of virtual bidding.

We expect that market power will be reduced with the introduction of virtual biding and financial traders on the market. There could be different specifications in order to figure out this impact of virtual bidding on market power. One alternative to measure this effect is by first computing the B-L model and then compute the market power variable for each month, so we can see how it changes with the implementation of virtual bidding. The problem with that approach is that we may expect virtual bidding to have some impacts on the behavior of the bidders, which could be reflected the determination of prices and quantities. In such a two-step approach, one may neglect such an impact on observed prices and quantities. Consequently, we believe that the impact of virtual bidding should be directly accounted for within the structural model in order to make full use information available to us. Our specification accounting for virtual bidding then becomes:

$$P = \beta_0 + \beta_Q Q + \beta_w W - \lambda Q^* + \beta_{VB} VBQ^* + \eta$$

Where VBQ* is the interaction variable between market power and virtual bidding.

As previously discussed, there have been three different market power mitigation programs between 1999 and 2005 in the New York market. It is important to account for these programs in our empirical analysis those changes in the model in order to differentiate their effects from the impact of the virtual bidding policy. In the same way as the virtual bidding variable, the market power mitigation programs might affect the strategic behavior of the agents and the final output of the market. Therefore, we introduced extra dummy variables for each of the time frame of the different programs in order to capture their effects on market power.

We introduced a dummy variable which takes the value of 1, from June 2001 to May 2002 and zero otherwise for the first program (AMPI). For AMPII, the dummy variable takes value of 1 from June 2002 to May 2004 and zero otherwise. Finally for the AMPIII program, the dummy variable will be 1 from May 2004 to December 2005. Like the virtual bidding variable, the dummy variables which describe the market power programs are including as interaction terms with Q* in the supply equation as follows:

$$P = \beta_0 + \beta_Q Q + \beta_w W - \lambda Q^* + \beta_{VB} VBQ^* + \beta_{AMP} AMPQ^* + \beta_{AMPII} AMPIIQ^* + \beta_{AMPIII} AMPIIIQ^* + \eta$$

With the introduction of various dummies that describe the market power programs, now the λ will represent not the general market power for the whole period, but just for the period before the implementation of the first program i.e., for the period from December 1999 to June 2001.

3.4 Data description

The data that we used in order to estimate our model correspond to monthly average data from December 1999 to December 2005 from the New York electricity market. It could be worthwhile to have more disaggregated data in order to capture short term dynamics, especially because auctions for the DAM and RTM are made on an hourly basis. However, some variables used in the model such as fuel prices and state economic index are variables that are not available in a more disaggregated level.

Monthly electricity prices and quantities are an average from the day-ahead market. In the New York market almost 95% of the energy is scheduled in the day-ahead market. As the market is mandatory, firms may have bilateral contracts but they should summit their bids into the market.

The New York electricity prices are the monthly average for day-ahead zonal prices published by NYISO. We consider all the regions in order to compute the average price, except the prices from external regional markets (HQ, NPX, OH, PJM). Price variable is measured in US dollars per Megawatt-hour.

Electricity quantities for DAM are not directly published in the NYISO web page. However, the bids for the DAM are published. As such, we can obtain the quantity of electricity through the bids. The methodology used is as follow: First, we consider the dispatched hourly generation bids in the DAM. As bids are submitted in a cumulative curve where generators specify the quantities and the prices that they want in order to the energy, there are six dispatched values. The bid publication does not specify the location of the generators. So, for each generator we took the higher bid if the price is lower or equal to the higher LBMP of any of the regions. We summed up all generators' dispatched bids for each hour as they represent hourly delivered electricity in the DAM and then we took the average for the month. The variable is measured in Megawatts.

3.4.1 Demand function

Previous studies (Hjalmarsson 2000, Vassilopoulos, 2003; Bask et al. 2009) have shown that the following exogenous variables shift for demand for electricity: temperature (temp), that represents demand for heating, the index of economic production (Ei) that represents the demand of electricity to support economic activities and day length (Dl) which indicates the demand for lighting. The temperature data is the monthly average from the New York State made by the National Oceanic & Atmospheric Administration (NOAA) which is part of the US Department of Commerce. It is measured in Celsius degrees. The “Index of Coincident Economic Indicators” for the New York state is taken from the Federal Reserve Bank of New York. The index measures the economic activity for the New York state, and 1992 is used as the based year to compute the index. The day length is the monthly average for the New York state, and the data is provided by the U.S. Naval Oceanography. This variable is measured as the number of hours and minutes of light per each day.

3.4.2 Supply function

Under competitive behavioral assumption and profit maximization generators bid their marginal costs. The main driver of marginal costs in electricity generation comes from fuel costs. Additionally, the United States has emission reduction programs as discussed in section 3.2. The emission programs' requirements add an extra cost to electricity markets, especially for fossil fuel dominated ones such as New York State. Other costs such as wages are expected to be relatively fixed in time, as Hjalmarsson (2000) and Vassilopoulos (2003) argued, the power industry is not labor intensive, so that labor costs should be negligible in the overall generation cost.

Generation from fossil fuels represents more than 50% of the generation mix in the New York market and it has not changed much during the years under study. Therefore we consider the prices of coal, natural gas and petroleum as variables that reflect changes on marginal cost. On the other hand, nuclear and hydroelectric are important part of the generation mix (40%) but they are usually considered as based load technologies, so we assumed that their costs do not have an impact on the marginal cost of the system. As discussed in section 3, fossil fuels technologies are determinant for the system price in about 87% of the hours. In addition, hydro power does not have a significant marginal cost, but the opportunity cost is usually determined to the thermal units' costs.

The fossil fuel prices in our data come from Energy Information Administration. The fuel oil prices are available on a monthly basis as this market is international and well organized. The same thing can be said for the gas market. The EIA publishes a price index for gas average prices aggregated at state level. Coal prices data are not published as the gas or petroleum prices. However in order to have an equivalent measure of all fuel prices, we use data from the form 423 of FERC on which the generators report the monthly fuel costs per type of fuel. We took the average monthly cost of the companies' reports for the State of New York in order to have an approximation of fuel prices. The costs are the FOB (free on board) purchase price and it is measured in cents of dollar per million of Btu (British Thermal Unit).

The best way to take into account emission costs in the model is to use emission prices for NOx and SO2 of the U.S emission markets. However, these prices are not freely available public information.[13] Emissions costs might be considered relevant for the present study due to the importance of fossil fuel sources in the New York state.[14] We will use emission quantities as instead of emission prices due to a lack of information on these latter variables. One may argue then both variables are strongly correlated. Emission quantities are taken from the EIA. As SO2

13 Brokerage firms such as Cantor Fitzgerald sell these prices but it was considered not affordable for this current study.

14 SO2 prices are highly volatile from 1999 to 2005. For the year 2003, they were about $69/ton to $270/ton. By the end of 2004 it passed the $700/ton threshold and in 2005 it reached values of $1578/ton. NOx prices were around $1000/ton at the end of 1999. For the rest of the OTC NOx Budget Program prices were around on average $1500/ton. Uncertainties regarding the use of emission control technologies lead to high prices in the Budget Trading Program to about $4000/ton.

market is at national level, so we considered all the emissions from electricity power plants in the U.S. On the other hand, for NOx, we considered quantities for those states that were part of the emission reduction program. As emission quantities are expressed in tons and for the national or regional level, they are large numbers with large variations that might affect the overall model results. Therefore, we introduced emission quantities in natural logarithms to avoid potential problems of heteroskedasticity by the introduction of emission level.

Our approach may have oversimplified the reality on electricity markets. For instance, we do not take into account costs related to the grid, outages cost, unit commitment costs and some other relevant costs for the electricity markets. However, the aim of the paper is not a strict replication of the market, but just to capture the essence of this market and to show the impact of virtual trading on market power.

3.4.3 Empirical model

Accounting for various control variables discussed above, our econometric specification becomes:

$$Q = \alpha_0 + \alpha_p P + \alpha_{temp} Temp + \alpha_{Ei} Ei + \alpha_{Dl} Dl + + \alpha_t t + \alpha_{Ptemp} PTemp + \alpha_{PEi} PEi + \alpha_{PDl} PDl + \alpha_{d_i} \sum_{i=2}^{12} d_i + \varepsilon$$

Where now $Q^* = \frac{-Q}{\alpha_p + \alpha_{Ptemp} Temp + \alpha_{PEi} Ei + \alpha_{PDl} Dl}$

$$P = \beta_0 + \beta_Q Q + \beta_{coal} Pcoal + \beta_{gas} Pgas + \beta_{fueloil} Pfueloil + \beta_t t + \beta_{SO2} \ln(SO2) + \beta_{NOx} \ln(NOx) + \lambda Q^*$$
$$+ \beta_{AMP} AMPQ^* + \beta_{AMPII} AMPIIQ^* + \beta_{AMPIII} AMPIIIQ^* + \beta_{VB} VBQ^* + \beta_{d_i} \sum_{i=2}^{12} d_i + \eta$$

Therefore, we obtain a set of simultaneous equations since the endogenous variables of one equation appear as explanatory variables in the other equation. With the simultaneous specification, the ordinary least square estimator may be biased and inconsistent. Therefore, it is necessary to use an adequate estimation methodology. There are available alternatives and more advance methodologies which deal with this issue such as two stage least squares, three stages least squares, full information maximum likelihood and non linear feasible least squares. Based on previous studies that use these methodologies we will make a brief discussion on an adequate estimation method that should be used.

Hjalmarsson (2000), Vassilopoulos (2003) and Bask et al. (2009) estimate the B-L model with two stage least squares. Nevertheless, this methodology is restricted in the sense that it does not use all the information available to estimate simultaneously the equation system. One may also use a maximization algorithm that iterates until the model converges to a solution to estimate the system of equations. Estimators that fall into this category include three stage least squares or full information maximum likelihood. These approaches are quite convenient for studies with non linearity specifications. In the B-L model, the non-linearity comes from the computation of Q* variable. Non linear feasible least squares is another such method to estimate simultaneous equations system. Non linear feasible least squares will maximize both equations at the same time and produce consistent results.

Non linear simultaneous equations estimator is a popular method to compute the B-L model. Delis et al. (2008) compare the results from nonlinear three stage estimation, maximum likelihood and generalized method of moments. They argue that non linear three stage estimators give better results in comparison with the other methodologies. For instance, they signal that generalized method of moments is very sensitive to the instruments used. This was tested in our study: the results changed dramatically when some instruments were withdrawn from the model,. Durevall (2004) used maximum likelihood estimation in the application of B-L model in order to compute the market power for the Swedish coffee market. Toolsema (2002) applied the B-L model to the Dutch consumer credit market and argues that for this methodology three stage least squares or full information maximum likelihood are proper estimators rather than more limited estimation method such as two stage least squares.

The variables used in our model present high seasonal variations. This leads us to control for seasonality by including dummies variables for each month of the year. We also introduced a time trend in both equations (t). Descriptive statistics on our data are provided in table 1.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
P	49,73	17,43	24,28	105,94
Q	7070,22	1432,99	4829	10825
temp	16,00	10,14	0,18	31,15
dl	11,94	2,22	9	15,19
ei	125,60	3,53	120,94	132,65
Coal Price	164,18	37,17	127,95	307,99
Fueloil Price	439,76	131,87	252,08	832,58
Gas Price	614,93	275,19	261,13	1464,14
ln(so2)	20,59	0,10	20,40	20,79
ln(nox)	18,11	0,67	17,20	19,20
t	37	21,22	1	73
VB	0,68	0,47	0	1
AMP	0,15	0,36	0	1
AMPII	0,33	0,47	0	1
AMPIII	0,27	0,45	0	1
N= 73				

All the non-dummies variables are monthly average. P is the average electricity prices for the New York state ($/MWh). Q represents electricity produced in the market (MW). Temp (ºC), dl(m) and ei are the shift variables for the demand function and represents respectively, the temperature, day length and economic index. On the supply side, the fuel prices for coal, gas and fueloil are measured in (cents$/MBtu). Ln(SO2) and ln(NOx) represents the natural logarithm of SO2 and NOx emissions (tons) for the different programs that New State is part.

The dummies variables are used to take into account the structural changes. VB measures the virtual bidding policy getting a value of zero if the policy has not been implemented and one otherwise. Same interpretation has the AMPs values, they control for the implementation of the different Automatic Mitigation Procedures, if the AMP takes the valued of one for the period of implementation and zero otherwise.

4. Empirical results

The results of the B-L static model are presented in tables two and three. We have estimated three different specifications of the model. The first two columns represent the full model previously specified. The next two columns represent the model without the control variables for the Automatic Mitigation Procedures (AMPs). Last two columns are the results for the model without control variable for Virtual Bidding policy neither for AMPs. Dummies variables that control for seasonality are not shown in the tables.

Table 3 shows that results for demand equation and table four for the supply equation. It is interesting to note that all the relevant variables in both supply and demand equation are significant in our various specifications.

Table 3: Demand equation

Estimation Method: Non-linear System of Equation, FGNLS

	Full model		Without AMP		Without AMP nor VB	
Variable	**Coefficient**	**Std. Err**	**Coefficient**	**Std. Err**	**Coefficient**	**Std. Err**
P	-402,50** (60,02)		-649,76**	69,78251	-100,51**	50,100
Temp	101,266**	39,55203	116,3**	34,0153	35,25**	14,408
DI	-409,804**	202,2334	-649,46**	206,2411	-225,76**	103,303
Ei	-10,995	14,2422	-111,51**	14,93848	-210,67**	9,341
t	21,127**	4,722833	13,73**	5,524701	-82,06**	9,846
Ptemp	-2,396**	0,5909539	-2,26**	0,5179188	-0,24*	0,124
PdI	16,351**	3,063133	17,64**	3,672026	0,7	0,580
Pei	2,229**	0,5345314	4,13**	0,6607173	2,06**	0,389
R-square:	0.70		0,60		-	
No of obs:	73					

*Significant at 90% **Significant at 95%

Table 4: Supply equation

Estimation Method: Non-linear System of Equation, FGNLS

	Full model		Without AMP		Without AMP nor VB	
Variable	**Coefficient**	**Std. Err**	**Coefficient**	**Std. Err**	**Coefficient**	**Std. Err**
Q	0,007**	0,0009567	0,0046**	0,0008099	0,014**	0,0027217
Coal Price	0,074**	0,033011	0,071**	0,0283361	-0,0024	0,0044589
Fueloil Price	0,037**	0,0089775	0,035**	0,0085375	0,0021*	0,001266
Gas Price	0,011**	0,0042921	0,012**	0,0039958	-0,0012*	0,0006432
Ln(SO2)	118,676**	18,77415	108,205**	1,422793	-1,315	2,677773
Ln(Nox)	-2,448	1,93316	-2,76	1,635579	0,247	0,2479184
t	0,081	0,1184641	0,21**	0,0921266	0,487**	0,0630558
Q*	0,060**	0,018188	0,05**	0,017007	1,244**	0,4382088
AMPQ*	-0,028*	0,0167634				
AMPIIQ*	-0,026	0,0171601				
AMPIIIQ*	-0,028*	0,0173916				
VBQ*	-0,033**	0,0131939	-0,054**	0,016		
R-square	0.80		0,83		0,59	
No of obs:	73					

*Significant at 90% **Significant at 95%

4.3.1 Demand equation

The R-square for the demand equation with non-linear simultaneous equation is 70%. The first two columns of table present the results of the full model estimation. As it is showed, price coefficient is significant at 99% and has the expected sign, showing a negative relation between price and quantities. The coefficient is -402 which means that if an increase of $1 in price will lead to a decrease in demand of 402MW. Day length variable is negative correlated with demand quantity. This shows that if there is more day light, the demand for electricity will decrease. Temperature and demand of electricity are positively correlated. This result is counter-intuitive at a first glance, but may be explained by the peak demand that occurs in summer time as a result of increasing use of air conditioning. The economic index is negative related with demand of electricity but the variable is not significant. The time trend is significant at 99%. This may be explained by factors that are affected by time such as increases in the market size. The interaction between the explanatory variables (day length, temperature and economic index) and the electricity price are significant at the 99%. This is important to our work because the coefficients of those variables are needed in order to identify market power and its interaction with the structural break dummies.

4.3.2 Supply equation

Table 3 shows the results for the supply equation. The first two columns show the estimates for our full model. The R-square for this equation is 80%. The supply relation is positive related with respect to quantity as expected, indicating that marginal costs will increase with the quantity of energy produced. The associated coefficient is estimated at 0,007 and is statically significant at 99%. Gas and fuel oil prices are also significant at 99% and have the expected positive sign. This means that gas and fuel oil prices are positively correlated with electricity prices. The estimated coefficient for coal prices is positive as well, implying a positive correlation with electricity prices. This coefficient is significant at 95%. The results signal that increase of fossil fuel prices will lead to an increase on electricity prices on the supply side.

Instead of emission prices we have used emission quantities as instruments (see section 2.2). The estimated coefficient for SO2 (in UNITS) is positive and is highly significant at 99%. This might indicate that the SO2 quantity works properly as instrument. This variable was used instead of prices as the variable is not public, but it might introduce some noise in the model. As far as NOx emissions are concerned, our estimate shows that such emissions do not have a significant impact on electricity supply. This may be due to the fact that our variable is inadequate to capture the impact of NOx emission on the supply function. Other factors might drive the behavior of NOx prices and our measure does not sufficiently account for such factors. Nevertheless, as discussed previously, NOx prices represent less than 1%of electricity prices so we believe that our estimations are still reliable.

Under the base B-L model without interactions variables (without VB or AMPs), the λ coefficient, which measures market power, is significant and has the expected sign. Although the value is out of the expected range it is statically below from 1 (Z test was used). This result suggests the existence of market power in the New York electricity market during the period under study. Under the second specification, we check if virtual bidding policy has had an impact on the reduction of market power. The coefficient of VBQ* (-0,054) is statically significant at 99%. It has the expected sign and within the range expected as well. This result shows that the virtual bidding policy has helped reducing market power. However, as we have noted before, NYISO has also implemented various market power mitigation policy during the period that we study. As these programs may also have an impact on reduction of market power, it is interesting to take them into account and to check whether virtual bidding still has a negative impact on market power. Our full specification takes this aspect into account.

In terms of the impact of market power mitigation programs, our estimations show that most of these programs did have a significant impact on reducing market power on the New York electricity market. Indeed, most of the associated variables are significant and fall within the expected range. The coefficient for Q* variable is significant at 99% and has the value of 0,06. This indicates the existence of market power from November 1999 to June 2001. The variables that measure the impact of the AMP and AMPIII programs are significant at the 90% which indicates that there are small decreases of market power due to the implementation of the programs. The variable associated with the AMPII program is weakly significant and suggests that the AMPII has had a lower impact on market power reduction in comparison with the other programs.

It is worthwhile to note that our estimates also show that the virtual bidding policy does contribute to reduce market power on the New York electricity market during the period under study, even after we account for the existence of various market power mitigation programs implemented by the NYISO. Indeed, this variable is significant at 99%. The coefficient suggests that virtual bidding has had a positive impact on the reduction of market power. Our result therefore suggests that virtual bidding has not only enhance the efficiency of the New York electricity market in terms of liquidity and market risk, as already suggested in the literature, but in terms of competitiveness of the market.

5. Conclusions

This paper explored the impact of virtual bidding on the competitiveness of electricity markets. While there have been different studies that evaluate virtual bidding policy in different U.S markets, almost none of them has investigate the impact of such a policy for the level of market competitiveness, only Saravia (2003) has looked at this issue but form a different perspective and using another methodology. To this end, we investigated whether the virtual bidding policy implemented in the New York electricity market has an impact on the exercise of market power using the methodology proposed by Bresnahan (1982) and Lau (1982). This methodology has been widely applied to various markets to understand the issue of market power. The New York market was chosen for our study as data is available for this market. Our results suggest that virtual bidding has had a positive effect in terms of reducing market power in the New York electricity market. This result to robust when we account for various market power mitigation programs that have been implemented, and shows that allowing traders to enter in the multi-settlement electricity market might lead to improvements on market efficiency and mitigation of abusive positions of some market players.

Nevertheless, we have been confronted to some data limitation problems in our study. In particular, we have had to compute some data such as quantity of traded electricity of the day-ahead market using data on bids, as well as relying on quantities instead of price of polluting emissions for our study. Such data problems may influence the quality of our estimations.

However, given that major variables in our regressions are significant and have the expected sign, we remain fairly confident on the consistency of the estimates that we have obtained.

Another potential shortcoming of our analysis is that we have only focused on one market—the New York electricity market. To be sure that virtual bidding can generally lead to a reduction of market power, one may want to analyze the impact of this policy on other markets where it has been implemented such as New England and PJM. The lack of market data before the implementation of this policy is these markets does not allow us to do so in this paper. We leave this aspect for future investigation.

Another useful extension to our work may be to adopt a dynamic analysis of the impact of virtual trading. In this paper, we have adopted a static framework as a starting point in our analysis. We believe that a dynamic framework may improve our understanding on how virtual bidding can help reduce market power in electricity markets.

Nevertheless, our results show that allowing traders to enter in the market might give some desired effects not only in terms of improvement market liquidity, price convergence, lower risk premium, flexible risk strategies, etc., but also in terms of mitigating local and global market power. One may be able to attained these results by changing market rules and structures like imposing the unbundling of generation and retail activities, limiting contractual arrangements between generation and retail business of the same group, auctioning off some generation production, increasing of interconnection capacity etc.. However, these changes may be more costly and more difficult to implement, and they may also take more time. In contrasts, experiences by corresponding authorities have shown that the implementation costs of virtual bidding are non-significant. This makes virtual bidding a particularly attractive policy option that could be considered to enhance the efficiency of electricity markets. However, virtual bidding might have a risk for gamming in the market, for instance by owners of FTRs. Good market rules are necessary to avoid those behaviors. Obviously, this also warrants more investigation on this mechanism in the future so that we can have a better understanding of virtual bidding.

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