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Virtual Power Plant Auctions in the Western Denmark Electricity Market:

An econometrics analysis

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ABSTRACT

In July 2006, two of Denmark's largest energy companies, Elsam A/S and DONG A/S, merged to form DONG Energy A/S. In the years directly leading up to this merger, Elsam had been accused of abusing its dominant position in the Western Danish spot market for wholesale electricity (DK1) by charging unreasonably high power prices. In light of this, and in an effort to prevent any anticompetitive effects that could result from the merger, the Danish Competition and Consumer Authority (DCA) required DONG Energy both to physically divest several power plants in DK1 and to sell off electric power production capacity through Virtual Power Plant (VPP) auctions. Although VPP auctions have been widely implemented in European power markets, there has been some debate over whether they effectively reduce market power; even the DCA expressed doubts about their effectiveness in DK1 shortly after the merger.

This paper explores the impact of the physical and virtual divestitures on competition in DK1 by using time series Ordinary Least Squares (OLS) and generalized autoregressive conditional heteroskedasticity (GARCH) model specifications to determine whether the price spread between DK1 and the competitive Swedish power market changed when these divestitures were implemented. After controlling for price determinants of electricity in DK1, the results of this analysis suggest that neither the VPP auctions nor the physical divestitures appear to have coincided with any significant procompetitive effects in DK1, thus confirming the suspicions of the DCA. The general implication that follows is that neither physical divestitures nor VPP Auctions are guaranteed to reduce market power in electricity markets even if they decrease concentration.

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1. Introduction

In mergers, divestment of physical operating capacity has been the traditional remedy to prevent the exercise of monopoly power by a surviving entity. In electricity markets, where power plants are difficult and expensive to build and operate, regulators have recognized that the sale of physical plants as a condition of merger approval is not always practical. Such a divestment requires another market participant to make a significant long-term capital and operational investment and to do so in the shadow of, and at the risk of competing unsuccessfully with, a more dominant firm.

As a consequence, for over a decade, as mergers of electricity producers have been approved throughout Europe, regulatory authorities have been using virtual power plant (VPP) auctions to attempt to offset the market power of merged entities. A VPP auction is the sale by a dominant firm of electricity capacity in the open market. The producer of the electricity offers to sell a fixed amount of electricity capacity during a specific window of time through an open auction. The successful bidder receives the right to that output at a specified or “strike” price. The purchase of production capacity through a VPP auction does not require the same long-term financial commitment and does not entail the same risk as the physical purchase of a plant; such “virtual” divestments therefore appeal to a larger pool of potential investors and can be implemented more quickly and with greater flexibility. Moreover, unlike plant sales, VPP auctions can be discontinued if competitive conditions in a market improve.

Although VPP auctions have been used in Europe since 2001, how successful they have been in promoting competition remains open to question. Based largely upon theoretical analyses, a number of authors have expressed concern that VPP auctions are not as effective as physical divestitures or are not effective at all. Schultz (2009) developed a Cournot model and concluded that incumbent firms could still realize monopoly prices if the contract duration of VPPs is short and the VPP auctions are competitive. Armstrong et al (2007) studied French VPP auctions and concluded that those auctions had minimal impact on market dynamics because those who purchased power through such auctions could just as easily have purchased it through the open market. Federico and Lopez (2009) assessed VPP auctions by using a stylized model of a wholesale electricity market where a dominant producer faces a competitive fringe with the same cost structure. They concluded, despite the hoped for advantages of VPP auctions, that VPPs were inferior to physical divestments increasing competition in electricity markets. Ausubel and Cramton (2010) concluded that VPP auctions have been ”effective devices for facilitating new entry into electricity markets and for developing wholesale markets,” but have not been large enough to successfully mitigate the effects of market concentration in spot markets.

On the other hand, Maurer and Barroso (2011) opine in their extensive recent report for the World Bank concerning the use of electricity auctions in Latin America that VPP auctions, if properly overseen and implemented, can be effective in developing countries to mitigate such challenges in developing electrical power capacity as uncertainty in load growth rates, limited access to financing, exposure to construction delays, and uncertain legal and regulatory institutional arrangements that fail to provide necessary incentives.[1]

The goal of this paper is to attempt to assess whether and the degree to which VPP auctions have been successful by focusing on the experience of the Western Denmark market during the period from 2003 to 2009, when a series of mergers led to consolidation of production capacity in a single firm, DONG Energy. Rather than analyze the impact of VPP auctions by using models, as some have, this paper will approach this issue through an econometric analysis of actual pricing data. Section 2 of this paper discusses European electricity markets and outlines why, despite the obvious disadvantages of allowing dominant firms with market power, they have remained highly concentrated in the recent past.[2] Section 3 describes the mechanics of how VPP auctions operate as a vehicle to mitigate the anti-competitive effects of mergers. Section 4 provides an overview of the Danish market and summarizes the series

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[1] The World Bank study notes:

“The experience of VPP auctions shows that they are a good instrument for facilitating market entry and promoting the development of wholesale power markets. For example, the French wholesale market is considered to be the third most active wholesale electricity market in Europe today. However, in 2001, there was barely a wholesale electricity market in France, to the point that data from the German wholesale market had to be used when setting reference prices for the early Electricité de France (EDF) auctions. Also, European utilities have been expanding their operations outside their principal markets partly due to the access to generation afforded by VPP auctions.”

Maurer and Barroso (2011), at page 125.

[2] It is recommended that readers who are unfamiliar with electricity markets read Appendix A to familiarize themselves with some of the terms used throughout the paper.

of mergers which led the Danish regulatory authorizes to require VPP auctions in an attempt to offset increasing market concentration. Section 5 describes the Nord Pool market and the market price formation process. Section 6 sets forth the pricing data from the two markets that will be analyzed and describes the econometric methodology chosen for the analysis. Section 7 outlines the results of the regressions and provides detailed analysis of the pricing data. Section 8 summarizes the conclusions reached, compares the results of this paper with previous studies and assessments, and offers avenues for future research.

2. Market Power in Electricity Markets

For a variety of reasons, wholesale electricity markets can be highly prone to market power and high firm concentration. Because of the physical nature of electric power transmission, supply and demand on electrical grids must always be exactly equal to one another. In addition, the majority of consumers do not buy wholesale power directly: instead, they purchase it from retailers. As a result, end-users do not face the real-time prices of power generation and causes demand to be highly inelastic, i.e. market demand for electricity is largely unresponsive to changes in price (see Stoft 2002 for a more in depth discussion). Third, and highly relevant in the case of DK1, limited transmission capacity may limit the ability of power to flow to a particular area. When power lines become *congested*, there may only be one firm within the resulting isolated market who can provide the extra power needed to balance supply and demand.

There are also historical and political reasons for highly concentrated power markets in Europe. Before electricity markets were restructured in the late 1990's, large, heavily-regulated monopolies controlled power production in most European countries. After markets were liberalized and opened up for competition amongst generators, some countries like the UK, broke up these utilities vertically and horizontally to foster a competitive domestic market for electricity production. Other countries, however, preferred to maintain these large monopolies in anticipation that they would be stronger competitors in a pan-European power market (Neumann et al. 2009). This continental integration, however, has happened more slowly than expected and as a result, domestic markets in countries like France, Belgium and Denmark are dominated by single firms with very limited competition.

The most widely-used formula for assessing market concentration and therefore the danger that any firm or firms will exercise market power is the Herfindahl-Hirschman Index (HHI). The HHI is calculated by squaring the market share of firm competing in the relevant market and then adding the resulting numbers:

$$\textbf{Herfindahl-Hirschman Index } (\boldsymbol{HHI}) = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{s_i^2}$$

where *s* is the percentage share of firm *i*. For example, for a market consisting of four firms with shares of 10, 40, 15, and 35 percent, the HHI is 3,150 (10^2+ 40^2 + 15^2 + 35^2 = 3,150). The HHI becomes smaller and approaches zero the participants in a market are numerous and have relatively equal market share. It becomes larger and reaches when there are fewer competitors and reaches its maximum of 10,000 points when a market is controlled by a single firm. Regulatory agencies such as the United States Department of Justice generally consider markets in which the HHI is between 1,500 and 2,500 points to be moderately concentrated; markets in which the HHI exceeds 2,500 points are considered highly concentrated (U.S. Department of Justice 2010). According to the U.S Department of Justice, transactions in highly concentrated markets that increase the HHI by more than 200 points are presumed likely to enhance market power.

HHI measurements will be use later in this paper to demonstrate the increasing concentration of market power in the Danish market during the period under study.

3. Virtual Power Plant Auctions

During the past decade and a half, competition authorities throughout Europe have attempted to improve competition in electricity markets by forcing firms to auction off electrical capacity through VPP auctions. As noted in the introduction, a VPP is an option contract for electric power production capacity; the holder of a VPP is entitled to purchase a certain quantity of production capacity from the incumbent firm at a pre-specified price called the *strike price* for a certain amount of time. In addition to Denmark, VPP auctions have been used in France, Spain, Portugal, Germany, the Netherlands, the Czech Republic, Belgium and Ireland.

As the name suggests, a VPP auction is an example of a *virtual divestiture*, since it does not force firms to physically sell assets such as power plants. Instead, it requires firms to sell the ability to produce electricity to competitors. Much like physical divestitures, VPP auctions have been used to reduce the market shares of dominant incumbent firms in highly concentrated markets. In France, the Netherlands and as we shall soon see, Denmark, VPP auctions have often been implemented to offset potential anticompetitive effects arising from mergers taking place in the electricity sector (Neumann et al. 2009).

There are a number of reasons why a competition authority may prefer a virtual divestiture to a physical one. To begin with, forcing firms to physically divest power plants can be drawn-out and costly process that is largely irreversible once it is carried out (Neumann et. al 2009). In addition, virtual divestitures provide the opportunity new firms to enter an electricity market without having to invest in expensive physical power production assets (Tangerås 2009). In select cases, there may be economies of scale present if the incumbent firm maintains control of the physical power plant. Managerial economies of scale was a factor at play when authorities allowed Electricité de France (EDF) to maintain ownership of its entire fleet of nuclear power plants after merging with the German firm EnBW in 2001. Since EDF had a long history of operational safety with these plants, the French competition authorities required that EDF auction off VPPs rather than force them to undergo physical divestitures (Ausubel & Cramton 2010). Last but not least, forcing a large energy company with partial state ownership to physically divest assets may be politically unpopular: virtual divestitures provide a means for competition authorities to decrease market concentration without any generation assets changing hands.

There are three main means by which regulators might hope that VPP auctions improve competition in electricity markets (Ausubel & Cramton 2010):

1. Provide sufficient available capacity to entice new firms to enter the market
2. Mitigate market power in the spot market for wholesale electricity
3. Further develop forward trading and liquidity for wholesale electricity

When regulators are most concerned with combating market power, the strike price is usually set equal to the marginal cost of energy production at the most efficient power plant in the market of interest to ensure that VPP contracts provide maximum competitive effects. For this reason, the VPP strike price is sometimes called the *energy price* (DONG 2008). When the spot market price of electricity exceeds this strike price, the VPP holder will be "in the money" and choose to purchase electricity. The contract-holder can then they can simply sell this electricity back onto the spot market. Theoretically, this should in turn increase electricity production in the market and thereby put downward pressure on prices.

Ausubel & Cramton (2010) provide a thorough overview of VPP auction design. According to the authors, nearly every VPP auction to date has taken the form of a "simultaneous ascending-clock auction with discrete rounds." Despite the name, this is actually rather straightforward auction design. As with most auctions, a VPP auction begins with an auctioneer, usually the market operator, announcing the sale of a specific quantity of VPPs and any other important characteristics like the contract duration, strike price, etc. Interested bidders then register for the auction which is carried out via an internet portal. Once the participating bidders have all logged on to this portal at the specified date and time, the auctioneer begins the first round of the auction by giving the bidders an interval of prices, $[p_{t=1}^{LOW}, p_{t=1}^{HIGH}]$ where t=1 denotes "round 1." Each of bidders then simultaneously submits the quantities of VPP contracts that they would be willing to purchase for the prices that lie within this interval. In other words, the bidders submit their demand functions relevant to the first round price interval. These demand functions are required to be downwards sloping in order to prevent strategic behavior among the auction participants (Ausubel & Cramton, 2010).

When all of the bidders have submitted their demand functions, the first round ends (hence the term "discrete rounds"). The auctioneer then aggregates all of these individual demand functions to calculate the bidders' aggregate demand for VPPs over the first round price interval. If this aggregate demand is equal to or below the available supply of VPPs then the auction is over and the clearing option price for these contracts, p*, is set at the lowest price where this inequality is satisfied. The VPPs are then allocated to each individual auction participant according to their demand for the VPPs at p*. If the aggregate demand for VPP contracts exceeds the available supply then a second round commences where bidders offer quantities demanded over the price interval [$p_{t=2}^{LOW}$, $p_{t=2}^{HIGH}$] where $p_{t=2}^{LOW} = p_{t=1}^{HIGH}$. This process repeats until aggregate demand is less than or equal to the available supply of VPPs and a clearing price can be obtained. For interested readers, Ausubel & Cramton (2010) also outline some design differences that occur across VPP auctions but these are not essential to understanding the analysis undergone in this paper.

It is important to note that VPPs can either be contracts for the physical delivery of electricity or purely financial instruments. In instances where the VPP holder may actively decide how much production capacity is used in the relevant market, the VPP is said to be a physical contract. This stands in contrast to purely financial VPPs where holders simply hold a coupon for power and are reimbursed by the generator for the difference if the spot price of electricity exceeds the strike price (Willems 2006). Since owners of physical VPPs can actually control the production of the underlying physical asset being traded, they should be considered active spot market participants. Due to this fact, one might expect physical VPPs to have stronger pro-competitive effects than purely financial VPPs (Willems 2006).

4. The Danish Electricity Market and its Mergers, 2000 to 2009

4.1 The Structure of the Danish Market

Due to large stretches of water that separate its islands, Denmark has evolved into a country with two separate power grids: Western Denmark (DK1) and Eastern Denmark (DK2). DK1 is comprised primarily of the Jutland Peninsula and, due to its close proximity, the island of Funen. DK2 in turn covers Denmark's largest island, Zealand, along with the smaller surrounding islands.

Since the 1950's, Denmark has steadily built a number of high-voltage transmission lines that connect both DK1 and DK2 to neighboring grids. Lines that specifically connect two different electrical in this manner are often called *interconnectors*. By the year 1995, the Eastern Danish grid had four interconnectors with Sweden and one with Germany. The Western Danish grid, owing to its closer proximity to Germany and Norway, boasts four interconnections with Germany, one with Norway and two with Sweden. The buildup of these interconnectors had allowed both DK1 and DK2 to increasingly import cheap and abundant hydropower from Norway and Sweden (DCA 2003). As mentioned previously, the Great Belt interconnector that connects DK1 and DK2 was recently built as a concession for the DONG-Elsam merger and not operational until August 2010 (Energinet.dk 2014).

Both DK1 and DK2 are price areas in the Nordic electricity market, Nord Pool Spot. This means that absent transmission capacity constraints, energy companies in Denmark compete with energy companies in Sweden, Norway, Finland and the Baltic countries in an open market. When there is congestion, DK1 and DK2 become separate markets and can have prices that differ from one another and other price areas in Nord Pool. This will be discussed in greater detail in section 4.

Figure 1 comes from the Danish grid operator, Energinet.dk, and provides a visual representation of the two Danish electricity grids. It also shows the interconnectors between the Danish grids and neighboring countries.

Figure 1: Map of the Danish Electricity Markets

Source: Energinet.dk (2014)

Excluding the hydro and nuclear power imported from surrounding countries, there are three main sources of power generation located within both DK1 and DK2: thermal, wind and decentralized combined heat and power (DCHP). Almost of all of Denmark's thermal power production comes from burning coal in large, centralized plants. DCHP comes as a result of what is known as combined heat and power district heating, where decentralized thermal power plants burn fossil fuels to generate heat. The high-temperature heat that is produced from this process is too hot to be used to normal heating purposes and instead used to power a turbine and produce electricity. The low-temperature or "waste heat" that is left over is then pumped to surrounding commercial buildings and private residences via heat pipes where it is used both for space and hot water heating. At the time of the Elsam-DONG merger in 2006, central power plants, wind power and DCHP accounted for 47.0%, 32.0% and 21.4% of the total domestic production capacity in DK1 respectively (DCA 2007). Combined, this represented 7,586 MW of production capacity.

In addition to owning 100% of all central power plants, Elsam owned 12.7% of the DCHP capacity and 16.3% of the wind power production capacity in DK1.

Wind power and DCHP are both considered *inflexible* power production technologies. When wind speeds are high, the wind mills churn out significant amounts of power but when the wind stops blowing, so too does the flow of electricity. Similarly, when it is cold outside, the demand for heat increases and more generation can come from DCHP. This is not the case with thermal power generation which is a *flexible* power production technology. Owners of coal- or natural gas-fired power plants can decide precisely what quantity of power to produce at any given time and are not dependent on weather patterns to determine their output. Furthermore, the DCA characterizes inflexible power generation as “not being connected to and dependent on the market price of electricity” (DCA 2007).

Up until the DONG merger was completed, Elsam faced no competition for flexible production: it owned 100% of the centralized thermal power plants in DK1. It’s only other competitors within DK1 were wind and DCHP. Elsam did own a small amount of wind power and DCHP production prior to the merger but it was their monopoly share of centralized power plants that most concerned the Danish Competition Authority (DCA 2007).

4.2 Consolidation in the Western Danish Electricity Market

In 2000, six major utility companies in DK1 merged together to form Elsam A/S, which, as mentioned above, held a 100% share of all centralized power production in DK1. Almost immediately after Elsam’s formation, the Danish Competition and Consumer Authority (DCA) received complaints from energy traders that spot prices for power in DK1 had risen considerably. In response to these complaints, the DCA carried out an investigation to determine if Elsam was abusing their dominant market position to charge prices unreasonably above their production costs. In 2003, the DCA reported that Elsam did in fact change their pricing behavior when there was high demand for power in DK1 but because the Danish electricity market had been newly restructured in 1999, the DCA attributed this behavior to Elsam simply learning optimal strategies in a new market environment. As such, the DCA concluded that there was insufficient evidence to prove that Elsam had violated the Danish Competition Act that prohibits firms from charging consumers “unreasonably high” prices (DCA 2003). In addition, Elsam signed an agreement with the DCA promising to charge prices more closely aligned with neighboring price zones (DCA 2003). The traders withdrew their complaints and everything seemed to be in good order.

In August of 2003, Eltra, the grid-operator responsible for DK1 price zone, again voiced concerns that Elsam had been charging excessive wholesale electricity prices during that summer (DCA 2005). When the power market operators at Nord Pool echoed these suspicions shortly thereafter, the DCA decided to re-investigate claims of market power abuse.

Meanwhile, in early 2004, Elsam and an electricity company in the Eastern Danish electricity market (DK2) called NESA A/S, announced plans to merge. The DCA approved this merger but attached to their approval several conditions:

1. NESA was to physically divest all of their transmission assets.
2. The newly merged firm would be responsible for building a transmission line with a capacity of 600 MW between DK1 and DK2
3. The newly merged firm would have to sell off 600 MW worth of options contracts for power production capacity via Virtual Power Plant (VPP) Auctions in DK1

Rather than force the firm formed from this merger to divest all 600 MW of capacity of once, the DCA, Elsam and NESA agreed on a schedule to incrementally increase the capacity offered in the VPP auctions. As of January 1, 2006, the new firm was to offer 250 MW of capacity, followed by 500 MW in 2007 and the full 600 MW beginning in 2008.

In December 2004, the state-owned oil and natural gas company Dansk Olie og Naturgas A/S (DONG) and Elsam announced that they too planned to merge. Though the Danish government founded DONG in 1972 to explore for oil and natural gas in the Danish economic zone of the North Sea and manage the Danish natural gas storage and distribution infrastructure, DONG entered the electricity sector in the early 2000’s, systematically acquiring more and more utility companies (DONG 2014). As a concession for the merger, DONG offered to physically divest two large thermal plants in DK1, Fynsværket and Nordjyllandsværket, as well as one plant in DK2 to the Swedish energy company Vattenfall who owned a 35% stake in Elsam. Together, these two plants comprised about 32% of centralized production capacity in DK1 (DCA 2007). Feeling that a merger of this size could impact countries outside of Denmark, the DCA passed this merger case to the European Commission for approval. The DCA stated early on that even with the approval of the

European Commission and the physical divestiture of plants in DK1 and DK2, DONG Energy would have to uphold all of the requirements set forth in the Elsam-NESA merger and would likely be subject to additional requirements (DCA 2007).

In November 2005 the DCA released the results of its second investigation of Elsam. This time, it determined that from the summer 2003 through December 31st, 2004, Elsam had been intentionally creating transmission bottlenecks, i.e. congestion, in order to isolate the DK1 price zone from neighboring markets in order to take advantage of their dominant market position in centralized power production. Armed with Elsam's production cost data, the DCA also determined Elsam's price mark-up to be "unreasonably high" and consequently found Elsam to be in violation of section 11(1) of the Danish Competition Act (DCA 2005).

In light of this finding, the DCA moved to impose a strict ceiling on prices that Elsam was allowed to bid into the wholesale market. In addition, the DCA firmly warned Elsam against withholding production capacity to try and raises prices and stated that the market would hereby be monitored more closely to prevent this type of abuse. Elsam, however, maintained its innocence and fought the DCA: the price injunction was overturned by the Danish Competition Council as it was deemed unnecessary in light of the structural changes soon to be realized from the DONG-Elsam merger (DCA 2007)

As planned, the first VPP auction was held in November of 2005 and 250 MW worth of VPPs became active on January 1st 2006. The European Commission approved the DONG-Elsam merger in March 2006 and on July 1st, 2006 it was completed when DONG Energy made its physical divestitures to Vattenfall (DONG 2014). On January 1st, 2007 the virtual divestiture was increased to 500 MW for the entire year and one final time to 600 MW on January 1st 2008.

Using the Elsam investigations undertaken by the DCA, along with production capacity information about Western Danish power plants readily available from Vattenfall and DONG, we can see how market shares changed in Western Denmark around the time of the Elsam/DONG merger. In addition, since we know the exact amount of virtual capacity required to be auctioned off as a result of this merger, we can examine what portion of the Western Danish market these auctions constitute. Market shares are also useful in the sense that they provide a *structural* description of the market: they allow us to see how competitive conditions might be changing in the market since lower (or higher) market shares will theoretically affect the ability of any individual firm to determine prices (Tirole 1988).

Table 1 shows the degree of market concentration in the Western Denmark electricity market from 2005 to 2008 using the HHI:

Table 1. Herfindahl-Hirschman Index for centralized power production in Western Denmark from 2005-2008

Year	Event	HH Index (scaled as decimals)	HH Index
2005	Pre-VPPs and Merger	$= (1)^2$ $= 1$	10,000
2006 (Jan - Jun)	VPP Auctions for contracts totaling 250 MW	$= (0.93)^2 + (0.07)^2$ $= 0.8649 + 0.0049$ $= 0.8698$	8,698
2006 (Jul - Dec)	Merger completed: DONG Energy physically divests Nordjyllandsværket and Fynsværket power plants to Vattenfall	$= (0.61)^2 + (0.32)^2 + (0.07)^2$ $= 0.3721 + 0.1024 + 0.0049$ $= 0.4917$	4,794
2007	VPP Auctions for contracts totaling 500 MW	$= (0.55)^2 + (0.32)^2 + (0.14)^2$ $= 0.3025 + 0.1024 + 0.0196$ $= 0.4245$	4,245
2008	VPP Auctions for contracts totaling 600 MW	$= (0.52)^2 + (0.32)^2 + (0.17)^2$ $= 0.2704 + 0.1024 + 0.0289$ $= 0.4017$	4,017

At the time of the merger, the total centralized power capacity in DK1 was approximately 3491 MW. Nordjyllandsværket and Fynsværket, which have power production capacity ratings of 667 MW and 463 MW respectively, collectively accounted for approximately 32% of the centralized thermal power production in DK1. All 600 MW of VPPs represented about 7.2% of all centralized production capacity. Thus, from January 1st, 2006 to January 1st, 2008, the HHI index dropped from 10,000 to 4,017.

Since 2007, DONG Energy's new ventures have mostly been re-focused on oil exploration in the North Sea, securing new agreements for natural gas supply in Denmark and developing new wind power projects both in and Northern Europe (DONG 2014). The Great Belt interconnector was built in 2010 and constitutes the most dramatic structural change in the Danish power markets to have occurred in recent years.

There has been much concern, however, that both the VP auctions and physical divestitures failed to reduce market power in DK1. Below is an excerpt taken from the DCA article titled "Elsam" that reports on the Danish Competition Council meeting that took place on June 20th, 2007:

> *"Statistics for 2006 show that the winners at the VPP-auctions have chosen to produce electricity in 99 pct. of all hours in 2006, which means that Elsam can predict the amount of VPP-production – and hence the competitive pressure – with close accuracy. Furthermore the amount of capacity offered as VPP in 2006 has not had an impact on Elsam's position as residual monopolist. Thus the Competition Authority concludes that Elsam holds a dominant position on the relevant market. This is the case before July 2nd 2006 as well as after seeing as how Vattenfall's bids on Nord Pool show that there has been no clear or competitive strategy behind Vattenfall's bidding practice as of the day of the takeover on July 2nd 2006. This means that the presence of Vattenfall in Western Denmark has not sufficiently improved competition on the market."*

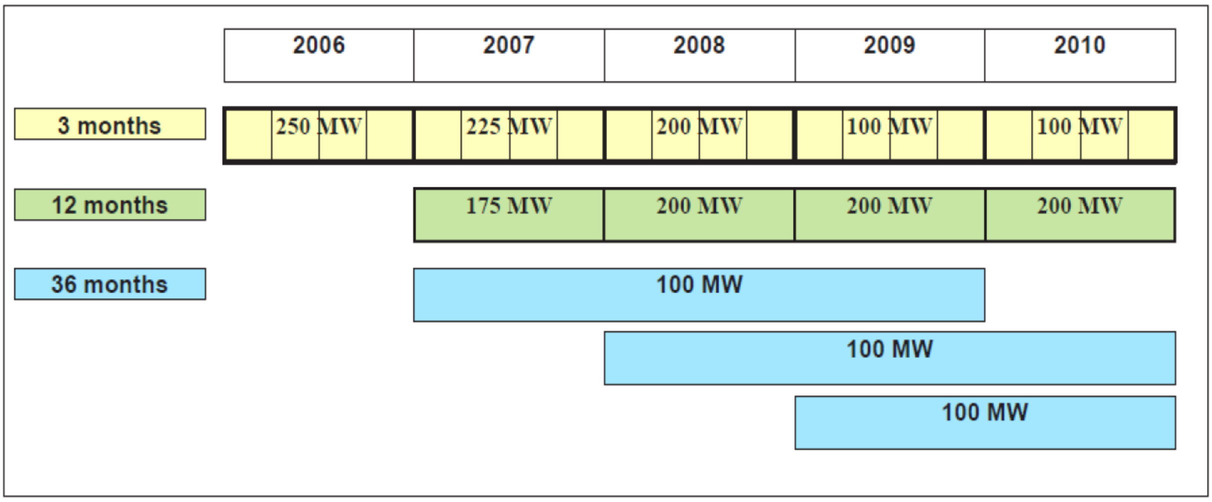
Despite these doubts about their efficacy, the VPP auctions have continued to the day. The economic analysis performed later in this paper seeks to further investigate the assertion made in the above quote by the DCA. In addition, this analysis will include data that extends two and a half years' past when the DCA released this report. This allows for the possibility that the divestitures did eventually have some long-term procompetitive effects in DK1.

4.3 The Danish VPP Auctions

The VPP Auctions in DK1 are administered directly by Nord Pool Spot. The VPPs in DK1 are contracts for physical delivery and the contract holder is actively allowed to decide how much virtual capacity is used in DK1 the following day. As a result of this, participation in the DK1 VPP auction is restricted to relevant electricity market players: generators, distribution companies, end-users, energy traders and TSOs. In addition, bidders must be approved by the Danish Competition authority in order to participate (DONG 2008). As in other VPP markets, Danish regulators set the VPP strike price equal to the marginal cost of electric power production at DONG's most efficient power plant in DK1 to ensure that VPP contracts provide the maximum competitive effect (KYOS 2010).

VPPs in DK1 are sold for three different contract durations: 3, 12 and 36 month contracts. The sale of VPPs, however were phased in over time: in 2006, only 250 MW of virtual capacity was sold and all in the form of short-term 3 month contracts. In 2005, the quantity of contracts was doubled to 500 MW and different contract-length durations were introduced. Sales for the 3-month contracts are held quarterly and the year-long and 36-month contract sales happen every November.

Figure 2: Timeline of contract quantities offered in DK1 VPP Auction of from 2006-2010



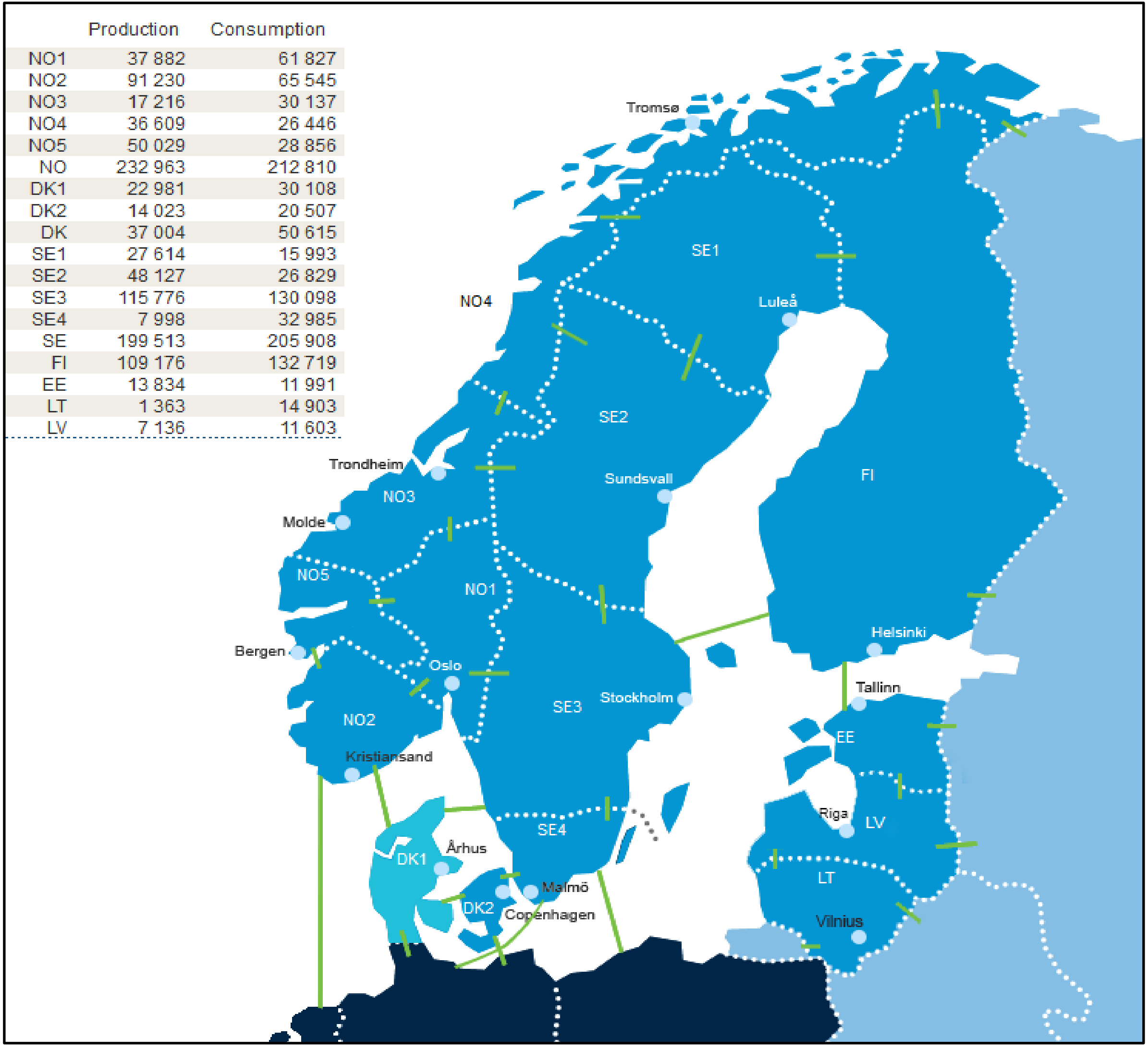
Source: KYOS (2010)

Once an entity owns VPPs, they choose how much electricity they wish to deliver for each hour of the following day. They then submit this information to Nord Pool, who acts as the "Nomination Aggregator," i.e. collects all of these VPP dispatch orders. Nord Pool in turn relays the VPP generation information submitted by the VPP holders to DONG who executes the order according to the hourly schedule the following day.

5. Nord Pool

The Western Danish wholesale electricity is a sub-division of the wider Nordic Power market, Nord Pool Spot AB. Nord Pool Spot was founded in the mid-1990's when Norway and Sweden began to trade power. By the year 2000, Finland and Denmark had also joined and from 2010 through 2013, it expanded to include the Baltic countries Estonia, Latvia and Lithuania. Nord Pool Spot is jointly owned by the transmission system operators (i.e. grid operators) of each of the countries that are members (Nord Pool Spot, "About Us"). Figure 3 provides a map of the Nord Pool market in its entirety as of May 2014.

Figure 3: Map of the Nord Pool Power Market



	Production	Consumption
NO1	37 882	61 827
NO2	91 230	65 545
NO3	17 216	30 137
NO4	36 609	26 446
NO5	50 029	28 856
NO	232 963	212 810
DK1	22 981	30 108
DK2	14 023	20 507
DK	37 004	50 615
SE1	27 614	15 993
SE2	48 127	26 829
SE3	115 776	130 098
SE4	7 998	32 985
SE	199 513	205 908
FI	109 176	132 719
EE	13 834	11 991
LT	1 363	14 903
LV	7 136	11 603

Source: Nord Pool Spot AB (2014)

Though Nord Pool is one continuous market, notice from Figure 3 that it is split into many different price areas. DK1 is highlighted in a slightly lighter shade of blue for no other reason than to make it more readily identifiable for readers. The green lines extending between price zones represent interconnectors.

Prices in Nord Pool are determined through auctions. Power suppliers from every price area submit offers to sell power to Nord Pool in the day-ahead market (Elspot) and load-serving entities from every area submit bids to purchase power. Nord Pool then aggregates these supply and demand bids to create supply and demand curves and sets a clearing price where the two intersect called the “System price.” The system price is calculated without taking into consideration transmission constraints and reflects the market-wide price that would occur if all market participants could trade freely without transmission constraints (Nord Pool, “Price Calculation”).

If, however, there are significant differences between demand and supply between regions and the interconnectors that connect them reach their thermal limits (i.e. they become congested), Nord Pool breaks apart into different price zones where each zone price reflects the supply and demand unique to that zone. Recall from the earlier section on market power that the regional markets that arise from this may be subject to market power since firms located within that zone no longer compete generators in the wider Nordic market. A detail that will be important later in the analysis is that Sweden was not split into price zones until 2011. Prior to this, there was no SE1, SE2, SE3, and so on, but merely SE.

Table 2: Population and Production Capacity Statistics for Countries in the Nord Pool Power Market

Country	Population	Percentage share of Total Market population	Production Capacity (GW)	Percentage share of Total Market Production Capacity	Production Capacity Per Capita (KW)
Denmark	5,569,077	17.06	13.71	12.96	2461.80
Estonia	1,257,921	3.85	2.751	2.60	2186.94
Finland	5,268,799	16.14	16.68	15.76	3165.80
Latvia	2,165,165	6.63	2.166	2.05	1000.38
Lithuania	3,505,738	10.74	3.82	3.61	1089.64
Norway	5,147,792	15.77	30.18	28.52	5862.71
Sweden	9,723,809	29.79	36.51	34.50	3754.70
TOTAL	**32,638,301**	**100**	**105.817**	**100**	**N/A**

Source: CIA World Factbook (2014)

Given the fact that there is often limited transmission capacity between countries, one might expect prices to be higher in price zones where there is a larger population (higher demand for power) and lower generation capacity. Table 2 illustrates the relative population and power production capacity shares of each of the countries in Nord Pool.

We see here that Denmark, along Finland and the Baltic countries, has a higher share of the market population, 17.06%, than it does of the market production capacity, 12.96%. In contract, fellow Scandinavian countries and neighbors Sweden and Norway have much more balanced percentages: Sweden has nearly equal shares of both and Norway has nearly double the percentage share of production capacity than it does of the population. As we shall see later on in the Data Description section, Denmark does indeed have higher average prices than Sweden and Norway.

As one of the world's first power markets, market power in Nord Pool has been the subject of much research. Hjalmarsson (2000) uses a Bresnahan-Lau structural econometric model to determine if market power was present in Nord Pool's spot market (Elspot) from 1996 to 1999. After building the model that controls for a wide array of demand and supply shift factors, Hjalmarsson finds insufficient evidence to reject the null hypothesis of perfect competition. Keep in mind, however, that Hjalmarsson (2000) is looking at the market power on the System price, not prices zones once they become separated due to congestion.

Fridolfsson & Tangerås (2009) provides a thorough overview of market power in Nord Pool and discusses a multitude of models that have been built to test for market power at the System level. The authors conclude that there is indeed insufficient evidence to suggest that short-term market power exists in Nord Pool at the System level, i.e. no single firm has the ability to raise the System price above the competitive equilibrium by changing their production. They caution, however, that there is evidence of regional market power when limited transmission capacity separates Nord Pool into separate price areas. They also point out that long-term market power could still be an issue in Nord Pool, i.e. certain firms could be strategically under-investing in generation capacity to keep long-run prices high.

Based on the results from these studies, we will consider the Nord Pool System price as a competitive market benchmark in the econometric analysis later on.

6. Methodology

The following section outlines the steps taken to specify econometric models that account for the movement of the dependent variable of interest, the price spread between DK1 and the Swedish spot market for wholesale electricity (SE). There are several reasons that motivate this choice and they are thoroughly explained in the Data Description section.

If the combined procompetitive effect of the virtual and physical divestitures exactly offset the DONG-Elsam merger, then one would expect the price spread between DK1 and a competitive benchmark, i.e. the Swedish market, to remain exactly the same.

The analysis covers the time period beginning on January 1st, 2003 up until December 31st, 2009.This time period was chosen to eliminate potential "young market" effects that could have occurred after DK1 was first open up to competition in 1999 and any confounding effects after construction of the Great Belt interconnector between Western and Eastern Denmark was completed in Summer 2010.

The following is a short overview of the Methodology section. The "Data Description" section introduces the spot prices, control variables and structural indicator variables used to carry out the regressions in this analysis. In the "Stationarity and Unit Root Testing" Augmented Dickey-Fuller and Generalized Least Squares Dickey-Fuller Tests are performed to identify non-stationary data. Both non-stationarity and correlation is present in select variables so all data is transformed in log-differences which are interpreted as returns, or percentage increases. In the "Model Specification Section," the autocorrelation and partial autocorrelation functions for the DK1-SE spread are presented and a number of autoregressive (AR) and moving average (MA) terms are chosen. In addition, electricity prices express heteroskedastic volatilities and to correct for this, ARCH and GARCH models are introduced. Finally, the Diagnostics and Robustness section offers several means by which to check the post-estimation performance of the chosen models.

All statistical tests and regressions in this paper were performed using STATA 11.

6.1. Data Description

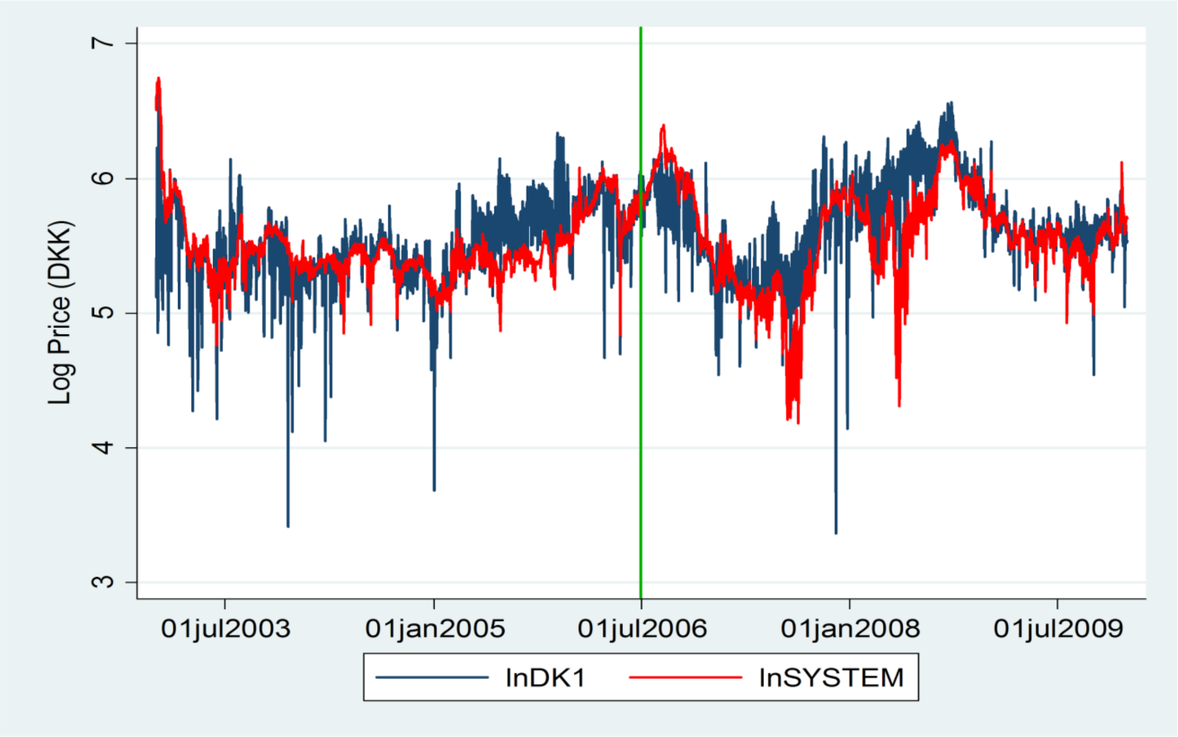
In this section, I provide some general descriptive statistics of the data used in the econometric analysis.

6.1.1 Spot Prices for Wholesale Electricity

I first introduce the spot price data, which were taken from the website of the Danish grid operator, Energinet.dk. We shall examine price data from DK1, DK2, Norway (NO), Sweden (SE), Germany (DE) and the Nord Pool System price, hereafter simply referred to as "System price." Again, remember that during the time period of this analysis, Sweden represented only one price zone. All of the prices are measured in Danish crowns (DKK). Though the price series were originally hourly, I transformed the data into daily averages to reduce volatility.

To begin, we look at the evolution of spot market prices in DK1 and the System price. Figure 4 depicts the natural logarithm of daily prices from January 1st, 2003 until December 31st, 2009 for DK1 and System price. The green line indicates July 1st 2006, the date that the DONG-Elsam merger was completed and DONG Energy physically divested two power plants in DK1 to Vattenfall. We keep in mind that there is insufficient evidence to show that the System price is subject to price manipulation by market players. Consequently, it should be thought of as a competitive benchmark price.

Figure 4: Log DK1 and System Spot Market Prices from 1 January 2003 through 31 December 2009



It is readily apparent from Figure 4 that the DK1 price is more volatile than the System price. In 2003 and 2004, DK1 prices tend to be slightly higher than the System price. We can also very clearly see that during most of 2005, the spot prices in DK1 were considerably higher than the System price. Once again, recall that in their second and third investigations of Elsam, the DCA determined that Elsam abused their dominant market position in DK1 from summer 2003 through 2006. Several months before the merger, around when the VPP auction for 250 MW was introduced, the two prices appear to follow one another more closely and the System price even ends up being higher than DK1. This pattern continues up until summer 2007 when the DK1 price once again consistently lies above the System price until 2009. From this picture alone, it does not appear that the relationship between the DK1 and System prices changed significantly after the divestitures took place. In 2009 it appears that the prices again move much more closely to one another but the pattern does not look unlike it did in 2003 and 2004.

For a broader market overview of price behavior, Table 3 provides summary statistics for the daily spot prices for the Nord Pool areas taken from Energinet.dk. We again look at the time period from January 1st 2003 through December 31st 2009 but this time I have used raw prices in DKK for easier comparison. *N* stands for the number of observations in the sample, i.e. 2557 days.

Table 3: Summary Statistics for Selected Nord Pool Area Prices in DKK from 1 January 2003 until 31 December 2009, N=2557

	DK1	DK2	NO	SE	DE	SYSTEM
Average	283.52	291.01	259.08	276.94	307.81	267.30
Standard Deviation	98.78	105.66	94.84	96.67	128.32	90.34
Minimum	-0.76	62.39	15.4	60.14	-153.51	65.47
Maximum	838.07	851.15	851.15	851.15	737.84	851.15
Observations	2557	2557	2557	2557	2557	2557

Indeed we see that prices in DK1 over this time period were, on average, higher than the System price. The standard deviation for DK1 is also higher than the System price which indicates that the prices in DK1 are in fact more volatile. Interestingly, daily spot prices in DK2 are, on average, both higher and more volatile than DK1: this may be partially due to the fact that DK1 did not have direct transmission capacity with Norway which had lower average prices and lower volatility than even the System price. The average daily German price (DE) is much higher and more volatile than any of other prices but it is not part of the Nord Pool power exchange. Also note that the market with both the closest average price and volatility to DK1 is the Swedish power market.

Though this paper seeks to answer how VPP auctions affected competition in DK1, it was mentioned in earlier that the econometric models will analyze the price spread between DK1 and prices from a competitive benchmark. Figures 5a and 5b below are meant to provide an illustration of the reasoning behind examining a price spread instead of merely the prices in DK1.

Figure 5a: Evolution of Log Coal Price and Log DK1 Price from 1 January 2000 until 28 February 2014

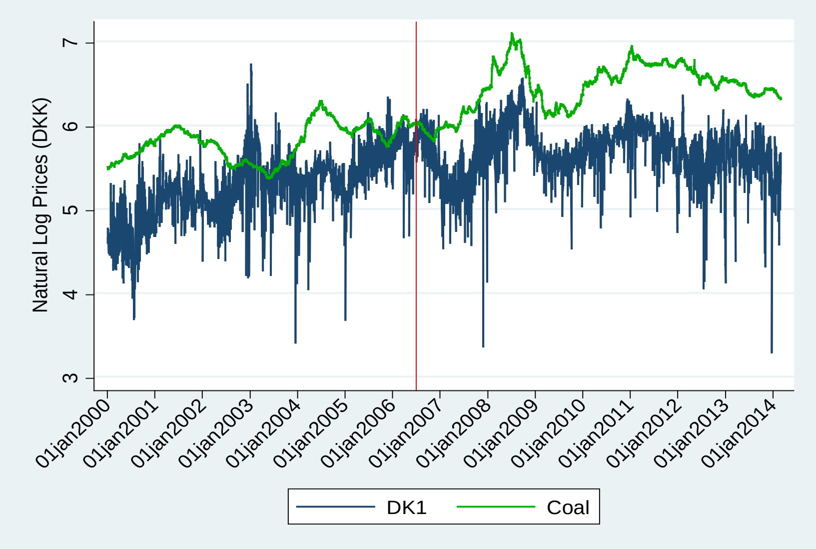
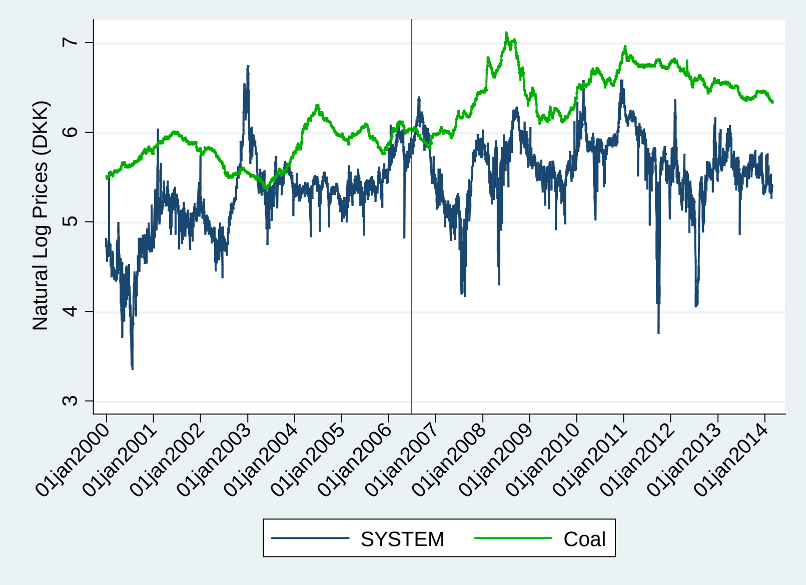


Figure 5b: Evolution of Log Coal Price and Log Nord Pool System Price from 1 January 2000 until 28 February 2014



If one were to only look at the relationship between DK1 and the price of coal in Figure 5a, it might be easy to conclude that there was a change in the relationship between the two price series directly after the DONG-Elsam merger, represented by the red line. Before the merger, the coal price and DK1 cross one another several times and appear to show a roughly inverse relationship. This relationship changes almost immediately after the DONG-Elsam merger took place: now the coal price remains steadily above the DK1 price and the two follow one another's movements far more closely.

As soon as one inspects Figure 5b, however, it becomes apparent that this same general pattern was present in the *entire Nordic market* and not unique to DK1. Thus, unless the DONG-Elsam merger affected Nord Pool in its entirety, the change in relationship between coal price and DK1 prices was not a result of the DONG-Elsam merger. Without comparing both the DK1 and System prices to coal, however, it might seem obvious that this was the case. Since we don't want our econometric models to mistakenly attribute changes in the relationship between DK1 and coal prices to the VPP auctions or physical divestitures we instead analyze the price spread between DK1, our market of interest, and a competitive benchmark to encompass market-wide trends.

In addition, inspecting the price spread also significantly reduces the need to account for certain control factors such as a sunlight and temperature: the entire Nordic region will experience the same seasonal weather patterns. When it is winter in Denmark it is also wintertime in Norway. Of course temperatures and daylight will vary from region to region but the daylight schedule in Denmark will be exactly the same from year to year and the same is true everywhere else in the Nordic market.

But which price spread is the best to use? We have already established that the System price can be thought of as a competitive benchmark but it is possible that some events can affect all of the individual Nord Pool price zones, competitive or not, without affecting the System Price. Table 4 provides summary statistics of the price spreads between the System price and DK1, DK2, NO, and SE. There are three time periods explored: the entire time window of the analysis, from January 1st, 2003 to June 30th, 2006 (pre-merger) and then from July 1st, 2006 until December 31st, 2009.

As we see from the table, the Swedish and Norwegian markets followed the system price quite closely throughout the entire time window. The average System price spreads in SE and No were also quite small during the pre-merger window in comparison to those in the rest of the zones. Thus, we see that these two price zones very closely follow the competitive market benchmark of the System price.

Table 4: Summary Statistics of Daily Price Spread between System Price and Select Nord Pool Price Zones (DKK)

From 1 January 2003 until 31 December 2009, N=2557					
	DK1	**DK2**	**NO**	**SE**	**DE**
Average price spread	16.22	23.71	-8.22	9.64	40.51
Standard Deviation	73.88	57.77	27.67	30.79	114.68
Minimum	-690.93	-249.31	-245.7	-113.19	-737.6
Maximum	312.69	324.1	88.71	234.83	356.38
Observations	2557	2557	2557	2557	2557
From 1 January 2003 until 30 June 2006, N=1277					
	DK1	**DK2**	**NO**	**SE**	**DE**
Average price spread	6.74	9.09	1.77	-2.05	19.82
Standard Deviation	69.23	38.60	9.89	13.42	116.31
Minimum	-690.93	-113.19	-106.76	-113.19	-737.6
Maximum	312.69	277.82	88.71	84.65	356.38
Observations	1277	1277	1277	1277	1277
From 1 July 2006 until 31 December 2009, N=1280					
	DK1	**DK2**	**NO**	**SE**	**DE**
Average price spread	25.67	38.29	-18.18	21.30	61.15
Standard Deviation	77.11	68.97	35.13	37.98	109.24
Minimum	-309.66	-249.31	-245.7	-67.16	-422.8
Maximum	290.35	324.1	80.39	234.83	329.33
Observations	1280	1280	1280	1280	1280

There was, however, a significant increase in volatility in all Nord Pool price zones sometime after July 2006. There are two possible explanations for this. The first is that in October 2007, Nord Pool introduced a new electronic trading platform called SESAM that allowed market participants to more easily submit bids and offers. It is possible that this may have led to higher price volatilities since market participants could now more easily adjust their bids. The second is the global financial crisis that hit world markets in 2008. Regardless of the reason, something appears to have sent a volatility shock throughout the entire market that affected competitive markets and DK1 alike.

Table 5 presents the differences between the DK1-System price spread and System price spreads in the other Nord Pool price areas. One can see that the relationship between DK1 and SE was nearly unchanged even after the increased market-wide volatility. In other words, whatever event triggered higher price volatilities throughout the Nordic power market, affected the DK1 and SE price zones in almost the same exact way. For this fact, and because the Swedish price zone appeared to very closely follow the System price in table 4, I choose to use the DK1-SE price spread as my dependent variable in the econometric analysis instead of the DK1-System price.

Table 5: Absolute values of Average Price Spreads between DK1 and Select Nord Pool Price Zones

	DK2	NO	SE	DE
1 Jan 2003 until 30 Jun 2006	2.35	4.97	8.79	13.08
1 Jul 2006 until 31 Dec 2009	12.62	43.85	4.37	35.48
Δ Spread	10.27	38.88	4.42	22.4

For readers interested in a visual comparison of the two price spreads, figure B1 in Appendix B shows the DK1-SE price spread from January 1st, 2003 up until December 31st, 2009 and figure B2 shows the DK1-System price spread through the same time period. Again, the red line represents the completion date of the DONG-Elsam merger. Notice that two spreads are nearly identical up until around July 2007 when the DK1-System price spread becomes slightly higher on average while the DK1-Swedish spread appears to maintain a more stable relationship.

6.1.2 Control Variables

Electricity prices are determined by a number of seasonal, weather-based and economic factors. In order to isolate the effect of the virtual and physical divestitures in DK1, the econometric model used for the analysis includes data from these factors. First, since the Nordic electric market is dominated by hydropower, I have collected daily precipitation data from the Norwegian Meteorological institute. We would expect heavy rainfall in Norway to be highly correlated with heavy rainfall in Sweden. At the same time, DK1 has interconnections directly to Norway as well so the effect of higher rainfall on the DK1-SE spread is not immediately obvious. In any event, by including precipitation data, the model will capture an effect if there is any.

It will be important to control for wind power production in DK1 as well since it directly affects prices in DK1. Wind is a near-zero marginal cost production technology so one would expect increased wind production in DK1 to decrease prices in DK1 and thereby reduce the spread. In addition, Sweden is not endowed with significant amounts of wind power so one might expect wind power production in DK1 to affect the price spread.

Thermal power plants in Denmark burn coal to produce electricity so I include the Hamburg Institute of International Economics (HWWI) European coal price in the regressions. For an indicator of aggregate economic demand, the model includes the OMX Copenhagen 20 Stock Index as well. Both of these are daily price series and were accessed on Thompson-Reuters DataStream.[3]

Table 6 shows the summary statistics for the four control variables used in the econometric analysis.

Table 6: Summary Statistics for Electricity Price Determinant Control Variables

	Norwegian Rainfall (mm)	**Wind Power Production in DK1 (MW)**	**OMX Copenhagen 20 Stock Index (DKK)**	**Hamburg WWI European Coal Price (DKK)**
From 1 January 2003 until 31 December 2009 **N=2557**				
Average	5.99	566.47	340.62	475.26
Standard Deviation	5.21	455.24	88.56	194.64
Minimum	0	3.2	169.04	216.04
Maximum	42.04	2136	517.67	1229.72
From 1 January 2003 until 30 June 2006 **N=1277**				
Average	5.64	536.47	292.51	365.40
Standard Deviation	5.03	428.71	64.72	84.01
Minimum	0	6.4	169.04	216.04
Maximum	42.04	2136	415.68	547.85
From 1 July 2006 until 31 December 2009 **N=1280**				
Average	6.35	596.20	388.62	584.86
Standard Deviation	5.36	478.57	82.92	211.15
Minimum	0	3.2	213.11	338.58
Maximum	31.78	2047.3	517.67	1229.72

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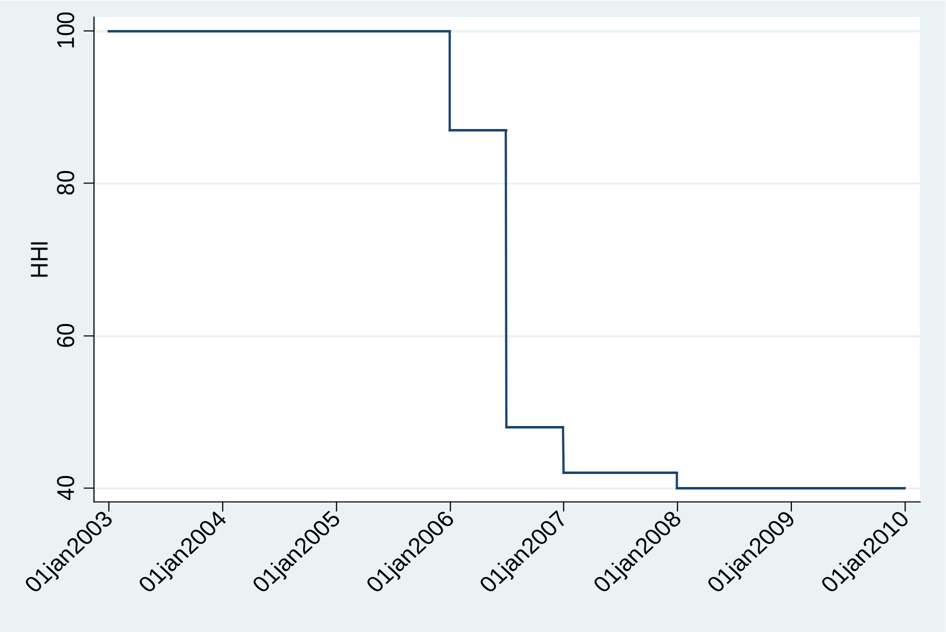
[3] Both HWWI coal prices and the OMX CPH20 Index do not have weekend values. To account for this, I simply averaged the Friday and Monday prices surrounding a given weekend and plugged them into Saturday and Sunday. While this method is not perfect

6.1.3 Structural Indicators

There are two similar ways in which the econometric models specified in this analysis attempt to capture the effect of the VPP auctions and physical divestitures in DK1. The first is to use the HHI as a control variable which is shown in figure 6a.

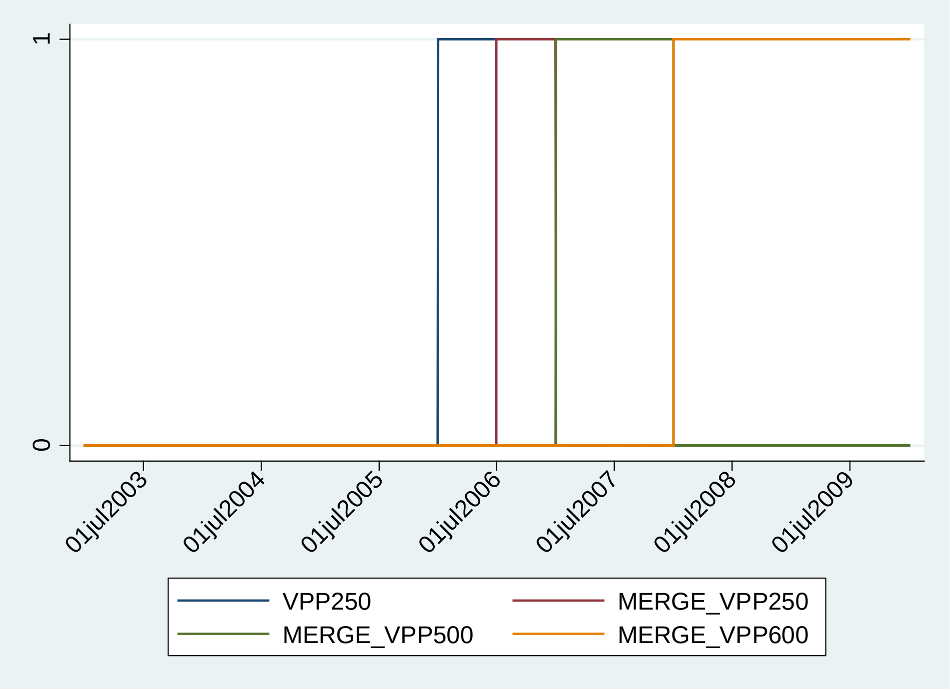
Figure 6a: The Herfindahl-Hirschman Index for Centralized Power Generation in DK1 from 1 January 2003 until 31 December 2009



The advantage of using the HHI to try to capture the effects of these divestitures is that it offers an actual numerical measure of market concentration. For example, the coefficient for HHI generated in a log-log regression (i.e. both the independent and dependent variables are measured in logarithms) could be read as “a 1% increase in the HHI leads to a 0.5% increase in the DK1-SE on average.” As we will see, however, the disadvantage of using the HHI to capture structural changes is that it varies extremely rarely: there are four changes in the HHI during the time period that this paper analyzes which is a very small amount of variation.

The second method used to measure structural changes in DK1 is to include dummy variables to indicate when the virtual and physical divestitures were implemented in DK1. This includes the introduction of the 250 MW VPP auctions on January 1, 2006, the merger of Elsam and DONG Energy on July 1st 2006 that included large physical divestitures to Vattenfall, and the two incremental increases in virtual capacity that took place in 2007 and 2008 and pushed the total VPP capacity to 500 and 600MW respectively. Recall that dummy variables are binary variables that take on a value of 0 or 1 and are used to simply check if data behaves differently due to certain characteristics, events or time periods. For instance, the MERGE_VPP500 dummy is equal to 1 if the date is any time during 2007 and 0 otherwise. It will thus capture all of 2007 when both the physical divestitures and 500 MW worth of VPPs had been implemented in DK1. Figure 6b illustrates the four structural dummy variables used in the regressions. They are named to clearly identify which structural changes "state of the universe" they capture.

Figure 6b: The Herfindahl-Hirschman Index for Centralized Power Generation in DK1 from 1 January 2003 until 31 December 2009



If the coefficient for the MERGE_VPP500 variable in a log-log regression is -0.10 then it could be read as "during 2007, the DK1-SE price spread was 0.10% lower than compared to other years." If the virtual and physical divestitures had a lasting effect procompetitive effect in DK1 that increased over time then the dummy variables would grow more negative over time. For example, if the coefficient for VPP250 was 0.00, the coefficient for MERGE was -0.01, the coefficient for MERGE_VPP500 was -0.10 and the coefficient for MERGE_VPP600 was -0.10 then this would provide evidence that the DK1-SE price gap closed beginning after the physical divestitures took place and then increased again during 2007 when the VPP capacity was increased to 500 MW: Since there was no change between MERGE_VPP500 and MERGE_600 then this would suggest that the extra 100 MW of virtual capacity did not add any additional competitive effects.

6.2 Stationarity and Unit Root Tests

In order to use hypothesis testing on coefficients that are generated in a time-series econometric analysis, the data used in the model must be *stationary*, i.e. it must possess the same basic statistical properties such as mean, variance and autocovariance across time. If a data series is non-stationary, then a regression may produce standard errors that lead to invalid statistical inference. This in turn may cause researchers to declare that a relationship does (or doesn't) exist between variables when the opposite is true. This type of false relationship between variables of interest is known as a *spurious regression*. Clearly, researchers wish to prevent spurious regressions as it obfuscates the true nature of an economic relationship. One must therefore test time-series data for stationarity, and if necessary, transform it so that it becomes stationary before running any regressions.

The Dickey-Fuller unit root test is a common stationary test. In simple terms, this test shows to what extent a time-series data set is affected by past values of itself. If one were to imagine a time-series variable that could be described with a simple Auto regressive (1) process , $y_t = \alpha + \beta^* y_{t-1} + e_t$, this variable would be said to have a *unit root* if β were equal to 1. In such a scenario, past values of y will affect future values of y ad infinitum: even $y_{t-10,000}$ would have a measurable effect on y_t and the variable would be said to exhibit a random walk. The presence of a unit root thus makes a time-series data set non-stationary. The Dickey-Fuller test uses hypothesis testing to test data for a unit root by adopting the null hypothesis that $\beta\text{-}1 = 0$. If the test statistic generated in by the Dickey-Fuller test does not fall outside of the critical value range, then one cannot reject the null hypothesis that a unit root is present. Consequently, if the data fails the Dickey-Fuller test, then they must be transformed so that they become stationary.

The Augmented Dickey-Fuller (ADF) test works exactly like the normal Dickey-Fuller test yet it takes into account more potentially complicated dynamics of the dataset being tested by adding more autoregressive terms (see Stock & Watson 2007 for a more technical explanation of the ADF test). The Generalized Least Squares Dickey-Fuller (GLS-DF) test offers even more power than the regular augmented Dickey Fuller test. This means that the DF-GLS test it is more likely to reject the null hypothesis against the stationarty alternative when the alternative is true: better at distinguishing between an actual unit root and a root that is large but less than 1 (Stock & Watson 2007).

In Table C1 in Appendix C lie the results of both the DF-GLS and ADF tests for all of the variables used in the econometric models. The DF-GLS tests provide a maximum lag where one ought to test for a unit root that is based on the length of the data set. This maximum lag is also used in the ADF test. While most of the variables reject the null hypothesis of a unit root, the CPH20 Index, coal price and HHI do not and must therefore be considered non-stationary.

In the event that data is non-stationary, there are two common methods for adjusting them so that they become stationary. The first is taking the logarithm of the data: this works in effect to minimize the effect of changing variance that the data might be experiencing over time. If one logarithmic variable is regressed upon another, the interpretation of coefficients is in percentages: a coefficient of 0.5 of ln(y) regressed on ln(x) signifies that a 1% increase in x leads to a 0.5% increase in y. The second method is called differencing: it involves analyzing the *changes* between data points in time as opposed to the actual data points themselves. Using differenced data leads to poorer model fit and higher standard errors but the advantage from having stationary data far outweighs these disadvantages. In most price time series data, first differencing is usually enough to achieve stationarity, i.e. the first difference of x_t $= d1.x = x_t - x_{t-1}$.

Another benefit of differencing data is that it reduces multicollinearity between the explanatory variables. When explanatory variables are correlated with one another, the regression may produce biased estimators since the movement in one variable will also cause the movement in another and the resulting coefficients will not represent the isolated causal effect of the explanatory variables on the dependent variable (Stock and Watson 2007).

Tables 7a and 7b show the correlations between the raw data and log-first differenced data.

Table 7a: Correlations Between Control Variables

	Coal price	CPH20	Precipitation	DK1 Wind Production	HHI
Coal price	1.00	-	-	-	-
CPH20	0.38	1.00	-	-	-
Precipitation	-0.04	-0.04	1.00	-	-
DK1 Wind Production	0.00	0.06	0.41	1.00	-
HHI	-0.59	-0.56	-0.06	-0.06	1.00

Table 7b: Correlations Between Log-differenced Control Variables

	Coal price	CPH20	Precipitation	DK1 Wind Production	HHI
Coal price	1.00	-	-	-	-
CPH20	-0.02	1.00	-	-	-
Precipitation	-0.01	0.01	1.00	-	-
DK1 Wind Production	-0.01	0.01	0.10	1.00	-
HHI	0.00	0.00	-0.02	0.04	1.00

One can see that there is considerable correlation between certain control variables when they are expressed in their normal, level forms. The economic and structural control variables CPH20, coal price and HHI are all highly correlated with one another and even the stationary weather-driven variables Wind Power Production and Precipitation are highly correlated with one another. As shown in Table 7b, these correlations all but disappear after they are transformed into log-differences.

6.3 Model Specification

The following two regressions specify the simple time series OLS models to be used in the analysis:

$$\mathrm{DK1SEspread}_t = \mu + \beta_1 \mathrm{WIND}_t + \beta_2 \mathrm{PRECIP}_t + \beta_3 \mathrm{COAL}_t + \beta_4 \mathrm{CPH20}_t + \beta_5 \mathrm{HHI}_t + \varepsilon_t$$

$$\begin{aligned}\mathrm{DK1SEspread}_t & \\ &= \mu + \beta_1 \mathrm{WIND}_t + \beta_2 \mathrm{PRECIP}_t + \beta_3 \mathrm{COAL}_t + \beta_4 \mathrm{CPH20}_t \\ &+ \sum_{n=1}^{4} \beta_n \mathrm{Structural\ Dummy}_n + \varepsilon_t\end{aligned}$$

where μ is a constant, β is a parameter and ε_t is the error term at time t.

In time series econometrics, it is common for past values of a data generating process to contain some predicative power about today's value. For instance, if the price of electricity is 250 DKK on Tuesday, then it is highly likely that the price on Wednesday will be similar. To account for this fact, this analysis uses autoregressive (AR) and moving average (MA) terms in the model specifications to capture these dynamics.

Below is an example of a general AR(p) process where p is the number of AR terms:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t$$

Below is an example of a general MA(q) process where q is the number of MA terms:

$$y_t = \mu + \sum_{i=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

Combined, these terms form an ARMA(p,q) process:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

To determine how many AR or MA terms once should account for in the econometric model, I follow the traditional Box-Jenkins approach and look at shape of the autocorrelation (AC) and partial autocorrelation (PAC) functions for the DK1-SE price spread returns. The AC function describes the relationship between the price spread and its own past values. It thus allows us to see how today's price spread return is related to yesterday's (lag 1), the day before that (lag 2), and so on. The PAC function, in turn, also describes the relationship between today's price spread return and its past values but eliminates any effects that arise from intermediate lags. For example, if we were looking at the third lag of a variable of interest, the AC function would give us a relationship between the variable at time t and time t-3 but this relationship would include information from times t-1 and t-2 as well. The PAC function would exclude the information from these intermediate lags when describing the relationship between the variable at times t and t-3. See Brooks (2008) for a more in-depth discussion of the mechanics behind the AC and PAC functions.

Generally speaking, when the AC function decays slowly over time and the PAC function shows several statistically significant lags followed suddenly by insignificant lags, this indicates that the data follows an AR process (Brooks 2008). The number of significant lags in the PAC function determines the AR order (i.e. 3 significant lags indicates an AR(3) process). The opposite is true with MA processes: they will have a PAC that decays slowly over time and an AC with several significant lags that suddenly become insignificant at a certain lag.

Figures 7a and 7b show the AC and PAC functions for the DK1-SE price spread returns. We notice immediately that these two functions do possess some patterns but they do not allow for easy identification of the underlying relationship.

Figure 7a: The Partial Autocorrelation Function for the DK-SE Price Spread Returns

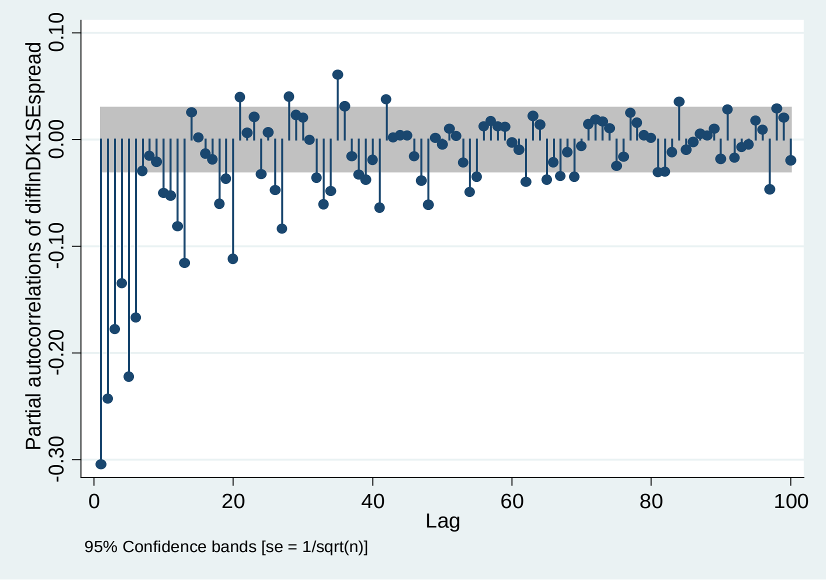
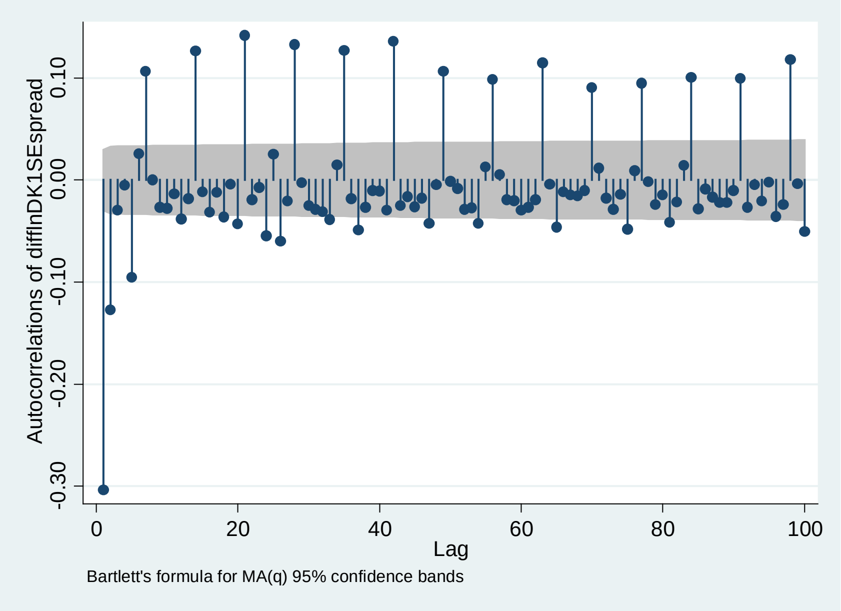


Figure 7b: The Autocorrelation Function for the DK-SE Price Spread Returns



In the PAC diagram, there appears to be exponential decay of the lags with a damped sinusoidal shape which is indicative of a moving average process. The first six lags are negative and highly significant but then suddenly jump nearly to zero at lag number seven. After that, every sixth lag represents another sharp drop downwards and every seventh lag bounces back to being positive. At approximately lag 40, there is a drop-off in positively significant lags and the negative lags drop out at around lag 70. Since the first partial autocorrelations are negative, it appears that the DK1-SE spread may have be over-differenced when transformed into returns: adding MA terms should partially correct for this fact.

The AC diagram is a bit more puzzling. Lags one, two and four are highly statistically significant and negative though the third lag drops nearly to zero. Afterwards, almost all of the lags are negative and statistically insignificant except for every 7th lag which are all positive and statistically significant.

Though it is impossible to say exactly what type of ARMA process best describes the data from these functions, there seems to be two potential types of structural components:

1) Due to the decaying PAC function and highly significant first, second and fourth lags in the AC function, it is highly likely that the DK1-SE price spread returns follow a moving average process with 2 or possibly 4 MA terms.
2) There is very clearly a weekly AR term present. This makes intuitive economic sense since we would expect electricity prices this Saturday to be correlated with prices next Saturday, prices this Sunday to be correlated with prices next Sunday, and so on.

Since the AC and PAC diagrams for the DK1-SE price spread unfortunately do not provide a very clear picture of the spread's underlying dynamics, I rely on *information criteria* to help further guide my model identification. Information criteria are "goodness-of-fit" measurements that provide the researcher with some statistical evidence of how well the specified model accounts for movements in the data. The most commonly used goodness-of-fit measurement is the R-squared which is defined as:

$$\text{R-squared} = 1 - \frac{\text{Squared Sum of Residuals}}{\text{Total Sum of Squares}}$$

In simple terms, the R-squared compares how far away the residuals lie from the regression line to how far away they lie from the simple average value of the data. The better the regression line “fits” the data, the smaller the Squared Sum of Residuals will be and the higher the R-squared value will be ceteris paribus.

Like the R-squared, information criteria identify the model with the smallest residual sum of squares compared to the total sum of squares but also encourage model parsimony by including a punishment for adding too many extra explanatory variables (Brooks 2008). The two most widely used information criteria are the Akaike Information Criterion (AIC) and Schwarz’s Bayesian Information Criterion (BIC). They are calculated as follows:

$$\text{AIC} = \ln(\hat{\sigma}_t^2) + \frac{2k}{T}$$

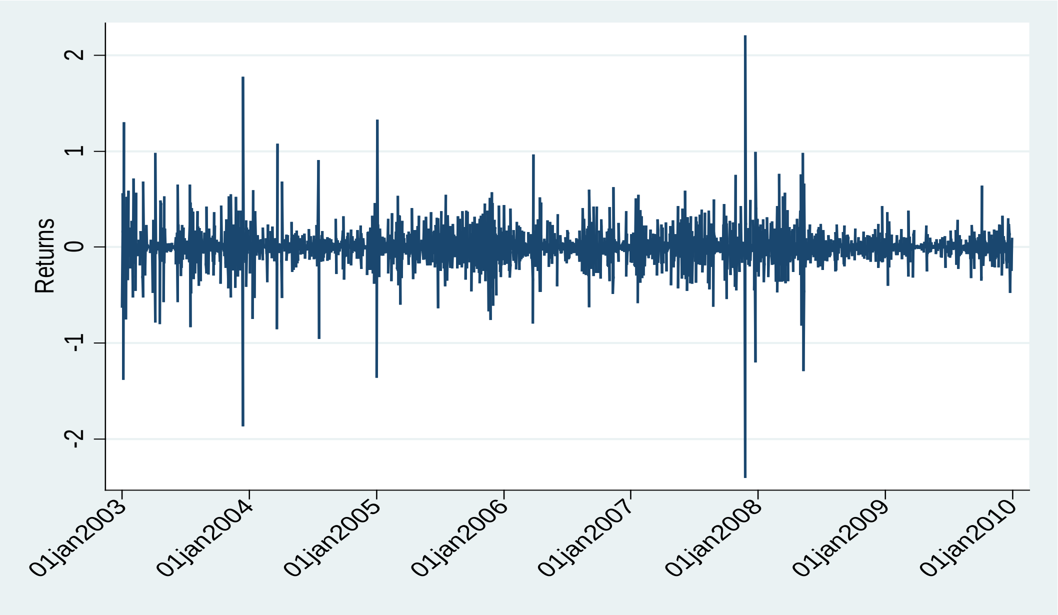
$$\text{BIC} = \ln(\hat{\sigma}_t^2) + \frac{k}{T}\ln(T)$$

where $\hat{\sigma}_t^2$ is the variance of the residuals, T is the sample size and k is the total number of parameters estimated. Since the penalty from adding extra variables increases the values of the information criteria, the smallest AIC/BIC values indicate the best fitting models. The BIC more heavily penalizes adding additional variables and is considered to be a more conservative information criterion. I will therefore place more emphasis on the BIC when identifying the “best” model specification.

6.3.1 Volatility Clustering

Electricity price returns exhibit a property common to assets traded in financial markets called “volatility clustering.” This means that high returns of electricity prices yesterday are more likely to predict high returns today and low returns yesterday are more likely to predict low returns today (Brooks 2008). In statistical terms, this means that the error terms exhibit heteroskedasticity, i.e. variance that is not constant over time, and can cause problems when estimating standard errors (Stock and Watson 2007). Figure 8 shows the volatility of the DK1-SE spread from 1 January 2003 until 31 December 2009.

Figure 8: Log DK1-SE Price Spread Returns from 1 January 2003 until 31 December 2009



Notice how the periods of very high returns are clumped together and likewise with the low returns. The DK1-SE price spread very clearly demonstrates volatility clustering and our simple OLS regressions and ARMA models will most likely not capture the dynamics that result from this.

Fortunately, there exist several models that are capable of describing the dynamics that arise from volatility clustering. Autoregressive conditional heteroskedasticity (ARCH) models and the closely related generalized autoregressive conditional heteroskedasticity (GARCH) models make the explicit assumption that the variance of errors in a data series is *not* constant over time. More specifically, these models parameterize past components of the variance in order to measure the effect that they have on the current value of variance. The ARCH model does this by specifying the following relationship:

$$y_t = \mu + \beta_i X_{it} + \varepsilon_t$$

$$\varepsilon_t = z_t * \sqrt{\sigma_t^2}$$

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2$$

Where X_{it} is control variable *i* at time *t*, $\sigma_t^2$is the conditional variance at time *t*, ω is a constant term, z_t is a parameter, $u_{t-1}^2$is the first lag of the squared residual, and $\alpha_1$measures the relationship between σ_t^2 and u_{t-1}^2. This equation is an example of an ARCH(1) model as there is one lagged term of the squared residuals in the model specification. One could extend this model to an ARCH(n) model by having n total lags.

In practice, however, ARCH models are very rarely used since, among other disadvantages, it can be nearly impossible to know how many ARCH terms should be included (Brooks 2008). To address these problems, one may use a GARCH model, a very popular extension of the ARCH model. The GARCH(1,1) is composed of the following three equations:

$$y_t = \mu + \beta_i X_i + \varepsilon_t$$

$$\varepsilon_t = z_t * \sqrt{\sigma_t^2}$$

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2$$

where σ_{t-1}^2 is the first lag of the variance and γ_1 is a parameter that describes the relationship between σ_t^2 and σ_{t-1}^2.

Again, the ARCH and GARCH model specifications are simply trying to take into account the fact that the past values of volatility (read variances) have some predictive power about volatility today by estimating a linear mathematical relationship between these compoenents.

Putting together the control variables, ARMA terms and GARCH(1,1) specification yields the full model used in the final round of regression in the analysis:

$$y_t = \mu + \beta_1 \mathrm{WIND}_t + \beta_2 \mathrm{PRECIP}_t + \beta_3 \mathrm{COAL}_t + \beta_4 \mathrm{CPH20}_t + \beta_5 \mathrm{HHI}_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t = z_t * \sqrt{\sigma_t^2}$$

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2$$

6.4 Diagnostics and Robustness Checks

Engle's LM Test for ARCH effects

Though it is well-established that electricity prices exhibit volatility clustering (see Liu 2013) and it is clearly evident in Figure _ that this is the case with the DK1-SE price spread returns, to be thorough, I employ Engle's Lagrange Multiplier (LM) test to test for ARCH effects in my OLS models. This test was developed in Engle (1982) and assesses if the variance of residuals from the OLS regressions are constant over time. If the test statistic is statistically significant then we reject the null hypothesis of "no ARCH effects" and will then want to use ARCH or GARCH model specifications to account for these effects. I include the results of these tests with my OLS regressions in the "Results" section. As the reader can probably already surmise, the results of the LM test for the OLS regressions reject the null hypothesis of "no ARCH effects" and act as further justification to specify ARCH and GARCH models for the DK1-SE price spread returns.

Residual Analysis

In a final step, I wish to test that my model adequately fits the data. To do this, I test to see that the model residuals are stationary using an ADF test with low and high-order lags. I also inspect the residual means to see if they are close to zero. I have included the results of these tests are included at the end of the final round of regressions, i.e. the ARMA-GARCH(1,1) models since these models use the most complicated specifications. I have also included the AC and PAC functions for the best fitting ARMA-GARCH(1,1) model for those readers who are well-versed in forecasting and control model design.

7. Results and Analysis

Table 8 below shows the results from the time series OLS model specifications.

Table 8. Time series OLS Regressions Results on DK1-SE Price Spread Returns from Jan 1 2003 until December 31, 2009

Independent Variable	Model Specification					
	1	2	3	4	5	6
Constant	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.006)	0.001 (0.006)	0.002 (0.006)
Wind Production DK1	-0.055*** (0.004)	-0.055*** (0.004)	-0.057*** (.004	-0.055*** (0.004)	-0.055*** (0.004)	-0.056*** (0.004)
Norwegian Precipitation	-0.008*** (0.003)	-0.008*** (0.003)	-0.007** (.003)	-0.008*** (0.003)	-0.008*** (0.003)	-0.007** (0.003)
Lag 1 precipitation			0.003 (0.003)			0.003 (0.003)
Coal Price		0.106 (0.245)	-0.056 (0.239)		0.104 (0.243)	-0.056 (0.239)
Lag 1 Coal			-0.577** (.232)			-0.578** (.223)
Lag 2 Coal			0.800*** (.279)			0.800*** (.277)
CPH20		0.381 (0.222)	0.336 (0.226)		0.280 (0.223)	0.335 (0.226)
Lag 1 CPH20			-0.241 (0.210)			-0.245 (0.210)
Lag 2 CPH20			0.057 (0.342)			0.055 (0.343)
HHI	0.565 (0.609)	0.563 (0.609)	0.575 (0.604)			
VPP250				-0.002 (0.014)	-0.001 (0.014)	-0.001 (0.014)
MERGER & VPP250				-0.002 (0.013)	-0.002 (0.013)	-0.002 (0.013)
MERGER & VPP500				0.001 (0.015)	0.001 (0.015)	-0.002 (0.015)
MERGER & VPP600				-0.002 (0.008)	-0.001 (0.008)	-0.002 (0.008)
AIC	-1110.27	-1106.97	-1079.481	-1104.01	-1100.69	-1073.17
BIC	-1087.08	-1072.187	-1015.90	-1063.43	-1048.52	-992.25
Observations	2433	2433	2392	2433	2433	2392
Log Likelihood	559.14	559.48	550.7403	559.00	559.35	550.58
R-squared	0.077	0.077	0.082	0.076	0.077	0.082
ARCH-LM (lag 1)	552.53***	552.98***	544.194***	552.14***	552.59***	544.36***
ARCH-LM (lag 7)	724.42***	725.09***	712.685***	723.58***	724.27***	713.10 ***

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level
Standard Errors in parenthesis

Recall that when a coefficient is said to be “statistically significant” that the relationship that the coefficient measures between the independent and dependent variable is unlikely to have been caused by chance. The higher the “level,” the more likely that the coefficient represents a true causal link between the two variables, i.e. statistical significance at the 1% level is a stronger result that statistical significance at the 5% level. Statistical significance at the 10% level is not typically considered to indicate strong evidence of a causal link but if a coefficient is significant at the 10% level then this might be a clue that there are underlying causal dynamics between the independent variable that generated the coefficient and the dependent variable.

From the OLS regression results presented in table 8, there seem to be several very persistent trends across all of the model specifications. The coefficient for wind power production in DK1 is both negative and statistically significant at the 1% level in each regression which indicates that it is extremely likely that increased wind power production decreased the price spread between DK1 and the Swedish power market. This result is intuitively satisfying: since the marginal cost of wind power production is nearly zero, we would expect an increase in wind production to put downward pressure on prices in DK1. This downward pressure would in turn close the gap between prices in DK1 and a more competitive market like Sweden. In addition, there is almost no variation for the wind power coefficients across specifications: in models 1, 2, 4 and 5 our coefficient for wind power indicates that for a 1% increase in wind power production, the DK1-SE spread decreased and average of 0.055%.

There is a similar pattern with the coefficients for Norwegian precipitation: the coefficients are nearly identical across all model specifications. In models 1, 2, 4 and 5, the coefficient is statistically significant at the 1% level and says that “a 1% increase in precipitation in Norway led to a 0.008% decrease in the DK1-SE spread on average.” Again, this result makes economic sense since more precipitation in Norway will lead to larger hydropower reserves. Like wind power, the marginal cost of hydro production is nearly zero so higher rainfall will lead to more low-cost hydro production coming from Norway. Since Sweden also has a large share of hydropower production and high precipitation in Norway will almost certainly be correlated with higher precipitation in Sweden, the DK1-SE spread is affected only very slightly by higher rainfall. Nevertheless, the effect is highly statistically significant.

In models 3 and 6, the coefficient for the 1st lag of Norwegian precipitation is not statistically significant which indicates that increased precipitation appears to affect market prices quickly. This result does not rule out that there are possible lagged effects of heavy snowfall that occur long after the snow has fallen but these models do not account for such analysis. Also note that the coefficients for precipitation drop in magnitude slightly in models 3 and 6 but the general result remains the same.

The coefficients for the CPH20 Stock index are positive but statistically insignificant in every model specification and the same is true of their lags. Though it is impossible to say for sure why this is the case, this result may arise because the Scandinavian countries are close trading partners and share similar macroeconomic trends. Stock index decreases in Denmark that lead to lower industrial demand could very well be highly likely to affect Sweden similarly. Whatever the reason may be, movement in the Danish market does not appear to affect the electricity price spread between Denmark and Sweden. The coefficient for coal price is statistically insignificant but the first and second lags are significant at the 5% and 1% levels respectively. The coefficient for the first lag of coal is negative whereas the coefficient for the second lag is positive and larger than the first. It is hard to interpret exactly what is going on here but the significant coefficients indicate that coal prices may affect the DK1-SE spread over several time periods.

Now it is time to discuss the structural variables. Models 1, 2 and 3 included the Herfindahl index to act as the structural indicator. In each model the coefficient for the HHI is positive and quite large compared to the other variables but highly statistically insignificant. In other words, these time series OLS models provide no evidence to suggest that the VPP auctions or physical divestitures have had any impact on the price spread between DK1 and the Swedish wholesale power market. Models 4, 5 and 6 instead used the structural dummy variables to indicate the time periods in which the VPP auctions and physical divestitures occurred. Every coefficient for each dummy in these models is close to zero and statistically insignificant which indicates that, taking into account the weather and economic control variables, these models offer no evidence to suggest that the DK1-SE price spread was impacted by the virtual and physical divestitures in DK1.

After running Engle’s ARCH LM test, we see that each of these models appears to contain ARCH effects in the residuals: in each of the models, the tests reject the null hypothesis of “no ARCH effects” at the 1% significance level. After inspecting the price spread return data in the Methodology section, this was the anticipated this result.

In response to this, I run six models with ARCH, GARCH and ARCH-in-mean terms to assess which terms best capture the behavior of my data. For both the HHI and structural dummy variables, I run an ARCH(1), GARCH(1,1) and GARCH(1,1)-in mean model that include the weather and economic control variables. The results from these regressions are in Table E1 in Appendix E. All the coefficients for the control variables and structural indicators are almost exactly the same as in the time series OLS regressions. These models still provide no evidence that the VPP auctions played a role in closing the DK1-SE price spread.

There are a few notable results worth mentioning from these regressions. The first is that, while still highly statistically significant and robust across model specifications, the coefficient for DK1 power production dropped in magnitude to -0.038. The second is that the coal coefficient in the GARCH (1,1) model using the dummy variables was statistically significant at the 10% level. Neither of these is extraordinary: the ARCH/GARCH models, like the OLS models, still show strong evidence that the DK1-SE spread decreases when wind production increases and that coal prices appeared to increase the spread though the dynamics were not straightforward. In addition, while the coefficient for HHI was still highly insignificant in models 1 through 3 in Table E1, it dropped extremely close to zero (-0.001 in model 6).

More importantly, the AIC and BIC values for each of these models dropped significantly in value when compared to the time series OLS regressions. This indicates that these ARCH and GARCH models explain the movement in the data far better than the simple time series OLS regressions. When using both HHI and the structural dummies to measure the effects of the divestitures, the BIC value was lowest with the GARCH(1,1) specification despite the fact that the GARCH term was not statistically significant. In addition, the BIC values for all of the regressions using the structural dummies were lower than those using the HHI. This indicates that the dummy variables “fit” the model specification better and might provide a clearer picture of the data than the HHI. Of all of the models, the GARCH(1,1) using the structural dummies was the lowest, with a value of -1840.97.

Having found that the GARCH(1,1) seems to fit the data best, a new series of regressions is run, this time using the ARCH(1) and GARCH(1) terms to see if there are any changes in the coefficients of the control variables. These results are presented in Table 9.

Table 9. GARCH/ARCH Regressions from Jan 1 2003 until December 31, 2009

Independent Variable	Model Specification					
	1	2	3	4	5	6
Constant	0.006 (0.006)	0.006 (0.006)	0.006 (0.006)	0.002 (0.010)	0.002 (0.010)	0.002 (0.010)
Wind Production DK1	-0.038*** (0.007)	-0.038*** (0.008)	-0.038*** (0.008)	-0.037*** (0.004)	-0.037*** (0.007)	-0.037*** (0.007)
Norwegian Precipitation	-0.008* (0.005)	-0.008* (0.005)	-0.008* (0.005)	-0.007** (0.003)	-0.007** (0.003)	-0.007** (0.003)
Coal Price		0.670 (0.536)	0.657 (0.529)		0.569* (0.245)	0.555* (0.335)
Lag 1 Coal		-0.521** (0.208)	-0.515** (0.190)		-0.562*** (0.212)	-0.555*** (0.210)
Lag 2 Coal		0.237 (0.232)	0.247 (0.195)		0.258 (0.202)	0.268 (0.201)
CPH20		0.180 (0.182)			0.221 (0.172)	
HHI	0.040 (0.609)	0.033 (0.441)	0.035 (0.442)			
VPP250				-0.005 (0.012)	-0.004 (0.011)	-0.004 (0.011)
MERGER & VPP250				-0.008 (0.012)	-0.008 (0.012)	-0.008 (0.012)
MERGER & VPP500				0.041 (0.027)	0.040 (0.025)	0.041 (0.026)
MERGER & VPP600				-0.002 (0.010)	-0.000 (0.010)	-0.002 (0.010)
ARCH	0.792*** (0.298)	0.858** (0.358)	0.855*** (0.354)	0.940** (0.399)	0.974** (0.387)	0.972** (0.387)
GARCH	0.058 (0.055)	0.058 (0.053)	0.058 (0.053)	0.058 (0.045)	0.060 (0.044)	0.060 (0.044)
OMEGA	0.015*** (0.003)	0.014*** (0.003)	0.014*** (0.003)	0.013*** (0.003)	0.013*** (0.003)	0.013*** (0.003)
AIC	-1875.741	-1883.98	-1885.30	-1906.04	-1914.889	-1915.77
BIC	-1835.163	-1820.214	-1827.33	-1848.071	-1833.732	-1840.41
Observations	2433	2433	2433	2433	2433	2433
Log Likelihood	944.87	952.99	948.5989	963.0201	971.4443	967.6578

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level
Standard Errors in parenthesis

Since they added little analytical value in the time series OLS regressions, none of these models include the lag terms for precipitation or the CPH20 index.

The results from this second round of GARCH (1,1) regressions are almost identical to the first round. Again, the BIC values are lower for the regression specifications that use the dummy variables. Interestingly, the coefficients for the first and second lags for coal price in models 5 and 6 cancel eachother out perfectly although the first lag is only significant at th 10% level and the second is significant at the 1% level. Once again, these models provide no evidence whatsoever that the virtual or physical divestitures had an impact on the DK1-SE price spread. The coefficients for the structural dummy variables are all close to zero and highly insignificant

In a final round of models, these GARCH(1,1) models are expanded to include the MA and seasonal AR terms suggested by the AC and PAC functions. Due to the size of the models, here I present only the coefficients for the control variables and the BIC in Table 10 below. I have included the full regression results with the MA, AR and ARCH/GARCH terms in Table E2 under Appendix E.

Table 10. ARMA-GARCH(1,1) Regressions from Jan 1 2003 until December 31, 2009

Independent Variable	Model Specification					
	1	2	3	4	5	6
Constant	-0.003 (0.003)	-0.003 (0.002)	-0.004 (0.002)	-0.004 (0.002)	0.000 (0.001)	-0.004 (0.002)
Wind Production DK1	-0.041*** (0.005)	-0.041*** (0.006)	-0.040*** (0.006)	-0.040*** (0.005)	-0.041*** (0.005)	-0.040*** (0.006)
Norwegian Precipitation	-0.010** (0.004)	-0.009** (0.004)	-0.009** (0.004)	-0.010** (0.004)	-0.010** (0.005)	-0.009** (0.004)
Coal Price	0.321 (0.276)	0.252 (0.280)	0.352 (0.305)	0.367 (0.201)	0.333 (0.331)	0.358 (0.201)
Coal lag 1	0.021 (0.228)	-0.148 (0.204)	-0.009 (0.216)	-0.008 (0.215)	0.036 (0.215)	-0.007 (0.215)
Coal lag 2	-0.067 (0.372)	-0.051 (0.298)	-0.111 (0.344)	-0.121 (0.355)	-0.127 (0.379)	-0.117 (0.358)
CPH20	-0.234 (0.225)					
HHI					0.431* (0.261)	
VPP250	0.002 (0.004)	0.002 (0.004)	0.003 (0.004)	0.003 (0.004)		0.003 (0.004)
MERGER & VPP250	0.005 (0.004)	0.004 (0.005)	0.005 (0.004)	0.005 (0.004)		0.005 (0.004)
MERGER & VPP500	0.007** (0.003)	0.010 (0.006)	0.008** (0.004)	0.008** (0.003)		0.008** (0.003)
MERGER & VPP600	0.005* (0.003)	0.004 (0.002)	0.005** (0.003)	0.005** (0.003)		0.005** (0.003)
BIC	-2385.88	-2387.50	-2388.93	-2388.97	-2390.84	-2396.60

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

Due to the fact that the previous GARCH (1,1) models with dummy variables have had lower BIC values, 5 of these models use the dummy variables. In these ARMA-GARCH(1,1) models, the BIC values dropped lower still to -2396.00 in model 6 in Table E indicating that these models provide more explanatory power than the simple GARCH(1,1) models.

The coefficients for wind power production in DK1 and precipitation look like they have in past models: negative and highly statistically significant. In these models, neither the price of coal nor its two lags are statistically significant in any model and, as expected, the coefficient for CPH20 is insignificant when included in model 1. The first four MA terms and AR terms at lag 7, lag 14, lag 42 and lag 70 are all highly statistically significant at the 5% level or higher.

Surprisingly, the MERGE_VPP500 and MERGE_VPP600 dummies are both statistically significant at the 5% level and positive. They are, however, extremely close to zero: the spread was, on average, about 0.008% wider during 2007 than for the other time periods and 0.005% during 2008. Given the fact that the DK1-SE spread increased slightly from increased volatility alone around 2007, it is unlikely that the positive coefficients can be attributed to the VPP auctions and physical divestitures *decreasing* competition in DK1. It certainly does not, however, add any weight to the hypothesis that the virtual and physical divestitures increased competition in DK1. In the 5th model in Table 10, the coefficient for HHI is positive which would indicate that higher concentration leads to a higher gap in prices and vice versa. It is, however, just barely statistically significant at the 10% level which, again, does not provide strong evidence that the divestitures have improved competition in DK1.

The residuals for all of the models in Table E are stationary at both low and high order lags indicating that there is no severe model mispecification. Appendix F shows the AC and PAC functions for model 6 in Table E. Though there is some autocorrelation among the residuals, it is not present in the first or second lags. Furthermore, in Figure F3 which shows the AC diagram out to 650 lags, we see that there appears to be some light seasonality but that vast majority of lags are insiginificant and resemble white noise.

8. Conclusions

This paper seeks to shed light on what impact, if any, Virtual Power Plant auctions have had on competition in the Western Danish spot market for wholesale electricity (DK1). The Danish Competition Authority (DCA) implemented VPP auctions in combination with physical divestitures in an attempt to reduce market power in DK1 and offset anticompetitive effects that could result from the July 2006 merger between the Danish energy companies DONG and Elsam. Though VPP auctions have become quite common in European electricity markets in recent years, there have been few empirical studies that seek to directly measure any procompetitive effects they may provide in electricity markets. The analysis performed in this paper does exactly that.

Using a variety of time series model specifications that control for both weather-based and economic factors that shift the supply and demand for electricity in DK1, the results presented in this paper presents no evidence that the VPP auctions led to a decrease in the DK1-SE price spread, even when combined with the large physical divestitures that occurred contemporaneously. In other words, the introduction of VPP auctions in DK1 does not appear to have coincided with a reduction in market power in the DK1. As the models are progressively expanded from Ordinary Least Squares to include ARCH, GARCH and ARMA terms, there is even evidence to suggest that the DK1-SE spread increased very slightly sometime after 2007, despite the fact that increasingly more virtual capacity was being auctioned off to competitors during this time. This is more likely due to system-wide volatility that occurred several years after the merger, due either to a new a new trading system that Nord Pool introduced into the market or the global financial crisis of 2008.

These results reaffirm earlier statements made by the DCA in 2007 that neither the VPP auctions nor physical divestitures appeared to have improved competitive conditions in DK1. Whereas the DCA carried out their analysis of competition in DK1 using confidential cost data, the methods used in this paper instead compare the relationship between spot prices DK1 and spot prices in Swedish market which closely follow the competitive Nord Pool System price but also take into account increased volatility that appears to have occurred in all market price areas in mid-2007. Since the results generated from this analysis were similar to those of the DCA, perhaps these methods offer a way for researchers to independently assess the impact of VPP auctions (and physical divestitures) without confidential information. The autocorrelation function of the “best” ARMA-GARCH(1,1) model did show some autocorrelation in the residuals but aside from some weak seasonality, the autocorrelation between the residuals appears to die out relatively quickly. The author makes no claims of having developed perfect models but, with a few exceptions, the results from the more complicated regressions are quite consistent with those in the simple time series OLS regressions.

Whether or not VPP auctions in DK1 have been “successful” depend on how one frames the issue: if the DCA hoped that the VPP auctions would actually *reduce* market power in DK1 then it appears they may have been disappointed. If, however, the DCA only wished to maintain the status quo and prevent any anticompetitive effects from the merger then it is possible that the VPP auctions, combined with the physical divestitures contributed to this. At the same time, Elsam already held a monopoly share of flexible centralized power generation prior to the merger so it stands to reason that DK1 couldn’t really have gotten significantly much less competitive than it already was prior to the merger.

There are several possible reasons to why these divestitures have been ineffective in promoting competition in DK1. The first is that DK1 was a competitive market in the first place and there was no problem to fix. Given the fact that the DCA produced no less than three extremely thorough and well-executed investigations with confidential cost data included, this seems highly unlikely. A far more likely reason is that even when DK1 was transformed from a de facto monopoly into what was effectively a triopoloy with DONG Energy, Vattenfall and the fringe VPP holders, this was not substantial enough to make DK1 competitive: an HHI value above 4000 is still considered by competition authorities to be highly concentrated (US Dept. of Justice 2010). Furthermore, since Vattenfall had previously owned a large stake in Elsam, they knew their “new” opponent, DONG Energy, quite well and vice versa. Yet another reason is that the VPP auctions could have been mechanistically inferior to the physical divestitures as Schultz (2009) suggests.

Because this analysis examined the VPP experience in only one market it would be unwise to make broad statements about VPP auctions based on these results alone. The most general implication that arises from these results is that even when combined with large physical divestitures, VPP auctions at their current size are not guaranteed to mitigate market power in electricity spot markets. The “current size” comment is relevant here because at 17% of central power production capacity, the VPP auctions in DK1 were actually rather sizeable in percentage terms compared to most other VPP auctions that have been implemented.

But if VPP auctions in DK1 don’t appear to have improved competition then why do they continue to take place? It could be because the VPP contracts provide some of the other procompetitive effects mentioned in Ausubel & Cramton (2010) such as allowing new entrants to participate in the DK1 market. Assuming that competition for the VPPs among bidders is not so fierce as to drive the premiums up to where they offer zero economic profits, it is also possible that end-users in DK1 are able to realize savings from holding VPP contracts.

There are many opportunities for future empirical research of VPP auctions. For those interested specifically in DK1, the analysis performed in this paper may be expanded to include other control variables such as the price of EU Emissions Trading Scheme carbon permits, uranium prices to account for the cost of nuclear power production in Sweden, Danish industrial exports, and so on. Those with access to very rich price, production and import/export data for power (as is the case with DK1) could attempt to inspect for the mechanism proposed in Schultz (2009) which postulates that incumbent firms could continue to realize monopoly prices when VPP auctions are competitive and occur frequently by simply reducing their own power output. Furthermore, researchers are by no means limited to DK1 to study VPP auctions: it may interest some to study the impact of VPP auctions on larger markets such as Spain or Germany. Others may choose to use more sophisticated econometric methods than those used in this thesis: by transforming data into log returns, one eliminates the problems that accompany non-stationary data but ends up sacrificing valuable long-run information contained within the data (Hjalmarsson 2000). To maintain this long-run time component, future studies could instead use cointegration techniques in order to examine if certain characteristics of the relationship between prices over time, such as the rate of convergence, have been significantly impacted by VPP auctions. In addition, some may wish to examine the other potential procompetitive effects of VPP auctions such as increased forward trading. Perhaps this could be accomplished by examining trading volume for futures contracts in power markets after the introduction of VPP auctions.

Whatever avenues future researchers choose to follow, there is still much to be discovered about VPP auctions.

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APPENDIX A

A Brief Introduction to Power Markets

The following section borrows material from Stoft (2002), as well as the Energy Information Administration.

Electricity is a commodity with unique characteristics that sets it apart from other commodities. As a consequence, electricity markets have several unique design features that are important to understand VPP auctions and the analysis of their effects in the DK1 price zone.

In the electric power industry, the supply of electricity over a specific time period is often called *generation* and the demand for electricity is called *load*. The demand for electricity is not constant over time. During the day when people are awake and active, the demand for electricity is higher than during the nighttime when people are less active sleeping. The highest amount of energy demanded during a given day is called *peak load*: this often times occurs somewhere in the early afternoon when people are at work and school. In contrast, *base load* refers to the baseline or minimum amount of power that is needed to meet demand at all hours of the day.

In addition, the term *generator* is loosely used to describe both a piece of equipment that produces electric power and the owner of said equipment. Generation can be thought of as the actual amount of electric power that has been supplied and is measured in megawatts hours (MWh), a unit that measures energy. *Capacity* in turn, is a flow variable defined as the maximum amount of electricity that a piece of equipment can produce. It is measured in megawatts (MW). For example, a power plant with a nameplate capacity of 300 MW can produce up to 300 MW of electricity at any given time. As we shall soon see, VPP contracts are also measured in capacity since they represent a power plant.

To more clearly illustrate the difference between generation and capacity, consider the following example. Imagine a power plant has a capacity of 50 MW. If this power plant produces 50 MW of electricity over the course of one hour then it will have produced 50 MWh. If it produces 50 MW of electricity over the course of 30 minutes then it will have produced 25 MWh. The capacity does not change over time but the generation does.

Electric power is delivered from generators to consumers via long, metallic cables called *transmission lines*. A large system of these lines forms a *transmission grid*, the network which connects all suppliers of electricity to their customers. In the Nordic countries, transmission grids are owned, maintained and developed by state-controlled, non-profit organizations called *transmission system operators* (TSO). In addition to other physical characteristics such as voltage and current, transmission lines are often measured by *power rating*, the maximum amount of electrical flow that the line can safely deliver. Just like a pipe can only transport a certain amount of water flow, transmission lines can only deliver a certain amount of power. If a line's power rating is exceeded, then there is a significant risk that the line will melt and break. As a result, transmission lines act as a constraint when TSOs and power exchanges calculate electricity prices: the computer algorithm that solves the dispatch allocation and price formation takes into account the power rating of transmission lines so that their power ratings are not exceeded. The Western Danish market is connected to Norway, Sweden, Germany and as of 2010, DK2 by high voltage transmission lines. A line that specifically connects electrical grids to one another in this manner is often called an *interconnector*.

Perhaps the most striking feature of electricity markets is that the demand and supply for electricity must always be exactly equal to one another. The reason for is due to the physical laws governing electricity transmission. In modern day grids, power is transmitted via *alternating current* (AC) distribution where the electricity actually changes charge in set time intervals. These intervals, measured by *frequency*, must always be exactly synchronized everywhere on the grid. As a direct result, if the amount of electric power being put onto the grid differs from the amount being taken off, then the system frequency will deviate and cause equipment failure and subsequent system collapse. It is the job of the TSO to ensure grid security and reliability by constantly balancing power supply and demand through dispatching market participants.

Sometimes there is insufficient transmission capacity to balance the demand and supply for electricity across geographic regions. For example, the demand for electricity in densely populated cities can sometimes exceed the amount of power that transmission lines can safely deliver. When this is the case, *congestion* is said to occur.

One important implication of congestion is that it can cause large, integrated power markets to become divided into smaller sub-markets. As we discussed above, the supply and demand of electric power must always be exactly equal. Consequently, if a region or city demands more power than power lines from the outside grid can supply, then a local generator located within the high-demand area must supply the extra power needed to balance the system. When local markets form and there are only a few number of firms available to balance supply and demand, then these firms may possess *market power*, the ability to charge prices that far exceed the cost of producing a unit of electricity.

APPENDIX B

Figure B1: The DK1-SE Price spread from 1 January 2003 through 31 December 2009, measure in Danish crowns

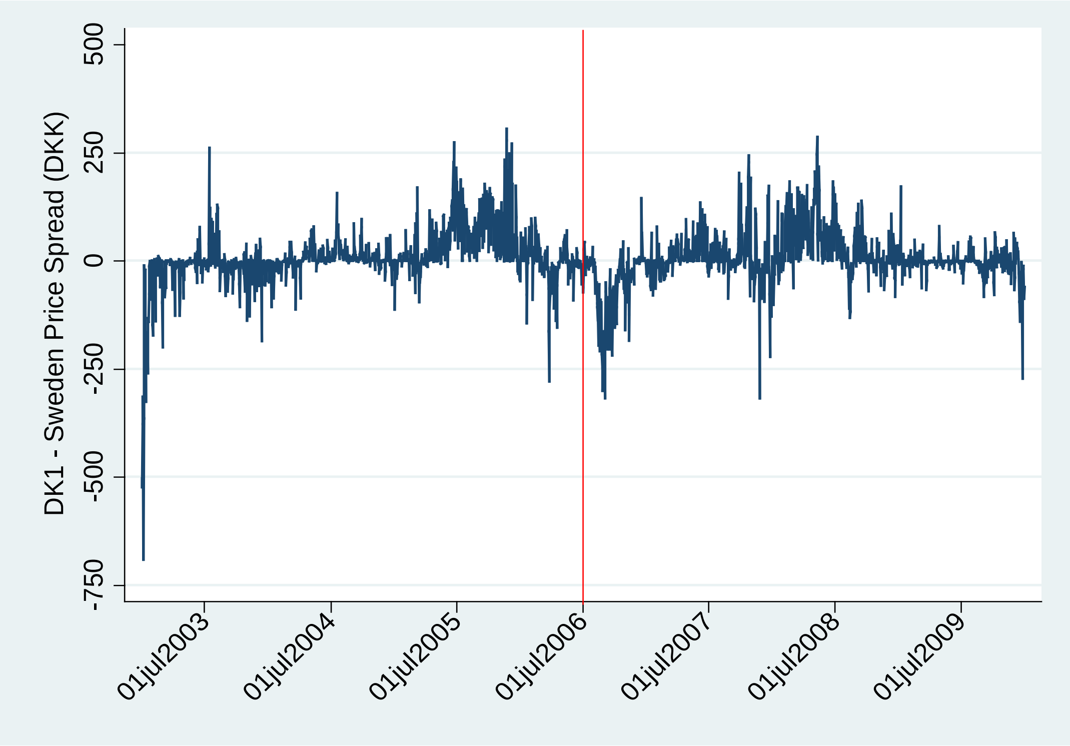
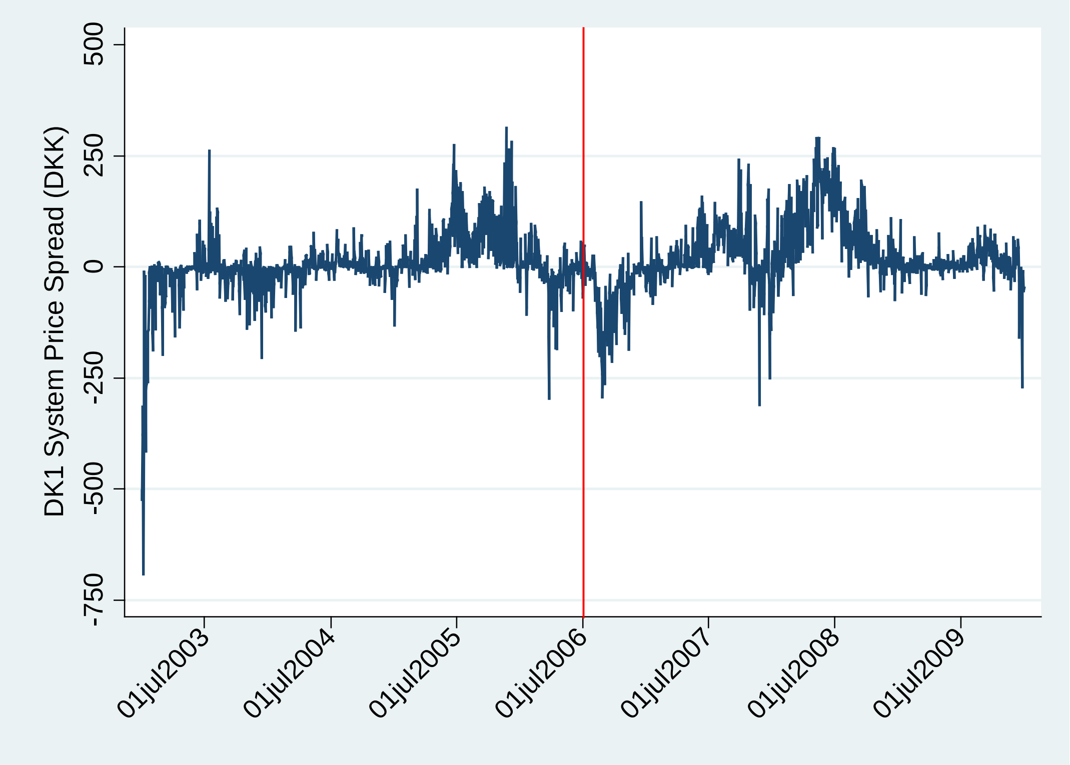


Figure B2: The DK1-System Price spread from 1 January 2003 through 31 December 2009, measured in Danish crowns



APPENDIX C

Table C1: Table C2: Generalized Least Squares Dickey-Fuller Unit Root Test Results and Augmented Dickey-Fuller Unit Root Test Results for Variables used in Econometric Analysis

Variable	DF-GLS tau t-stat	Augmented DF
DK1 Price N=5140	-3.492*** (lag 32)	-3.609*** (lag 32)
SE Price N=4291	-5.070*** (lag 30)	-3.970*** (lag 30)
SYSTEM Price N=5140	-4.318*** (lag 32)	-4.224*** (lag 32)
DK1-SE price spread N=4291	-6.228*** (lag 30)	-21.503*** (lag 30)
CPH20 N=5139	-1.141 (lag 32)	0.517 (lag 32)
Coal N=5139	-2.279 (lag 32)	-1.816 (lag 32)
Wind DK1 N=5140	-6.972*** (lag 32)	-5.328*** (lag 32)
Precip N=5140	-5.038*** (lag 32)	-7.033*** (lag 32)
HHI **N=5141**	-1.304 (lag 32)	-0839 (lag 32)

*   indicates statistical significance at the 10% level
**   indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level

Table C2: Augmented Dickey-Fuller Unit Root Test Results for Log-differenced Variables used in Econometric Analysis

Log-Differenced Variable	Augmented DF
DK1 Price N=5069	-17.354*** (lag 32)
SE Price N=4290	-13.378*** (lag 32)
SYSTEM Price N=5139	-15.208*** (lag 32)
DK1-SE price spread N=4257	-14.393*** (lag 32)
CPH20 N=5138	-11.953*** (lag 32)
Coal N=5138	-11.017*** (lag 32)
Wind DK1 N=5139	-19.787*** (lag 32)
Precip N=3034	-12.040*** (lag 32)
HHI N=5141	-12.925*** (lag 32)

*** indicates statistical significance at the 1% level

APPENDIX D

Figure D1: Autocorrelation Function for Daily Average Spot Prices in the Western Danish Price Area (DK1)

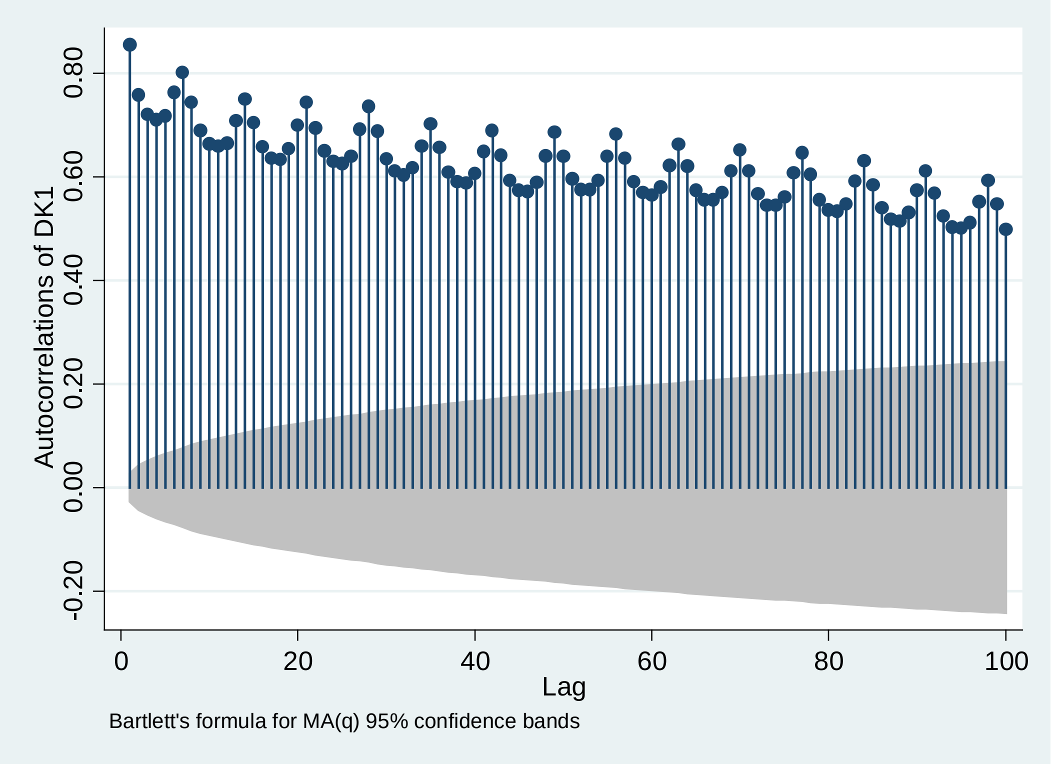


Figure D2: Autocorrelation Function for Daily Average Spot Prices in the Swedish Price Area (SE)

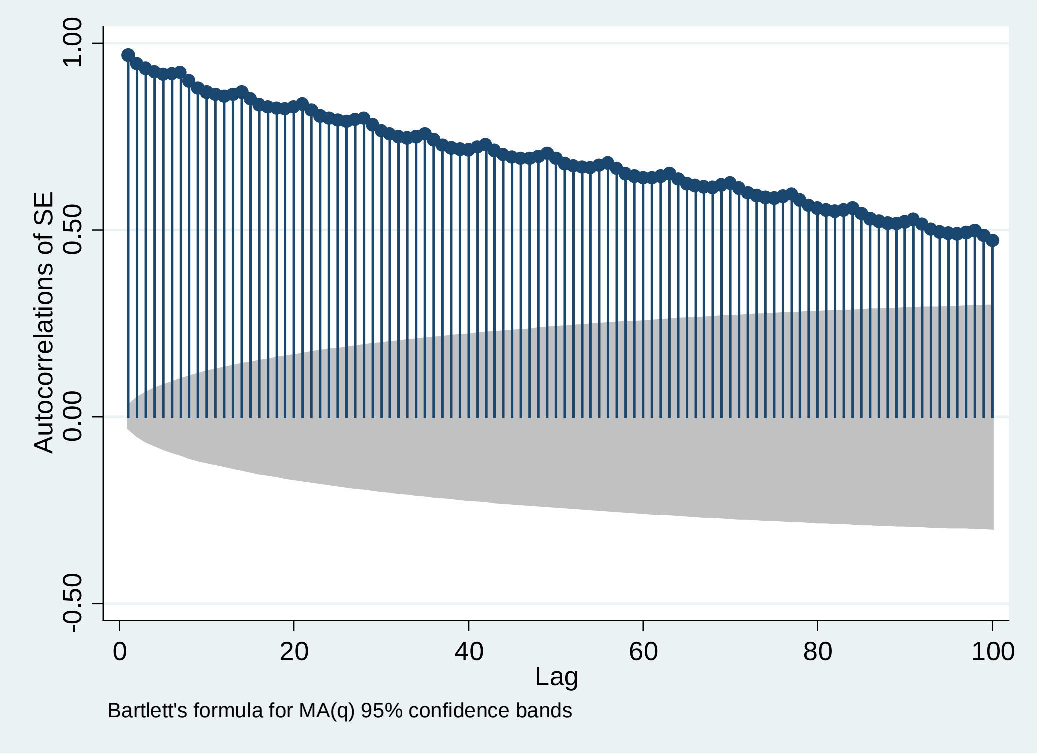


Figure D3: Autocorrelation Function for Daily Average Spot Prices in the Western Danish Price Area (DK1)

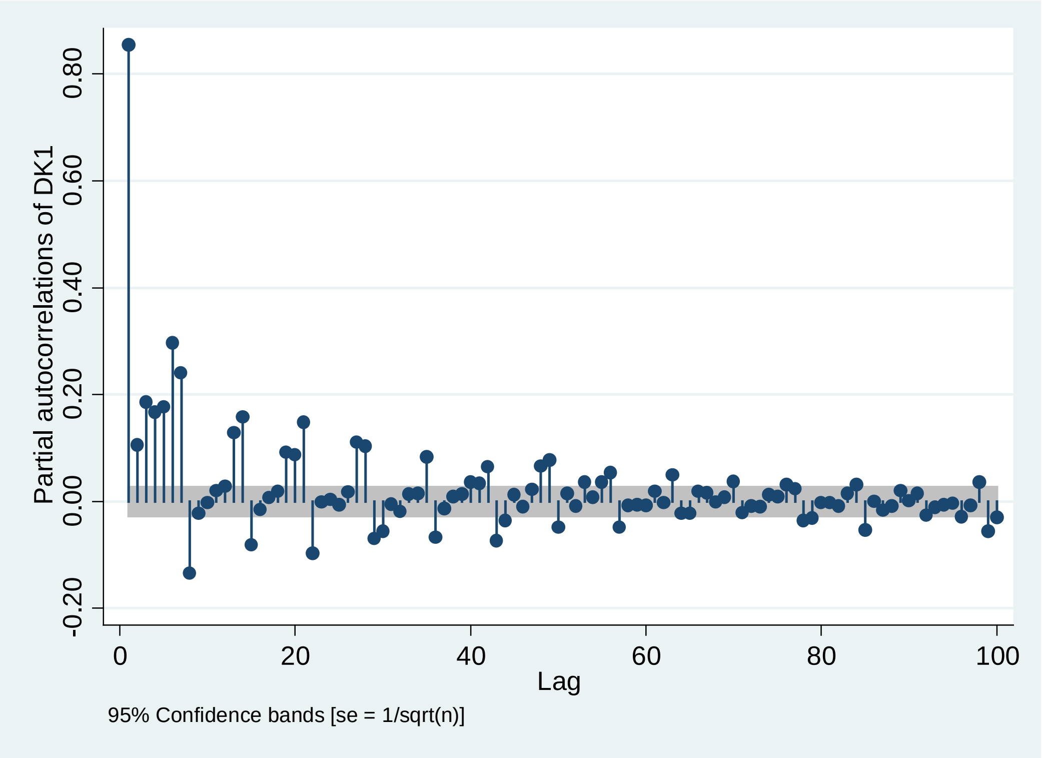
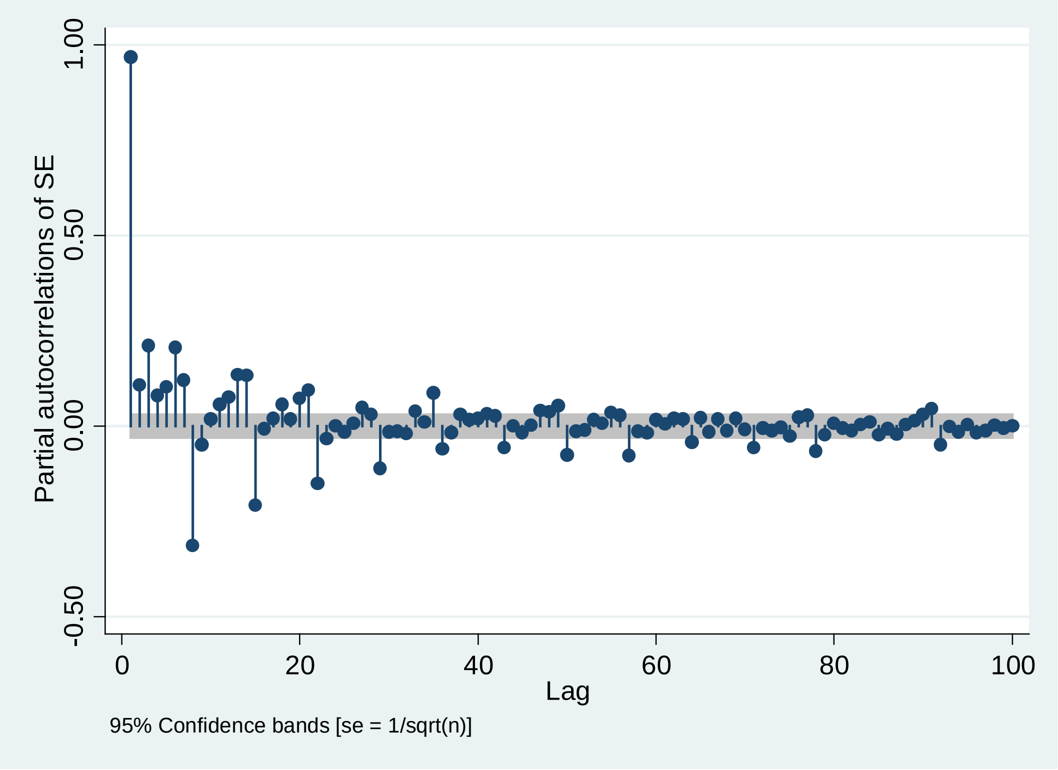


Figure D4: Partial Autocorrelation Function for Daily Average Spot Prices in the Swedish Price Area (SE)



APPENDIX E

Table E1: ARCH/GARCH/GARCH-M Regressions Results on DK1-SE Price Spread Returns from Jan 1 2003 until December 31, 2009

Independent Variable	Model Specification					
	1	2	3	4	5	6
Constant	0.005	0.006	-0.002	0.001	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.009)	(0.010)	(0.010)
Wind Production DK1	-0.038***	-0.038***	-0.038***	-0.038***	-0.037***	-0.037***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Norwegian Precipitation	-0.008*	-0.008*	-0.009*	-0.007**	-0.007**	-0.007***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Coal Price	0.667	0.699	0.638	0.579	0.602*	0.583
	(0.513)	(0.513)	(0.539)	(0.354)	(0.338)	(0.374)
CPH20	0.176	0.177	0.135	0.195	0.217	0.216
	(0.173)	(0.186)	(0.186)	(0.169)	(0.170)	(0.179)
HHI	0.052	0.006	-0.001			
	(0.451)	(0.442)	(0.442)			
VPP250				-0.003	-0.005	-0.005
				(0.011)	(0.012)	(0.012)
MERGER/ VPP250				-0.006	-0.008	-0.009
				(0.011)	(0.012)	(0.012)
MERGER/ VPP500				0.037	0.039	0.039
				(0.025)	(0.025)	(0.027)
MERGER/ VPP600				0.001	0.001	0.000
				(0.010)	(0.010)	(0.010)
ARCH 1	0.833***	0.845**	0.771**	0.927***	0.956**	0.913*
	(0.323)	(0.358)	(0.365)	(0.362)	(0.390)	(0.468)
GARCH 1		0.058	0.094		0.060	0.085
		(0.053)	(0.070)		(0.045)	(0.079)
ARCH-M			0.366			0.257
			(0.307)			(0.603)
OMEGA	0.016***	0.014***	.014***	0.015***	0.013***	0.013***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Log Likelihood	943.01	949.74	952.97	957.94	967.27	969.47
AIC	-1870.02	-1881.49	-1885.94	-1893.89	-1910.54	-1912.95
BIC	-1823.65	-1829.32	-1827.97	-1830.12	-1840.97	-1837.59
Observations	2433	2433	2433	2433	2433	2433

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level
Standard Errors in parenthesis

Table E2: ARMA-GARCH(1,1) Regression Results on DK1-SE Price Spread Returns from Jan 1 2003 until December 31, 2009

Independent Variable	Model Specification					
	1	2	3	4	5	6
Constant	-0.003 (0.003)	-0.003 (0.002)	-0.004 (0.002)	-0.004 (0.002)	0.000 (0.001)	-0.004 (0.002)
Wind Production DK1	-0.041*** (0.005)	-0.041*** (0.006)	-0.040*** (0.006)	-0.040*** (0.005)	-0.041*** (0.005)	-0.040*** (0.006)
Norwegian Precipitation	-0.010** (0.004)	-0.009** (0.004)	-0.009** (0.004)	-0.010** (0.004)	-0.010** (0.005)	-0.009** (0.004)
Coal Price	0.321 (0.276)	0.252 (0.280)	0.352 (0.305)	0.367 (0.201)	0.333 (0.331)	0.358 (0.201)
Coal lag 1	0.021 (0.228)	-0.148 (0.204)	-0.009 (0.216)	-0.008 (0.215)	0.036 (0.215)	-0.007 (0.215)
Coal lag 2	-0.067 (0.372)	-0.051 (0.298)	-0.111 (0.344)	-0.121 (0.355)	-0.127 (0.379)	-0.117 (0.358)
CPH20	-0.234 (0.225)					
HHI					0.431* (0.261)	
VPP250	0.002 (0.004)	0.002 (0.004)	0.003 (0.004)	0.003 (0.004)		0.003 (0.004)
MERGER & VPP250	0.005 (0.004)	0.004 (0.005)	0.005 (0.004)	0.005 (0.004)		0.005 (0.004)
MERGER & VPP500	0.007** (0.003)	0.010 (0.006)	0.008** (0.004)	0.008** (0.003)		0.008** (0.003)
MERGER & VPP600	0.005* (0.003)	0.004 (0.002)	0.005** (0.003)	0.005** (0.003)		0.005** (0.003)
AR 7	0.129*** (0.035)	0.131*** (0.047)	0.126*** (0.036)	0.125*** (0.037)	0.131*** (0.038)	0.126*** (0.035)
AR 14	0.072*** (0.024)	0.064*** (0.022)	0.070*** (0.024)	0.070*** (0.024)	0.076*** (0.025)	0.070*** (0.023)
AR 21	0.031 (0.020)	0.031 (0.022)	0.029 (0.021)	0.029 (0.021)	0.026 (0.021)	0.029 (0.021)
AR 28	0.030 (0.041)	0.011 (0.075)	0.028 (0.050)	0.028 (0.053)	0.029 (0.035)	0.028 (0.052)
AR 35	-0.026 (0.026)	-0.024 (0.030)	-0.027 (0.027)	-0.027 (0.026)	-0.028 (0.027)	-0.026 (0.026)
AR 42	0.132*** (0.038)	0.136*** (0.036)	0.136*** (0.036)	0.136*** (0.036)	0.142*** (0.039)	0.136*** (0.036)
AR 49	0.005 (0.026)	0.022 (0.021)	0.009 (0.024)	0.008 (0.025)	0.015 (0.022)	0.009 (0.024)
AR 56	0.019 (0.033)	0.023 (0.044)	0.016 (0.038)	0.016 (0.038)	0.015 (0.042)	0.016 (0.038)
AR 63	0.076** (0.031)	0.080** (0.036)	0.073** (0.029)	0.074** (0.031)	0.083** (0.033)	0.074** (0.031)
AR 70	0.086*** (0.028)		0.086*** (0.028)	0.085*** (0.029)	0.083*** (0.034)	0.085*** (0.028)
AR 77	0.005 (0.028)			0.006 (0.028)		
MA 1	-0.562*** (0.040)	-0.556*** (0.043)	-0.559*** (0.048)	-0.562*** (0.044)	-0.548*** (0.045)	-0.557*** (0.044)
MA 2	-0.158***	-0.150***	-0.158***	-0.158***	-0.167***	-0.158***

	(0.032)	(0.039)	(0.034)	(0.034)	(0.036)	(0.034)
MA 3	-0.096*	-0.089**	-0.092**	-0.090**	-0.090**	-0.090**
	(0.049)	(0.035)	(0.047)	(0.042)	(0.038)	(0.042)
MA 4	-0.079***	-0.068**	-0.082**	-0.081**	-0.093***	-0.081**
	(0.030)	(0.032)	(0.032)	(0.032)	(0.034)	(0.032)
MA 5			0.006			
			(0.033)			
ARCH	1.151***	1.103***	1.152***	1.151***	1.164***	1.151***
	(0.412)	(0.426)	(0.412)	(0.418)	(0.484)	(0.412)
GARCH	0.020	0.023	0.024	0.023	0.023	0.024
	(0.022)	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)
OMEGA	0.009***	0.010***	0.009***	0.009***	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
AIC	-2554.00	-2538.22	-2551.25	-2551.28	-2529.96	-2553.11
BIC	-2385.88	-2387.50	-2388.93	-2388.97	-2390.84	-2396.60
Log likelihood	1306.00	1295.11	1303.62	1303.64	1288.98	1303.56
Observations	2433	2433	2433	2433	2433	2433
ADF residuals lag 1	-43.42***	-44.36***	-43.67***	-43.72***	-43.93***	-43.75***
ADF residuals lag 32	-8.16***	-8.40***	-8.17***	-8.15***	-8.47***	-8.16***
ADF residuals lag 50	-7.28***	-7.63***	-7.27***	-7.25***	-7.81***	-7.27***

* indicates statistical significance at the 10% level
** indicates statistical significance at the 5% level
*** indicates statistical significance at the 1% level
Standard Errors in parenthesis

APPENDIX F

Figure F1: Autocorrelation Function out to lag 100 for Residuals from ARMA (7 14 21 28 35 42 49 56 63 70, 0, 4)-GARCH(1,1) Regression on DK1-SE Price Spread Returns (Model 6 in Table 6)

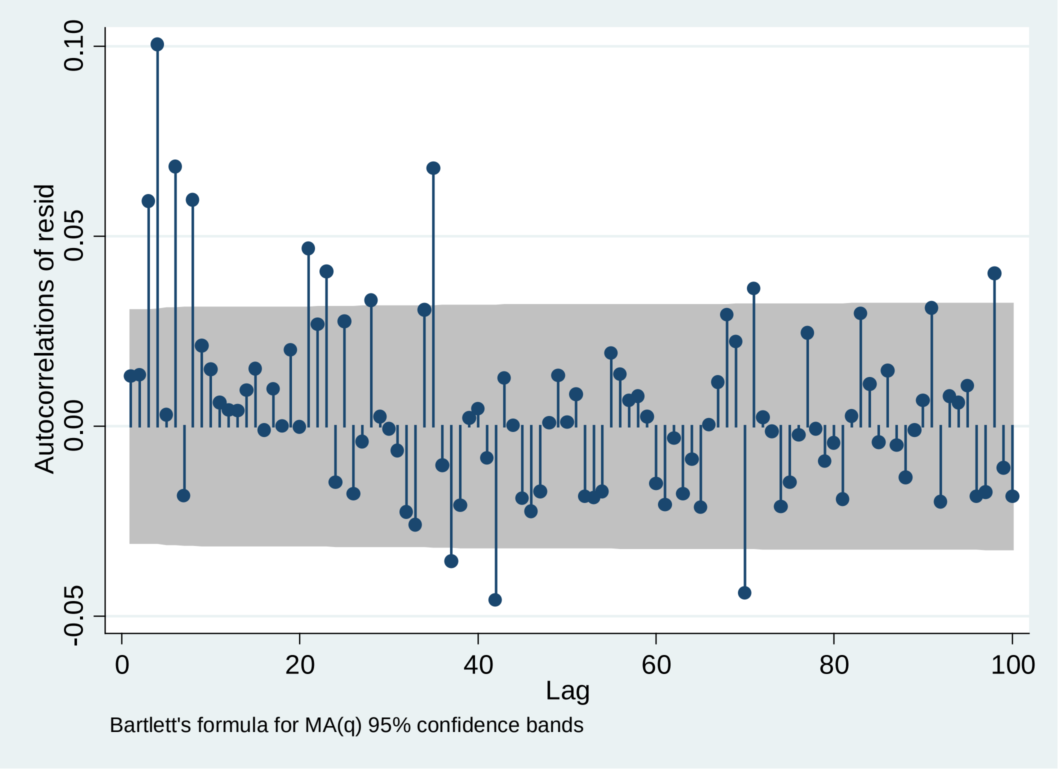


Figure F2: Partial Autocorrelation Function out to lag 100 for Residuals from ARMA (7 14 21 28 35 42 49 56 63 70, 0, 4)-GARCH(1,1) Regression on DK1-SE Price Spread Returns (Model 6 in Table 6)

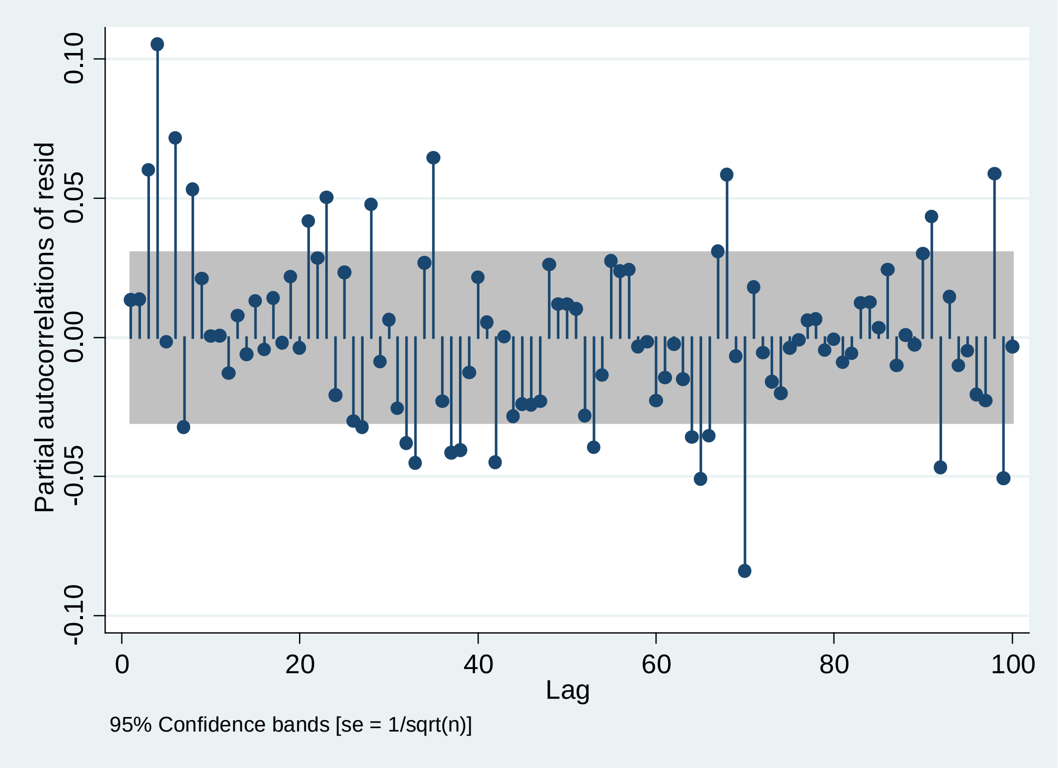


Figure F3: Autocorrelation Function out to lag 650 for Residuals from ARMA (7 14 21 28 35 42 49 56 63 70, 0, 4)-GARCH(1,1) Regression on DK1-SE Price Spread Returns (Model 6 in Table 6)