Default Supply Auctions in Electricity Markets: Challenges and Proposals

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Abstract

This paper studies consequences of default supply auctions in electricity markets on premiums over spot prices got by winning bidders, and on speculation and hedging activities in power derivatives markets. Data comes from sixty-four auctions, those of CESUR in the Spanish OMEL electricity market from 2007 to 2013, and those of Basic Generation Service auctions (PJM-BGS) in New Jersey's PJM market from 2006 to 2015. Winning bidders got an average yearly premium of 10.15% (CESUR) and 112% (PJM-BGS) over electricity spot prices. Premiums and number of bidders are negatively related. In CESUR, hedging-driven trading in power derivatives markets is predominant around auction dates, but in PJM-BGS, speculation-driven trading prevails. We test several methods as alternative to auctions. In Spain, price risk aversion boosts consumers' preference for auctions over spot prices. New Jersey consumers never choose methods based on auction prices, preferring methods based on based on derivatives contracts or spot prices. In both markets, the higher the price risk aversion the stronger the preference for methods based on derivatives contracts.

Keywords: Electricity markets; Default supply auctions; speculation and hedging; power derivatives

JEL Codes: C51; G13; L94; Q40

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1. Introduction

Liberalization processes of electricity markets around the world face many challenges, such as how to supply electricity to different customers at prices consistent with market circumstances. Auction mechanisms have played a salient role in many countries in the effort to match supply and demand (Maurer and Barroso, 2011) as an alternative to other pricing systems, for instance, those based on predictions of expected spot prices during delivery periods. In particular, in deregulated markets, the way to supply electricity to customers whose contracted capacity is small and are not served by alternative suppliers is a question of particular concern to regulatory authorities. The reason is that the bulk of those customers are households and small firms. Providers of last resort, designated by the corresponding public utility commission, must get electricity from somewhere and must supply energy to those customers. Retail electricity prices contain two elements: the cost of supplying electricity and the national "government wedge" (taxes, levies, and other charges to finance public policies). In this paper, we focus on procedures for computing the first element of final electricity prices. We call this element "the cost of energy" element that has two elements: a fixed factor related with contracted capacity and a variable factor related to electricity prices.

One way of setting this variable factor is buying energy for Providers of Last Resort (POLR) by means of Default Supply Auctions (DSA). In these auctions, POLRs buy electricity forward contracts from winning bidders (WB) at prices determined by the specific auction mechanisms (e.g. sealed bid, ascending auctions, descending clock auction (DCA)[1]). Market regulators use DSA-based prices for computing the variable factor of the

[1] In ascending auctions, the auctioneer begins with a low asking price for the product being acquired, which is increased by bids from participants. Price and allocation are determined in an open competition among the bidders. The bidders willing to pay the most win. In DCAs, in each round the Auctioneer announces a price for the product being acquired. Bidders bid for the right to provide the quantity of the product they

cost of energy part. When choosing DSA as a method for procuring electricity to POLRs, market administrators assume at least two hypotheses: (1) DSA provides efficient generation resources at competitive prices[2], and (2) DSA gives agents incentives to engage in hedging activities, presumably using power derivatives[3]. This paper studies the extent to which these two hypotheses are consistent with empirical evidence from actual experiences in Spain and in the State of New Jersey. While most regulatory agencies are required to issue analysis of intended consequences of regulations along with regulations themselves, electricity market regulators rarely did so. Even less common are reports of unintended consequences after actual application of new regulations. In this paper, we present the first try to this analysis with DSA, using data from sixty-four default supply auctions, the most comprehensive empirical evidence available, as far as we know. We document the challenges faced by DSA and propose several alternatives to meet these challenges.

In a DSA, POLRs buy forward contracts from WB. The administrator of the auction awards contracts by a descending-clock auction. Spain implemented[4] from 2007 to 2013 twenty-five quarterly auctions of energy contracts for last resort supply (CESUR[5]

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wish to supply at the price announced by the Auctioneer. Bidders decide what quantity of the product they wish to offer to provide in a particular round of the auction. Following the end of a round, the Auctioneer adds up all bids received at the price for that round. If the total quantity of the product bid is greater than the quantity to be acquired, the Auctioneer announces a lower price for the following round. Bidders then decide how much to offer to supply at the new, lower price. The quantity of the product that a bidder offers to supply in the next round can be the same as or smaller, but not larger, than it offered in a previous round. A bidder must submit bids in every round, and cannot re-enter the auction once it abstains from bidding in a round. When the total quantity bid by all bidders matches the total quantity sought by the Auctioneer, the auction closes. The winners are the bidders in the last successful round of the auction.

[2] According to New Jersey Board of Public Utilities (BPU), the auction is designed to procure supply for PJM-BGS customers "at a cost consistent with market conditions". More details of PJM-BGS auctions can be found at http://www.BGS-auction.com/BGS.auction.overview.asp. The Royal Decree 1634/2006 regulating CESUR auction states: "the goal is to adapt tariffs (auction prices) to market prices". CESUR auctions, (see Order ITC/400/2007) help in the pricing of the energy component included in tariffs charged to final consumer. They also intend to prevent further tariff deficits.

[3] According to New Jersey Board of Public Utilities (BPU), auctions provide an opportunity for energy trading and marketing companies to provide PJM-BGS supply. One key goal of CESUR auctions is "encourage forward contracting", CNE (2008).

[4] Ministerial Order ITC/400/2007

[5] Contratos de Energía para el Suministro de Último Recurso

auctions), as an instrument to calculate the electricity price to be charged to regulated consumers and to promote forward contracting[6]. The State of New Jersey implemented, from 2002 to the present, the Basic Generation Service (PJM-BGS)[7]. This yearly auction is the procedure by which electric distribution companies get electricity to supply customers who are not served by a third party supplier. Although other jurisdictions implemented DSA mechanisms sporadically (Maurer and Barroso, 2011 Chapter 3), CESUR and PJM-BGS are the longer lasting and best documented of all, and so we concentrated on them.

In spite of its economic importance, literature analyzing the consequences of DSA is scarce. In Spain, Federico and Vives (2008) analyzed results from the first five CESUR auctions and concluded that CESUR prices are close to prices of derivatives contracts with similar characteristics. Cartea and Villaplana (2012) analyze the ex-post risk premium calculated from CESUR auctions from 2007 to 2012 and find alternating quarterly periods with positive and negative ex-post forward risk premium. Fabra and Fabra Utray (2012) document an average positive ex-post yearly forward premium of 10% during CESUR auctions from 2009 to 2012 and argue that positive forward premium are likely because they are consistent with the incentives faced by vertically integrated electricity producers enjoying market power. Capitán Herráiz (2014), points out possible arbitrage opportunities between contracts auctioned in CESUR and contracts traded in power derivatives markets. He focuses on the first sixteen auctions, and documents a positive ex-post yearly forward premium, suggesting that winning bidders got positive rents from the mechanism[8]. In the U.S., Loxley and Salant (2004) study auctions in New Jersey, from the point of view of the

[6] CNE (2008)

[7] Other states, such as the state of Illinois in 2006, also implemented BGS auctions, but none of them has historical records comparable to New Jersey.

[8] See also Capitán Herráiz and Rodríguez Monroy (2009, 2012).

design of auction procedures[9]. They analyze the first auction and conclude that its design was right. Lacasse and Wininger (2007) compare Maryland and New Jersey's last resort electricity procurement methods and conclude that both systems[10] present pros and cons, but no method dominates in all circumstances. Maurer and Barroso (2011) state that New Jersey's auction mechanism has been "successful" since 2002 but do not analyze economic impacts on suppliers, consumers nor effects on derivatives markets. Results of Illinois' auction during 2006 are analysed in de Castro, Negrete-Pincetic and Gross (2008) who consider that this auction was a failure. The reason is that contracts contained a non-manageable risk and this, together with the specific structure of Illinois's electric generation facilities[11], made it very difficult for bidders to price contracts, resulting in high prices.

In this paper, we use the 2006-2015 sample from PJM-BGS and 2007-2013 CESUR auctions to test the hypothesis (1) and (2) and get the following conclusions. First, winning bidders in CESUR and PJM-BGS got an average yearly premium of 10.15% and 112% respectively, over electricity spot prices set in OMEL (Spain) and PJM (New Jersey) markets respectively. CESUR prices refer only to the energy part of total price charged to final consumers, but prices in PJM-BGS auctions include other services (e.g., capacity,

[9] New Jersey auctions offered tranche contracts. Such contracts differ substantially from CESUR contracts. The main difference is that, while CESUR contracts specify the total amount of the energy to be provided, tranche contracts specify the percent of demand that the supplier must satisfy during the delivery period. The amount of demand is unknown at the time the contract is signed. In consequence, tranche-based products shift all the uncertainty from the distribution companies to the generation sellers. De Castro et al. (2008) stress the fact that product definition is one of the key issues in the auction design. Negrete-Pincetic, de Castro and Pulgar-Painemal (2015) analyze the impacts that product definition has on the market outcomes, suggesting guidelines for improving the product definition in electricity auctions. In particular, the definition of products must consider the attributes of the physical system (e.g. flexibility).

[10] Maryland's approach is based on a request for proposal, which is similar to the process commonly used to procure new capacity. New Jersey's method is based on BGS auctions. In both cases, the contract is to supply a "full requirements" service. In other words, suppliers must supply a percentage of a POLR's load for a given customer type, whatever the load may be.

[11] In Illinois during 2006, almost 50% of electricity generation capacity comes from nuclear plants. www.eia.doe.gov/cneaf/electricity/st_profiles/sept05il.xls. Nuclear plants are appropriate as baseload units, but they are not appropriate as cycling or peaking units. Nuclear units cannot provide tranche products because they are not load-following entities.

ancillary services, risk management) besides the cost of energy, and volumetric risk. In spite of these facts, those high premiums are difficult to justify in terms of risk management and present a challenge to DSA-based mechanisms. We stress the fact that price risk measures of the relevant spot markets (OMEL and PJM) suggest PJM's volatility is double than OMEL's and PJM's tail risk is four times higher than OMEL's. However, PJM-BGS' average premium is eleven times higher than CESUR's. Second, we document a negative relationship between the number of bidders in auctions and ex-post premium. This suggests that lack of enough competitive pressure may be one reason explaining those premiums, so presenting a challenge to DSA-based mechanisms. Third, trading activity in power derivatives markets increased significantly in days surrounding CESUR and PJM-BSG auctions. Fourth, with CESUR auctions, hedging-driven strategies seem to be predominant around auction dates, but with PJM-BGS auctions, speculation-driven trading prevails. Therefore, empirical results are not consistent with the hypothesis (2) in the case of New Jersey, and high and persistent premium over spot prices enjoyed by winning bidders in both markets present a challenge to the hypothesis (1).

Therefore, we detect two major challenges to DSA, namely, high ex-post premium, possibly related to lack of competitive pressure, and unintended speculative activity in power derivatives markets. To meet these challenges, we compare several alternative methods to work out the cost of energy part. We assume that agents would prefer a method that minimizes average payments and the price risk of these payments. As measures of price risk, we consider two alternatives: variance and semivariance of the price distribution. In Spain, consumers indifferent of price risk prefer spot-based prices, followed by methods based on derivatives contracts, and auction-based methods. Increases in price risk aversion imply stronger preference for methods based on derivatives contracts.

Strong price risk aversion boosts consumers' preference for methods based on auctions over methods based on spot prices. In New Jersey, consumers never choose methods based on auction prices. When price risk aversion is zero, consumers prefer methods based on spot prices in one-third of cases and methods based on liquid swap contracts in the remaining two-third of cases. If volatility aversion is one, the corresponding proportions are ten per cent and ninety per cent. Increases in price risk aversion hint at stronger preference for methods based on liquid swap contracts.

The rest of this paper is organized as follows. Section 2 presents the main characteristics of CESUR and PJM-BGS auctions. Section 3 presents measures for distinguishing between hedging and speculation in derivatives markets. We report the empirical analysis in Section 4. In Section 5, we discuss alternative methods for computing the cost of energy part. Section 6 contains conclusions and policy recommendations.

2. Default Supply Auctions: CESUR and PJM-BSG

2.1 CESUR

As an additional step in the liberalization of the Spanish electricity market, Ministerial Order ITC/400/2007 implemented a quarterly auction (CESUR auctions); to support the calculation of the energy price to be passed through[12] to regulated consumers[13]. The basic mechanism of CESUR auctions is as follows. The government (Secretaría General de la

[12] Final electricity prices contains two elements: (i) cost of supplying electricity (including the price of energy based on CESUR prices in 2007-2013 plus the regulated cost of providing network services) and (ii) national "government wedge". This wedge includes taxes, levies, and other charges to finance public policies such as feed-in tariff support to renewables and payments of interests to investors in securitized 'tariff debt' traded in international financial markets. Spain's "government wedge" is the second highest in Europe (after Germany) and is the main reason for the rise in retail electricity prices since 2008; see Robinson (2015). It accounts for approximately 60% of final electricity prices.

[13] Households and small firms connected in low tension (< 1kV) and contracted load lower or equal than 10 kW. 22 million consumers in 2015.

Energía, SGE) announces the amount of energy to be auctioned, first price and auction dates. SGE also announces delivery periods; usually the trimester immediately after the month in which auctions take place (Q1 in market parlance). Second, auction opens with a very high price and allowed bidders present their first offers (amount to deliver). Normally, at a high price, supply overwhelms demand. Therefore, the Auctioneer decreases the price (using a secret algorithm) and less efficient bidders decrease their supply offers. The Auctioneer decreases the price again, and so on until supply equals demand. There are five POLR, designated by the government. Their share as buyers in CESUR auctions is set by the government. The firms (shares) are ENDESA (35%), IBERDROLA (35%), EDP (12%), FENOSA (11%), HIDROCANTÁBRICO (4%) and VIESGO (3%)[14]. Given that winning bidders sell forward contracts to POLRs. Winning bidders may hedge their position with physical resources (i.e. generation assets) or by taking offsetting long positions in forward markets (e.g. organized markets such as OMIP or OTC). The Government appointed the National Energy Commission as trustee of the auctions (CNE, Comisión Nacional de Energía, later subsumed into the CNMC, Comisión Nacional de los Mercados y la Competencia, from October 2013). CNE contracted an independent consulting firm to conduct the first five auctions, which started in June 2007. From the sixth auction onward until December 2013, the managing body responsible for organizing and managing the auctions has been OMEL, the electricity market operator. The 25th CESUR auction (December 19, 2013) produced a final price that was deemed "too high" and the auction was annulled by the Spanish government on allegations of "manipulations"[15]. Since then, CESUR auctions are suspended.

[14] After the 5th auction, shares changed as follows: ENDESA 29%, IBERDROLA 40%, EDP 12%, FENOSA 6%, HIDROCANTABRICO 12%, VIESGO 1%.

[15] This is a controversial issue. See the extensive report by the market regulator CNMC (2014) which points out to some "atypical" circumstances. For instance, the auction closed after seven rounds. In all previous cases, the minimum figure was twelve rounds.

From July 2007 until March 2014, the price of energy part included in retail prices was referenced to CESUR prices. Since April 2014 to the present, the Spanish Government adopted a new system based on PVPC (*Precio Voluntario para el Pequeño Consumidor,* Volunteer prices for small consumers) tariffs in which the price of energy components is calculated using hourly prices of the wholesale electricity market. Therefore, small consumers affiliated to PVPC are exposed to daily fluctuations in prices, that is, to market price risk. Such exposure causes growing concern both to consumers and to government officials[16]. Small consumers also can sign "free-market" contracts with commercial suppliers[17].

In CESUR auctions, quantities auctioned are always smaller than the amount needed to fulfill regulated consumers' needs. In most cases, auctions included three-month base-load contracts, amounting to an average of 3,500 MW, or less than 30 percent of expected needs. An average of thirty domestic and international allowed bidders take part in the bidding and contracts are awarded to an average of twenty WB, including retailers, generators, and marketers. All CESUR auctions are simultaneous descending clock auctions. On average, auctions closed after twenty-three rounds. Cash flows between WB and POLR resulting from CESUR auctions are computed each hour during the delivery period by differences between CESUR prices and spot (wholesale) market prices.

[16] According to the National Institute of Statistics' Living Conditions Survey (LCS) (http://www.ine.es/dyngs/INEbase/en/operacion.htm?c=Estadistica_C&cid=1254736176807&menu=ultiDatos&idp=1254735976608), 10.6 percent of Spaniards could not warm up properly in 2015. According to the association of consumers Facua, (www.facua.org) the electricity bill of average Spanish users grew by more than 40 per cent between April 2016 and January 2017 and was 28% higher in January 2017 than in January 2016.

[17] According to the regulator of the Spanish electricity market, CNMC, on January 2017, 11.9 million costumers (46.3%) were affiliated to PVPC, whereas 13.9 million (53.7%) have "free-market" price agreements with commercial suppliers (https://www.cnmc.es/sites/default/files/1506042.pdf). In this sense, free market means that consumers are perfectly free to negotiate terms and conditions with commercial suppliers. According to CNMC (https://www.cnmc.es/node/270517), during the first semester of 2016 "free-market" agreements proved to be more expensive to consumers than PVPC.

2.2 PJM-BGS

Since 2002 to the present, four designated POLR: Public Service Electric & Gas Company (PSE&G), Atlantic City Electric Company (ACE), Jersey Central Power & Light Company (JCP&L), and Rockland Electric Company (RECO) serve PJM's Basic Generation Service (BGS) customers through auctions held in February. Each POLR serves a specific geographic area (ACE, PSE&G, JCP&L, RECO) within the overall PJM system[18]. A given area has its specific spot price, provided by PJM. BGS refers to the service of customers who are not served by a third party supplier or competitive retailer. Two auctions are held concurrently, one for larger customers (BGS-CIEP) and one for smaller commercial and residential customers (BGS-RSCP, BGS-FP). In this paper, we concentrate on the latter because its final customers are like CESUR's. We call it PJM-BSG. Auction's goals are: (i) supply BGS customers at a cost consistent with market conditions and (ii) open an opportunity for energy trading and marketing companies to supply BGS customers. An average of twenty-five authorized bidders takes part in the bidding and contracts are awarded to an average of twenty WBs (Winning Bidders)[19]. On average, auctions closed after twenty-three rounds. Contract's winners must give electricity supply from June 1st through May 31st of the following year[20]. In contrast with CESUR, the products in PJM-BGS auctions are full requirements supply. A WB supplies a percentage of a POLR's load, whatever the load may be. Thus, a WB who wins 10% of a POLR's load provides all services necessary to serve 10% of that POLR's load. Note that WBs bear risks associated with load level, which can be large. So, WB is exposed to price and quantity (volumetric)

[18] The four utilities decided sell their generation assets or transfer them to affiliates, thus becoming electric distribution companies (EDC). An EDC is a "wires only" company. This means that the only assets it owns are wires (a "natural monopoly") and the firm is within the ambit of the market regulator.

[19] WBs become BGS suppliers and provide full-requirements service for final customers. AS Load includes capacity, energy, ancillary services and transmission, and any other service as PJM may require. ASs assume migration risk, and must satisfy the state's renewable energy portfolio standard.

[20] For their BGS-RSCP Load, the POLRs use a rolling procurement structure, where each year one-third of the load is secured for a three-year period.

risk. Winning bidders receive an all-in payment based on auction price for a POLR. In summer and winter, each WB receives auction price times a POLR-specific season factor for every kWh of load served for that POLR. Usually, summer payment factor is around 1.2 and winter payment factor is around 0.9. BGS-RSCP customers pay retail rates in which the energy part derives from BGS auction prices. More details on PJM-BGS auctions are in Lacasse and Wininger (2007).

3. Measures of hedging and speculation

We are interested in measuring relative activity of hedgers and speculators in power derivatives markets. Extant literature agrees that key variables to be considered in this regard are daily trading volume and open interest, see Leuthold (1983) and Bessembinder and Seguin (1993). For a given contract, daily trading volume accounts for its trading activity and reflects movements in speculative trading because this measure includes intra-day positions. Open interest is the number of outstanding contracts at the end of the trading day and captures mostly hedging activity, because, by definition, excludes all intra-day positions[21].

A natural step is to combine both variables to produce a measure of relative trading activity of hedgers and speculators. García, Leuthold, and Zapata (1986) suggest the volume-to-open-interest ratio, defined as follows:

$$R1(t) = \frac{V(t)}{OI(t)} \tag{1}$$

Notice that R1 is the ratio of a flow variable (V(t)) with respect to a stock variable (OI(t)) and so is open to criticisms on these grounds. Notice that the behavior of R1(t) depends on the whole past history of the contract up to day t, besides market activity on day t. For that

[21] Many studies support the underlying assumption that hedgers tend to hold their positions longer than speculators, see for instance Ederington and Lee (2002).

reason, ap Gwilym, Buckle and Evans (2002) proposed an alternative measure by relating two flow variables, the ratio of volume to absolute change in open interest, defined as:

$$R2(t) = \frac{V(t)}{|\Delta OI(t)|} \tag{2}$$

In which ΔOI(t) = OI(t) – OI(t-1). Notice that the behavior of R2(t) depends only on market activity on day t. Furthermore, notice that R2(t) discriminates between short-term speculation (day trades), which impact on V(t) but do not impact on ΔOI(t) , and the newly taken hedging positions (held overnight) which impact equally on V(t) and on ΔOI(t) . The higher the relative importance of speculative (hedging) demand is, the higher (lower) the value of R1(t) and R2(t). This would imply a positive correlation between R1(t) and R2(t)[22].

4. Empirical Analysis

In the following sections, we present tests and talk about to what extent available empirical evidence is consistent with the two hypotheses formulated in the introduction. In other words, we study to what extent DSA provides efficient generation resources at competitive prices, and whether DSA gives incentives to agents to engage in hedging activities in power derivatives markets, specifically trading futures (swap) contracts.

4.1. Ex-post forward premium

In this section, we study whether ex-post premiums on CESUR and PJM-BSG last resort auctions are consistent with the purported goal of providing efficient generation resources at competitive prices. Although market regulators do not give clear definitions of "competitive prices", one possibility is to interpret this definition implies auction prices should be "close" to actual wholesale market prices during delivery periods. This

[22] Lucia and Pardo (2010) discuss the relative merits of each measure and propose alternative measures.

closeness would imply relatively small ex-post premiums, which, on average, might be close to zero. On the other hand, winning bidders are taking price risk by selling forward contracts and may require a risk premium. This risk premium should imply auction prices are set above expected spot prices[23]. The reason is generation costs (for fossil generators) fluctuate daily and spot market prices show these fluctuations, thus providing a natural hedge to producers selling electricity in the spot market. However, sellers of forward contracts (if they are fossil generators) are exposed to higher volatility in their profits and need a compensation for this situation. Non-fossil generators do not face those risks. Therefore, if fossil generators are predominant, we should expect positive ex-post premiums because sellers need a compensation for assuming price risk[24]. To shed light on this point, we compute premium during delivery periods, by comparing realized spot prices in OMEL and PJM markets against auction prices. Basic facts of CESUR auctions are in Table 1 (base-load contracts).[25]

[INSERT TABLE 1 HERE]

Columns in Table 1 contain auction number, date, product[26], final auction price (CESUR price), and average spot price during the delivery period, premium, percentage premium and average yearly premium. The premium (defined as the difference between CESUR price and average OMEL spot price during the delivery period) ranges from -19.53% to 55.36%. Yearly averages are positive and their average is 10.15%. Therefore, winning bidders always got positive yearly premium. The other side of the coin are consumers

[23] In addition to that, the objective of reducing volatility of final prices serves the interest of risk-averse consumers wishing to avoid the price fluctuations that are usual in electricity spot markets. Presumably, such risk-averse consumers shall pay a moderate risk premium for the security of more stable prices.

[24] This situation contrasts with other derivatives markets in which buyers require this compensation, and in consequence, forward prices tend to be below expected spot prices.

[25] We analyze baseload contracts only. CESUR introduced Peak load contracts in 2008 but they amount to less than 10% of total capacity auctioned.

[26] For instance, product Q3-07 refers to a contract for delivering electricity from Monday to Sunday, 00:00-24:00, during July, August and September of 2007.

supplied by POLRs. From 2007 to 2013, final consumers paid near €1,000 million over spot market prices[27].

[INSERT TABLE 2 HERE]

Table 2 reports results on PJM-BGS for each POLR and zone. The premium (defined as the difference between PJM-BGS auction price in each zone and average PJM spot price during the delivery period) is always positive and ranges from 36% to 286%. Yearly averages are 111.34% (AECO), 103.47% (JCP&L), 110.43% (PSE&G) and 123.08% (RECO). Overall, the yearly average is 112.08%. As it was the case with CESUR, winning bidders got a positive yearly premium, suggesting they require a considerable risk premium in this market. The size of the premium is eleven times higher than with CESUR. However, in contrast with CESUR auctions, PJM-BGS auction price includes volumetric risk besides energy costs and also services of capacity, ancillary services, transmission, and any other service PJM may require. In summary, we document high and persistent premiums over spot prices enjoyed by the winning bidders (suppliers to POLRs) because of CESUR and PJM-BGS auctions. Those facts are consistent with a situation in which sellers need a compensation for assuming price risk, but the size of the risk premium, particularly in the PJM-BGS case, may put into question the hypothesis DSA provides efficient generation resources at competitive prices.

Sizable risk premiums are usually related to significant price risk in the spot market. Price risk manifests in high volatility and heavy right tail of the price distribution. To gauge whether price risk in the spot market may explain those risk premiums, Figure 1 presents histograms for daily electricity spot prices in Spain (OMEL market) and in New Jersey's

[27] We calculate economic results in millions of Euro by taken into account capacity offered in each auction, conversion factors, and comparing CESUR prices with wholesale spot prices. The conversion factor implies that each MW of Capacity is equivalent to 2,200 MWh. Detailed results are available on request.

AECO[28] (PJM) from January 1, 2007, until December 31, 2013.

[INSERT FIGURE 1 HERE]

The shape of the empirical distributions is different. OMEL prices follow a symmetrical distribution with a kurtosis coefficient of 3.81 (higher than the Normal distribution). AECO's prices present a skewness coefficient of 7.71, suggesting strong right asymmetry, and a kurtosis coefficient of 109.05, suggesting the probability of prices far away from the mean is much higher than with the Normal distribution. The coefficient of variation is 0.29 with OMEL, and 0.61 with AECO. This suggests price risk, as measured by volatility, in the latter is more than double than in the former. To further exploring this point, Table 3 presents the statistics of daily spot prices illustrating tail risk in both markets.

[INSERT TABLE 3 HERE]

To illustrate tail risk, we use normalized data and compare values of extreme quantiles (99%, 99.5% and 99.9%) for OMEL and AECO against the corresponding figures for the standardized Normal distribution. With OMEL, the figure for quantile 99% is 2.28, close to the normal distribution (2.33). However, AECO's figure for quantile 99% is 2.93, 25% higher than under normality. In extreme quantiles (99.5% and 99.9%), OMEL's quantiles are 1% and 11% higher than the normal's, but AECO's are 65% and 410% higher. AECO's 99.9% quantile is 3.7 times higher than OMEL's.

In summary, with OMEL, evidence of tail risk (in comparison with normal distribution) is not compelling. Therefore, CESUR's persistent positive forward premiums are unlikely to

[28] JCPL, PSEG and RECO are very similar to AECO. Detailed results on all of them are available on request.

be explained by this reason. With AECO (and in other PJM markets) price risk can be relevant and could explain, up to a point, these high and persistent forward premiums required by participants in auctions. We stress the fact that price risk measures suggest AECO's volatility is double than OMEL's and AECO's tail risk is almost four times higher than AECO's. However, AECO's average premium is eleven times higher than OMEL's.

We now turn to the question of which explanatory variables can be related to those excess premiums. In the first place, we consider variables related with auctions processes. Key variables are the number of allowed bidders and the number of bidding winners. Presumably, a higher number of competitors and winners would imply lower premium, because auction prices are likely to be similar to (expected) future spot prices, because of stiffer competition. We include variables related to the level of uncertainty in spot markets and an estimate of spot market price volatility before each auction. We use CESUR and PJM-BGS data jointly in a panel data specification. To take into account different average and volatility levels, each premium is standardized by segments[29]. Results are in Table 4. This table reports results of a panel regression in which the dependent variable is the standardized yearly excess premium over electricity spot prices during the delivery period. Explanatory variables are: *Wbidders*, the number of winning bidders; *Startbidders*, the number of authorized bidders; and *vol30* is spot price volatility the month before the auction, estimated as the standard deviation of daily price log returns. We include all CESUR and PJM- BSG auctions. The dataset includes yearly data from 2002 until 2013. Model (4) presents the highest adjusted r-squared and therefore we summarize its results. Variable *Startbidders* is significant at conventional levels and presents expected sign. An increase in this variable implies a reduction in the premium. Variable *vol30* is marginally

[29] We consider five segments: CESUR, AECO, JCPL, PSEG and RECO. For instance , in CESUR average value is 0.0859 and volatility is 0.0880, but in AECO average value is 1.1133 and volatility is 0.5951.

significant and positive suggesting that increases in market uncertainty increase premium. Variable *Wbidders* is non-significant in all cases.

[INSERT TABLE 4 HERE]

These findings deserve two comments. First, literature on auctions (Kemplerer, 2004), considers the number and characteristics of bidders as important determinants of competition level and our results concur with this view. Based on the best-fitting model in Table 4 we may infer that increases in the number of start bidders are associated with decreases in the premium[30]. Second, *vol30* is marginally significant, even when we add auction-related variables into the model. This suggests all market-related information is not totally included into auction-related variables. An interesting question is whether the lack of competitive pressure is a problem of the auction (design or product offered) or is a market structure problem. If the reason is the former, a policy implication for the market administrators is to look for contracts attractive to prospective bidders and offering alternative products fitted to the characteristics of the suppliers. However, if the reason is a market structure problem, actions should be taken to open the market to new entrants, by lowering barriers to entry. As Fabra and Fabra (2012) point out, with CESUR this lack of competitive pressure is unlikely to be an auction design problem because auction prices converge to forward prices in OTC markets and organized exchanges. Therefore, it looks like a market structure problem based on incentives to raise prices by integrated firms enjoying market power. With PJM-BSG, we do not know published papers addressing this issue.

[30] The specific quantitative impact varies across segments. For instance in CESUR the coefficient is 0.0075 (0.088*0.0857) , but in AECO the coefficient is 0.0514 (0.5951*0.0857). The effect in AECO is seven times higher than in CESUR.

4.2. Trading activity in power derivatives markets

In this section, we analyze whether market data is consistent with the hypothesis DSA gives incentives to agents to engage in trading activities in power derivatives markets. We analyze volume, open interest, R1, and R2 measures, around auction dates. We compare values of these variables near auction dates with average values in periods without auctions. Next, we test whether significant differences between these measures in normal times and in days surrounding auctions. The estimation window is the first sample available for each price or measure, apart from days surrounding auctions[31]. In doing so, the idea is to capture the 'normal' or "baseline" behavior of each variable or R measure. The length of the event window is a key point when setting up an event study. But in spite of importance for the analysis, there is not a general agreement among researchers on proper length. Therefore, we explore whether traders take speculative or hedging positions days before the event. The market may need a few days to show the impact of news on the results of each auction. As for the event window, MacKinlay (1997) suggests using (-1, +1), but other windows are common. For example, Miyajima and Yafeh (2007) use (-5, +5). In this paper, we consider five trading days before auctions and five trading days after the auction, the conservative (-5, +5) interval.

4.2.1. CESUR

Data set comprises daily data from July 3, 2006, until February 1, 2016, on daily trading volume and open interest for baseload swap contracts traded in OMIP (The Iberian Energy Derivatives Exchange): Yearly, Quarterly, and Monthly. OMIP has provided the data. Specifically, we use OMIP's FTB (M, Q, Y) base-load futures for Spain, with daily settlement (Exchange codes FTBM, FTBQ, FTBYR). As example, the 1MW baseload

[31] The initial simple size is N and its average is M(N). We consider an event window of size N2 and the corresponding average is M(N2). Therefore, the sample excluding data within event window has size N1 = N – N2. Thus, its average is M(N1) = (N/N1)*M(N) – (N2/N1)*M(N2).

Jan13 contract is a monthly swap contract that gives the holder the obligation to buy 1MWh of energy for each hour of January 2013, paying the futures price in Euros/MWh. The seller provides the buyer 1MW × 24h × 31days. The settlement is financial.

We choose liquid contracts within each market segment which usually are the closest to maturity ones. Within each market segment, we choose three monthly contracts, three quarterly contracts and two yearly contracts. These contracts representing 99% (99%), 99% (99%) and 100% (100%) of total trading volume (open interest) with monthly, quarterly and yearly contracts, respectively. Monthly, quarterly and yearly contracts account, on average during the sample, for around 95% of total volume of futures in OMIP market, since shorter-term (less than one month) contracts account for around 5% of total volume. During the last years, there has been an increase in the volume of shorter-term contracts. Recent CNMC bulletins (www.cnmc.es/es-es/energia/mercadosderivados) in 2103, (2014) show that shorter-term (less than one month) contracts accounted for 8.9% (10.4%) of total volume. but, during first years of the sample, the volume of short-term contracts was around 1-2%. For instance, daily, and weekend contracts were not available in OMIP until May 2011. Studies on the evolution of trading in this market are Capitán Herráiz, and Rodríguez Monroy (2012), Furió and Meneu (2010) and Capitán Herráiz (2014). Peña and Rodriguez (2016) study time-zero efficiency of European power derivatives markets, including Spain, assessing liquidity and representativeness of organized markets (OMP) versus OTC markets[32].

4.1.2.1. Volume and Open interest

In this section, we present stylized facts on trading volume and open interest. In Figures 2

[32] In the Spanish market, OMP's average market share is 15% in the period 2004-2012.

and 3, we present, for each contract, average trading volume, and open interest. Tables 5 and 6 summarize descriptive statistics. With trading volume, we may see noticeable differences among contracts[33]. Liquid contracts are M1, M2 and Q1, followed by Q2 and Y1, M2, Q3, and Y2. Medians are zero. This suggests relative low liquidity in this market. Regarding volatility in trading volume, values of the coefficient of variation suggest monotonic increase in volatility from M1 (2.10) to Y2 (15.02). All series present right asymmetry and high kurtosis and so Jarque-Bera tests reject the null hypothesis of normality in all contracts.

[INSERT FIGURE 2 HERE]

[INSERT FIGURE 3 HERE]

[INSERT TABLE 5 HERE]

[INSERT TABLE 6 HERE]

Open interest series present a similar profile to volume series as expected. The Highest liquidity corresponds to contracts M1, M2 and Q1 and volatility follows a similar pattern as in volume. Jarque-Bera tests reject the null hypothesis of normality in all contracts.

We turn to the analysis of the behavior of trading volume and open interest of derivatives contracts equivalent to contracts auctioned in CESUR. We concentrate on Q1 contract because a strategy based on the equivalent portfolio made up using monthly contracts might prove difficult to carry out because of low liquidity of contract M3. Figure 4 presents t-statistics for trading volume of Q1 contract in days surrounding CESUR

[33] Yearly contracts provide supply for 8760 hours, quarterly contracts provide supply between 2159 and 2209 hours and monthly contracts provide supply between 720 and 745 hours. Contract units are MWh. Therefore, to present comparable figures in Tables 3 and 4, we divide quarterly figures by 3 and yearly figures by 12. Therefore, we report volume and open interest data in monthly-equivalent figures.

auctions. The null hypothesis is: the average of these days and the average of the full sample (but apart from the auction days) are equal. As we may see, we reject the hypothesis at 1% level on the day of the auction and at 5% level in the day before the auction. Therefore, trading volume increased significantly the day before and the day of CESUR auctions.

[INSERT FIGURE 4 HERE]

Figure 5 presents t-statistics for the open interest of Q1 contract in days surrounding CESUR auctions. The null hypothesis is the average of these days and the average of the full sample (but excluding these days) are equal. As we may see, we may reject the hypothesis at 1% level on the day of the auction and at 5% level in the day before the auction. In summary, open interest increased significantly the day before and the day of CESUR auctions.

[INSERT FIGURE 5 HERE]

4.1.2.2. Measures of speculation and hedging

Given results in the earlier section suggesting increases in trading activity related with CESUR auctions, we are interested in knowing whether hedging or speculative strategies drive market's activity. To this effect, in this section, we present stylized facts on measures of speculation and hedging R1 and R2. Figures 5 and 6 show measures and Tables 7 and 8 show summary statistics.

[INSERT FIGURE 6 HERE]

[INSERT FIGURE 7 HERE]

[INSERT TABLE 7 HERE]

[INSERT TABLE 8 HERE]

With R1, average values vary from M3 (0.104) to Y1 (0.010). The higher the average value, the higher is the speculative trading in a contract. Thus, this measure suggests contracts M3, M2 and M1are more likely to be used for speculative trading. Volatilities present a range of variation going from M3 (0.557) to Q1 (0.036). High volatility in a contract suggests wide variations between speculative and hedging situations. Medians are zero; this happens when trading volume is zero. This suggests low liquidity. All series present right asymmetry and high kurtosis and so Jarque-Bera tests reject the null hypothesis of normality in all cases. The sample size varies from 2,402 (M1) to 1,074 (M3) because of the different number of N/A days, those days in which R1 cannot be computed due to lack of data availability.

With R2, average values vary from M1 (1.84) to M3 (0.56). The higher the average value, the higher is the speculative trading in a contract and so this measure suggest contracts M1, M2, Q1, Q2, and Y1 are more likely to be used for speculative trading. Volatilities present a range of change going from M1 (4.25) to Y2 (1.015). High volatility in a contract suggests wide variations between speculation and hedging. Median values are higher for M2, M1, Q2, Q1 and Y1 suggesting again these contracts are more likely to be used in speculative trading. All series present right asymmetry and high kurtosis and so Jarque-Bera tests reject the null hypothesis of normality in all cases. The sample size varies from 1,212 (M1) to 210 (Y2) because of the different number of N/A days, those days in which R1 cannot be computed due to lack of data availability. Summarizing the results, measure R1 suggests contracts M3, M2 and M1 are more likely to be used for speculative trading,

but R2 suggests the contracts M1, M2, Q1, Q2, and Y1.

[INSERT TABLE 9 HERE]

We turn to the analysis of measures R1 and R2 in dates surrounding each CESUR auction. Table 9 summarizes t-statistics for contracts and measures. We compare the mean of days surrounding CESUR auctions against the mean of the rest of the sample. If t-stats are positive (negative) and significant, the corresponding measure (R1 or R2) is significantly higher (lower) during this day than in the rest of the sample. In Table 9 there are 94 significant t-stats out of 176; 91 of them are negative and 3 are positive. Decreases (increases) in R measures are associated with increases in hedging (speculative) activity. Therefore, the bulk of evidence suggests hedging increased in dates surrounding CESUR auctions in detriment of speculative activities. This effect is particularly strong in M1, M2, Q1, Q2 and Y2 contracts.

4.2.2. PJM-BGS

CME provides futures prices for three different hubs: Dayton Hub, N. Illinois Hub and Western Hub. After analyzing the relative liquidity of contracting in each Hub, we choose Western Hub as the most liquid and representative and contract E4 (PJM WESTERN HUB DAY AHEAD OFF – PEAK CALENDAR – MONTH 5 MW FUTURES) as the most liquid. We analyze monthly contracts from M4 to M15 because they span (one year) auction's delivery period. Daily data are from 2006 to 2016. In what follows, we present the analysis of trading volume and open interest of derivatives contracts equivalent to contracts auctioned in PJM-BGS. As an illustration, we concentrate in the front contract M4[34]. Figure 8 presents t-statistics for trading volume of M4 contract in days surrounding auctions. The null hypothesis is the average of those days and the average of the full

[34] Results for other contracts are similar and are available on request.

sample (except auction days) are equal. Data rejects the null hypothesis at 1% level on the day of the auction and at 5% level in the day before the auction. Therefore, trading volume increased significantly the day before and the day of PJM-BGS auctions.

[INSERT FIGURE 8 HERE]

Figure 9 presents t-statistics for the open interest of M4 contract in days surrounding auctions. The null hypothesis is the average of these days and the average of the full sample (apart from auction days) is equal. Data do not reject the null hypothesis at conventional significance levels. In summary, open interest did not increase significantly the days surrounding auctions.

[INSERT FIGURE 9 HERE]

Therefore, empirical evidence supports the hypothesis (2) to some extent, because trading activity, in contracts with similar characteristics to contracts auctioned, presents increases in trading volume but not in open interest. We turn to the analysis of measures R1 and R2 in dates surrounding each auction.

[INSERT TABLE 10 HERE]

Table 10 summarizes t-statistics for all contracts and all measures. We compare the mean of days surrounding PJM-BGS auctions against the mean of days of the rest of the sample. If the t-stat is positive (negative) and significant, the corresponding measure (R1 or R2) is significantly higher (lower) during this day than in the rest of the sample. We report, in Table 8, 264 t-statistics of which 58 are significant and positive. Of these 58 significant cases, 32 (55%) appear in the auction day or the day before the auction. Increases in R measures are associated with increases in speculation. Therefore, empirical evidence

suggests speculative activity increased in dates surrounding auctions in detriment of hedging activities. This result is consistent with the earlier evidence on trading volume and open interest.

5. Alternative methods for cost of energy

The DSA method for calculating the cost of energy part yields problematic results as empirical evidence suggests. In this section, we talk about other methods for computing this component. We consider that, from the point of view of a consumer, an attractive method should fulfill the following characteristics: (i) consumers should know electricity prices before actual delivery periods; (ii) the cost of energy should be based on market electricity prices if this market is liquid and efficient; (iii) suppliers may want a risk premium, and (iv) an objective criterion should be used to choose between alternative proposals. We consider each of these characteristics in turn. About point (i), the reason for favoring this characteristic is that small consumers rarely have easy access to risk management instruments and so prefer flat price contracts. This stems from consumers' aversion to price volatility and monitoring and controlling amount used, see Glachant, Finon and de Hauteclocque (2011). On point (ii), a crucial consideration to take into account is whether wholesale electricity markets are liquid, efficient and transparent enough to give reliable price signals. In this sense, as Reguant (2014) remarks, a key point is whether firms with market power exist and are able and willing to exercise this market power. About point (iii), electricity risk premium fluctuates over time, depending on market conditions and structure, Cartea and Villaplana (2008), Redl, Haas, Huber and Bohm (2009), among others. Therefore, a transparent (market-based) assessment of this risk premium is desirable.

5.1. Objective function

Regarding point (iv), we posit agents prefer a method that minimizes average payments and the price risk of these payments. As measures of price risk, we consider two alternatives: volatility and semivolatility of the price distribution. These ideas are embodied in the following mean-price risk specification:

$$F(P_i, t, k, \sigma) = \frac{1}{N}\sum_{t=1}^{N} P_i(t) + k\alpha_{P_i(t)} \quad (3)$$

Where $P_i(t)$ are actual payments during delivery periods 1 to N under method *i*, *k* measures price risk aversion and α can be: (1) σ, the total volatility of $P_i(t)$, and (2) σ^+, the volatility of $P_i(t)$ values higher than the mean. We posit consumers want to minimize objective function (3). This implies choosing prices (i.e. alternative *i*) minimizing (3). Function (3) has two elements, first, average costs and second, a penalty term increasing with the price risk of costs. This penalty term reflects consumer's desire for certainty as to costs. From the point of view of consumers and for a measure of parameter α, alternative *i* is more desirable than alternative *j* if $F(P_i,t,k,\alpha) < F(P_j,t,k,\alpha)$.

5.2. Alternative Methods

In this section, we detail several alternative methods we test. For a given period, we compute the two elements in (3), average payments and the price risk of payments. Then, we compute the overall value of (3) and report the number of periods (e.g. months) in which a method produces the lowest value of (3). We consider the following methods:

(i) Method DSA: prices are the ones got in the corresponding auction (CESUR or PJM-BSG). Here, the price risk of payments is zero, because prices are known before actual delivery periods.

(ii) Method SPOT: prices are wholesale spot daily prices. The price risk is the one corresponding to these prices.

(iii) Method M1: prices are swap prices corresponding to the contract available for the monthly delivery period (front contract), recorded on the day in which a DSA takes place. The price risk of payments is zero because consumers know prices before the delivery period.

(iv) Method M1_REC: prices are averages of swap prices of contracts corresponding to monthly delivery periods, during the life of the contract, but excluding the last week of trading. The price risk of payments is zero, for the same reason as in (iii).

(v) Method M1_15: price corresponds to day 15 of swap prices of liquid contracts corresponding to monthly delivery periods. The price risk of payments is zero, as in (iv).

(vi) Method M4_M15: prices are swap prices corresponding to the liquid contract available for monthly delivery periods from M4 to M15, recorded on the day in which a DSA takes place. This method applies to PJM-BGS because is the equivalent portfolio to products auctioned in this auction. The price risk of payments is zero because consumers know prices before the delivery period.

(vii) Method M4_M15_REC: prices are averages of swap prices of contracts M4 to M15 corresponding to consecutive monthly delivery periods, during the life of contracts, but excluding the last week of trading. This method applies to PJM-BGS because is the equivalent portfolio to products auctioned in this auction. The price risk of payments is zero, for the same reason as in (iii).

(viii) Method M4_M15_15: price corresponds to day 15 of swap prices of contracts M4 to M15 corresponding to consecutive monthly delivery periods. This method applies to PJM-BGS because is the equivalent portfolio to products auctioned in this auction. The price risk of payments is zero.

(ix) Method Q1: prices are the average of the swap price corresponding to the liquid contract spanning quarterly delivery periods. We use this method because is based on a contract equivalent to those auctioned in CESUR. The price risk of payments is zero because prices are known before the delivery period.

5.2 Spanish market

In Tables 11A and 11B we report results using different alternatives as detailed in the previous section.

[INSERT TABLE 11A HERE]

[INSERT TABLE 11B HERE]

When aversion to total volatility is zero, consumers prefer SPOT-based prices in 50% of cases; methods based on derivatives contracts[35] in 35% of cases, and DSA in 15% of cases. If volatility aversion is one, the corresponding proportions are 29%, 54%, and 17%. Increases in volatility aversion suggest stronger preference for methods based on liquid swap contracts. Is interesting to point out that, for high values of volatility aversion (k=2) consumers prefer methods based on auctions in 31% of cases, but only in 4% of cases with spot prices. Therefore, the degree of price risk aversion is a crucial concern determining consumer's choice in this market. With semivariance as price risk measure, results are similar.

5.3 New Jersey

Tables 12 and 13 report results from different alternatives applied to four market segments, AECO, RECO, JCPL, and PSEG.

[35] M1 (3%), M1_REC (3%), M1_15 (11%) , and Q1 (22%).

[INSERT TABLE 12 HERE]

[INSERT TABLE 13 HERE]

Consumers never choose methods based on DSA contracts because of very high prices. When volatility aversion is zero, consumers prefer methods based on spot prices in 27% of cases and methods based on liquid swap contracts (in this case, average prices of contracts M4 to M15) in the remaining 73% of cases[36]. If volatility aversion is one, the corresponding proportions are 9.5% and 90.5%. Increases in volatility aversion hint at stronger preference for methods based on liquid swap contracts. With semivariance as price risk measure, results are similar. So, despite volatility aversion, consumers do not choose prices based on DSA if other alternatives are available. With no price risk aversion, prices based on a portfolio of derivatives contracts mimicking the delivery period of DSA-based contracts are the best consumer's choice in 73% of cases. Increases in aversion to volatility increase this figure.

6. Conclusions and Policy Implications

Empirical evidence on the economic impact of auctions for last resort supply in electricity markets has not received the attention it deserves so far. In this paper, we study differences between spot prices during delivery periods and prices obtained by winning bidders, and speculation and hedging activities in power derivatives markets in dates near auctions. We posit two hypotheses. First, market administrators and regulators support DSA because they believe that these mechanisms are superior to others in providing efficient generation resources at competitive prices. Second, they think auctions should

[36] 21.43% M4_M15, 29.76% M4_M15_REC, and 21.43% M4_M15_15.

encourage forward contracting (i.e. hedging), presumably using electricity derivatives.

Using an extensive database of DSA in Spain (CESUR auctions) and in New Jersey (PJM-BSG auctions), we document the following facts. First, winning bidders in CESUR and PJM-BGS obtained an average yearly premium of 10.15% and 112% respectively, in excess of electricity spot prices set in OMEL (Spain) and PJM (New Jersey) markets respectively. These high premiums are difficult to justify in terms of risk management and present a challenge to DSA-based mechanisms. Price risk measures suggest PJM's volatility is double than OMEL's and PJM's tail risk is almost four times higher than OMEL's. However, PJM-BGS's average premium is eleven times higher than CESUR's. Second, we document a negative relationship between the number of bidders in auctions and ex-post premium. This fact suggests that lack of enough competitive pressure may be one reason explaining those premiums. Third, trading activity in power derivatives markets increased significantly in days surrounding CESUR and PJM-BSG auctions. Fourth, in the case of CESUR auctions, hedging-driven strategies seem to be predominant around auction dates, whereas, in the case of PJM-BGS auctions, speculation-driven trading prevails. Therefore, empirical results are consistent with the hypothesis (2) to some extent, but it is unclear whether the high and persistent premium over spot prices enjoyed by winning bidders is consistent with the hypothesis (1).

Therefore, two major challenges to DSA arise, high ex-post premium and significant speculative trading. To meet these challenges, we study several procedures to calculate the cost of energy part. We assume that agents prefer a method that minimizes average payments and the price risk of these payments. As measures of price risk, we consider two alternatives: variance and semivariance of the price distribution. Results differ in Spain and

in New Jersey. In Spain, when aversion to price risk is zero, consumers prefer spot-based prices, followed by methods based on derivatives contracts, and in the last place, auction-based methods. Increases in price risk aversion imply stronger preference for methods based on derivatives contracts. Strong price risk aversion boosts consumers' preference for methods based on auctions over methods based on spot prices. Therefore, the degree of price risk aversion is a crucial concern determining consumer's choice in this market. In New Jersey, consumers never choose methods based on auction prices because these prices are high in comparison with spot or derivatives prices. When price risk aversion is zero, consumers prefer methods based on spot prices in one-third of cases and methods based on liquid swap contracts in the remaining two-third of cases. If volatility aversion is one, the corresponding proportions are ten per cent and ninety per cent. Increases in price risk aversion hint at stronger preference for methods based on liquid swap contracts.

Whilst the use of several techniques in this paper has provided useful insights, there are some limitations related to the kind of contracts employed in the analysis. Shorter-term contracts and contracts based on peak prices should also be taken into account in order to obtain a fuller perspective on the issue of hedging versus speculative activities. Looking forward, application of our methodology to other default supply auctions, power derivatives markets, and alternative objective functions are immediate extensions, which we left for future research.

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Table 1: CESUR auctions basic facts

This table reports basic facts on CESUR auctions (baseload products). Columns contain auction number, date, capacity offered, equilibrium price, and average spot price during the delivery period, premium defined as the difference between equilibrium price and spot price during the delivery period, and premium in percentage.

AUCTION Number	Date	Product	CESUR Price (€/MWh)	Average Spot price delivery period	Premium	Premium%	Yearly Average
1	19/06/2007	Q3-07	46.27	36.45	9.82	26.94%	
2	18/09/2007	Q4-07	38.45	47.78	-9.33	-19.53%	
3	18/12/2007	Q1-08	64.65	65.85	-1.2	-1.82%	1.86%
4	13/03/2008	Q2-08	63.36	56.92	6.44	11.31%	
4	13/03/2008	Q2Q3-08	63.73	63.7	0.03	0.05%	
5	17/06/2008	Q3-08	65.15	70.41	-5.26	-7.47%	
5	17/06/2008	Q3Q4-08	65.79	67.53	-1.74	-2.58%	
6	25/09/2008	Q4-08	72.49	64.65	7.84	12.13%	
7	16/12/2008	Q1-09	58.86	43.1	15.76	36.57%	8.33%
8	26/03/2009	Q2-09	36.58	36.99	-0.41	-1.11%	
9	25/06/2009	Q3-09	42	35.05	6.95	19.83%	
9	25/06/2009	Q4-09	45.67	32.87	12.8	38.94%	
10	15/12/2009	Q1-10	39.43	25.38	14.05	55.36%	
10	15/12/2009	Q2-10	40.49	34.97	5.52	15.78%	25.76%
11	23/06/2010	Q3-10	44.5	44.07	0.43	0.98%	
12	21/09/2010	Q4-10	46.94	43.33	3.61	8.33%	
13	14/12/2010	Q1-11	49.07	45.22	3.85	8.51%	5.94%
14	22/03/2011	Q2-11	51.79	48.12	3.67	7.63%	
15	28/06/2011	Q3-11	53.2	54.23	-1.03	-1.90%	
16	27/09/2011	Q4-11	57.99	52.01	5.98	11.50%	
17	20/12/2011	Q1-12	52.99	50.64	2.35	4.64%	5.47%
18	21/03/2012	Q2-12	51	46.07	4.93	10.70%	
19	26/06/2012	Q3-12	56.25	49.09	7.16	14.59%	
20	25/09/2012	Q4-12	49.25	43.16	6.09	14.11%	
21	21/12/2012	Q1-13	54.18	40.34	13.84	34.31%	18.43%
22	20/03/2013	Q2-13	45.41	34.26	11.15	32.55%	
23	25/06/2013	Q3-13	47.95	49.81	-1.86	-3.73%	
24	24/09/2013	Q4-13	47.58	54.73	-7.15	-13.06%	5.25%
Averages			51.82	47.74	4.08	11.20%	10.15%

Table 2: PJM-BGS auctions basic facts

This table reports basic facts on PJM-BSG auctions (for smaller commercial and residential customers, BGS-RSCP o BGS-FP). Columns contain auction date, POLR, equilibrium price, and average spot price during the delivery period, premium defined as the difference between equilibrium price and spot price during the delivery period, and premium in percentage.

Year	POLR	PJM-BGS Price ($/MWh)	Avg spot June 1-May 31	Premium	Premium %	POLR	PJM-BGS Price ($/MWh)	Avg spot June 1-May 31	Premium	Premium %
2015	AECO	86.06	25.47	60.59	238%	JCP&L	80.42	25.05	55.37	221%
2014	AECO	87.8	46.95	40.85	87%	JCP&L	84.44	47.13	37.31	79%
2013	AECO	87.27	56.22	31.05	55%	JCP&L	83.7	57.40	26.30	46%
2012	AECO	85.1	37.76	47.34	125%	JCP&L	81.76	38.03	43.73	115%
2011	AECO	100.95	38.53	62.42	162%	JCP&L	92.56	38.47	54.09	141%
2010	AECO	98.56	51.82	46.74	90%	JCP&L	95.17	51.75	43.42	84%
2009	AECO	105.36	41.29	64.07	155%	JCP&L	103.51	41.08	62.43	152%
2008	AECO	116.5	66.66	49.84	75%	JCP&L	114.09	65.19	48.90	75%
2007	AECO	99.59	70.73	28.86	41%	JCP&L	99.64	73.48	26.16	36%
2006	AECO	103.99	56.21	47.78	85%	JCP&L	100.44	53.81	46.63	87%
Average				47.95	111.34%				44.43	103.47%
2015	PSE&G	99.54	25.82	73.72	286%	RECO	90.66	25.72	64.94	253%
2014	PSE&G	97.39	49.80	47.59	96%	RECO	95.61	50.50	45.11	89%
2013	PSE&G	92.18	60.12	32.06	53%	RECO	92.58	59.41	33.17	56%
2012	PSE&G	83.88	40.17	43.71	109%	RECO	92.51	40.58	51.93	128%
2011	PSE&G	94.3	38.89	55.41	142%	RECO	106.84	37.72	69.12	183%
2010	PSE&G	95.77	52.44	43.33	83%	RECO	103.32	50.15	53.17	106%
2009	PSE&G	103.72	41.72	62.00	149%	RECO	112.7	40.80	71.90	176%
2008	PSE&G	111.5	66.57	44.93	67%	RECO	120.49	64.91	55.58	86%
2007	PSE&G	98.88	72.41	26.47	37%	RECO	109.99	71.46	38.53	54%
2006	PSE&G	102.51	55.93	46.58	83%	RECO	111.14	55.54	55.60	100%
Average				47.58	110.43%				53.91	123.08%
Average Premium %				112.08%						

Table 3: Tail Risk: OMEL vs AECO

This table reports the comparison of some tail risk measures of spot prices of OMEL market (Spain) and AECO PJM-BGS market. Dataset consists of daily data from January 1, 2007, until December 31, 2013. The sample size is 2557. Quantiles are computed on normalized data (subtracting the mean and dividing by the standard deviation).

Series	**99% Quantile**	**99.5% Quantile**	**99.9% Quantile**
Normal distribution	2.33	2.57	3.08
PMD Omel	2.28	2.61	3.41
AECO	2.93	4.25	12.62
PMD/Normal	0.98	1.01	1.11
AECO/Normal	1.26	1.65	4.10

Table 4: Panel Regression Premium

This table reports the results of a panel regression in which the dependent variable is the standardized (by markets) yearly excess premium over electricity spot prices during the delivery period. Explanatory variables are: *Wbidders* is the number of winning bidders; *Startbidders*, is the number of authorized bidders; *vol30* is spot price volatility the month before the auction. We include all auctions in CESUR and PJM- BSG. Dataset consists of yearly from 2002 until 2013. ***, **, and * are significant at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Wbidders			0.0723		-0.00143	0.00768
			(1.47)		(-0.19)	(0.36)
Startbidders	-0.0245***		-0.102	-0.0857**		-0.0917**
	(-9.65)		(-1.82)	(-3.42)		(-3.32)
vol30		2.612**		5.464*	2.654**	5.255*
		(3.32)		(2.58)	(2.86)	(2.38)
Constant	0.00743	-0.763***	0.955	0.170	-0.764***	0.265
	(0.39)	(-5.88)	(1.36)	(1.73)	(-5.69)	(1.12)
Observations	43	47	43	43	47	43
R-squared	0.926	0.936	0.941	0.964	0.936	0.965
Adjusted R-squared	0.889	0.908	0.908	0.945	0.905	0.943
rss	2.663	2.300	2.127	1.278	2.299	1.273
rmse	0.308	0.268	0.281	0.218	0.272	0.221
t statistics in parentheses						
* p<0.10, ** p<0.05, *** p<0.01						

Table 5: OMIP Daily Trading Volume

This table reports summary statistics of daily trading volume at OMIP. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2. Dataset consists of daily data from July 3, 2006, until February 1, 2016. Units are MWh. We report volume data in monthly-equivalent figures.

	VOLM1	VOLM2	VOLM3	VOLQ1	VOLQ2	VOLQ3	VOLY1	VOLY2
Mean	13749.40	6938.69	1635.99	7250.42	3656.64	1267.79	1827.55	412.44
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	496800.00	178560.00	178560.00	154728.33	140576.00	103086.67	36500.00	29200.00
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev.	28863.11	16942.91	9170.81	26434.42	16815.13	9869.35	14012.42	6194.07
Skewness	5.23	4.61	10.48	4.16	5.65	8.96	3.56	7.43
Kurtosis	52.04	30.65	143.98	27.37	51.08	115.25	20.04	82.22
Jarque-Bera	252393.00	85300.46	2039893.00	66596.34	244979.60	1297529.00	34223.68	548761.70
Probability	0	0	0	0	0	0	0	0
Sum	33122305	16722246	3942724	52420534	26437508	9166134	52786872	10032264
Sum S Dev.	2.01E+12	6.92E+11	2.03E+11	5.05E+12	2.04E+12	7.04E+11	5.67E+12	9.33E+11
Observations	2410	2410	2410	2410	2410	2410	2407	2027

Table 6: OMIP Daily Open Interest

This table reports summary statistics of daily open interest at OMIP. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2. Dataset consists of daily data from July 3, 2006, until February 1, 2016. Units are MWh. We report open interest data in monthly-equivalent figures.

	OIM1	OIM2	OIM3	OIQ1	OIQ2	OIQ3	OIY1	OIY2
Mean	854568.80	427458.00	45663.66	646205.00	348072.00	160974.80	247247.17	54530.65
Median	811230.00	178560.00	0.00	644191.00	295063.33	25480.00	228384.00	33672.00
Maximum	2274408.00	2005357.00	1691280.00	1669304.00	1228204.00	1023503.33	876730.00	311710.00
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev.	541695.40	490705.50	146966.00	574786.03	538524.33	446206.43	634459.74	205533.69
Skewness	0.30	1.04	6.54	0.28	0.69	1.82	0.85	1.43
Kurtosis	2.21	2.70	52.69	2.80	2.58	5.27	3.95	5.40
C.V.	0.63	1.15	3.22	0.89	1.55	2.77	2.57	3.77
Jarque-Bera	97.60	440.34	265148.00	34.50	206.71	1850.63	383.00	1177.83
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	2.06E+09	1.03E+09	1.10E+08	4.67E+09	2.52E+09	1.16E+09	7.14E+09	1.33E+09
Sum SDev.	7.07E+14	5.80E+14	5.20E+13	2.39E+15	2.10E+15	1.44E+15	1.16E+16	1.03E+15
Observations	2410	2410	2410	2410	2410	2410	2407	2027

Table 7: OMIP R1 Measure

This table reports summary statistics of measure R1. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2. Dataset consists of daily data from July 3, 2006, until February 1, 2016.

	R1_M1	R1_M2	R1_M3	R1_Q1	R1_Q2	R1_Q3	R1_Y1	R1_Y2
Mean	0.025477	0.04998	0.10437	0.013022	0.017559	0.016968	0.010768	0.011677
Median	0	0	0	0	0	0	0	0
Maximum	0.75	1.876263	12	1	1	1.176471	1	1
Minimum	0	0	0	0	0	0	0	0
Std. Dev.	0.069289	0.154678	0.557983	0.036663	0.077491	0.096573	0.045769	0.07085
Skewness	5.657398	4.994039	13.39105	11.60969	9.597456	8.94963	14.26461	10.46545
Kurtosis	42.13969	33.06167	235.9168	248.19	110.5525	90.22494	259.5484	130.5252
Jarque-Bera	166132.3	94869.32	2459796	6063200	1055340	573169.8	5866305	1136349
Probability	0	0	0	0	0	0	0	0
Sum	61.1959	113.4053	112.0929	31.23951	37.26077	29.43975	22.75339	19.06924
Sum SDev.	11.52699	54.26255	334.0736	3.223379	12.73624	16.17176	4.424199	8.192158
Observations	2402	2269	1074	2399	2122	1735	2113	1633

Table 8: OMIP R2 Measure

This table reports summary statistics of measure R2. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2. Dataset consists of daily data from July 3, 2006, until February 1, 2016.

	R2_M1	R2_M2	R2_M3	R2_Q1	R2_Q2	R2_Q3	R2_Y1	R2_Y2
Mean	1.848846	1.35659	0.563092	1.469482	1.334844	0.843046	1.116017	0.753739
Median	1	1	0	1	1	0.5	0.569444	1
Maximum	92	100	21	35	36.66667	16	36	8
Minimum	0	0	0	0	0	0	0	0
Std. Dev.	4.252992	3.854141	1.471531	2.767091	2.419231	1.60716	2.50118	1.015665
Skewness	11.22837	18.82289	8.834696	6.050949	6.84163	5.649208	7.994224	3.663155
Kurtosis	194.5815	467.7524	107.2211	55.16612	77.53702	44.90714	88.99694	22.87786
Jarque-Bera	1878993	8370361	183909.5	130961	173725.7	29435.35	253761.6	3927.035
Probability	0	0	0	0	0	0	0	0
Sum	2240.802	1253.489	222.4214	1610.553	969.0965	316.1423	888.3496	158.2852
Sum S Dev.	21904.5	13710.61	853.1688	8384.186	4243.191	966.0279	4973.44	215.5991
Observations	1212	924	395	1096	726	375	796	210

Table 9: R1 and R2 around CESUR auctions

This table reports t-statistics for measures R1 and R2 during auction days in comparison with the rest of the sample of all contract in the five days before and after CESUR auctions.

	-5	-4	-3	-2	-1	0	1	2	3	4	5	Total
R1M1	1.00	0.85	-0.05	0.35	0.04	2.16	1.20	1.15	-0.51	1.00	-0.80	
R2M1	-7.18	0.57	-13.98	-5.11	-7.32	-3.85	-4.62	-7.75	-11.00	-4.89	-5.81	
R1M2	6.64	-0.22	1.56	-1.70	-0.78	1.56	0.23	-0.73	-1.83	-1.54	-4.27	
R2M2	-8.36	-6.04	-3.24	-9.32	-2.97	-0.23	-7.67	-10.95	-6.66	-9.52	-3.85	
R1M3	-5.02	-3.63	-3.38	0.36	-1.40	1.14	-0.73	-0.22	-7.00	-7.59	-0.42	
R2M3	-3.99	0.66	-3.05	-1.81	-6.15	0.20	-2.88	-3.51	-10.55	-7.75	-7.71	
R1Q1	-1.51	-1.86	0.98	0.74	1.26	2.48	0.02	1.27	-1.10	0.36	0.64	
R2Q1	-1.96	-5.60	-1.31	-3.81	-0.75	0.92	-4.31	0.02	-7.56	-1.21	-3.59	
R1Q2	-1.26	-2.96	-0.03	1.07	-2.77	0.42	-2.60	0.80	-4.49	-1.99	-3.72	
R2Q2	-7.12	-8.49	-1.37	-1.20	-8.36	-2.64	-11.46	-5.06	-4.92	-4.46	-11.04	
R1Q3	-1.78	-0.01	-0.72	-0.37	-8.39	-3.78	-0.41	0.78	0.60	0.62	-2.08	
R2Q3	-6.92	-9.87	-4.88	-2.38	-15.69	-12.66	-3.61	-6.10	-10.37	-7.53	-15.68	
R1Y1	0.99	-1.93	-0.22	-5.05	-0.94	-0.70	0.70	-0.93	0.99	0.81	-0.52	
R2Y1	-3.94	-9.21	-6.53	-3.86	-9.38	-6.09	-5.77	-4.55	-5.97	-5.95	0.06	
R1Y2	0.81	-3.50	1.01	-0.29	-4.01	-0.84	-8.16	-4.47	-0.12	-8.16	-1.11	
R2Y2	-8.56	-8.38	-0.98	-4.63	-36.75	-5.49	-36.75	-11.51	-11.51	-36.75	-5.26	
Positive	1.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	0.00	0.00	0.00	3
Negative	8.00	9.00	6.00	7.00	8.00	6.00	10.00	8.00	10.00	9.00	10.00	91

Table 10: R1 and R2 around PJM-BGS auctions

This table reports t-statistics for measures R1 and R2 during auction days in comparison with the rest of the sample of all contract in the five days before and after PJM-BGS auctions.

R1			T-TEST										Total
		-5	-4	-3	-2	-1	0	1	2	3	4	5	
	E4_M4	-0.24	8.41	5.14	-0.24	8.14	6.77	-0.08	0.55	-0.24	-0.24	0.76	
	E4_M5	-0.25	8.29	5.06	-0.25	8.02	6.67	-0.09	0.53	-0.25	-0.25	0.30	
	E4_M6	-0.40	3.42	1.73	-0.40	2.29	2.38	-0.34	-0.08	-0.41	-0.41	0.94	
	E4_M7	-0.40	3.33	1.68	-0.40	2.22	2.43	-0.34	-0.07	-0.41	-0.41	0.83	
	E4_M8	-0.42	3.26	1.63	-0.42	2.16	2.37	-0.36	-0.09	-0.43	-0.43	0.92	
	E4_M9	-0.41	3.24	1.62	-0.41	2.16	2.24	-0.35	-0.10	-0.42	-0.42	0.81	
	E4_M10	-0.41	2.90	1.44	-0.41	1.93	2.00	-0.35	-0.13	-0.41	-0.41	0.68	
	E4_M11	-0.41	2.80	1.38	-0.41	1.86	1.93	-0.36	-0.14	-0.41	-0.41	0.69	
	E4_M12	-0.42	2.91	1.44	-0.41	1.93	2.00	-0.36	-0.13	-0.42	-0.42	0.68	
	E4_M13	-0.43	2.61	1.28	-0.43	1.76	1.85	-0.37	-0.14	-0.43	-0.43	0.93	
	E4_M14	-0.43	2.92	1.45	-0.43	1.98	2.08	-0.37	-0.11	-0.44	-0.44	0.81	
	E4_M15	-0.43	2.60	1.26	-0.43	1.70	1.76	-0.38	-0.15	-0.43	-0.43	0.68	
R2													
	E4_M4	-0.27	-0.27	-0.27	-0.27	13.98	1.26	-0.27	-0.27	-0.27	-0.27	-0.27	
	E4_M5	-0.32	-0.32	-0.32	-0.32	12.60	1.71	0.31	-0.32	-0.32	-0.32	0.49	
	E4_M6	-0.39	0.16	2.96	-0.39	0.17	12.06	-0.39	0.16	0.12	-0.39	0.69	
	E4_M7	-0.46	0.22	3.25	-0.46	0.20	3.48	-0.46	0.22	0.19	-0.46	0.79	
	E4_M8	-0.35	0.04	1.80	-0.35	0.01	14.58	0.28	0.04	-0.35	-0.35	0.49	
	E4_M9	-0.52	0.05	2.90	-0.52	0.13	5.41	0.51	0.05	-0.52	-0.52	0.60	
	E4_M10	-0.55	0.15	3.53	-0.55	0.18	2.89	0.67	0.16	-0.54	-0.54	0.83	
	E4_M11	-0.50	0.02	2.67	-0.50	0.10	9.75	0.45	0.03	-0.50	-0.50	0.58	
	E4_M12	-0.58	0.22	3.68	-0.58	0.09	2.37	-0.58	0.33	-0.58	-0.58	0.90	
	E4_M13	-0.48	-0.32	2.17	-0.48	0.07	2.40	7.66	-0.36	-0.47	-0.47	-0.47	
	E4_M14	-0.47	-0.26	2.35	-0.47	0.19	1.98	7.93	0.16	-0.47	-0.47	-0.47	
	E4_M15	-0.44	-0.24	2.56	-0.44	0.33	2.51	8.64	1.55	-0.44	-0.44	-0.44	
Positive		0	12	11	0	11	21	3	0	0	0	0	58
Negative		0	0	0	0	0	0	0	0	0	0	0	0

Table 11: CESUR Alternative Methods

This table reports results on alternative methods to CESUR and PVPC. Objective function is

$$F(P_i, t, k, \sigma) = \frac{1}{N}\sum_{t=1}^{N} P_i(t) + k\sigma_{P_i(t)}$$

Where $P_i(t)$ are actual payments during delivery periods 1 to N under alternative i, k measures volatility aversion and σ is the volatility of $P_i(t)$. The sample is from 3/7/2006 to 31/1/2017. The number of months is 112. We compute the overall value of F and report the number of periods (e.g. months) in which a given method produces the lowest value.

k =	0	%
(DSA)	17	15%
(SPOT)	56	50%
(M1)	3	3%
(M1_REC)	3	3%
(M1_15)	11	10%
(Q1)	22	20%
k =	0.5	%
(DSA)	23	21%
(SPOT)	43	38%
(M1)	6	5%
(M1_REC)	3	3%
(M1_15)	12	11%
(Q1)	25	22%
k =	1	%
(DSA)	32	29%
(SPOT)	19	17%
(M1)	11	10%
(M1_REC)	5	4%
(M1_15)	15	13%
(Q1)	30	27%
k =	2	%
(DSA)	35	31%
(SPOT)	4	4%
(M1)	16	14%
(M1_REC)	6	5%
(M1_15)	20	18%
(Q1)	31	28%

Table 12: PJM-BSG Alternative Methods

This table reports results on alternative methods to PJM-BSG in the four areas: AECO, RECO, JCPL, PSEG. Objective function is

$$F(P_i, t, k, \sigma) = \frac{1}{N}\sum_{t=1}^{N} P_i(t) + k\sigma_{P_i(t)}$$

Where $P_i(t)$ are actual payments during delivery periods 1 to N under alternative i, k measures volatility aversion and σ is the volatility of $P_i(t)$. The sample is from 3/7/2006 to 31/1/2017. The number of months is 84. We compute the overall value of F and report the number of periods (e.g. months) in which a given method produces the lowest value.

	AECO		RECO		JCPL		PSEG	
K=0	#	%	#	%	#	%	#	%
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT)	23	27,38%	23	27,38%	22	26,19%	22	26,19%
(M4_M15)	18	21,43%	19	22,62%	18	21,43%	18	21,43%
(M4_M15_REC)	25	29,76%	24	28,57%	26	30,95%	26	30,95%
(M4_M15_DAY15)	18	21,43%	18	21,43%	18	21,43%	18	21,43%
K=0,5								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT)	16	19,05%	15	17,86%	17	20,24%	13	15,48%
(M4_M15)	21	25,00%	21	25,00%	21	25,00%	22	26,19%
(M4_M15_REC)	27	32,14%	28	33,33%	27	32,14%	29	34,52%
(M4_M15_DAY15)	20	23,81%	20	23,81%	19	22,62%	20	23,81%
K=1								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT)	8	9,52%	8	9,52%	7	8,33%	6	7,14%
(M4_M15)	25	29,76%	25	29,76%	25	29,76%	25	29,76%
(M4_M15_REC)	29	34,52%	30	35,71%	29	34,52%	30	35,71%
(M4_M15_DAY15)	22	26,19%	21	25,00%	23	27,38%	23	27,38%
K=2								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT)	3	3,57%	3	3,57%	2	2,38%	3	3,57%
(M4_M15)	27	32,14%	27	32,14%	28	33,33%	27	32,14%
(M4_M15_REC)	30	35,71%	30	35,71%	30	35,71%	30	35,71%
(M4_M15_DAY15)	24	28,57%	24	28,57%	24	28,57%	24	28,57%
K=4								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(M4_M15)	29	34,52%	29	34,52%	29	34,52%	29	34,52%
(M4_M15_REC)	31	36,90%	31	36,90%	31	36,90%	31	36,90%
(M4_M15_DAY15)	24	28,57%	24	28,57%	24	28,57%	24	28,57%

Table 13: PJM-BSG Alternative Methods

This table reports results on alternative methods to PJM-BSG in the four areas: AECO, RECO, JCPL, PSEG. Objective function is

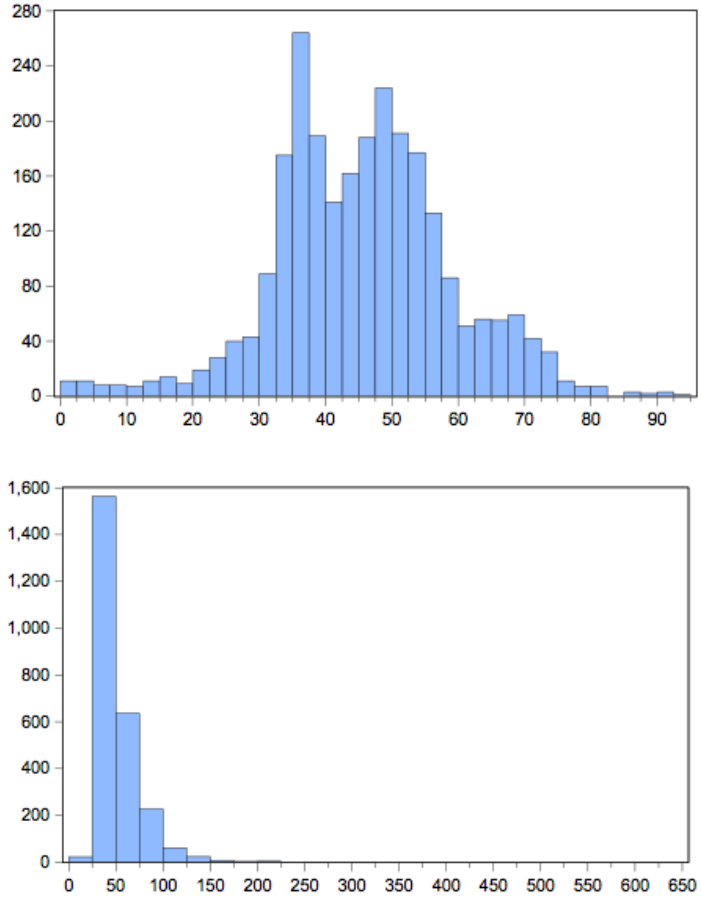
$$F(P_i, t, k, \sigma) = \frac{1}{N}\sum_{t=1}^{N} P_i(t) + k\sigma_{P_i(t)}$$

Where $P_i(t)$ are actual payments during delivery periods 1 to N under alternative i, k measures volatility aversion and σ is the volatility of $P_i(t)$. The sample is from 3/7/2006 to 31/1/2017. The number of months is 84. We compute the overall value of F and report the number of periods (e.g. months) in which a given method produces the lowest value.

	AECO		**RECO**		**JCPL**		**PSEG**	
K=0	#	%	#	%	#	%	#	%
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT: σ+)	23	27,38%	23	27,38%	22	26,19%	22	26,19%
(M4_M15)	18	21,43%	19	22,62%	18	21,43%	18	21,43%
(M4_M15_REC)	25	29,76%	24	28,57%	26	30,95%	26	30,95%
(M4_M15_DAY15)	18	21,43%	18	21,43%	18	21,43%	18	21,43%
K=0,5								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT: σ+)	18	21,43%	15	17,86%	19	22,62%	15	17,86%
(M4_M15)	19	22,62%	21	25,00%	20	23,81%	22	26,19%
(M4_M15_REC)	27	32,14%	28	33,33%	27	32,14%	27	32,14%
(M4_M15_DAY15)	20	23,81%	20	23,81%	18	21,43%	20	23,81%
K=1								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT: σ+)	11	13,10%	8	9,52%	12	14,29%	10	11,90%
(M4_M15)	23	27,38%	25	29,76%	22	26,19%	24	28,57%
(M4_M15_REC)	28	33,33%	30	35,71%	29	34,52%	29	34,52%
(M4_M15_DAY15)	22	26,19%	21	25,00%	21	25,00%	21	25,00%
K=2								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT: σ+)	5	5,95%	3	3,57%	5	5,95%	4	4,76%
(M4_M15)	26	30,95%	27	32,14%	26	30,95%	26	30,95%
(M4_M15_REC)	30	35,71%	30	35,71%	30	35,71%	30	35,71%
(M4_M15_DAY15)	23	27,38%	24	28,57%	23	27,38%	24	28,57%
K=4								
(DSA)	0	0,00%	0	0,00%	0	0,00%	0	0,00%
(SPOT: σ+)	3	3,57%	0	0,00%	0	0,00%	0	0,00%
(M4_M15)	27	32,14%	29	34,52%	29	34,52%	29	34,52%
(M4_M15_REC)	30	35,71%	31	36,90%	31	36,90%	31	36,90%
(M4_M15_DAY15)	24	28,57%	24	28,57%	24	28,57%	24	28,57%

Figure 1: Spot Prices Distributions: OMEL vs AECO

This figure presents histograms and summary statistics of spot prices of OMEL market (Spain) and AECO PJM-BGS market. Dataset consists of daily data from January 1, 2007, until December 31, 2013. The sample size is 2557 observations.



	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
PMD OMEL	45.612	45.640	93.110	0.000	13.462	-0.073	3.817	73.302	0.000
AECO	52.094	43.150	628.430	19.220	32.154	7.710	109.056	1223699	0.000

Figure 2: OMIP Volume series

This figure illustrates average values of daily trading volume at OMIP. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2. Dataset consists of daily data from July 3, 2006, until February 1, 2016. Units are MWh. We report volume data in monthly-equivalent figures.

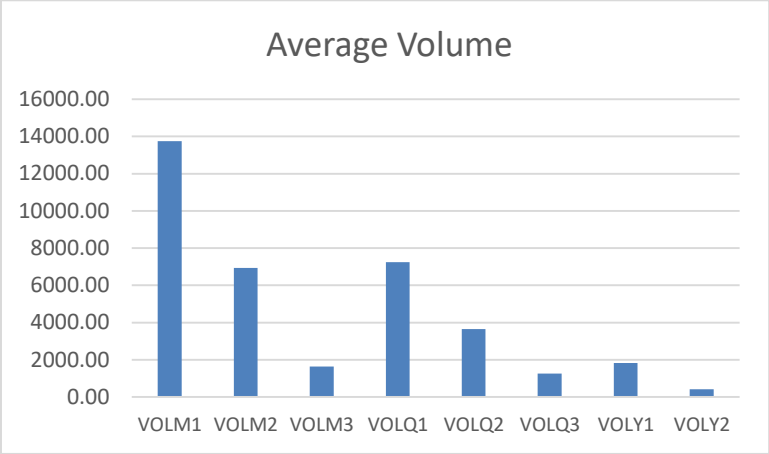


Figure 3: OMIP Open interest series

This figure illustrates average values of open interest at OMIP. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2.Our data set consists of daily data from July 3, 2006, until February 1, 2016. Dataset consists of daily data from July 3, 2006, until February 1, 2016. Units are MWh. We report open interest data in monthly-equivalent figures.

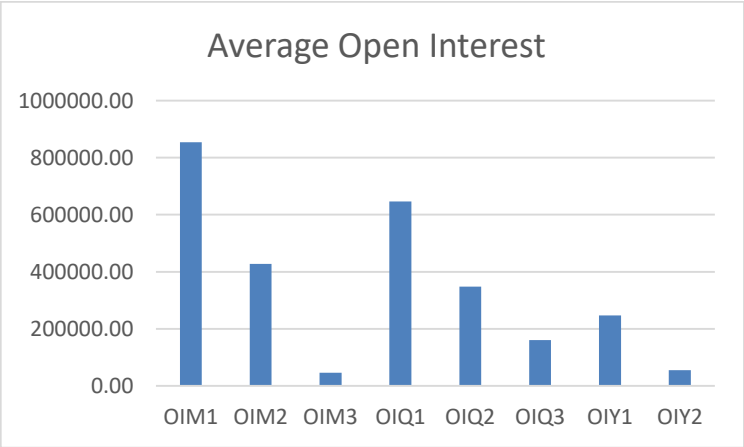


Figure 4: Trading Volume T-statistic around CESUR auctions

This figure illustrates the evolution of t-statistic near dates of CESUR auctions. The null hypothesis is that the average of these days and the average of the full sample (but excluding the days) are equal. As we may see, we reject the hypothesis at 1% level on the day of the auction and at 5% level in the day before the auction.

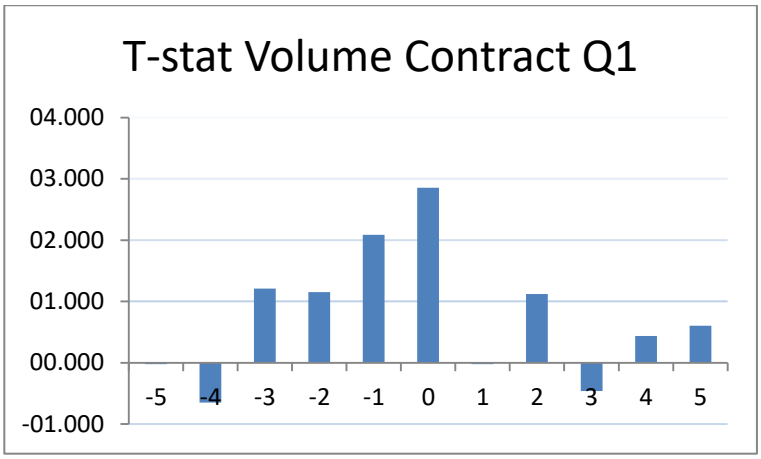


Figure 5: Open Interest T-statistic around CESUR auctions

This figure illustrates the evolution of t-statistic near dates of CESUR auctions. The null hypothesis is that the average of these days and the average of the full sample (but excluding the days) are equal. As we may see, we reject the null hypothesis at 1% level on the day of the auction and at 5% level in the day before the auction.

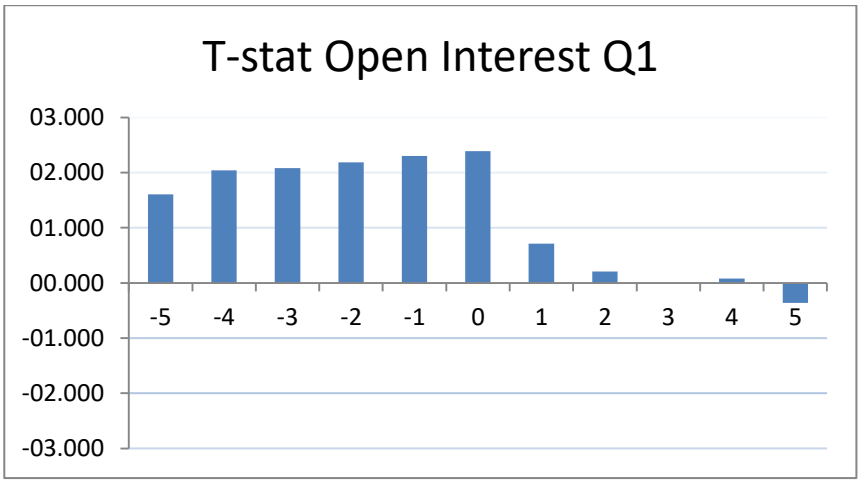


Figure 6: OMIP R1 time series

This figure illustrates the evolution over time of R1 at OMIP. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2.Our data set consists of daily data from July 3, 2006, until February 1, 2016, Sample size varies depending on N/A cases.

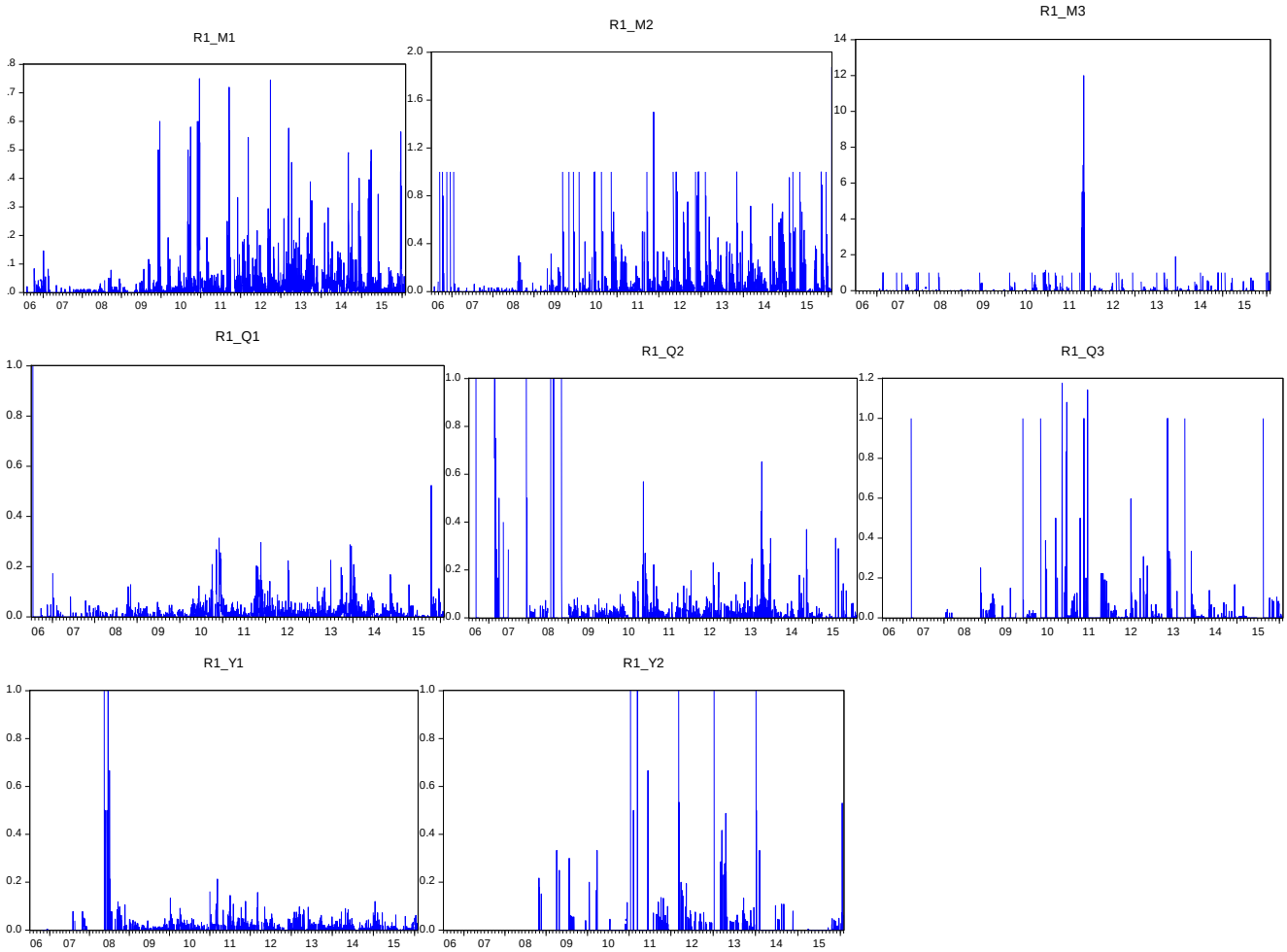


Figure 7: OMIP R2 time series

This figure illustrates the evolution over time of R2 at OMIP. Contracts are M1, M2, M3, Q1, Q2, Q3, Y1 and Y2. Dataset consists of daily data from July 3, 2006, until February 1, 2016, Sample size varies depending on N/A cases.

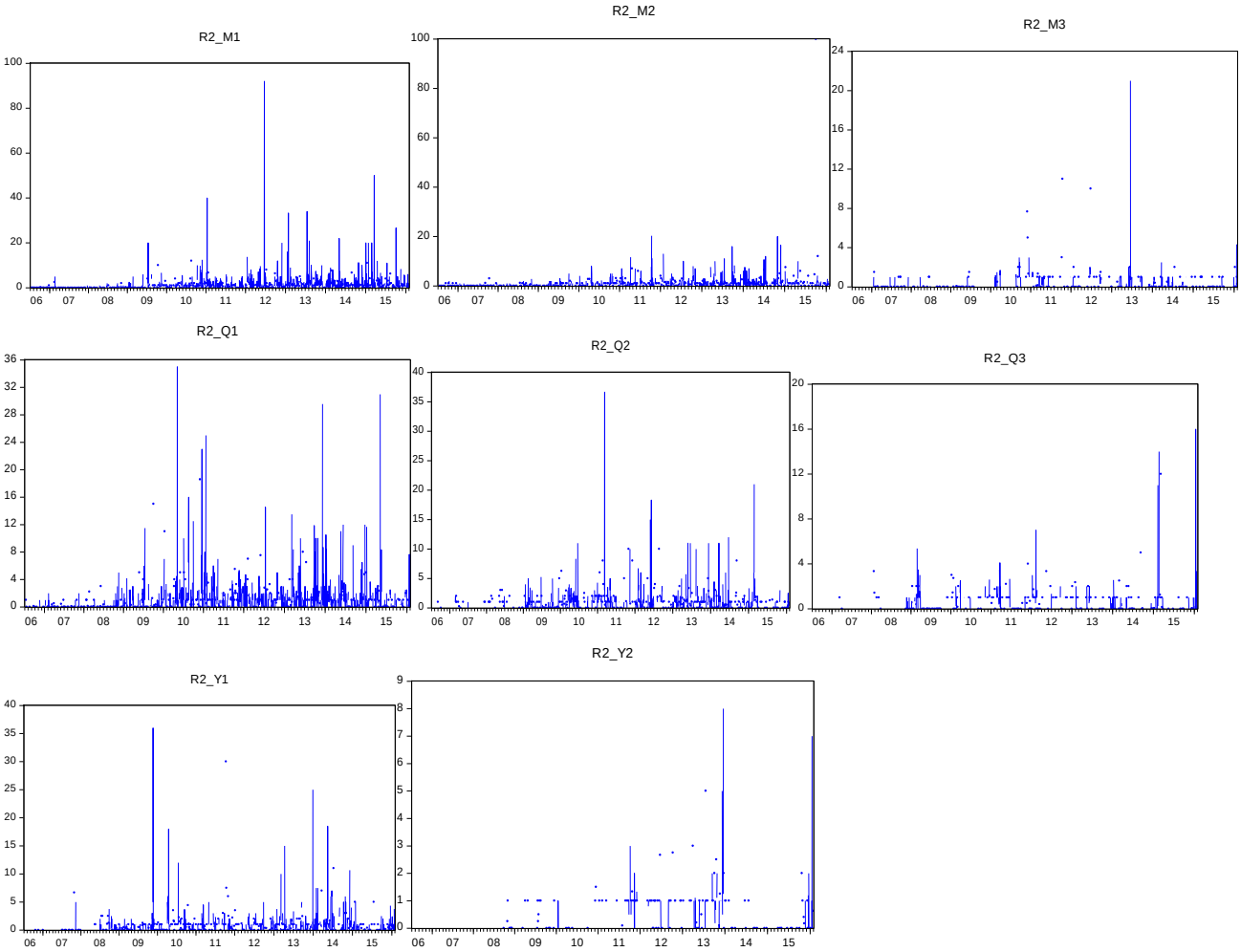


Figure 8: Trading Volume T-statistic around PJM-BGS auctions, Western Hub

This figure illustrates the evolution of t-statistic near dates of PJM-BGS auctions. The null hypothesis is that the average of these days and the average of the full sample (but excluding the days) are equal. As we may see, the hypothesis is rejected at 1% level on the day of the auction and at 5% level in the day before the auction.

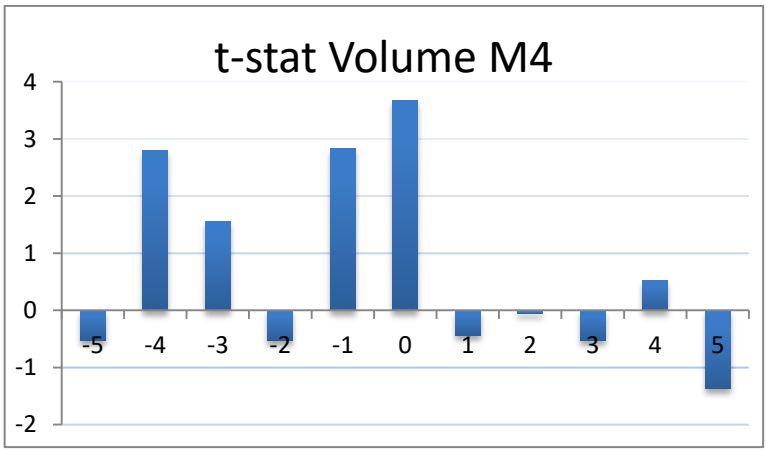


Figure 9: Open Interest T-statistic around PJM-BGS auctions, Western Hub

This figure illustrates the evolution of t-statistic near dates of PJM-BGS auctions for the M4 contract. The null hypothesis is that the average of these days and the average of the full sample (but excluding the days) are equal. As we may see, the hypothesis is not rejected.